RIETI Discussion Paper Series 26-E-064

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The Evolution of Comparative Advantage in the 21st Century

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RIETI Discussion Paper Series 26-E-064
September 2026

Does Skill Abundance Still Matter?
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Abstract

This paper documents that skill-abundant countries no longer have a comparative advantage in skill-intensive sectors. While this empirical relationship was strong in the 1980s, it weakened in the 1990s and disappeared by the 2000s. Using a quantitative trade model incorporating automation, I find that lower trade costs and automation are the key factors. Trade costs contribute via market access, while automation changes comparative advantage through task reassignment. Lower trade costs and automation increase skill premia primarily by reassigning tasks to capital rather than reallocating factors across sectors. Lower trade costs also amplify automation's effects on skill premia and welfare.

Keywords: automation, comparative advantage, offshoring, skill premium, structural change

JEL classification: F14, F11, F16, O14

[1]This study is a part of the project "Roles of International Finance in Industry Specialization and the Macroeconomy" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). The draft of this paper was presented at the RIETI DP seminar for the paper. I would like to thank participants of the RIETI DP Seminar for their helpful comments. I am thankful to Xiang Ding for providing me with the data in Ding (2026).

1 Introduction

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

In the first half of the paper, I document that skill abundance has become much less important for comparative advantage in skill-intensive sectors. Figure 1 illustrates this finding using Balassa (1965)'s revealed comparative advantage (RCA) of the G10 bloc. For each sector, the index divides that sector's share in G10 exports by its share in total exports by all countries in the sample. Skill intensity is measured from U.S. data as non-production workers' payroll divided by value added. If skill-abundant countries have a comparative advantage in skill-intensive sectors, G10 RCA should rise with skill intensity. The estimated slope used to be positive and significant in 1980 but became negative and insignificant in 2015. The first empirical contribution of the paper is to show more systematically how this relationship weakened after the periods studied by Romalis (2004); Morrow (2010); Chor (2010).

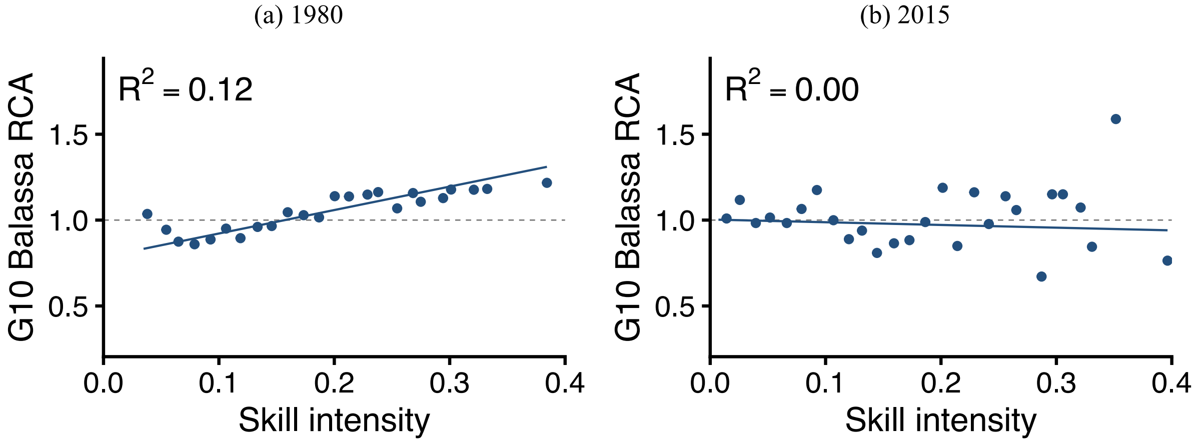
In the second half of the paper, I decompose these changes in comparative advantage and draw macroeconomic implications. To this end, I develop a multi-sector quantitative trade model with automation. Starting from the 1980 economy, I introduce the inferred shocks in automation, trade costs, and offshoring through 2014. I use exact Shapley decompositions to measure each shock's contribution to comparative advantage and to allocate each one-shock change across direct, unit-cost, and expenditure channels. Using the same model, I then study how trade costs and automation jointly shape skill premia and welfare.

Does Skill Abundance Still Matter? Expanding on Figure 1, Section 2 examines systematically whether a country's skill abundance predicts comparative advantage in skill-intensive sectors. Every five years from 1980 to 2015, I regress bilateral trade flows at the exporter-importer-sector level on the interaction between an exporter's skill abundance and a sector's skill intensity. This specification follows Chor (2010), Costinot et al. (2012), and Levchenko and Zhang (2016), which use bilateral trade flows to measure comparative advantage.[1] If the coefficient on this interaction is positive, skill-abundant countries export relatively more in skill-intensive sectors; that is, they have a comparative advantage in these sectors.

I find that skill-abundant countries specialized in skill-intensive sectors during the earlier part of the sample. This aligns with papers that find a positive coefficient and interpret it as support for factor-proportions theory (Romalis, 2004; Levchenko, 2007; Nunn, 2007; Morrow, 2010; Chor, 2010). Baseline estimates are positive and statistically significant in 1980, 1985, 1990, and 1995. Their 95% confidence intervals include

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

Figure 1: G10 Revealed Comparative Advantage and Sector Skill Intensity



Notes: This figure shows G10 RCA and sector skill intensity using the 390-sector four-digit SIC87dd manufacturing classification. G10 RCA is the sector's share in G10 exports to destinations in the analysis sample divided by the sector's share in all sample exports to those destinations. Skill intensity is non-production workers' payroll divided by value added in the U.S. NBER-CES Manufacturing Industry Database. The G10 bloc includes Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States. The sample excludes sectors at or below the 1st percentile or at or above the 99th percentile of the within-year RCA distribution. Dots show means within 40 equal-width skill-intensity bins defined over a common range across years; empty bins are omitted. Lines and R^2 values use the sector-level observations.

zero in 2000 and 2005, and the estimates never return to positive and significant afterwards. The traditional positive association thus weakens, and in some cases reverses, by the end of the sample. This finding is robust to specifications previously used in the literature and to holding both countries' skill abundance and sectors' skill intensity fixed at common benchmark years.

Theoretical Framework. To understand this evolution of comparative advantage, I develop a multi-sector, multi-factor Eaton-Kortum model with input-output linkages (Caliendo and Parro, 2015) and combine it with the task framework for automation (Acemoglu and Restrepo, 2022b).

In this model, automation reallocates tasks from low-skilled labor to capital. It allows low-skill-scarce countries such as Germany or Japan to remain competitive in low-skill-intensive sectors by substituting capital for low-skilled labor. General-use trade-cost changes affect both general- and intermediate-use sourcing, while the offshoring shock changes the additional wedge on intermediate sourcing relative to general use. Both sourcing changes shift demand given unit production costs and can alter comparative advantage in either direction.

I theoretically characterize the changes in the key coefficient estimated in Section 2 in terms of primitives and shocks. I show how each of the shocks can change the pattern of comparative advantage via different channels, which I investigate in Section 4.

Quantitative Relevance. Section 4 uses the calibrated model to ask what explains the weakening relationship between countries' skill abundance and their specialization in skill-intensive sectors. Starting from the 1980 economy, I solve a set of counterfactual combinations under different shocks and decompose how each changes the coefficient β on skill-based comparative advantage.

