The Skill Premium Across Countries

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Abstract

This paper examines how technological progress, structural transformation, and international trade shaped the evolution of the skill premium across 37 countries at different stages of development from 1995 to 2009. I argue that observed patterns of structural transformation mask competing forces that operate in opposite directions, a feature that is particularly strong in developing economies where sectoral skill intensities differ sharply. In such settings, the rising share of college-educated workers and skill-biased technological change should, absent offsetting forces, reallocate workers toward sectors less reliant on college-educated labor, such as agriculture. The fact that workers instead moved away from agriculture implies that technological progress in this sector was especially fast, lowering relative prices of agricultural goods and driving up the skill premium. Calibrating a multi-sector model, I find that technological progress raised the skill premium by 152% in low-income countries, compared with 38% in middle- and high-income countries. By contrast, changes in trade patterns played only a minor role in most cases.

JEL Classification: E24, F16, J24, and J31.
Keywords: Skill Premium, Technological Change, Structural Transformation, International Trade.

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1 Introduction

Several features of modern economies have important consequences for wage inequality. First, automation tends to replace routine jobs while complementing more qualified workers. Second, as economies develop, value-added shifts toward services, a sector that typically employs more qualified workers. Third, international trade alters the relative demand for commodities across sectors, with non-trivial effects on the demand for different types of labor. In this paper, I analyze the role that each of these mechanisms has played in shaping the hourly wage of workers with a college degree relative to those without one—commonly referred to as the skill premium—between 1995 and 2009 in 37 countries at different stages of development. I will refer to college-educated workers as high-skill and workers without a college degree as low-skill.

I make three main arguments. First, the structural transformation patterns observed in the data mask competing forces, some of which actually reallocate value-added and workers toward low-skill-intensive sectors, and these forces are stronger in developing countries. Second, as a result, technological progress must have had a larger impact on the skill premium in less developed countries. Third, changes in the composition of net exports of final goods and services had quantitatively small effects on the skill premium in most countries.

A large literature documents a sustained rise in the U.S. skill premium, typically attributed to skill-biased technological change: modern technologies tend to complement skilled labor while replacing unskilled labor. But this pattern is not unique to the U.S. Using data for 37 countries at different stages of development between 1995 and 2009, I document a U-shaped relationship between changes in the skill premium and GDP per worker. On average, the skill premium increased by 32% in low-income countries, declined by 4% in middle-income countries, and rose by 1% in high-income countries.

To interpret these patterns and analyze the driving forces, I build a static general equilibrium model with two types of labor—high skill and low skill—and two sectors, one intensive in high-skill labor and one intensive in low-skill labor, as in Buera et al. (2021). Two crucial primitives of the model determine the skill premium: the relative supply of high- to low-skill labor and the nature of technological change.

An increase in the relative supply of skilled labor lowers the skill premium. Beyond supply, the model accommodates two types of technological change, which influence the skill premium through distinct channels. Skill-biased technological change raises the skill premium by making skilled labor relatively more productive. Skill-neutral technological change does not alter relative productivity directly, but it affects the skill premium through structural reallocation across sectors. With non-homothetic preferences, overall productivity growth generates an income effect that shifts expenditure shares and workers across sectors. In addition, sector-specific skill-neutral technological change alters relative goods prices and induces reallocation of value added and workers. Throughout the paper, I refer to this reallocation of workers across sectors as structural transformation.

I show that the extent of skill-intensity heterogeneity across sectors plays a crucial role in shaping structural transformation. In an economy where the share of skilled labor is increasing and technological change is skill-biased, production in high-skill-intensive sectors becomes relatively cheaper. If commodities produced in different broad sectors of the economy are net complements, as typically found in the literature,[1] this mechanism induces a reallocation of value added and workers toward low-skill-intensive sectors. However, in the data we observe the opposite pattern: workers move away from low-skill-intensive sectors. This contrast implies that the standard forces of structural transformation must be strong enough to offset the upward pressure from skill-biased technological change and the rising share of skilled workers.

I document that developing countries exhibit greater heterogeneity in skill intensity across sectors, implying that their observed patterns of structural transformation mask strong but offsetting sources of reallocation. In India, for example, the share of hours worked in high-skill-intensive sectors grew by 17% between 1995 and 2009—only moderate relative to other countries in my sample, despite the economy's rapid growth. At first glance, such a modest reallocation could be taken as evidence of weak structural transformation, perhaps reflecting near-homothetic preferences or relatively even technological progress across sectors. Through the lens of my model, however, this interpretation is misleading. In India, sectors are highly heterogeneous in skill intensity, and the share of high-skill labor rose by 70% over the same period, which on its own would have sharply reduced the relative price of commodities produced in high-skill-intensive sectors and driven workers out of them. The fact that workers nonetheless moved into these sectors—albeit moderately—implies that the standard drivers of structural transformation

[1] See for example Herrendorf, Rogerson and Valentinyi (2013)

must be especially strong: non-homothetic preferences and faster technological progress in low-skill-intensive sectors.

I calibrate the model separately for each country using data from 1995 and 2009. The relative supply of high- versus low-skill workers is taken directly from the observed share of hours worked by education group in the World Input-Output Database (WIOD), aggregated with sectoral value-added weights. Skill-biased technological change is disciplined by the observed evolution of sectoral skill intensities: the parameters governing the productivity of skilled labor relative to unskilled labor in each sector are chosen to replicate these shares. Skill-neutral technological change is disciplined by the evolution of relative commodity prices and aggregate output: sectoral total factor productivities are calibrated to match both the observed changes in relative prices across sectors and the growth of aggregate GDP.

With this calibration in hand, I use the model to quantify the role of technological progress in shaping the skill premium by asking the following question: how much higher was the skill premium in 2009 compared to a counterfactual world where the state of technology remained at its 1995 level, while the relative supply of skilled labor evolved as observed. I find that the impact of technological progress on the skill premium was considerably higher in developing countries: it increased the skill premium on average by 152% in low-income countries, and by 38% in both middle- and high-income countries. The contribution of skill-neutral technological change is higher for countries with larger structural transformation and more heterogeneous skill intensity across sectors. On average across all countries, skill-neutral technological change accounts for 33% of the overall technology effect on the skill premium.

I extend the model by exogenously introducing net exports by sector, which allows me to quantify a Stolper–Samuelson channel operating through changes in trade patterns exogenous to the model. By shifting relative demand across sectors, such changes alter the relative price of factor inputs and thereby affect the skill premium. This mechanism, however, turns out to be quantitatively limited: for most countries, trade pattern changes explain only a small share of the observed variation in the skill premium. On average across all countries, they account for just 4% of the total change in the demand for skills required to rationalize observed movements in the skill premium.

1.1 Related Literature

My paper contributes to three branches of the literature: one on the role of skilled biased technological change as a driver of the skill premium, one on the drivers of structural transformation, and one that links the skill premium to international trade.

The role of skill-biased technological change. A large literature—e.g., Katz and Murphy (1992), Bound and Johnson (1992), Murphy and Welch (1992), and Berman, Bound and Griliches (1994)—argues that SBTC is the primary force behind the rise in the U.S. skill premium since 1980. In contrast, and following Buera et al. (2021), I use a multi-sector environment in which skill-neutral technological change also influences the skill premium via structural transformation, allowing me to decompose the overall technology effect into skill-biased and skill-neutral components. Relative to Buera et al. (2021), I extend this decomposition to a broader cross-country sample that includes both developed and developing economies and show that both the magnitude of technology's effect on the skill premium and its skill-biased/skill-neutral split vary systematically with the stage of development. Relatedly, Berman, Bound and Machin (1998) provide cross-country evidence consistent with skill biased technological change in developing economies; my contribution is to quantify its importance across countries while explicitly distinguishing it from the skill-neutral channel.

Drivers of structural change. The literature on structural change has typically focused on shifts in value added and employment across broad sectors—first from agriculture to manufacturing, and later from manufacturing to services. Early work includes Baumol (1967), with more recent contributions by Kongsamut, Rebelo and Xie (2001) and Ngai and Pissarides (2007). A comprehensive overview is provided by Herrendorf, Rogerson and Valentinyi (2013). Following Buera et al. (2021), I classify industries by their skill intensity and study how the skill premium interacts with structural transformation, that is, the reallocation of workers between low- and high-skill intensive sectors. Buera et al. (2021) emphasize the role of skill-neutral technological change and show that it is the only quantitatively important driver of U.S. structural transformation over 1970–2005.

My contribution to this literature is threefold. First, I formally derive conditions under which structural transformation is driven solely by skill-neutral technological change, with homogeneity of sectoral skill intensity as a key requirement. Second, I document that skill intensity is more heterogeneous across sectors in developing economies, implying that observed patterns of structural transformation in these countries mask strong but offsetting forces. Third, I show quantitatively that rising skill shares and skill-biased technological change slowed down structural transformation toward the skill-intensive sector in developing countries between 1995 and 2009.

The role of international trade. A branch of the literature links international trade to the skill premium, often by quantifying the effect of lower trade costs through various mechanisms. The classic Stolper–Samuelson channel, arising from changes in the composition of net exports, has generally been found to be dominated by other forces: in Parro (2013) and Burstein, Cravino and Vogel (2013) by the complementarity between equipment and skilled labor; in Burstein and Vogel (2017) by the reallocation of value added and employment toward more productive firms within sectors; and in Caron, Fally and Markusen (2020) by income effects that induce structural transformation. My contribution is to quantify a Stolper–Samuelson mechanism that remains largely unexplored: the effect of any change in trade patterns—not only those triggered by changes in trade costs—on the skill premium. The closest paper to mine is Cravino and Sotelo (2019), but there are two key differences. First, they measure trade pattern changes between goods and services, whereas I distinguish between high- and low-skill intensive commodities. Second, they compare the observed skill premium to a counterfactual in which the economy is closed, while I ask a different question: of the total increase in demand for skills needed to account for changes in the skill premium, how much can be attributed to trade pattern changes?

The rest of the paper is organized as follows: in Section 2 I describe the data and document some cross-country patterns. In Section 3 I describe the basic model and its equilibrium conditions, discuss the sources of structural transformation, and extend the model to incorporate trade patterns. In Section 4 I describe how I discipline the model to match key features of the data. In section 5 I perform several counterfactual analyses and deliver the main quantitative results. In section 6 I outline a set of related issues that could be addressed in a dynamic framework. I conclude in Section 7.

2 Skill Premium Across Countries: Empirics

2.1 Data Sources

The main data source for the facts reported in this section as well as for the calibration of the model is the Socio-Economic Accounts of the WIOD, 2014 release. It contains yearly data on inputs and outputs by industries classified according to the International Standard Industrial Classification (ISIC) for 40 countries between 1995 and 2011. Crucially, it includes information on disaggregated hours worked and labor compensation by three education levels. I group two of them together and end up with two levels: workers with at least some tertiary education degree, and the rest. I refer to the first group as high-skill workers or skilled workers and to the second as low-skill workers. I compute the skill premium in each country as the average hourly wage of high-skill workers divided by the average hourly wage of low-skill workers.

Although the original database contains information up to 2011, I drop the last two years since they are not available for many countries. Additionally, I drop three countries that have missing data for some industries: Cyprus, Latvia and Sweeden. The final database is a balanced panel with yearly data from 1995 to 2009 for 37 countries that are heterogeneous in their stage of development.