Measured on the model's own sample and skill interaction, the empirical coefficient falls from 1.38 in 1980 to -0.23 in 2015. The Shapley decomposition attributes 67.0 percent of this decline to lower trade costs, the largest contribution, and 39.8 percent to automation, the second largest, while offshoring offsets 15.3 percent of the decline. The three model shocks account for 91.4 percent of the empirical change.

The channel accounting attributes 86.6 percent of the trade-cost contribution to market access. Because the automation shock is common across origins, it has no direct Ricardian productivity effect. It changes comparative advantage through unit-cost and expenditure responses, with task reassignment as the central within-sector mechanism.

Macro Implications. Section 5 places the measured automation and trade-cost changes against the observed expansion of skill supplies. Skill deepening alone would have lowered the skill premia in every economy by 137 log points at the median. Automation and lower trade costs each push against that force, and together raise the premium by 59 log points at the median. Factor-market clearing attributes both effects primarily to the reassignment of tasks from low-skilled labor to capital, rather than reallocation across sectors.

Moreover, automation and lower trade costs work as complements. Lower trade costs amplify the effects of automation on skill premia by 15 log points and on welfare by 16 log points at the median, with positive interaction effects in all 25 economies.

Literature. First, this paper contributes to the large literature that empirically investigates the sources of comparative advantage (Leamer, 1984; Bowen et al., 1987; Trefler, 1993, 1995; Davis and Weinstein, 2001; Yeaple, 2003; Romalis, 2004; Schott, 2004; Nunn, 2007; Levchenko, 2007; Costinot, 2009b; Morrow, 2010; Chor, 2010; Costinot et al., 2012; Bombardini et al., 2012; Davis and Dingel, 2020). Most empirical work on the sources of comparative advantage is cross-sectional. A smaller literature studies its evolution through mean reversion or convergence (Hanson et al., 2015; Levchenko and Zhang, 2016). Related theoretical work makes comparative advantage endogenous through technological change (Redding, 1999) or factor accumulation in a dynamic Heckscher-Ohlin environment (Caliendo, 2010). My paper documents that a country's skill abundance has become less important for comparative advantage in skill-intensive sectors. Baseline estimates are positive and statistically significant in 1980, 1985, 1990, and 1995. The first baseline estimate whose 95% confidence interval includes zero occurs in 2000. The model provides a common quantitative framework for comparing automation with the other calibrated changes.

The closest paper on the mapping from national factor endowments to sectoral trade patterns is Morrow and Trefler (2022), which provides a model-based decomposition of how differences in skill abundance across countries are absorbed in trade patterns. They find that within-industry skill intensities are more important than between-industry output mixes in 2006. I complement their cross-sectional findings by documenting how the relationship between skill abundance and skill intensity evolves over time. The quantitative analysis uses the model to assess how automation and the other inferred shocks affect this evolution. The automation results emphasize task reallocation within sectors rather than output reallocation across sectors, broadly consistent with their finding.

Second, this paper contributes to the literature on the interaction between technology, globalization, and inequality, including Wood (1994), Ventura (1997), Berman et al. (1998), Krugman (2000), Leamer (2000), and Matsuyama (2007).[2,3] The classical within-between diagnostic is developed by Katz and Murphy (1992), Berman et al. (1994), and Berman et al. (1998); Feenstra and Hanson (1996) show that offshoring can also generate within-industry skill upgrading. Previous work connects falling equipment prices to skill demand through capital-skill complementarity (Greenwood et al., 1997; Krusell et al., 2000; Burstein et al., 2013). More specifically, my paper relates to work that embeds high- and low-skilled labor in multi-sector quantitative trade models to study the implications of trade and technology for the skill premium (Parro, 2013; Burstein et al., 2013; Caron et al., 2014; Burstein and Vogel, 2017; Burstein et al., 2019; Cravino and Sotelo, 2019; Furusawa et al., 2022).[4,5] The paper revisits the classical trade-versus-technology debate by showing that lower trade costs and automation operate through the same within-sector task margin and that lower trade costs amplify the distributional effect of automation.

Finally, this paper relates to recent work on automation and trade, including Wang (2021), Krenz et al. (2021), Freund et al. (2022), Artuc et al. (2023), and Fontagné et al. (2024). These papers focus on how automation affects trade volumes. My paper shows that automation changes patterns of comparative advantage and studies the associated changes in skill premia and welfare.

2 Skill Abundance as a Source of Comparative Advantage?

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

2.1 Baseline Specification

Theoretical Motivation I motivate the main regression with the multi-sector Eaton-Kortum model (Eaton and Kortum, 2002). Following Chor (2010), I link countries' skill abundance to sectors' skill intensity.

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

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

[2]Earlier studies distinguish the effect of exogenous technological change on trade patterns (Krugman, 1979) from the effect of trade on the direction or rate of innovation (Grossman and Helpman, 1991).

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

[4]While I assume that adoption of automation is endogenous in the task framework, innovation of automation technology is exogenous. Several papers discuss the role of trade in directing technological change, including Wood (1994), Acemoglu and Zilibotti (2001), Acemoglu (2003), Thoenig and Verdier (2003), Epifani and Gancia (2008), and Loebbing (2022).

[5]Related work studies the incidence of trade shocks through labor-market adjustment frictions (Caliendo et al., 2019), factor-demand and factor-price responses (Adão et al., 2022), and worker heterogeneity in sector-specific skills (Adão, 2026). I abstract from within-skill-group heterogeneity and adjustment frictions; the margin here is the reassignment of tasks between low-skilled labor and capital within country-sector cells.

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

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

Consider the unit production cost

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

where w_i^H and w_i^L are the wages of high- and low-skilled workers, and α_s^H is the high-skill share of the sector's labor payments. I call α_s^H the sector's skill intensity.

Combining the unit cost function with equation (1) and taking logs yields

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

where $\eta_{i,j}$ and $\eta_{j,s}$ are

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

The specification (2) reveals the comparative advantage of countries with different relative skill premia, $\frac{w_i^H}{w_i^L}$, across sectors with different skill intensities, α_s^H. In particular, a country with a lower skill premium has higher exports in a sector with higher skill intensity, which is the classic prediction of factor-proportions theory.

Skill prices are rarely observed in cross-country data. Thus, previous studies (e.g., Romalis (2004); Chor (2010)) use relative skill abundance, $\frac{H_i}{L_i}$, instead of the skill premium, $\frac{w_i^H}{w_i^L}$. I summarize their negative relationship as

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

where $\gamma_{HL} > 0$. This negative relationship means that skill-abundant countries have lower relative wages of skilled labor—that is, lower skill premia.[6]

Substituting equation (3) into equation (2) gives

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

where $\beta = \theta \gamma_{HL} > 0$.

This is the standard specification for measuring the comparative advantage of countries with different relative skill abundance, $\frac{H_i}{L_i}$, across sectors with different skill intensities, α_s^H.[7] The model predicts $\beta > 0$ because skill-abundant countries (with higher $\frac{H_i}{L_i}$) have lower skill premia (lower $\frac{w_i^H}{w_i^L}$), which gives them a larger cost advantage in more skill-intensive sectors. Relative to Bangladesh, the U.S. unit-cost and export

[6] Figure A.1 in Appendix A shows this negative cross-country relationship in the data.

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

advantage should therefore increase with sector skill intensity.

Specification Building on equation (4), for each year t separately, I estimate the following equation by Poisson pseudo-maximum likelihood (PPML):

$$\mathbb{E}[X_{i,j,s,t}] = \exp\left(\beta_t \left[\alpha^H_{s,t} \ln\left(\frac{H_{i,t}}{L_{i,t}}\right)\right] + \eta_{i,j,t} + \eta_{j,s,t}\right). \tag{5}$$

Here, $X_{i,j,s,t}$ is the bilateral trade flow from exporter i to importer j in sector s at time t; $\alpha^H_{s,t}$ is sectoral skill intensity; $\frac{H_{i,t}}{L_{i,t}}$ is the exporter's relative skill abundance; and $\eta_{i,j,t}$ and $\eta_{j,s,t}$ are exporter-importer and importer-sector fixed effects. PPML accommodates zero trade flows and is standard in gravity estimation (Silva and Tenreyro, 2006). Standard errors are clustered by exporter-sector. For the baseline, I weight each observation by the exporter's total 2015 exports in that sector and hold the exporter-sector weights fixed across destinations and years.

2.2 Data

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

Bilateral Trade Flows Bilateral trade flows are reported directly by importers in the UN Comtrade bulk files.[8] I retain manufacturing products and aggregate reported dollar values by exporter, importer, product, and year.[9] The source classification is SITC Revision 1 before 1980 and SITC Revision 2 from 1980 onward.[10] SITC products are mapped to six-digit HS 1996 products using United Nations concordances and then to four-digit SIC87dd manufacturing industries using the crosswalk associated with Autor et al. (2013): reporter-specific SITC-HS96 allocation weights are constructed from BACI trade values and normalized to sum to one within reporter and SITC product, and the HS96-SIC87dd weights allocate products that map to multiple industries.

Skill Abundance Skill abundance across countries comes from the Barro-Lee Educational Attainment Dataset (Barro and Lee, 2013), which is commonly used in previous studies, including Hall and Jones (1999) and Romalis (2004). I measure relative skill endowment as the ratio of college-educated to non-college-educated people aged 25–64.[11]

[8] Bulk downloads are available from the UN Comtrade website. The SITC-HS concordances are available from the United Nations Statistics Division; the HS-SIC crosswalk is available from David Dorn's website. SIC87dd modifies the 1987 SIC classification to improve consistency over time; see Autor et al. (2013).

[9] Consistent service-trade coverage is unavailable over the full sample.

[10] Reporting entities are harmonized over time: the construction maps the former German Democratic Republic to Germany, Luxembourg to Belgium, the former Netherlands Antilles to the Netherlands, the former Democratic Yemen to Yemen, and South Sudan to Sudan, and Comtrade numeric code 490 is treated as Taiwan and subject to the same screening rules as other reporters.

[11] The original data extend through 2010; the extension through 2015 used here is available on the Barro-Lee website.

Skill Intensities Skill intensities come from the NBER-CES Manufacturing Industry Database (Becker et al., 2021).[12] The baseline measure is non-production workers' payroll divided by total payroll in each of 390 four-digit SIC87dd manufacturing sectors. The descriptive RCA exercise instead uses non-production workers' payroll divided by value added. Specifications that add capital use skill and capital payments divided by value added, so that the included factor shares have a common denominator.

Sample Because Barro-Lee factor endowments are available every five years, the baseline uses five-year observations from 1980 through 2015, for 8 periods. To smooth annual trade fluctuations, each target year is a centered three-year average, so an annual flow enters at most one nonoverlapping three-year window. The 2000 observation, for example, is the arithmetic mean of 1999, 2000, and 2001.

The country sample requires complete Barro-Lee coverage from 1980 through 2015. It also requires at least one year with manufacturing exports above $100 million and at least one year with manufacturing imports above $100 million during that period (Atkin et al., 2026), both expressed in 2015 U.S. dollars using the U.S. CPI (OECD, 2010); the conversion is used for sample eligibility only, since the year-specific estimates never compare nominal trade levels across years. These restrictions yield 143 countries.[13] Zero flows account for 74.2% of observations.

For sectors, I use all 390 four-digit SIC87dd manufacturing sectors that can be consistently linked to the NBER-CES data.

2.3 Main Results: Declining Importance of Skill Abundance

Figure 2 reports estimates of β_t and 95% confidence intervals based on standard errors clustered by exporter-sector. Baseline estimates are positive and statistically significant in 1980, 1985, 1990, and 1995. A positive coefficient means that skill-abundant countries export relatively more in skill-intensive sectors. The estimates can therefore be compared with those reported by Chor (2010) using 1990 bilateral trade flows, Morrow (2010) using data from 1985 to 1995, and Romalis (2004); Nunn (2007); Levchenko (2007) using data from the 1990s.

The estimate $\widehat{\beta}_t$ declines over time. The 95% confidence intervals include zero in 2000 and 2005, and the estimates are negative and statistically significant in 2010 and 2015. The point estimate changes from 1.66 in 1980 to -0.74 in 2015. Thus, the traditional positive association between skill abundance and specialization in skill-intensive sectors weakens and eventually reverses.

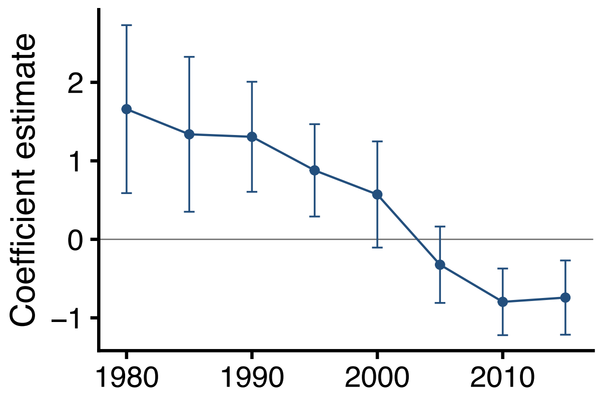
2.4 Robustness and the Model Counterpart

Figure 3 reports eight robustness checks and the empirical counterpart used in the quantitative analysis.

[12] Following Romalis (2004); Nunn (2007); Chor (2010), I use U.S. sector data to obtain a common benchmark that is comparable across countries and over time.

[13] The balanced panel codes absent bilateral-sector records as zero. Also, I do not impose an additional minimum reporting threshold by importer.

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



Notes: This figure shows year-specific estimates of β_t in equation (5). Observations are weighted by exporter-sector total exports in 2015, with the weights held fixed across destinations and years. The bars show 95% confidence intervals based on standard errors clustered by exporter-sector.

Other sources of comparative advantage The first two panels address omitted sources of comparative advantage. Panel 3a adds the interaction between capital abundance and capital intensity to the baseline specification:

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

Because the baseline includes only the interaction of a country's skill abundance and a sector's skill intensity, other country and sector characteristics could bias the estimates. In the extended specification, skill intensity $\alpha^H_{s,t}$ is non-production payroll divided by value added, and capital intensity $\alpha^K_{s,t}$ is capital payments divided by value added, both from the NBER-CES Manufacturing Industry Database (Becker et al., 2021). Capital abundance $\frac{K_{i,t}}{L_{i,t}}$ is real capital stock per non-college-educated worker, combining the Penn World Table with Barro-Lee educational attainment (Feenstra et al., 2015).[14] Panel 3b further adds the interaction of sectoral contract intensity and country-level rule of law, following Nunn (2007). Both robustness estimates show the same overall decline as the baseline.

Log OLS specification Panel 3c estimates the log-linear specification in equation (4) separately by year using OLS on positive bilateral trade flows. This log specification drops all cells with zero trade flows by construction. While PPML specifications are preferable (Silva and Tenreyro, 2006, 2011), this specification yields a similar trend in $\widehat{\beta}_t$.