Data on net exports by industry and by country is obtained from the United Nations Comtrade Database. Both imports and exports of goods by industry are available for the period 1995-2009, but data on services is only available starting in the year 2000. Most of the industries that will be classified as high-skill intensive to calibrate the model are actually services, so having their net exports both at the beginning and at the end of the period will be crucial to have a notion of how the composition of net exports by skill intensity evolves. Additionally, some trade data is missing for Belgium and Taiwan. Therefore, the trade data shown in this section as well as the results obtained in section 5.3 where trade data is used corresponds to the period 2000-2009 and does not include Belgium and Taiwan.

A difficulty in merging the Comtrade and WIOD data arises since Comtrade does not classify industries according to the ISIC classification. I obtain the international trade data in the Standard International Trade Classification (SITC) from Comtrade, then match SITC to ISIC industries using the concordance R package developed by Liao et al. (2020).

Lastly, information on GDP by country (adjusted by purchasing power parity) and total number of workers are obtained from the Penn World Table, version 10.0.

2.2 Classification of Industries

To take the model to the data, I classify industries into two sectors: the high-skill intensive, and the low-skill intensive. The classification is country-specific and fixed over time in order to keep track of the relative size of sectors.

I proceed in three steps. In step one, I define the skill intensity of industry j in country i at time t as the share of hours worked by skilled workers in the total number of hours worked. In step two, I define the sectors by year: industry j in country i at time t is assigned to the high-skill intensive sector if and only its skill intensity is higher than the average in country i at time t. In step three, I summarize the yearly classification into a unique one: industry j in country i is assigned to the high-skill intensive sector if and only if it was classified as high-skill intensive in at least half of the years in step 2. A table with all industries describing the classification for all countries is included in Appendix A. In general, industries producing services are classified as high-skill intensive more often than other industries.

2.3 Cross Country Patterns

There is a body of literature establishing and analyzing the increase in the skill premium in the US since 1980, but such an increase is not a unique feature of the US economy: several countries exhibit sharp increases in their skill premium between 1995 and 2009 as shown in the top panel of Figure 1 where the percentage change in skill premium is plotted against GDP per worker. The solid line is the best quadratic fit for the 37 countries in the graph, and the dashed line is the best quadratic fit after weighting countries by the number of workers in 1995. Remarkably, two of the poorest countries in the sample experience some of the highest increases in skill premium: China and Indonesia. There is more in general a U-shape pattern: the slope of the best quadratic fit is increasing. To better quantify this pattern, I split countries into three groups based on their GDP per worker: below 20% of the US, between 20% and 80% of the US, and above 80% of the US. I refer to these groups as low income, medium income, and high income respectively.

The cut-offs are arbitrary and simply picked so that the last country assigned to a group is not "too close" to the first country in the next group. Among low-income countries, the skill premium increased on average 32% between 1995 and 2009, where the average is weighted by countries' number of workers. For medium-income countries, the skill premium actually decreased on average by 4%, and for high-income countries, it increased on average by %1. I will try to understand the forces underneath this pattern through the lens of a model where the skill premium is driven by different forces shaping the supply and demand for skills.

In the literature, technological change has been found to be the main force driving the increase of the skill premium observed in the US, especially skill-biased technological change. Whether these results hold more in general for all countries does not follow from the top panel of Figure 1 since the observed change in skill premium is the result of interactions between supply and demand forces. In India for instance, the fact that the skill premium is flat does not directly imply the absence of skill-biased technological change. In fact, the share of skilled labor in total labor shows an increase of roughly 60% in India as shown in the bottom panel of Figure 1, so absent any demand changes, the skill premium should have actually dropped. But those demand changes that are required to compensate for the increase in the relative supply of skills in India, as in other countries, do not necessarily have to be linked to skill-biased technological change: even skill-neutral technological change can generate skill premium movements via structural transformation, as it will be shown in Section 3. Making a cross-country comparison of the role of technological change in the evolution of skill premium, as well as distinguishing between the role of skill-biased and skill-neutral technological change requires a theory of demand for skills.

One of the channels through which technological change can affect the skill premium is international trade, even in a simple Heckscher-Olhin environment where the composition of net exports in an economy is determined by its comparative advantages, which in turn depend on the state of technology. More in general, we would expect shifts in the composition of net exports toward industries that are intensive in high-skill (low-skill) workers to be associated with increases (decreases) in the skill premium, regardless of where those shifts originate. I refer to this mechanism as Stolper-Samuelson. The direction in which it should affect the skill premium in 1995 is illustrated in Figure 2 where for better visualization, I only include the ten largest countries in the sample by their number

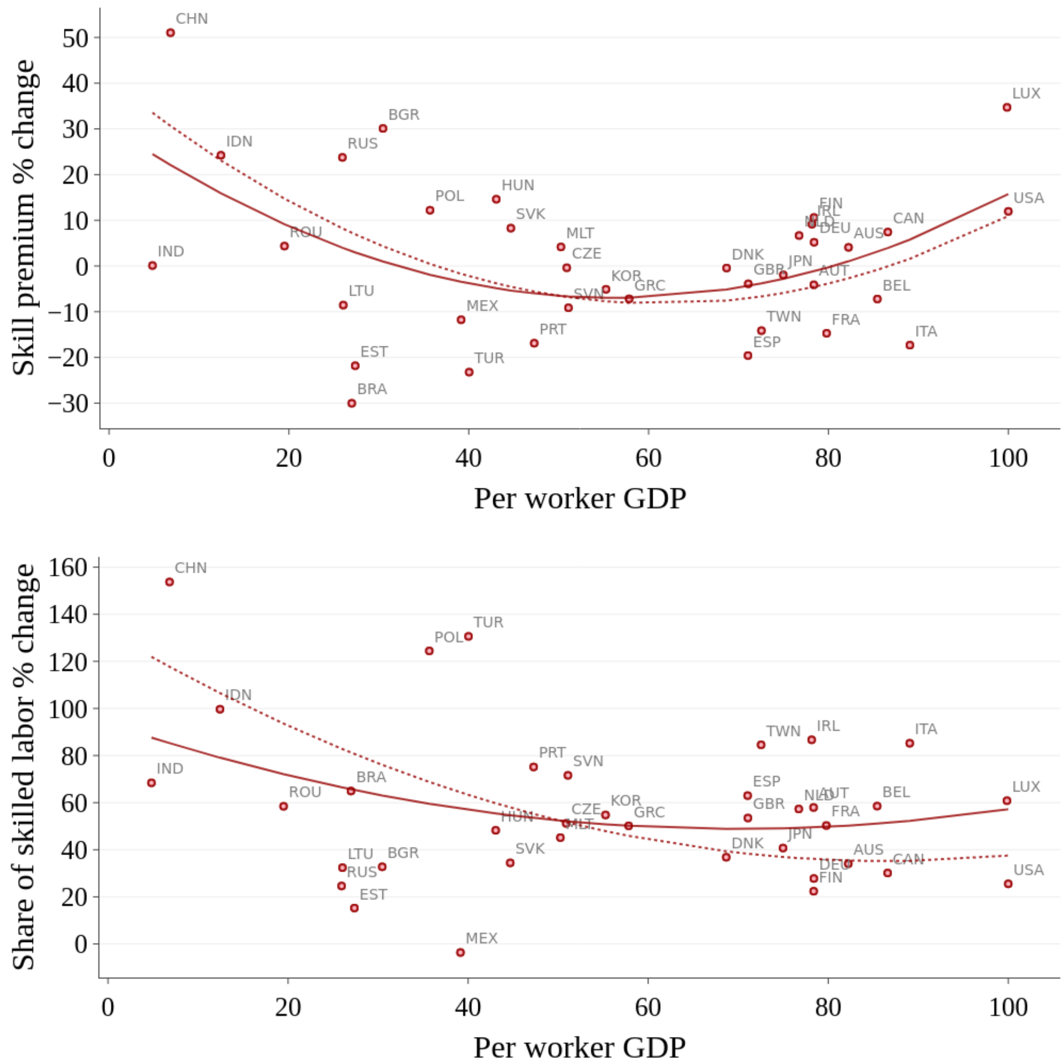

Figure 1: Skill premium and relative supply of skills

Notes: The horizontal axis in both panels shows GDP per worker in PPP in 1995 for each country, where the US is normalized to 100. In both panels, the solid line is the best quadratic fit to the scatter plot, and the dashed line is the best quadratic fit after weighting each country by the number of workers in 1995.

of workers in 1995 (the graph for all countries is included in Appendix E). The horizontal (vertical) axis is the percentage change in the share of net exports in value-added for the low-skill (high-skill) intensive sector, and the solid line is the 45-degree line. The Stolper-Samuelson mechanism should push the skill premium upward in countries above the 45-degree line and downward in countries below it. Can this mechanism alone compensate for the increase in the share of skilled labor in India, so that the skill premium remains flat as in the top panel of Figure 1? Can it play a quantitatively important role in the US?

How strong is it in other countries? I will address these questions using an extension of the basic model that incorporates a notion of trade patterns.

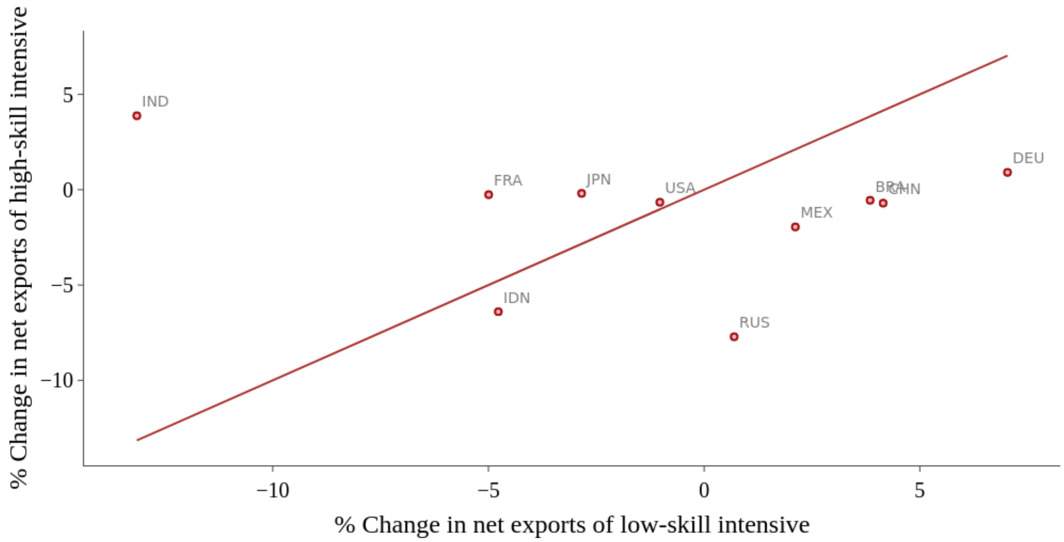

Figure 2: Changes in trade patterns

Notes: Percentage changes in the share of net exports in value added for the high and low-skill intensive sectors between the years 2000 and 2009. The ten largest countries according to their number of workers in 1995 are displayed. The solid line is the 45-degree line.