Chor (2010) Panel 3d instead follows Chor (2010) and measures U.S. sectoral skill intensity as the log ratio of non-production to production employment, rather than the baseline payroll share. While Chor (2010) controls for observed exporter-importer variables such as distance, common language, and trade agreements, equation (5) absorbs these determinants with exporter-importer fixed effects. The estimate $\widehat{\beta}_t$ continues to decline over the sample period.

[14] I multiply PWT employment by the Barro-Lee non-college share to construct the denominator.

Fixing right-hand-side variables Panels 3e and 3f address changes in the endowment and intensity measures. A decline in $\widehat{\beta}_t$ could reflect increasing measurement error in these time-varying inputs. For example, growth in college attainment may increase unobserved heterogeneity in education quality within the college-educated group and attenuate the estimate. The two panels therefore fix both country skill abundance and sector skill intensity at their 1980 values in one specification and at their 2015 values in the other. The overall decline persists in both cases.

Other specifications The next two panels change the identifying variation and the unit of observation. Panel 3g pools all years and includes exporter-sector fixed effects, alongside exporter-importer-year and importer-sector-year fixed effects. This specification absorbs time-invariant exporter-sector heterogeneity and identifies β_t from changes over time. Panel 3h instead aggregates bilateral flows across destinations, following Romalis (2004). The outcome is exporter-sector total exports, and the unit of observation is exporter-sector-year. I estimate the specification by PPML with exporter and sector fixed effects, weighting observations by exporter-sector total exports in 2015. Both estimates decline over the sample period.

Model counterpart Panel 3i aligns the empirical regression with the estimand used in Section 4. It uses observed trade flows among the 24 named model economies, combines Hong Kong with China, excludes the rest of the world, holds the skill interaction at its 1980 value, and is unweighted. The coefficient falls overall from 1.38 in 1980 to -0.23 in 2015.

Why a Model Is Needed Across the eight robustness checks and the model counterpart, $\widehat{\beta}_t$ shows an overall decline. The model counterpart aligns the empirical and quantitative estimands, but it does not separately identify the roles of country coverage, fixed regressors, or weighting.

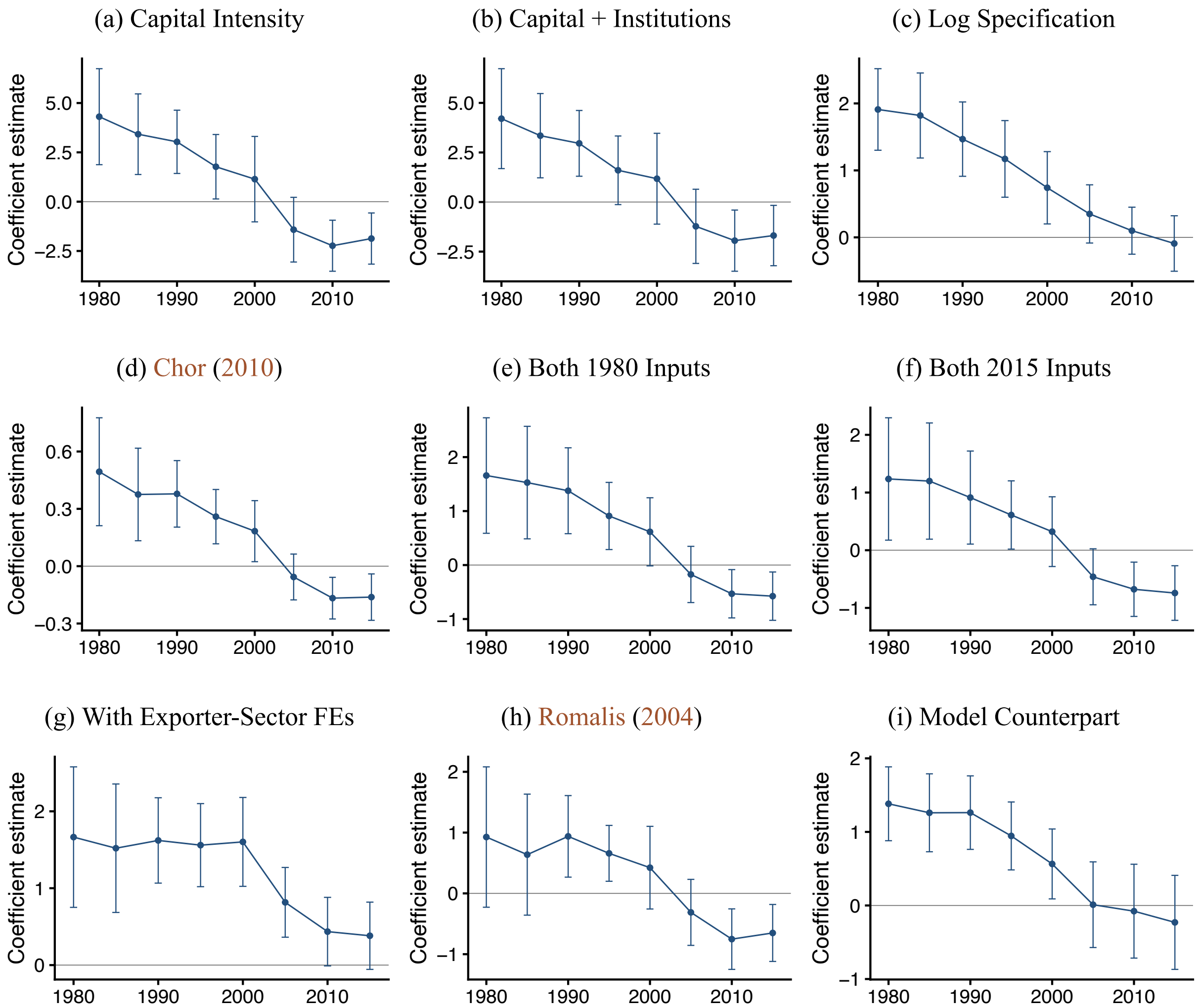
First, equation (5) summarizes comparative advantage over the full set of country-sector pairs, and several forces—including automation, offshoring, and changes in factor endowments—may reshape specialization at the same time. As Costinot (2009a) shows, even when factor endowments and technology each generate sharp predictions in isolation, their interaction through equilibrium specialization can reverse the association between country and sector characteristics within subsets of sectors.[15] A coefficient estimated within a subset, therefore, cannot be attributed to a particular underlying force.

Subsample estimates also face an equilibrium problem. For instance, dropping countries or sectors from the estimation does not remove them from the equilibrium that generated the remaining trade flows. Factor prices and input costs in the retained countries continue to reflect their interactions with the excluded observations. Attributing that decline requires a counterfactual framework that preserves these equilibrium linkages and changes one force at a time.

Section 3 develops this framework, and Section 4 uses it to quantify the contributions of automation, offshoring, and the other changes in the world economy.

[15] The counterexample in Section 6.2.1 of Costinot (2009a) constructs an economy in which factor supply and factor productivity are log-supermodular and yet aggregate output is not: the association between country and sector characteristics reverses across interior sector pairs. His Theorem 5 shows that only comparisons involving the two most extreme sectors remain robust.

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



Notes: This figure shows estimates of β_t under the listed robustness specifications. Unless stated otherwise, observations are weighted by exporter-sector total exports in 2015, with the weights held fixed across years and, where applicable, destinations. Panel 3a adds capital intensity interacted with capital abundance. Panel 3b also adds contract intensity interacted with rule of law. Panel 3c estimates equation (4) by OLS using positive bilateral trade flows. Panel 3d uses the skill-intensity measure in Chor (2010). Panels 3e and 3f hold country skill abundance and sector skill intensity fixed at their 1980 and 2015 values, respectively. Panel 3g pools years and includes exporter-sector, exporter-importer-year, and importer-sector-year fixed effects. Panel 3h aggregates bilateral flows to exporter-sector total exports following Romalis (2004) and estimates the specification by PPML with exporter and sector fixed effects. Panel 3i uses unweighted PPML on flows among the 24 named model economies, fixes the skill interaction at its 1980 value, includes Hong Kong flows with China, and excludes the rest of the world. The bars show 95% confidence intervals based on standard errors clustered by exporter-sector. Panel 3h instead clusters by exporter.

3 Trade Model with Automation

In this section, I develop a quantitative trade model with automation. I start from a standard multi-sector Eaton-Kortum model with input-output linkages (Eaton and Kortum, 2002; Caliendo and Parro, 2015). I extend it with the task framework of Acemoglu and Restrepo (2018, 2022a,b), where automation reassigns tasks between low-skilled labor and capital. After defining the equilibrium, I formulate its exact-hat solution and derive how each shock changes the PPML coefficient estimated in Section 2.

3.1 Environment and Technology

Countries, sectors, and primary factors. The economy has N countries and S sectors. I index countries by $i, j \in \mathcal{I}$ and sectors by $r, s \in \mathcal{S}$. Country i has $H_i > 0$ units of high-skilled labor and $L_i > 0$ units of low-skilled labor. Both labor types have inelastic supply, move across sectors within a country, and remain fixed across countries. Their wages are w_i^H and w_i^L. High- and low-skilled labor are the only primary factors, and sectoral goods are used to produce capital services. All markets are perfectly competitive.

Gross production. Each country-sector pair produces a continuum of varieties $\omega \in [0, 1]$. The production function for variety ω is

$$q_{is}(\omega) = Z_{is}(\omega)\big[H_{is}(\omega)\big]^{\alpha_{is}^H}\big[T_{is}(\omega)\big]^{\alpha_{is}^T}\big[M_{is}(\omega)\big]^{\alpha_{is}^M}, \qquad \alpha_{is}^H + \alpha_{is}^T + \alpha_{is}^M = 1, \tag{7}$$

where $T_{is}(\omega)$ is a task composite and $M_{is}(\omega)$ is an intermediate bundle. I require all three Cobb-Douglas shares to be positive and let them vary across countries and sectors.

Following Eaton and Kortum (2002), I draw productivity independently across countries, sectors, and varieties from the Fréchet distribution

$$\Pr[Z_{is}(\omega) \le z] = \exp\Big(-\lambda_{is} z^{-\theta}\Big), \qquad \lambda_{is} > 0, \quad \theta > 0. \tag{8}$$

The parameter θ governs productivity dispersion and is the trade elasticity. The elasticity of substitution among varieties within sector s is $1 < \sigma_s < 1 + \theta$.

Tasks and automation. Following Acemoglu and Restrepo (2018, 2022a,b), I combine a unit continuum of tasks using a Cobb-Douglas technology:

$$T_{is}(\omega) = \exp\left(\int_0^1 \ln T_{is}(\omega, x)\, dx\right). \tag{9}$$

Each task can be performed by either low-skilled labor or capital:

$$T_{is}(\omega, x) = \psi_{is}^L(x) L_{is}(\omega, x) + \psi_{is}^K(x) K_{is}(\omega, x). \tag{10}$$

The functions $\psi_{is}^L(x)$ and $\psi_{is}^K(x)$ determine low-skilled labor and capital productivity in task x.

Let w_{is}^K denote the price of one unit of capital service, and let $\widetilde{w}_{is}^L(x)$ and $\widetilde{w}_{is}^K(x)$ denote the task-specific unit costs of low-skilled labor and capital. Cost minimization gives

$$\widetilde{w}_{is}^{L}(x) \equiv \frac{w_i^L}{\psi_{is}^L(x)}, \qquad \widetilde{w}_{is}^{K}(x) \equiv \frac{w_{is}^K}{\psi_{is}^K(x)},$$

$$a_{is}(x) = \min\left\{\widetilde{w}_{is}^{L}(x), \widetilde{w}_{is}^{K}(x)\right\}, \tag{11}$$

$$w_{is}^T = \exp\left(\int_0^1 \ln a_{is}(x)\, dx\right). \tag{12}$$

I assume that ties occur on a set of measure zero. The task sets and their measures are

$$\mathcal{T}_{is}^L = \left\{x : \widetilde{w}_{is}^{L}(x) \le \widetilde{w}_{is}^{K}(x)\right\}, \qquad \Gamma_{is}^L = \int_{\mathcal{T}_{is}^L} dx,$$

$$\mathcal{T}_{is}^K = [0,1] \setminus \mathcal{T}_{is}^L, \qquad \Gamma_{is}^K = \int_{\mathcal{T}_{is}^K} dx, \qquad \Gamma_{is}^L + \Gamma_{is}^K = 1. \tag{13}$$

Because all tasks receive the same Cobb-Douglas weight, Γ_{is}^L and Γ_{is}^K are both task measures and shares of task-composite payments. Assignment depends on the two factor prices only through their ratio: task x goes to capital when $\frac{\psi_{is}^K(x)}{\psi_{is}^L(x)} > \frac{w_{is}^K}{w_i^L}$, so a decline in the capital-service price relative to the low-skilled wage expands $\mathcal{T}_{is}^K$ and raises Γ_{is}^K. I refer to this reassignment of tasks from low-skilled labor to capital as automation. The equipment-productivity shock, which I model as changes in λ_{is} in equipment sectors, operates through task reassignment by lowering the capital-service price w_{is}^K.

Capital and intermediate bundles. Sectoral composites produce capital services and intermediate inputs. For country i and sector s, let $Q_{i,rs}^K(\omega, x)$ denote the sector-r general-use composite used for capital service in task (ω, x), and let $Q_{i,rs}^M(\omega)$ denote the sector-r intermediate-use composite used for variety ω. The bundle technologies are

$$K_{is}(\omega, x) = \prod_{r \in \mathcal{S}} \left(\frac{Q_{i,rs}^K(\omega, x)}{\kappa_{i,rs}}\right)^{\kappa_{i,rs}}, \qquad \kappa_{i,rs} \ge 0, \quad \sum_{r \in \mathcal{S}} \kappa_{i,rs} = 1, \tag{14}$$

$$M_{is}(\omega) = \prod_{r \in \mathcal{S}} \left(\frac{Q_{i,rs}^M(\omega)}{\gamma_{i,rs}}\right)^{\gamma_{i,rs}}, \qquad \gamma_{i,rs} \ge 0, \quad \sum_{r \in \mathcal{S}} \gamma_{i,rs} = 1. \tag{15}$$

The weight $\kappa_{i,rs}$ gives sector r's share in the capital bundle for sector s, while $\gamma_{i,rs}$ gives its share in the intermediate bundle. I let these weights vary across countries and sectors of use but hold them fixed in counterfactuals. The intermediate-input coefficient for sector r equals $\alpha_{is}^M \gamma_{i,rs}$. Here, capital denotes the capital service produced from sectoral goods. It fully depreciates within the period, so the model has no capital endowment or accumulation equation. Let P_{ir}^G and P_{ir}^M denote the two composite prices.[16] Cost minimization gives

$$w_{is}^K = \prod_r (P_{ir}^G)^{\kappa_{i,rs}}, \qquad w_{is}^M = \prod_r (P_{ir}^M)^{\gamma_{i,rs}}. \tag{16}$$

[16]The labels G and M denote general and intermediate use. I use G, rather than F, for final use because this sourcing system covers both final consumption and purchases of equipment used in production.