3 Theoretical Pramework

To analyze the role of technology in shaping the skill premium as observed in the first panel of Figure 1, I build on the theoretical framework from Buera et al. (2021). It essentially consists of a static model depicting a closed economy where the skill premium is driven by three exogenous factors: relative supply of skilled labor, skill-neutral technology, and skill-biased technology. Therefore it allows quantifying the role of technological change on the skill premium, accounting for changes in the relative supply of skills. The role of technological change can be further decomposed into a skill-biased and a skill-neutral component. In the model, technological change can affect the skill premium in a direct way if it is skill-biased by altering the relative productivity of skills and shifting the demand for each type of worker. Similarly, changes in the relative supply of skills affect the skill premium directly by making one type of worker more abundant. But both technology and the relative supply of skills shape the skill premium in a more indirect way by inducing structural transformation where workers shift across sectors. After discussing the sources of structural transformation, I extend the model to incorporate international trade exogenously in order to quantify the effect of changes in trade patterns on the skill premium.

3.1 The Basic Model: A Closed Economy

There is a continuum of households with measure one, a fraction f_h of them endowed with one unit of high-skill labor, and a fraction $1 - f_h$ endowed with one unit of low-skill labor. Households supply their unit of labor inelastically and perceive wage w_h if high skilled or w_l if low skilled. Preferences are identical across households and defined over two commodities, indexed by 1 and 2. Utility from consuming the bundle $\{c_1, c_2\}$ is given by

$$u(c_1, c_2) = \left[a_1 (c_1 + \bar{c}_1)^{\frac{\epsilon - 1}{\epsilon}} + (1 - a_1)(c_2 + \bar{c}_2)^{\frac{\epsilon - 1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon - 1}} \tag{1}$$

where $\epsilon > 0$ governs the elasticity of substitution between commodities; $\bar{c}_1 \geq 0$ and $\bar{c}_2 \geq 0$ capture non-homotheticity of preferences; and $0 < a_1 < 1$ is a weight on commodity 1. Unlike Buera et al. (2021), this utility representation allows the expenditure share of either good 1 or 2 to be increasing in income, a feature that will be needed to match the evolution of expenditure shares in different countries.

On the production side, there is a continuum of firms with measure one producing each commodity $j \in \{1, 2\}$ using the production function

$$Y_j = A_j \left[\alpha_j H_j^{\frac{\rho - 1}{\rho}} + (1 - \alpha_j) L_j^{\frac{\rho - 1}{\rho}} \right]^{\frac{\rho}{\rho - 1}} \tag{2}$$

where H_j and L_j are high and low-skill labor inputs respectively, $\rho \geq 0$ is a constant elasticity of substitution between skills, $A_j \geq 0$ governs total factor productivity in sector j, and α_j governs the productivity of high-skill labor relative to low-skill labor in sector j. I assume $0 < \alpha_1 \leq \alpha_2 < 1$ which guarantees that in equilibrium sector 2 operates with higher skill-intensity. Thus, I refer to sector 1 as the low-skill intensive and to sector 2 as the high-skill intensive. Changes in the total factor productivity parameter A_j are referred to as skill-neutral technological change in the sense that they have no direct effect on the relative productivity of skills, although they can still impact the skill premium through structural transformation as will be discussed in section 3.3.

I emphasize that parameters $\{A_j, \alpha_j, \rho\}$ represent the state of technology in sector j in a broad sense. Changes in the skill-neutral parameter A_j capture any proportional change in the productivity of both factors, while changes in the skill-biased parameter α_j capture any changes in the productivity of high-skilled labor relative to low-skilled labor. Since I abstract from capital, this implies for instance that higher capital stock will be absorbed by A_j and α_j. Furthermore, international trade is not modeled explicitly but it will affect the calibration of technology parameters. For example, in a standard Heckscher-Ohlin environment, reductions in international trade costs would shift production and labor toward the sector where the country has a comparative advantage. Without a notion of net exports by sector and with constant preference parameters over time, as it will be imposed when the model is taken to the data, the model will necessarily interpret such shift as a response to technological change. Net exports by sector are introduced in Section 3.4 to isolate this mechanism.

3.2 Equilibrium

There are four markets in this economy, all assumed to be competitive: labor of high and low skill, commodity 1, and commodity 2. A competitive equilibrium consists of wages $\{w_h, w_l\}$, prices of commodities $\{p_1, p_2\}$, consumption plans $\{(c_{h1}, c_{h2}), (c_{l1}, c_{l2})\}$, production plans $\{Y_1, Y_2\}$, and labor demands $\{(H_1, L_1), (H_2, L_2)\}$ such that (c_{h1}, c_{h2}) maximizes (1) subject to the budget constraint

$$w_i = p_1 c_{i1} + p_2 c_{i2}, \tag{3}$$

firms in sector j maximize profits given prices by producing Y_j and demanding (H_j, L_j), and all markets clear. I will choose one unit of low-skill labor as a numeraire so that $w_l = 1$ and w_h is the skill premium.

The demand for commodity j by a household of type i is given by

$$c_{ij} = \frac{w_i}{p_j + p_k \left(\frac{p_j}{p_k}\frac{a_k}{a_j}\right)^{\epsilon}} + \frac{p_k \bar{c}_k}{p_j + p_k \left(\frac{p_j}{p_k}\frac{a_k}{a_j}\right)^{\epsilon}} + \frac{\bar{c}_j}{p_j + \frac{p_j}{p_k}\left(\frac{p_j}{p_k}\frac{a_k}{a_j}\right)^{-\epsilon}} \tag{4}$$

where $a_2 \equiv 1 - a_1$. This demand illustrates the role of the non-homothecity paramters: The ratio c_{ij}/c_{ik} is independent of income w_i if $\bar{c}_1 = \bar{c}_2 = 0$, but not in general.

Firms use a constant return-to-scale technology, so the scale of production is determined by households' demand. Regardless of the production level, the ratio between high-skill and low-skill labor input used by a firm in sector j is given by

$$\frac{H_j}{L_j} = \left(\frac{\alpha_j}{(1-\alpha_j)w_h}\right)^{\rho}. \tag{5}$$

Naturally, this relative demand for skills is decreasing in the skill premium and increasing in the relative productivity of high-skill labor. Three main drivers for the skill premium follow from equation (5): two exogenous ones, and structural transformation which emerges endogenously. The first exogenous mechanism is the share of skilled labor f_h: suppose it increases and abstract from any structural transformation, so suppose the total number of hours worked in each sector remains the same. Then the share of high-skill labor must increase in at least one sector to clear the labor markets. By (5), the skill premium must decrease.

For the second exogenous mechanism, suppose α_j increases and again, abstract from any structural transformation. If the skill premium did not adjust, then by (5) the share of high-skill labor increases in sector j and remains constant in the other sector. Without changes in the share of employment in each sector, labor markets would not clear. Then the skill premium must actually increase.

Finally, consider a structural transformation that shifts workers say from sector 1 to sector 2. To simplify, assume the structural change emerged due to changes in $\{A1, A2\}$ but not in $\{\alpha_1, \alpha_2, f_h\}$. If the skill premium did not adjust, by equation (5) both sectors would keep their shares of skilled labor constant. But if $\alpha_2 > \alpha_1$, then $H_2/L_2 > H_1/L_1$, so the aggregate demand for high-skill labor relative to low-skill labor increases and the labor markets cannot clear. Then the skill premium must increase. Similarly, structural transformation toward sector 1 would decrease the skill premium. I turn to the analysis of how structural transformation arises endogenously in the next section. A description of the algorithm used to compute the equilibrium is included in Appendix B.

3.3 Sources of structural change

When I take the model to the data, five parameters will be allowed to change over time and drive both the changes in the skill premium and structural transformation: A_1, A_2, α_1, α_2 and f_h. With non-homothetic preferences, increases in a measure of aggregate productivity generate structural transformation through an income effect. However, structural transformation arises endogenously even with homothetic preferences through a variety of mechanisms in this model, and the relative importance of each mechanism depends crucially on how different sectors are in terms of their intensity in the use of skills. Unfortunately, there is no closed-form solution for the share of total labor employed in sector j for the general model, but I discuss how structural transformation emerges making use of the following proposition.

Proposition 1 *Let preferences be homothetic and skill intensity be homogeneous across sectors. Then structural transformation is entirely driven by skill-neutral technological change. Moreover, if commodities are complements then the share of total labor employed in sector* 1 *is strictly decreasing in* $\dfrac{A_1}{A_2}$.

The proof is in Appendix C. Intuitively, with homogeneous skill intensity across sectors, i.e. $\alpha_1 = \alpha_2 = \alpha$, changes in α affect both sectors symmetrically so they do not alter relative prices. Moreover, changes in f_h affect the skill premium, but again with symmetric effects across sectors. Additionally, homothetic preferences prevent any income effect on the expenditure shares chosen by households. In absence of income effects and changes in relative prices, consumers keep their expenditure shares unchanged and the distribution of total hours worked by sector is unaffected. Skill-neutral technological change however does alter relative prices if it is uneven across sectors. In concrete, if A_1/A_2 increases then sector 1 becomes relatively more productive, and commodity 1 becomes relatively cheaper. If commodities are net complements as in the calibration that I will use, the expenditure share of commodity 1 decreases, and workers shift toward sector 2.

With non-homothetic preferences, the share of skilled labor can indeed induce structural transformation even with $\alpha_1 = \alpha_2$ by affecting the aggregate productivity of the economy. Moreover, skill intensity heterogeneity across sectors opens new sources of structural transformation because relative prices depend on the state of skill-biased technology and the share of skilled labor. In an economy where the share of skilled labor is increasing and technological change is skill-biased, production in sector 2 becomes relatively cheaper. If the two commodities are complements, as is typically assumed for goods and services, value-added and workers should reallocate to sector 1, the sector with lower skill intensity. Of course, this is not what we see in the data, where countries tend to reallocate value-added and workers from low-skill intensity sectors to high-skill intensity ones. To rationalize this fact through the lens of the model, the standard forces of structural change must be sufficiently strong to compensate for the effects of skill-biased technical change and the rise in the share of high-skill workers. That is, non-homotheticities must be strong enough to induce structural transformation towards high-skill sectors as income grows in the economy, and skill-neutral technical change must be strong in the low-skill intensive sectors to drive the price in this sector down. All these forces are quantified in section 5.

3.4 Incorporating trade

In the basic model, technology is the only demand-side driver of the skill premium, but other forces may also affect the relative demand for skills. A remarkable one is trade patterns: if the economy's net exports of goods and services that are intensive in high-skill labor increase, then we should expect the skill premium to increase, even absent any technological change. The goal with the extension in this section is precisely to isolate this mechanism and quantify its relevance across countries.

International trade patterns are introduced exogenously to the model. Specifically, net exports in sector j are a fraction $\phi_j \in [-1, 1]$ of sector j's production. Thus, the market clearing condition in sector j becomes

$$Y_j = f_h c_{jh} + (1 - f_h) c_{jl} + \phi_j Y_j$$

where the novelty with respect to the basic model is the term ϕY_j on the right-hand side. Furthermore, if the value of net exports is not zero then the net savings of the economy are not zero either. Put differently, absent any net savings (i.e. keeping them equal to zero) households spend all their income. Then that the total value of production, which equals aggregate households' income, will be equal to the total value of consumption. But this equality cannot hold if the total value of net exports is different from zero. Then the households' budget constraint must incorporate net savings, and it becomes

$$w_k = p_g c_{gk} + p_s c_{sk} + \underbrace{p_g \phi_j Y_j + p_s \phi_j Y_j}_{\textbf{net savings}}.$$

where aggregate production is taken by households as given. The solution for the household's problem is now different, although the firms' problem is unaffected. Intuitively, changes in trade patterns captured by (ϕ_1, ϕ_2) produce a Stolper-Samuelson effect on the skill premium: an increase in ϕ_1 increases the demand in the sector that is relatively intensive in low-skill labor, increasing the wage of low-skill workers and decreasing the wage of high-skill workers, thus lowering the skill premium. When both ϕ_1 and ϕ_2 change, the magnitude of these changes determines the direction of the adjustment in the skill premium.

4 Calibration

I calibrate the model independently country by country following the strategy in Buera et al. (2021). I use data for the years 1995 and 2009 to calibrate the basic model and for the years 2000 and 2009 to calibrate the extension with trade due to the data constraints discussed in Section 2. On the production side, ρ is considered constant over time and calibrated in accordance with existing estimates, whereas α_{jt} and A_{jt} target skill intensity by sector, growth of relative prices, and growth of the economy. Preference parameters are not allowed to change over time, and they are calibrated to target expenditure shares. Finally, the share of skilled labor is calibrated as a weighted average of the observed shares of skilled labor in each sector, where the weights are sectoral value-added shares. The advantage of this procedure is that it allows matching all targets almost exactly for all countries, as reported in Appendix D. The share of skilled labor by sector is one of the targets, but the aggregate share of skilled labor is not.

4.1 Technology parameters

There are nine technology parameters: $\{\rho, A_{jt}, \alpha_{jt}\}_{j\in\{1,2\},t\in\{0,T\}}$ where the first subscript denotes sector 1 or 2 and the second subscript denotes the time 0 or T. Once the elasticity of substitution between high-skill and low-skill labor ρ is determined, the other eight parameters can be calibrated to target (i) the skill intensity by sector, (ii) the growth of the relative price of commodities, and (iii) the growth of the economy. I set $\rho = 1.53$ following the calibration in Buera et al. (2021)[2].

I use condition (5) for labor demand to pin down α_j for each country at each period, where the measure of skill intensity on the left-hand side and the skill premium are taken from the data since they are targets and will be matched almost exactly.

The calibration of A_{jt} implies two choices of units, one for the volume of production in each sector. It is convenient to derive an equation that relates the price of each commodity p_{jt} to A_{jt} by combining the zero profit condition and (5)

$$p_j = \frac{1}{A_j}\left[\frac{\alpha_j^{\rho}}{w_h^{\rho-1}} + (1-\alpha_j)^{\rho}\right]^{\dfrac{1}{1-\rho}}. \tag{6}$$

I set $A_{10} = 1$ and choose A_{20} so that Equation (6) implies relative price of commodities equal to 1 at time 0, i.e. $p_{10} = p_{20}$. Then p_{2T}/p_{1T} in the model is the growth of the relative price of commodities, and using Equation (6) it is given by

$$\frac{p_{2T}}{p_{1T}} = \frac{A_{2T}}{A_{1T}}\left[\frac{\dfrac{\alpha_{2T}}{w_{hT}^{\rho-1}} + (1-\alpha_{2T})^{\rho}}{\dfrac{\alpha_{1T}}{w_{hT}^{\rho-1}} + (1-\alpha_{1T})^{\rho}}\right]^{\dfrac{1}{1-\rho}}. \tag{7}$$

The relative total factor productivity (TFP) at time T, A_{2T}/A_{1T}, is then chosen to match the relative price of commodities at time T observed in the data using Equation (7). Only

[2] Using their estimation strategy for ρ, I obtain an estimate close to 1 for the US. The estimation though is based on a time series analysis, and my series only includes 15 observations whereas Buera et al. (2021) have 36 since they use data for the period 1970-2005. Moreover, Katz and Murphy (1992) also estimate an elasticity of substitution between high-skill and low-skill labor that is considerably above 1. Therefore, I consider their estimate of ρ more reliable than mine.

the scale of the relative TFP at time T is left, and it is chosen to match the growth rate of the economy between times 0 and T. I first use the by-sector data to construct a Tornqvist index for the aggregate volume of production and measure the growth rate of the economy in the data as the growth rate of this index. I then choose the scale of relative TFP at time T to guarantee that the same index constructed with simulations in the model implies the same growth of the economy growth obtained with the actual data.

4.2 Preference parameters

There are four preference parameters: $\{\epsilon, a_1, \bar{c}_1, \bar{c}_2\}$, and they target the expenditure shares of households observed in the data at times 0 and T. Many combinations of these four parameters are consistent with the expenditure shares of households at two points in time though, so some restrictions need to be imposed. Studies in the literature such as Buera and Kaboski (2009), Herrendorf, Rogerson and Valentinyi (2013) and Święcki (2017) find low levels of substitutability between commodities produced in different broad sectors of the economy. I follow Buera et al. (2021) and set $\epsilon = 0.1$.[3]

The parameters $\bar{c}_1$ and $\bar{c}_2$ are meant to capture non-homotheticity in preferences, but having both of them different from zero would be redundant. I impose the restriction that at least one of them must be zero. I am left with three parameters to estimate, and three conditions: expenditure shares at times 0 and T, and $\bar{c}_1\bar{c}_2 = 0$. Even though the system is highly non-linear, in general, I numerically find a unique solution that allows me to match expenditure shares almost exactly, with the implication that all other targets are matched almost exactly as well. Details on how the model fits the targets are given in Appendix D.

4.3 Net exports

Calibrating net exports in the way I introduced them into the extended model is straightforward: I simply set ϕ_{jt} equal to the ratio between the value of net exports and the value of production at time t in sector j using data from the Comtrade Database.

[3]Findings in the literature, in general, were obtained for a different classification of commodities, typically as goods and services. Although I classify commodities by skill intensity, service industries are in general classified as high-skill intensive in most countries.

5 Counterfactual analysis

In this section, I use the model to quantify the effect of changes in technology and trade patterns on the skill premium for each country. I further decompose the effect of technological change into a skill-neutral and a skill-biased component and analyze quantitatively how they relate to structural transformation. The results obtained with the basic model correspond to the period 1995-2009, and the ones that use the extension with trade correspond to the period 2000-2009.

To quantify the effect of parameters in set X on the change in the skill premium, I do the following for each country: let $\hat{w}_{hT}$ be the skill premium implied by the calibrated model at time T, which is almost identical to the skill premium observed in the data as shown in Appendix D. Also let $\overline{w}_{hT,X}$ be the skill premium implied by the model using the calibration for period T in the case of parameters not in X, but the calibration for period 0 for the parameters in X. I interpret $\overline{w}_{hT,X}$ as the counterfactual skill premium that would have been observed at time T if the parameters in X and only in X were kept fixed at their values in the initial period. The effect of parameters in X on the change in the skill premium is measured as $\hat{w}_{hT} - \overline{w}_{hT,X}$. I emphasize that my counterfactual exercises abstract from any dependence of parameters not in X on parameters in X. Thus, they should be interpreted as accounting exercises to measure the direct effect of parameters in X on the skill premium, without considering any indirect effect through parameters that are not in X.

5.1 Change in skill premium: the role of technology

The discussion in Section 2 revealed a U-shape pattern across countries for the change in the skill premium during the period 1995-2009, where the increase was stronger in low-income countries. To better understand the role of technology in generating this pattern, I perform a counterfactual exercise where I fix the parameters in the set $tech = \{A_1, A_2, \alpha_1, \alpha_2\}$ at their calibrated values for the year 1995. The results are illustrated in Figure 3, where the technology percentage effect in the vertical axis is simply

$$100 \times \frac{\hat{w}_{hT} - \overline{w}_{hT,tech}}{\overline{w}_{hT,tech}}. \quad (8)$$

Remarkably, the contrast between low-income countries and the rest is still present: among low-income countries, technology increases the skill premium on average by 152%, whereas in both medium and high-income countries the effect is on average of 38%. China is responsible for most of the increase in the low-income group: the counterfactual skill premium in 2009 with fixed technology in China is only 0.74, compared to the observed skill premium of 2.1. But technology plays an important role also in Indonesia and India, even when the skill premium was flat in India. In fact, the effect of technology in India is substantially higher than in the US despite the fact that the skill premium increased in the US but remained flat in India. This result emphasizes the necessity of taking into account the relative supply of skills to assess the effect of technology adoption on the skill premium.

The magnitudes in the vertical axis of Figure 3 are considerably larger than the plain changes in skill premium, capturing the idea that the relative demand for skilled labor must not only increase to explain the rise in the skill premium but also to compensate for the increase in the relative supply of skills that took place in all countries in the sample.

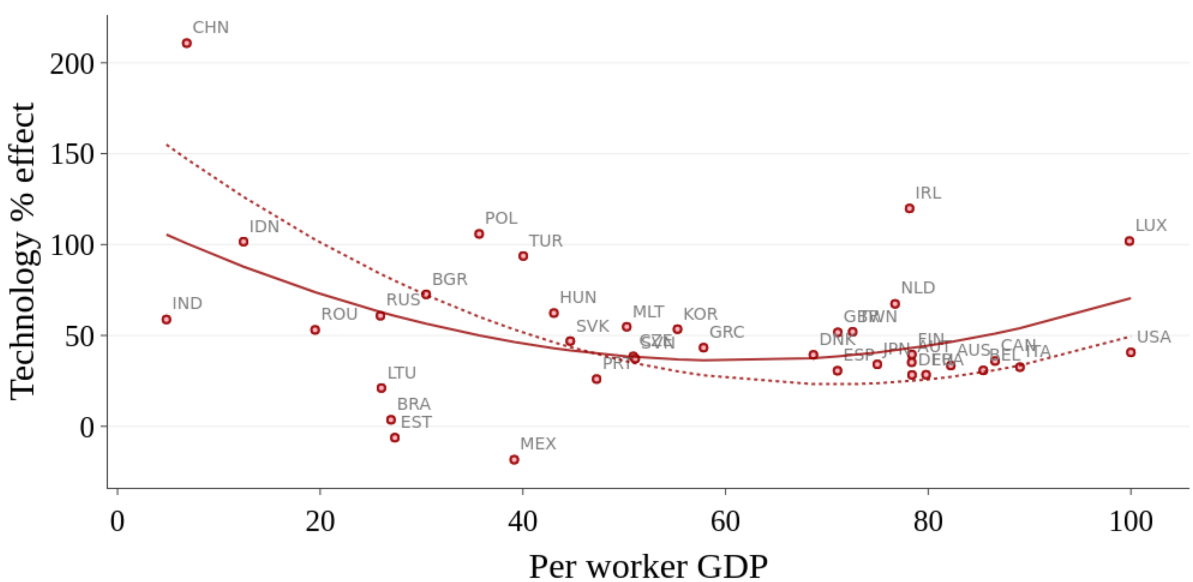

Figure 3: Effect of technology on the skill premium

Notes: Per capita GDP corresponds to the year 1995. The percentage technology effect on the skill premium corresponds to 1995-2009 and uses the expression (8). The solid line is the best quadratic fit to the scatter plot, and the dashed line is the best quadratic fit after weighting each country by the number of workers in 1995.