Unit costs. Given these prices, country i's unit production cost in sector s is

$$c_{is} = \Lambda_{is}(w_i^H)^{\alpha_{is}^H}(w_{is}^T)^{\alpha_{is}^T}(w_{is}^M)^{\alpha_{is}^M}, \qquad \Lambda_{is} = \prod_{f\in\{H,T,M\}} (\alpha_{is}^f)^{-\alpha_{is}^f}. \tag{17}$$

The factory-gate price of variety ω therefore equals $\frac{c_{is}}{Z_{is}(\omega)}$.

3.2 General- and Intermediate-Use Sourcing

Sourcing of sectoral goods. I assume that all sectors, including service sectors, are tradable. Shipping sector-r goods from country i to country j incurs the iceberg trade cost $\tau_{ijr} \geq 1$, with $\tau_{jjr} = 1$. These iceberg trade costs apply to both sourcing systems. Final consumption and capital purchases constitute general use and are sourced through system G; intermediate purchases use system M and face an additional multiplicative delivered-cost wedge $\chi_{ijr} > 0$ relative to general use. The wedge has no separately rebated revenue, and I normalize $\chi_{jjr} = 1$. Delivered unit prices are

$$p_{jr}^G(\omega) = \min_i \frac{c_{ir}\tau_{ijr}}{Z_{ir}(\omega)}, \qquad p_{jr}^M(\omega) = \min_i \frac{c_{ir}\tau_{ijr}\chi_{ijr}}{Z_{ir}(\omega)}. \tag{18}$$

Following Caliendo and Parro (2015), the trade block is a multi-sector Eaton-Kortum system with input-output linkages. The additional wedge distinguishes the two uses. If $\chi_{ijr} = 1$ for all i, j, r, final consumption and capital purchases face the same bilateral costs as intermediate purchases, so the two sourcing systems coincide.

The Eaton-Kortum price aggregators of the two sourcing systems are

$$\Phi_{jr}^G = \sum_i \lambda_{ir}(c_{ir}\tau_{ijr})^{-\theta}, \qquad \Phi_{jr}^M = \sum_i \lambda_{ir}(c_{ir}\tau_{ijr}\chi_{ijr})^{-\theta}, \tag{19}$$

and, for $u \in \{G, M\}$, the price indices and bilateral expenditure shares are

$$P_{jr}^u = \mathcal{C}_r(\Phi_{jr}^u)^{-\frac{1}{\theta}}, \qquad \mathcal{C}_r = \Gamma\left(1 + \frac{1-\sigma_r}{\theta}\right)^{\frac{1}{1-\sigma_r}}, \tag{20}$$

$$\pi_{ijr}^G = \frac{\lambda_{ir}(c_{ir}\tau_{ijr})^{-\theta}}{\Phi_{jr}^G}, \qquad \pi_{ijr}^M = \frac{\lambda_{ir}(c_{ir}\tau_{ijr}\chi_{ijr})^{-\theta}}{\Phi_{jr}^M}. \tag{21}$$

Here $\Gamma(\cdot)$ is the gamma function, distinct from the task measures Γ_{is}^L and Γ_{is}^K of equation (13). In this level model, finite costs and positive productivity scales imply $\pi_{ijr}^u > 0$.

Measuring Offshoring. I define offshoring in country j and sector s as the share of intermediate expenditure paid to foreign suppliers; it follows from the intermediate-use sourcing system.[17] Since the input-output weights sum to one,

$$o_{js} = \sum_{r\in\mathcal{S}} \gamma_{j,rs} \sum_{i\neq j} \pi_{ijr}^M = \sum_{r\in\mathcal{S}} \gamma_{j,rs}\left(1 - \pi_{jjr}^M\right). \tag{22}$$

Sectors within a country differ because they use different input mixes $\gamma_{j,rs}$.

[17] Offshoring, therefore, measures direct foreign sourcing within intermediates rather than a separate production or task technology.

3.3 Expenditure, Market Clearing, and Equilibrium

Households and trade deficits. The representative household in country i allocates expenditure across general-use sectoral composites according to Cobb-Douglas shares $\nu_{ir} > 0$, with $\sum_r \nu_{ir} = 1$. Its consumption price index is $P_i^C = \prod_r (P_{ir}^G)^{\nu_{ir}}$. Let V_i denote primary-factor income, V^W world primary-factor income, D_i the transfer, and I_i final expenditure:

$$V_i = w_i^H H_i + w_i^L L_i, \qquad V^W = \sum_i V_i, \qquad D_i = d_i V^W, \qquad I_i = V_i + D_i, \tag{23}$$

where $\sum_i d_i = 0$ and $I_i > 0$. A positive D_i denotes a trade deficit. The shares d_i are primitives. Each counterfactual specifies signed endpoint shares d_i'; when they are held fixed, deficits scale with world income.

Absorption and revenue. Let R_{is} denote gross revenue. Country j's final expenditure on sector r is

$$E_{jr}^F = \nu_{jr} I_j. \tag{24}$$

Cost minimization gives country j's expenditure on capital goods and intermediate inputs from sector r:

$$E_{jr}^K = \sum_s \kappa_{j,rs} \alpha_{js}^T \Gamma_{js}^K R_{js}, \tag{25}$$

$$E_{jr}^M = \sum_s \gamma_{j,rs} \alpha_{js}^M R_{js}. \tag{26}$$

General-use expenditure combines final and capital demand:

$$E_{jr}^G = E_{jr}^F + E_{jr}^K. \tag{27}$$

Let $X_{ijr}^u \equiv \pi_{ijr}^u E_{jr}^u$ denote country j's expenditure on goods from country i, and let $X_{ijr} \equiv X_{ijr}^G + X_{ijr}^M$. Goods-market clearing requires

$$R_{ir} = \sum_j \left(\pi_{ijr}^G E_{jr}^G + \pi_{ijr}^M E_{jr}^M \right). \tag{28}$$

Primary-factor markets. The high- and low-skilled labor markets clear when

$$w_i^H H_i = \sum_s \alpha_{is}^H R_{is}, \qquad w_i^L L_i = \sum_s \alpha_{is}^T \Gamma_{is}^L R_{is}. \tag{29}$$

Summing expenditures across the two sourcing systems and applying goods-market clearing (28) and factor-market clearing (29) gives the country budget identity

$$D_j = \sum_{i \neq j} \sum_r \left(X_{ijr}^G + X_{ijr}^M \right) - \sum_{i \neq j} \sum_r \left(X_{jir}^G + X_{jir}^M \right). \tag{30}$$

The trade-deficit equation follows from these accounts and does not impose an additional market-clearing condition.

Equilibrium. The model is a multi-sector Eaton-Kortum economy with input-output linkages, and task assignment is its only nonstandard element.