5.2 Technological change and structural transformation

Although it is natural to think of the technological change affecting the skill premium as skill-biased, skill-neutral technological change also affects the skill premium through structural transformation as discussed in Section 3.3. To measure the quantitative importance of this mechanism, I use the model to obtain two additional counterfactual skill premiums for the year 2009: $\overline{w}_{hT,A}$ is obtained by only fixing the skill neutral technology parameters in the set $A = \{A_1, A_2\}$ at their 1995 levels; $\overline{w}_{hT,\alpha}$ is obtained by only fixing the skill-biased technology parameters in the set $\alpha = \{\alpha_1, \alpha_2\}$. The technology percentage effect discussed in Section 5.1 can be decomposed as

$$100 \times \frac{\hat{w}_{hT} - \overline{w}_{hT,tech}}{\overline{w}_{hT,tech}} = \underbrace{100 \times \frac{\hat{w}_{hT} - \overline{w}_{hT,A}}{\overline{w}_{hT,tech}}}_{\text{skill neutral}} + \underbrace{100 \times \frac{\hat{w}_{hT} - \overline{w}_{hT,\alpha}}{\overline{w}_{hT,tech}}}_{\text{skill biased}} + \text{interaction}. \quad (9)$$

This decomposition is illustrated in Figure 4 for the ten largest countries in the sample by number of workers in 1995 (the graph for all countries is included in the appendix). For the US, I find that skill-neutral technological change accounts for 18% of the overall effect of technology on the skill premium. This is simply the quotient between the first term in the right-hand side of (9) and the left-hand side, or in Figure 4 the relative size of the skill-neutral bar in the entire bar of the US. This finding is close to the result obtained in Buera et al. (2021) where changes in skill-neutral technological change account for at most 21% of the effect of technological change on the skill premium, although they use data for the period 1977-2005.[4] It turns out, however, that in most countries the contribution of skill-neutral technological change is higher than in the US: out of the total technology effect on the skill premium, changes in A_j alone account for 31% in an average low-income country, 44% in an average medium-income country, and 25% in an average high-income country.

There are two fundamental reasons why skill-neutral technological change plays a larger role in most countries compared to the US, illustrated in Figure 5 where the horizontal axis is a measure of structural transformation toward the high-skill intensive sector, and the vertical axis is a measure of skill-intensity heterogeneity across sectors. First, structural transformation is smaller in the US than in most countries, then a weaker skill-

[4]Additionally, Buera et al. (2021) show that their result is consistent with the findings in Katz and Murphy (1992).

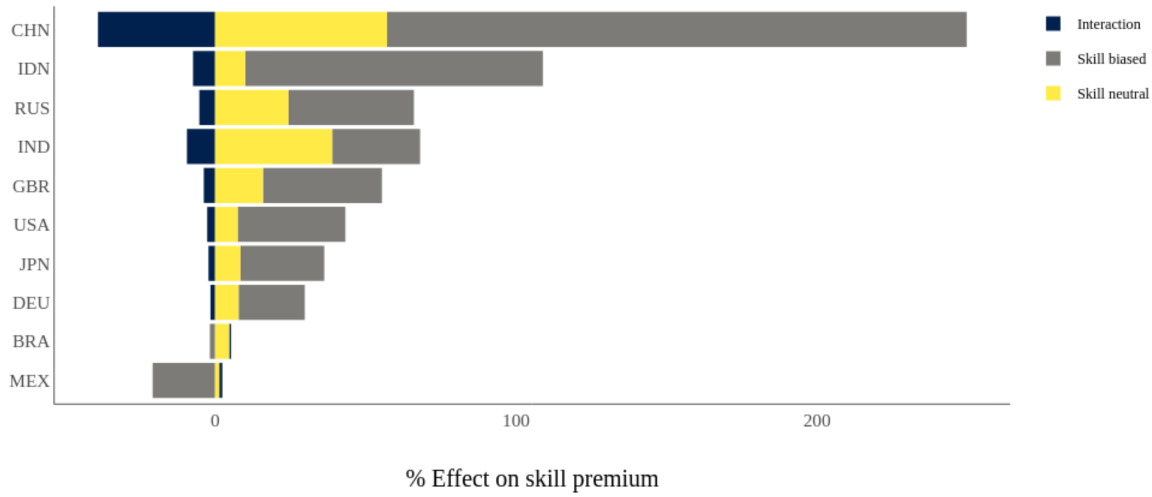

Figure 4: Technology effect decomposition

Notes: The figure shows a decomposition of the effect of technology on the skill premium in the period 1995-2009. The ten largest countries according to their number of workers in 1995 are displayed. The yellow and grey bars represent the effects of skill-neutral and skill-biased technological change respectively, and the dark-blue bar is an interaction effect.

neutral technological change is needed in the US to generate the observed shift toward the high-skill intensive sector. Second, skill intensity heterogeneity in the US is one of the lowest in the sample. It follows from the discussion in Section 3.3 that skill-biased technological change and the increase in the share of skilled labor have little ability to move workers toward the low-skill intensive sector in the US, and a small amount of skill-neutral technological suffices to compensate for those mechanisms.

To emphasize the role of skill-intensity heterogeneity, consider the case of India: the share of hours worked in the high-skill intensive sector grows by 17%, not exceptionally high in the sample, yet skill-neutral technological change explains 66% of the effect of technology on the skill premium, which was already large (59%). But the 17% structural transformation that we observe in India actually hides competing forces that play in different directions as illustrated in Figure 6, where structural transformation is decomposed into its sources for the ten largest economies[5]. Skill-neutral technological change plays such an important role in India, as well as in other countries, because it compen-

[5]The figure with all countries is included in Appendix E

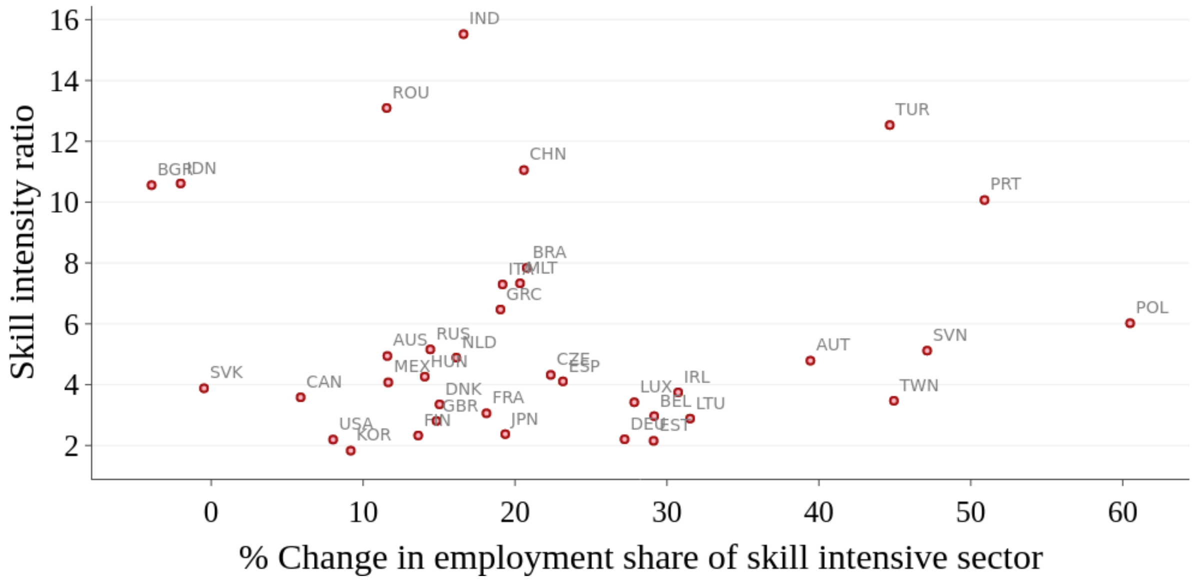

Figure 5: Technology effect decomposition

Notes: The percentage change in the employment share of the high-skill intensive sector shown in the horizontal axis corresponds to the period 1995-2009. The skill intensity ratio is measured in 1995 as $\frac{H_2/L_2}{H_1/L_1}$.

sates for other forces that arise strongly due to a large heterogeneity in skill intensity across sectors.

A more general cross-country pattern is illustrated in Figure 7: there is a clear negative correlation between the skill intensity in the high-skill intensive sector relative to the low-skill intensive sector and GDP per worker. Then structural transformation mostly reflects skill-neutral technological change in richer countries, consistent with the findings in Buera et al. (2021) for the US. In poorer countries, however, where skill intensity is more heterogeneous across sectors, both increases in the share of skilled labor and skill-biased technological change generate substantial reallocation of workers across sectors by making the skill-intensive commodity relatively cheaper as discussed in Section 3.3. An implication is that structural transformation is slowed down in poorer countries relative to a counterfactual case in which sectors were more homogeneous in their skill intensity, as we observe in developed countries.

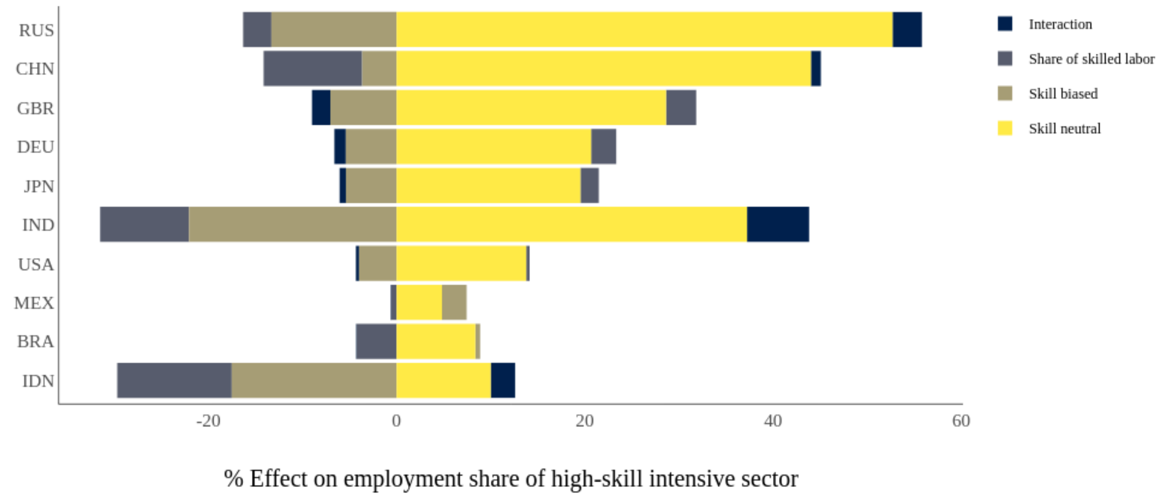

Figure 6: Structural transformation decomposition

Notes: The figure shows a decomposition of structural transformation during the period 1995-2009. Structural transformation is measured as the percentage change in the employment share of the high-skill intensive sector. The ten largest countries according to their number of workers in 1995 are displayed. The yellow and brown bars represent the effects of skill-neutral and skill-biased technological change respectively on structural transformation, the grey bar represents the effect of the aggregate share of skilled labor, and the dark-blue bar is an interaction effect.

5.3 Trade patterns

In Section 3.4, I argued that the trade patterns captured by ϕ_j in the extended model produce a Stopler-Samuelson effect on the skill premium. In this section, I quantify the importance of this mechanism by decomposing the total effect of changes in the relative demand for skills on the skill premium into a component that is captured by changes in trade patterns, and a residual that is not. In concrete, I obtain two counterfactual skill premiums: $\overline{w}_{hT,dem}$ where all drivers of relative demand for skills in the set $dem = \{A_1, A_2, \alpha_1, \alpha_2, \phi_1, \phi_2\}$ are held fixed at their calibrated value for the initial period (which is now the year 2000 due to trade data availability constraints); and $\overline{w}_{hT,trade}$ where only the trade parameters in the set $trade = \{\phi_1, \phi_2\}$ are held fixed. The results of the decomposition in the ten largest countries in the sample are shown in Figure 8. As before the figure including all countries is included in Appendix E.

In the US, I find a very small role for trade: only 1% of the demand effect on the skill

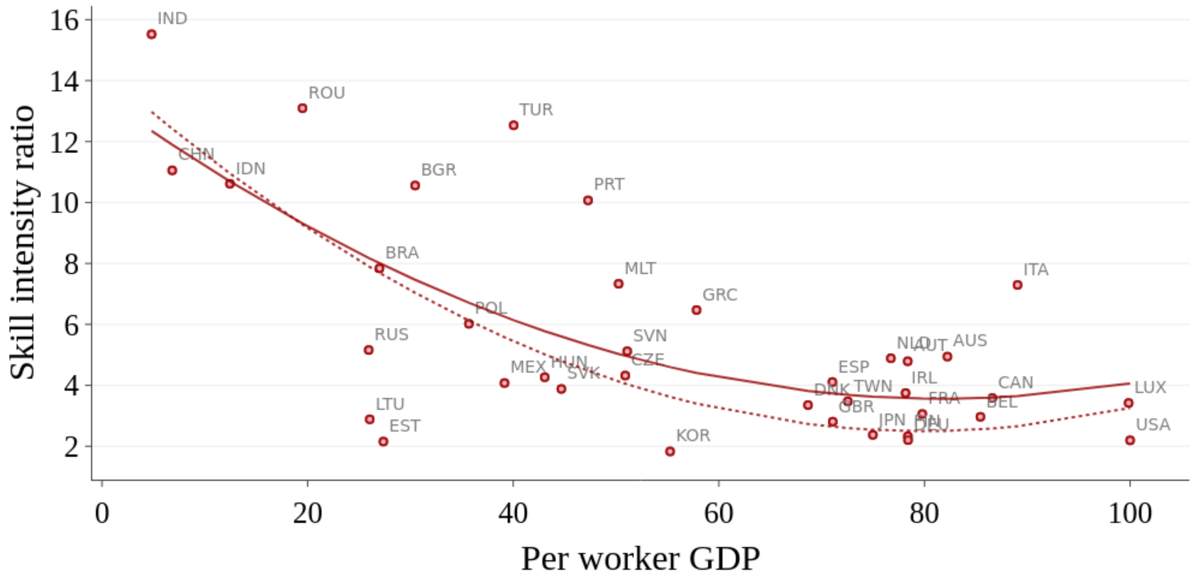

Figure 7: Relative skill intensity across sectors

Notes: The horizontal axis shows GDP per worker in PPP in 1995 for each country, where the US is normalized to 100. The skill intensity ratio in the vertical axis is measured also in 1995 as $\frac{H_2/L_2}{H_1/L_1}$. The solid line is the best quadratic fit to the scatter plot, and the dashed line is the best quadratic fit after weighting each country by the number of workers in 1995.

premium can be explained by changes in trade patterns, consistent with the findings in Buera et al. (2021). Moreover, for most large countries in the sample, trade patterns can only explain a small fraction of the demand effect on the skill premium, especially for countries where the overall demand effect is large. In China, for example, the value of net exports in the low-skill intensive sector as a share of the value of production increased from 2% in the year 2000 to 4% in 2009 while net exports in the high-skill intensive sector remained stable and close to zero, which explains the direction of the effect of trade patterns on the skill premium. However, the effect is relatively small: the skill premium is only 2% larger than it would be if trade patterns had stayed the same. India is an exception: the change in the relative demand for skills increases the skill premium by 35% between the years 2000 and 2009, and trade pattern changes explain roughly half of that effect. The importance of this mechanism in India is consistent with Figure 2: net exports became substantially more skill-intensive in that country. In an average high-income country, changes in trade patterns can explain less than 1% of the total effect of demand on the skill premium, and in an average low-income country they can explain

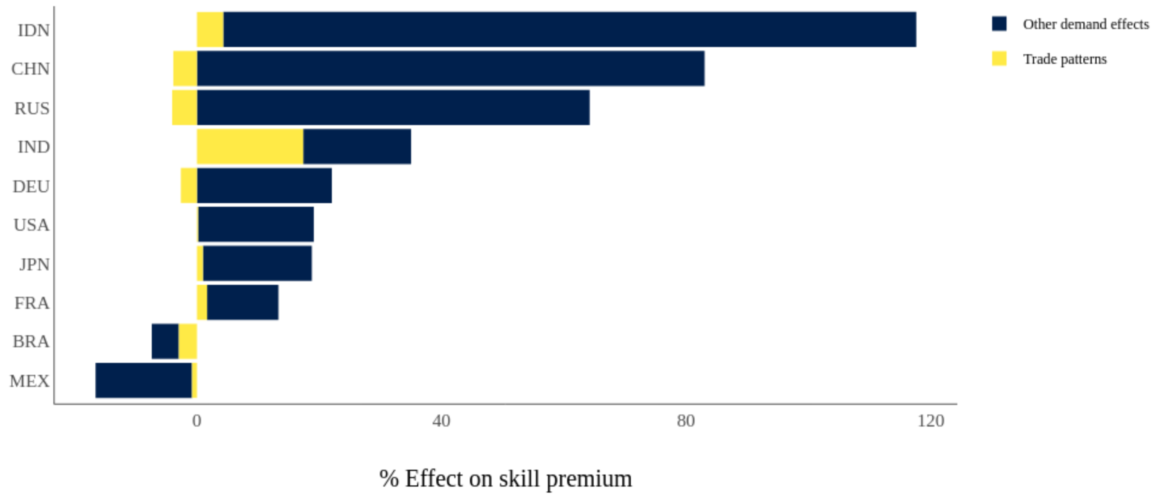

Figure 8: Contribution of changes in trade patterns

Notes: The figure shows a decomposition of the effect of changes in the relative demand for skills on the skill premium during the period 1995-2009. The ten largest countries according to their number of workers in 1995 are displayed. The yellow bar represents the demand effects that are captured by changes in trade patterns, and the dark-blue bar represents all other demand effects.

4%. In an average medium-income country, change in trade patterns actually decreased the skill premium by 4% since net exports became more low-skill intensive, but the overall demand effect was an increase of the skill premium by 22%.

The decomposition of demand effects on the skill premium illustrated in Figure 8 and discussed in this section should not be interpreted as distinguishing between a trade and a technology component. Indeed, technology and trade patterns are tightly linked, and my model does not allow isolating each of them. Even in a simple model of endogenous trade such as a Heckscher-Ohlin model, trade patterns in a country depend on relative productivity across sectors, hence on technology. Then the effect that I attribute to trade patterns actually contains a technology component. The main message from Figure 8 is that in most countries, even if trade patterns were held constant, most of the relative skill demand forces that affect the skill premium would have been in place, with some exceptions such as India. International trade could still play an important role in influencing the skill premium in other countries as I will discuss in Section 6, but the evidence in this paper suggests that it is hardly through a Stopler-Samuelson mechanism.

6 Further research: a dynamic approach

Using a static theory to analyze the skill premium imposes several limitations on the kind of questions that can be addressed. In this section, I briefly discuss three venues for research that could be undertaken in a dynamic theoretical framework: analyzing transition dynamics, incorporating investment decisions, and allowing endogenous trade imbalances.

Transition dynamics. The model used in this paper is silent about how the economy transitions from one equilibrium to another. For example, the result that in the US changes in trade patterns can only explain 1% of the demand effect on the skill premium, as all quantitative results in this paper, are a strict comparison between two points in time: 2000 and 2009 for the case of the results obtained using trade data. That is, if in 2009 trade patterns in the US were those of the year 2000, then the demand effect on the skill premium would be only 1% smaller than observed. Whether or not trade patterns played an important role in the transition from the year 2000 to 2009 remains unanswered. Similarly, the model would be able to make a prediction for the skill premium after a certain shift in trade patterns, once the economy reaches the new equilibrium; but questions such as how long it takes to reach the new equilibrium and what happens along the way would require a dynamic framework.

Investment decisions. A static framework is not able to incorporate investment decisions and how they affect the skill premium. For instance, in a static model, an increase in the relative supply of high-skill workers has no effect on the relative demand for skills, so the effect on the skill premium is unambiguous. However, in a dynamic model with investment, an increase in the relative supply of skilled labor could have a positive impact on the capital stock since skilled workers perceive higher income. If capital and skills are complements, then the relative demand for skills would shift upward, and the direction of the response of the skill premium would be ambiguous. In the approach I took in this paper, changes in the capital stock that shift the productivity of high-skill labor relative to low-skill labor are associated with changes in technology. But if we wished to predict the skill premium after a certain change in the share of high-skill workers and account for the fact that the stock of capital would be affected, a different environment would be needed. Consider for example a simple one-sector model where a composite of high-skill labor and capital is produced using a constant elasticity of substitution ϕ given by

$$X = \left(H^{\frac{\phi - 1}{\phi}} + K^{\frac{\phi - 1}{\phi}} \right)^{\frac{\phi}{\phi - 1}},$$

and the final good is produced using the composite X and low-skill labor with a Cobb-Douglas technology

$$Y = X^{\alpha} L^{1-\alpha}.$$

With competitive labor markets and taking factor supplies as given, the skill premium in this model is

$$\frac{w_h}{w_l} = \frac{\alpha}{1-\alpha}(1 - f_h) f_h^{\frac{-1}{\phi}} \left[f_h^{\frac{\phi - 1}{\phi}} + K_s^{\frac{\phi - 1}{\phi}} \right]^{\frac{1-\phi}{\phi - 1}}.$$

This expression is decreasing in the share of skilled labor f_h, and increasing in capital supply K_s if $\phi < 1$, i.e. if capital and skilled labor are complements. If an increase in the share of skilled labor causes aggregate investment to go up, then the direct effect of f_h on the skill premium would be at least partially compensated by the indirect effect through K_s. The overall effect could in principle go in either direction.

Endogenous trade imbalances. In this paper, I only quantify one channel through which international trade affects the skill premium, namely the Stolper-Samuelson mechanism, finding that in most countries it only plays a minor role in line with previous studies[6]. Other channels have been highlighted in the literature, and remarkably the effect of changes in trade costs on the skill premium via capital-skill complementarity has been found to be quantitatively important in static environments[7]. But how the interaction between trade costs and trade imbalances impacts the skill premium through capital accumulation remains unexplored. For instance, poor countries with low capital stocks may accumulate capital faster after a decrease in trade costs if capital goods are cheaper abroad

[6] See for example Parro (2013)

[7] See for example Parro (2013) and Burstein, Cravino and Vogel (2013)

and they can increase their trade deficit, thus experiencing more pronounced increases in their skill premium if high-skill workers and capital are net complements. Additionally, countries with a higher stock of net foreign assets position may find it easier to adjust their trade imbalances after a trade liberalization[8], hence their skill premium may react more strongly.

7 Conclusions

The skill premium evolves heterogeneously across countries in different stages of development: between 1995 and 2009, on average it increased by 32% in low-income countries, decreased by 4% in medium-income countries, and increased by 1% in high-income countries. In this paper, I used a quantitative model to analyze how this pattern is driven by different forces: the relative supply of skills, technological change both skill-neutral and skill-biased, and international trade. Quantitatively, I find that technological change must have played a stronger role in shaping the skill premium in developing countries: on average between 1995 and 2009, it increased the skill premium by 152% in low-income countries, and by 38% in both medium-income and high-income countries. Skill-neutral technological change can explain 18% of the total technology effect in the US, and it plays an even larger role in most countries: on average across countries, it accounts for 33% of the overall technology effect on the skill premium. Changes in international trade patterns have little ability to explain changes in the skill premium for most countries regardless of the stage of development, with a few exceptions such as India where net exports became considerably more skill-intensive in the period 2000-2009.