Definition 3.1. An equilibrium is a wage vector $\{w_i^H, w_i^L\}_{i\in\mathcal{I}}$ such that, for all i, j, r, and s:

(i) given wages, the task assignment Γ_{is}^L and Γ_{is}^K, the task-composite price w_{is}^T, the capital-service and intermediate-bundle prices w_{is}^K and w_{is}^M, the unit costs c_{is}, and the general- and intermediate-use price indices P_{ir}^G and P_{ir}^M are jointly determined by (11), (12), (13), (16), (17), (19), and (20);

(ii) given unit costs and the price aggregators, the general- and intermediate-use sourcing shares π_{ijr}^G and π_{ijr}^M follow from (21);

(iii) primary-factor incomes, transfers, and final expenditure follow from wages through (23) and (24), and capital, intermediate, and general-use absorption follow from (25), (26), and (27) given gross revenues;

(iv) goods markets clear, (28), so that revenues and absorption are determined by one linear system given wages and sourcing shares, and both labor markets clear, (29).

I set $w_{\text{US}}^L = 1$ and omit the U.S. low-skilled factor-clearing condition, which is redundant by Walras's law.

3.4 Exact Hat Algebra

Following Dekle et al. (2008), I express the counterfactual equilibrium in exact changes. For any positive variable z, let $\widehat{z} \equiv \frac{z'}{z}$; I consider equilibria with positive wages and revenues. The quantitative scenarios may change the Fréchet productivity scale $\widehat{\lambda}_{ir}$, the intermediate-use wedge $\widehat{\chi}_{ijr}$, iceberg trade costs $\widehat{\tau}_{ijr}$, and endowments $(\widehat{H}_i, \widehat{L}_i)$.[18]

Task, bundle, and unit-cost changes. For the quantitative implementation, I impose interior task shares, $0 < \Gamma_{is}^K, \Gamma_{is}^L < 1$, and assume that the task-share odds have constant elasticity. Let $\Omega_{is} \equiv \frac{\Gamma_{is}^K}{\Gamma_{is}^L}$, and let $\varepsilon > 0$ denote the elasticity of these odds with respect to w_i^L / w_{is}^K. This closure implies the exact odds, shares, and task-price changes

$$\Omega_{is}' = \Omega_{is} \left(\frac{\widehat{w}_i^L}{\widehat{w}_{is}^K} \right)^{\varepsilon},$$

$$\Gamma_{is}^{K\prime} = \frac{\Omega_{is}'}{1 + \Omega_{is}'}, \qquad \Gamma_{is}^{L\prime} = 1 - \Gamma_{is}^{K\prime}. \tag{31}$$

$$\widehat{w}_{is}^T = \widehat{w}_i^L \left(\frac{1 - \Gamma_{is}^{K\prime}}{1 - \Gamma_{is}^K} \right)^{\frac{1}{\varepsilon}}. \tag{32}$$

This parameterization specializes the task technology in Section 3.

Fixed Cobb-Douglas weights and production shares imply

$$\widehat{w}_{is}^K = \prod_r (\widehat{P}_{ir}^G)^{\kappa_{i,rs}}, \qquad \widehat{w}_{is}^M = \prod_r (\widehat{P}_{ir}^M)^{\gamma_{i,rs}}, \tag{33}$$

[18] Unless stated otherwise, deficit shares remain at their base-year values, $d_i' = d_i$. The six-block robustness exercise reported with the decomposition sets d_i' to the measured 2014 shares, while the zero-deficit and closed-economy environments of Section B.5 set $d_i' = 0$.

$$\widehat{c}_{is} = (\widehat{w}_i^H)^{\alpha_{is}^H} (\widehat{w}_{is}^T)^{\alpha_{is}^T} (\widehat{w}_{is}^M)^{\alpha_{is}^M}. \tag{34}$$

Price indices and trade shares. Set

$$\widehat{g}_{ijr}^G \equiv \widehat{c}_{ir}\widehat{\tau}_{ijr}, \qquad \widehat{g}_{ijr}^M \equiv \widehat{c}_{ir}\widehat{\tau}_{ijr}\widehat{\chi}_{ijr}. \tag{35}$$

The initial shares absorb the level productivity scales and all other baseline sourcing terms. The Fréchet-scale change $\widehat{\lambda}_{ir}$ enters both sourcing systems multiplicatively, while $\widehat{\tau}_{ijr}$ and $\widehat{\chi}_{ijr}$ enter through the delivered costs in equation (35). I impose $\widehat{\tau}_{jjr} = \widehat{\chi}_{jjr} = 1$ for normalization. For each destination-sector-use cell, let $\mathcal{O}_{jr}^u \equiv \{i : \pi_{ijr}^u > 0\}$ denote the initial origin support and require $j \in \mathcal{O}_{jr}^u$. The quantitative implementation holds this support fixed, so hats for the shares are defined only on this support.[19] Initial trade shares then give the exact changes in price indices and trade shares:

$$\widehat{P}_{jr}^u = \left[\sum_{i \in \mathcal{O}_{jr}^u} \pi_{ijr}^u \widehat{\lambda}_{ir} (\widehat{g}_{ijr}^u)^{-\theta} \right]^{-\frac{1}{\theta}}, \tag{36}$$

$$\widehat{\pi}_{ijr}^u = \widehat{\lambda}_{ir} \left(\frac{\widehat{g}_{ijr}^u}{\widehat{P}_{jr}^u} \right)^{-\theta}, \qquad u \in \{G, M\}, \quad i \in \mathcal{O}_{jr}^u. \tag{37}$$

Define the counterfactual level shares on every cell by

$$\pi_{ijr}^{u\prime} = \begin{cases} \pi_{ijr}^u \widehat{\pi}_{ijr}^u, & i \in \mathcal{O}_{jr}^u, \\ 0, & i \notin \mathcal{O}_{jr}^u. \end{cases}$$

The counterfactual offshoring share equals

$$o_{js}' = \sum_r \gamma_{j,rs} \left(1 - \pi_{jjr}^{M\prime} \right). \tag{38}$$

Section 4.2 constructs $\widehat{\tau}$ and $\widehat{\chi}$ from changes in general-use and intermediate sourcing shares and constructs $\widehat{\lambda}$ from relative equipment prices.

Income, absorption, and revenue. Counterfactual factor income, world income, and absorption are

$$\begin{aligned} V_i' &= w_i^H H_i \widehat{w}_i^H \widehat{H}_i + w_i^L L_i \widehat{w}_i^L \widehat{L}_i, \\ V^{W\prime} &= \sum_i V_i', \\ I_i' &= V_i' + d_i' V^{W\prime}, \qquad \widehat{I}_i = \frac{I_i'}{I_i}. \end{aligned} \tag{39}$$

Here d_i' is a signed endpoint share satisfying $\sum_i d_i' = 0$; it is not represented by a hat because the baseline share may be zero or change sign. Positive absorption $I_i' > 0$ is required. Write $R_{is}' = R_{is}\widehat{R}_{is}$. Counterfactual expenditures are

$$E_{jr}^{F\prime} = \nu_{jr} I_j',$$

[19] Zero trade share cells are treated as the infinite-cost limit and cannot become active in counterfactuals.

$$
\begin{aligned}
E_{jr}^{K\prime} &= \sum_s \kappa_{j,rs}\alpha_{js}^T\Gamma_{js}^{K\prime}R_{js}\widehat{R}_{js}, \\
E_{jr}^{M\prime} &= \sum_s \gamma_{j,rs}\alpha_{js}^M R_{js}\widehat{R}_{js}, \\
E_{jr}^{G\prime} &= E_{jr}^{F\prime} + E_{jr}^{K\prime}.
\end{aligned} \tag{40}
$$