A key mechanism throughout the paper is structural transformation, the reallocation of workers across sectors. The extent of heterogeneity in sectoral skill intensity is central for how this process shapes the skill premium. In developing countries, where this heterogeneity is greater, increases in the supply of skilled labor and skill-biased technological change tend to push workers toward low-skill-intensive sectors. As a result, structural transformation toward high-skill-intensive sectors is slower than it would be in economies with more homogeneous sectoral skill intensities.

A number of issues surrounding the skill premium would require a dynamic frame-

[8] Ravikumar, Santacreu and Sposi (2019) find evidence in this direction.

work to address them. I briefly discussed how the introduction of some intrinsically dynamic concepts into the theoretical framework could open the door for further research.

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Appendix

A Definition of sectors

Table A.1 shows all industries in the ISIC Rev. 4 classification, and the percentage of countries in which they were classified as high-skill intensive in this paper. Two industries were dropped due to lack of information for some countries: "Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel" and " Private households with employed persons".

Industry	% Frequency
Agriculture, Hunting, Forestry And Fishing	0
Mining And Quarrying	22
Food, Beverages And Tobacco	0
Textiles And Textile	0
Leather, Leather And Footwear	0
Wood And Of Wood And Cork	0
Pulp, Paper, Paper, Printing And Publishing	8
Coke, Refined Petroleum And Nuclear Fuel	11
Chemicals And Chemical	14
Rubber And Plastics	3
Other Non-Metallic Mineral	3
Basic Metals And Fabricated Metal	0
Machinery, Nec	3
Electrical And Optical Equipment	8
Transport Equipment	3
Manufacturing Nec; Recycling	0
Electricity, Gas And Water Supply	43
Construction	5
Wholesale Trade And Commission Trade, Except Of Motor Vehicles And Motorcycles	11
Hotels And Restaurants	3
Other Inland Transport	5
Other Water Transport	8
Other Air Transport	8
Other Supporting And Auxiliary Transport Activities; Activities Of Travel Agencies	8
Post And Telecommunications	11
Financial Intermediation	89
Real Estate Activities	95
Renting Of M&Eq And Other Business Activities	97
Public Admin And Defence; Compulsory Social Security	84
Education	100
Health And Social Work	97
Other Community, Social And Personal Services	49

Table A.1: Definition of sectors

Notes: The percentage frequency shown in the second column is the percentage of countries in which each industry was classified as high-skill intensive.

B Computing the equilibrium

It follows from Equation (6) that the price of both commodities is pinned down by the skill premium. Then a natural algorithm to compute the equilibrium is the following: guess a skill premium w_h, and use (6) to get the remaining prices. Use (4) and (3) to obtain the consumption bundle for each household. Obtain aggregate production using market clearing in each sector

$$Y_j = f_h c_{hj} + (1 - f_h) c_{lj}.$$

Use the production function (2) and relative labor demand (5) to get absolute labor demands. Check whether the market clearing condition for high-skill labor holds:

$$H_G + H_S = f_h.$$

If it does, then the low-skill labor market clears as well by Walras Law. If not, adjust the skill premium accordingly.

C Proofs

Proposition 1 *Let preferences be homothetic and skill intensity be homogeneous across sectors. Then structural transformation is entirely driven by skill-neutral technological change. Moreover, if commodities are complements then the share of total labor employed in sector* 1 *is strictly decreasing in* $\frac{A_1}{A_2}$.

Proof. Let $\alpha_1 = \alpha_2 = \alpha$. Using (5), the production function of sector j and (6), we get relative labor in sector 1 as

$$\frac{H_1 + L_1}{H_2 + L_2} = \frac{Y_1}{Y_2} \left(\frac{A_2}{A_1} \right)^{\rho}. \tag{A.1}$$

Using commodities market clearing and (4) for the homothetic case

$$\frac{Y_1}{Y_2} = \frac{\dfrac{1}{A_2} + \dfrac{1}{A_1}\left(\dfrac{A_1(1-a_1)}{A_2 a_1}\right)^{\epsilon}}{\dfrac{1}{A_1} + \dfrac{1}{A_2}\left(\dfrac{A_2(1-a_1)}{A_2 a_1}\right)^{\epsilon}}. \tag{A.2}$$

Combining (A.1), (A.2) and (6), we obtain

$$\frac{H_1 + L_1}{H_2 + L_2} = \frac{1 + \left(\dfrac{A_2}{A_1}\right)^{1-\epsilon}\left(\dfrac{1-a_1}{a_1}\right)^{\epsilon}}{1 + \left(\dfrac{A_1}{A_2}\right)^{1-\epsilon}\left(\dfrac{1-a_1}{a_1}\right)^{\epsilon}}$$

which is independent of f_h and α_j, and strictly increasing in $\frac{A_1}{A_2}$ for $\epsilon < 1$.

■

D Model fit

Table A.1 reports the distribution of deviations of the model from the targets. Each row is a target. The percentage of countries for which the model deviates from the target by less and more than 1% is shown in the first and second columns respectively. The maximum percentage deviation from the target among all countries is shown in the third column. Target $\Delta(p_2/p_1)$ is the growth rate for the relative price of commodities, and ΔY is the aggregate growth rate of the economy. Target s_t denotes the share of sector 2 in value-added:

$$s_{2t} = \frac{Y_{2t}p_{2t}}{Y_{2t}p_{2t} + Y_{1t}p_{1t}}$$

	$< 1\%$	$\geq 1\%$	**max %**
w_{h0}	89	11	3
w_{hT}	89	11	3
$\Delta(p_2/p_1)$	89	11	2
ΔY	100	0	0
H_{10}/L_{10}	86	14	5
H_{1T}/L_{1T}	86	14	5
H_{20}/L_{20}	86	14	5
H_{2T}/L_{2T}	86	0	1
s_0	84	14	6
s_T	84	16	5

Table A.1: Distribution of % deviations from the targets

Notes: The table reports the distribution of % deviations from the targets. Each row is a target, and the percentage of countries for which the model deviates from the target by less and more than 1% is shown in the first and second columns respectively. The maximum percentage deviation from the target among all countries is shown in the third column.

E Supplementary figures

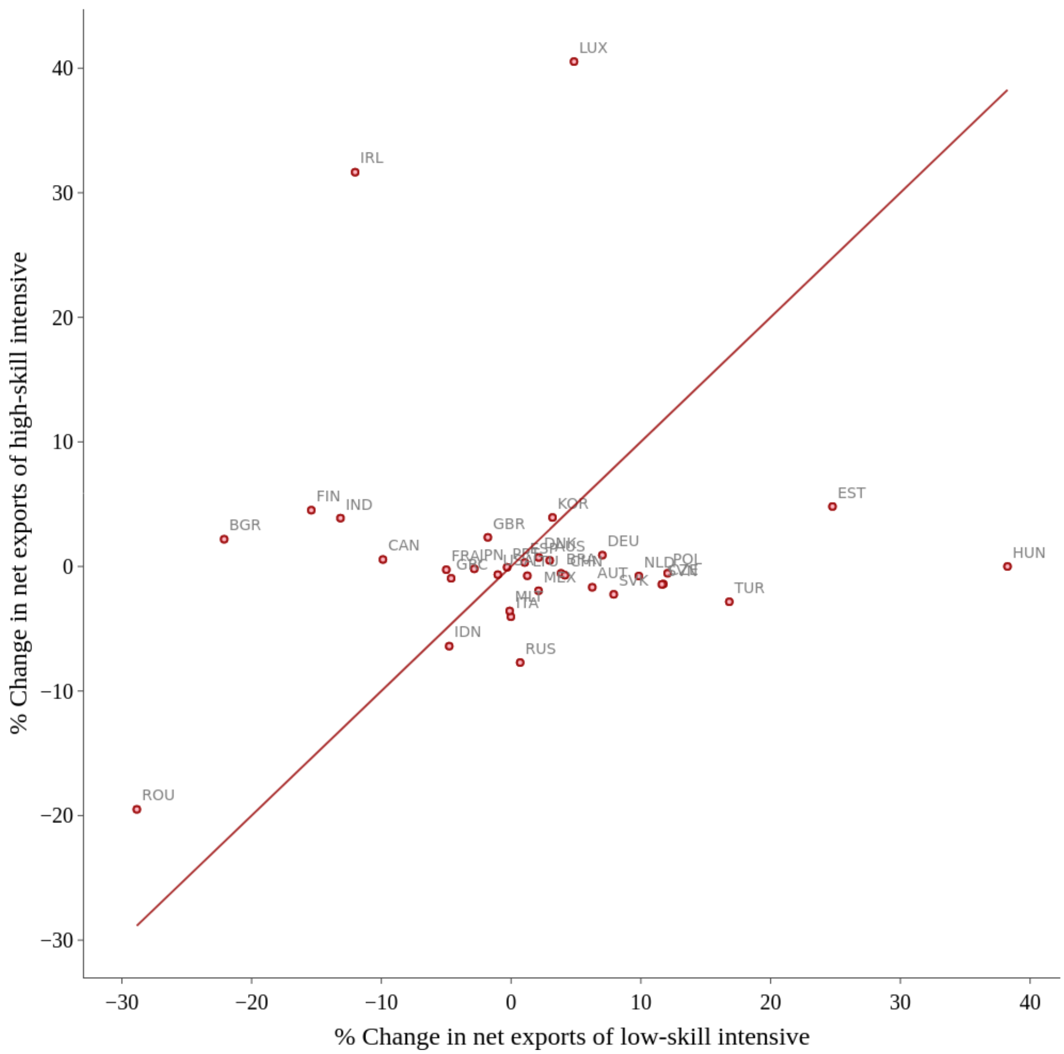

Figure A.1: Changes in trade patterns

Notes: Percentage changes in the share of net exports in value added for the high and low-skill intensive sectors between the years 2000 and 2009. The solid line is the 45-degree line.

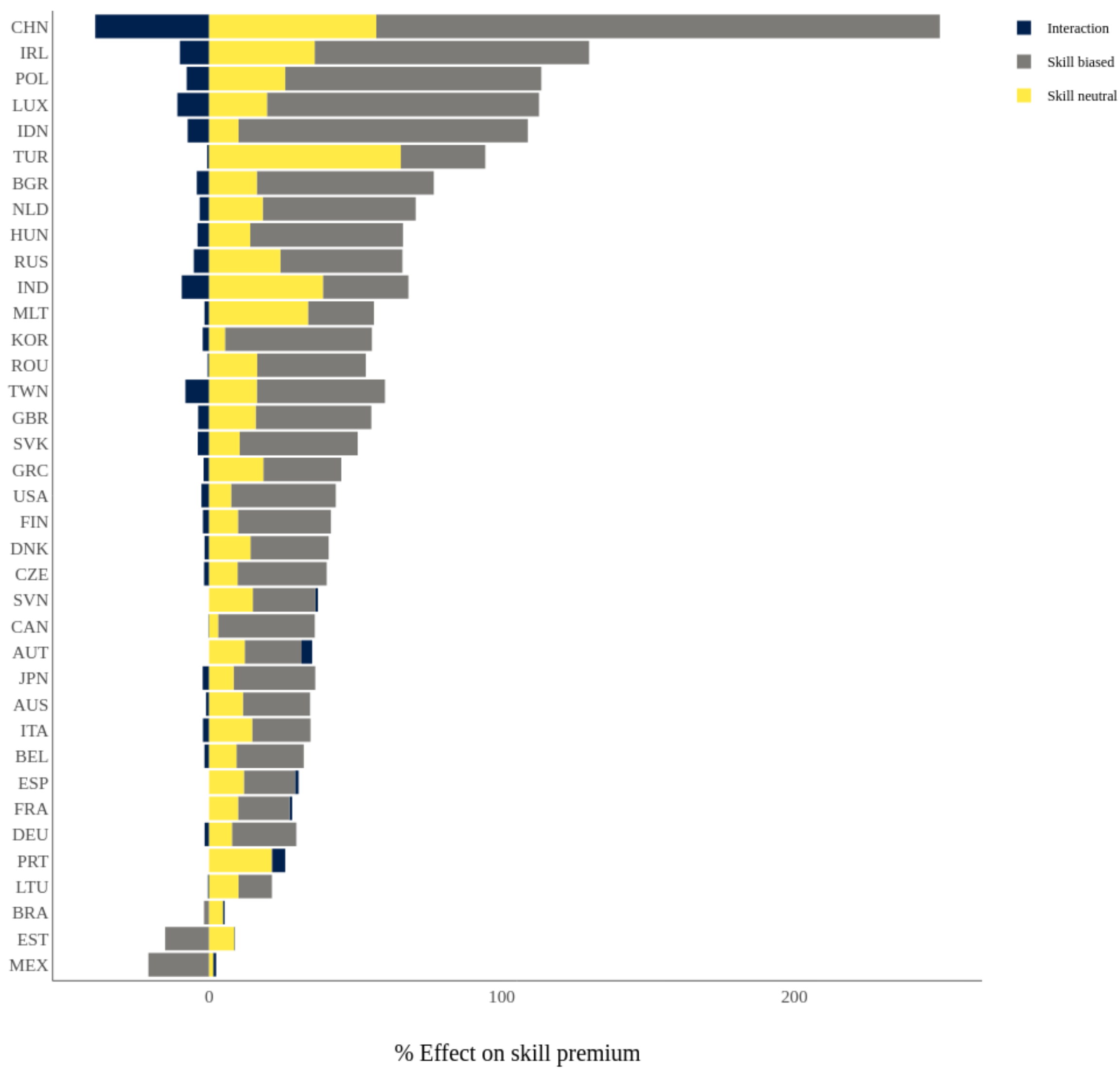

Figure A.2: Technology effect decomposition

Notes: The figure shows a decomposition of the effect of technology on the skill premium in the period 1995-2009. The yellow and grey bars represent the effects of skill-neutral and skill-biased technological change respectively, and the dark-blue bar is an interaction effect.

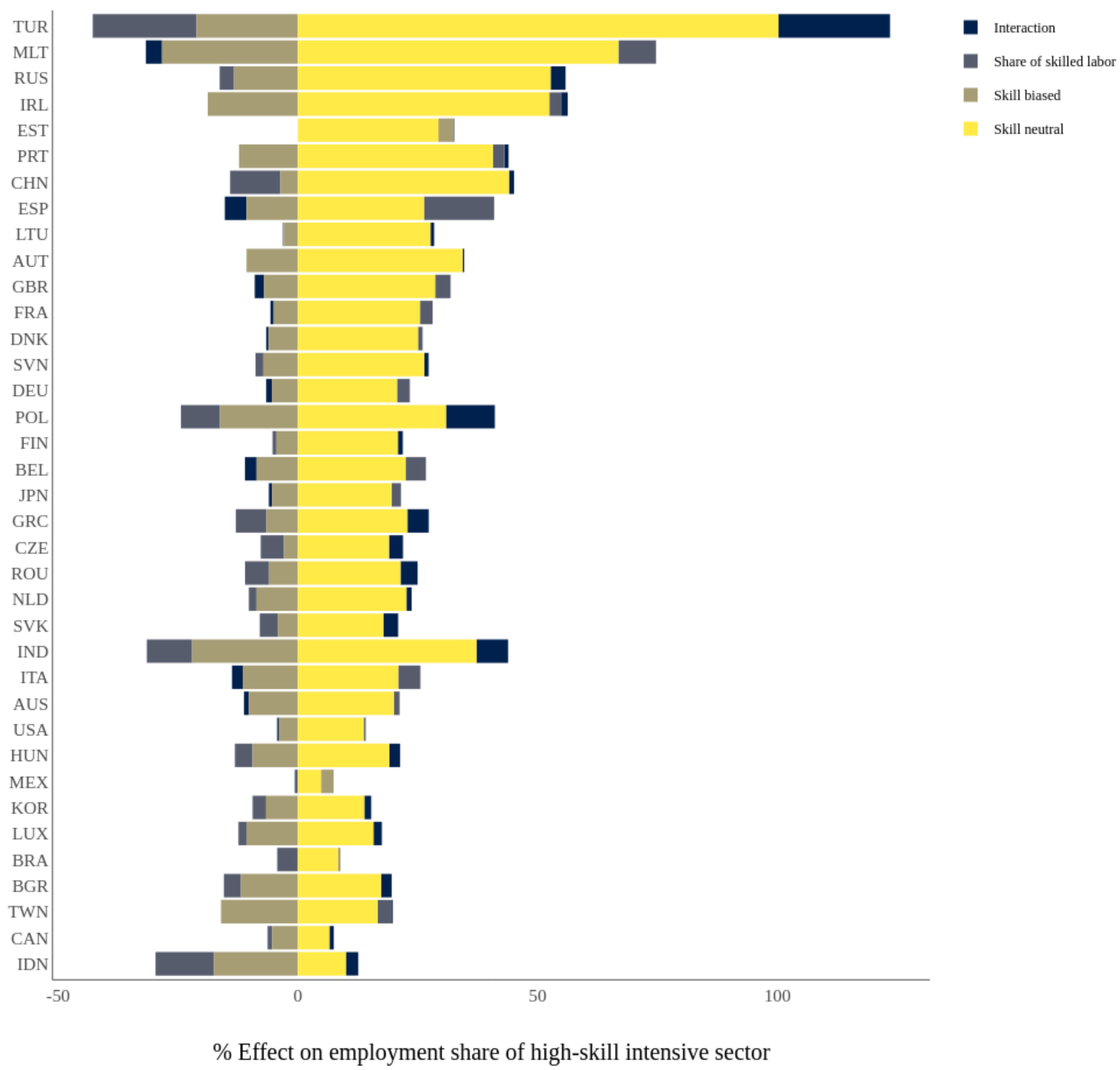

Figure A.3: Structural transformation decomposition

Notes: The figure shows a decomposition of structural transformation during the period 1995-2009. Structural transformation is measured as the percentage change in the employment share of the high-skill intensive sector. The yellow and brown bars represent the effects of skill-neutral and skill-biased technological change respectively on structural transformation, the grey bar represents the effect of the aggregate share of skilled labor, and the dark-blue bar is an interaction effect.

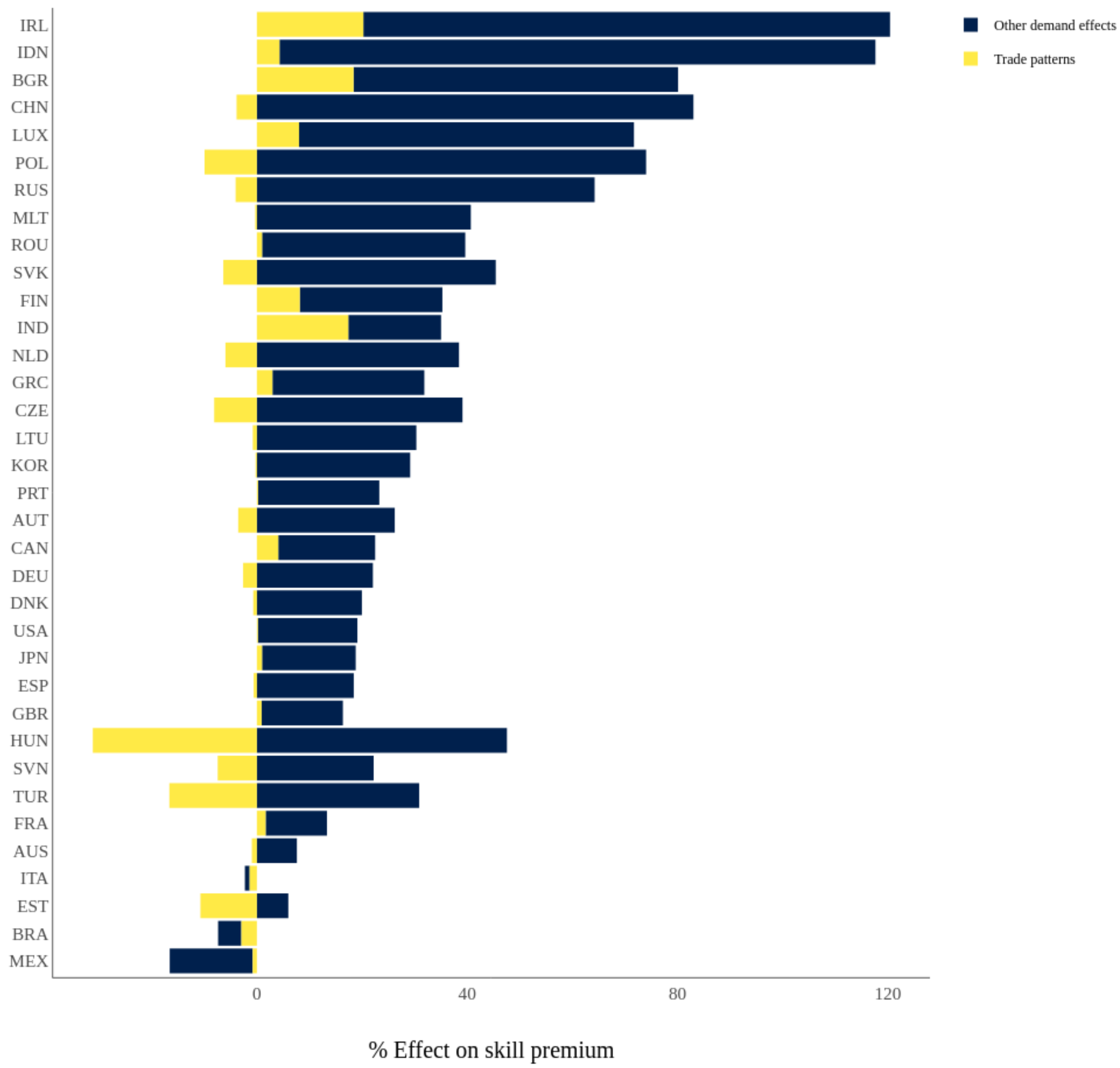

Figure A.4: Contribution of changes in trade patterns

Notes: The figure shows a decomposition of the effect of changes in the relative demand for skills on the skill premium during the period 1995-2009. The ten largest countries according to their number of workers in 1995 are displayed. The yellow bar represents the demand effects that are captured by changes in trade patterns, and the dark-blue bar represents all other demand effects.