Goods-market clearing in the counterfactual requires

$$
R_{ir}\widehat{R}_{ir} = \sum_j \left[\pi_{ijr}^{G\prime}E_{jr}^{G\prime} + \pi_{ijr}^{M\prime}E_{jr}^{M\prime}\right]. \tag{41}
$$

Factor clearing, deficits, and normalization. The counterfactual factor-market conditions are

$$
w_i^H H_i\widehat{w}_i^H\widehat{H}_i = \sum_s \alpha_{is}^H R_{is}\widehat{R}_{is}, \qquad w_i^L L_i\widehat{w}_i^L\widehat{L}_i = \sum_s \alpha_{is}^T\Gamma_{is}^{L\prime}R_{is}\widehat{R}_{is}. \tag{42}
$$

The counterfactual transfers, bilateral flows, country budget identity, and numeraire satisfy

$$
D_i' = d_i'V^{W\prime}, \qquad X_{ijr}^{u\prime} = \pi_{ijr}^{u\prime}E_{jr}^{u\prime}, \quad u \in \{G, M\}, \tag{43}
$$

$$
D_j' = \sum_{i\neq j}\sum_r \left(X_{ijr}^{G\prime} + X_{ijr}^{M\prime}\right) - \sum_{i\neq j}\sum_r \left(X_{jir}^{G\prime} + X_{jir}^{M\prime}\right), \tag{44}
$$

$$
\widehat{w}_{\text{US}}^L = 1. \tag{45}
$$

Equation (44) follows from the goods and factor accounts, so I omit one redundant clearing equation.

Together, equations (31)–(45) characterize the finite counterfactual equilibrium. I next derive how a change in the resulting trade flows affects the PPML coefficient that measures skill-based comparative advantage.

3.5 From Shocks to the Coefficient

A counterfactual changes $\widehat{\beta}$ only through the trade flows on which the coefficient is estimated. The derivation has two parts: the estimator's response to flows and the response of model flows to primitive shocks.

Let α_s^H denote the U.S. sectoral skill intensity in equation (5), and write $h_i \equiv \ln\left(\frac{H_i}{L_i}\right)$ and $z_{is} \equiv \alpha_s^H h_i$. The U.S. sectoral skill intensity α_s^H is distinct from the country-sector cost share α_{is}^H in equation (7). I hold z_{is} fixed across the equilibria being compared. The shocks may change productivity scales, general-use trade costs, and intermediate-use sourcing wedges.

The PPML Response. The estimator uses total flows $X_{ijs} \geq 0$ and the conditional mean $\mu_{ijs} = \exp(z_{is}\beta + f_{ij} + g_{js})$, where f_{ij} is an exporter-importer fixed effect and g_{js} is an importer-sector fixed effect. PPML accommodates zero flows and requires the conditional mean, rather than the conditional expectation of the log, to be correct (Silva and Tenreyro, 2006, 2011, 2022).[20] The estimator solves

$$
\sum_s (X_{ijs} - \mu_{ijs}) = 0 \;\; \forall (i,j), \qquad \sum_i (X_{ijs} - \mu_{ijs}) = 0 \;\; \forall (j,s), \qquad \sum_{ijs} (X_{ijs} - \mu_{ijs})\, z_{is} = 0. \tag{46}
$$

[20] See Correia et al. (2020) for implementation and Correia et al. (2019) for existence.

The first two conditions make the fitted flows reproduce every exporter-importer total and every importer-sector total, the adding-up property emphasized by Fally (2015). They do not imply that both sets of fixed effects are multilateral-resistance terms. The third condition pins down the coefficient by reproducing regressor-weighted total trade. Define $\widetilde{z}_{ijs} \equiv z_{is} - \widetilde{f}_{ij} - \widetilde{g}_{js}$ as the two-way within transformation of the regressor using fitted-flow weights,

$$\sum_{s} \mu_{ijs}\widetilde{z}_{ijs} = 0 \ \ \forall(i,j), \qquad \sum_{i} \mu_{ijs}\widetilde{z}_{ijs} = 0 \ \ \forall(j,s), \tag{47}$$

which determines $(\widetilde{f}_{ij}, \widetilde{g}_{js})$ only up to the normalizations required for the fixed effects, while $\widetilde{z}$ is unique.

Proposition 3.1. *Suppose the estimator defined by equation (46) has a finite, locally regular solution at the initial flows X on a fixed estimation sample, with fitted values μ and $\sum_{ijs} \mu_{ijs}\widetilde{z}_{ijs}^2 > 0$, and let the flows be differentiable functions of the shock. Then for any perturbation $\mathrm{d}X$ of the flows,*

$$\mathrm{d}\widehat{\beta} = \frac{\sum_{ijs} \widetilde{z}_{ijs}\,\mathrm{d}X_{ijs}}{\sum_{ijs} \mu_{ijs}\widetilde{z}_{ijs}^2}. \tag{48}$$

If, in addition, the support $\mathrm{supp}(X) \equiv \{(i,j,s) : X_{ijs} > 0\}$ is locally fixed, so $\mathrm{d}X_{ijs} = 0$ off it, then $\mathrm{d}X = X\,\mathrm{d}\ln X$ on the support and

$$\mathrm{d}\widehat{\beta} = \frac{\sum\limits_{(i,j,s)\in \mathrm{supp}(X)} X_{ijs}\widetilde{z}_{ijs}\,\mathrm{d}\ln X_{ijs}}{\sum_{ijs} \mu_{ijs}\widetilde{z}_{ijs}^2}.$$

The proof is in Appendix C. Equation (48) is the exact local derivative at the initial estimate and gives a first-order approximation to a finite perturbation; integrating it along a regular path gives the corresponding exact finite change. It accommodates zeros through $\mathrm{d}X_{ijs}$. If zero-support cells remain zero under the perturbation, the fixed-support display applies.

From Primitives to the Coefficient. The model determines flows through separate sourcing systems for general and intermediate use. Taking logs and differentiating each use's gravity equation in (21), and using $X^u_{ijs} = \pi^u_{ijs}E^u_{js}$, gives, for $u \in \{G, M\}$ and each origin i in that use's support $\mathcal{O}^u_{js}$,

$$\begin{aligned} \mathrm{d}\ln X^u_{ijs} = {} & \underbrace{\mathrm{d}\ln\lambda_{is} - \theta\,\mathrm{d}\ln\tau_{ijs} - \theta\,\mathbb{1}\{u=M\}\,\mathrm{d}\ln\chi_{ijs}}_{\text{direct}}\ \underbrace{-\,\theta\,\mathrm{d}\ln c_{is}}_{\text{unit cost}} \\ & + \underbrace{\mathrm{d}\ln E^u_{js}}_{\text{expenditure}} \underbrace{-\sum_{\ell\in\mathcal{O}^u_{js}} \pi^u_{\ell js}\left[\mathrm{d}\ln\lambda_{\ell s} - \theta\,\mathrm{d}\ln\tau_{\ell js} - \theta\,\mathbb{1}\{u=M\}\,\mathrm{d}\ln\chi_{\ell js} - \theta\,\mathrm{d}\ln c_{\ell s}\right]}_{-\,\mathrm{d}\ln\Phi^u_{js}\ \text{(normalization)}}. \end{aligned} \tag{49}$$

The Fréchet scale λ_{is} enters with coefficient one because, for buyers, a higher scale reduces delivered costs by $\frac{1}{\theta}\mathrm{d}\ln\lambda_{is}$. General-use trade costs, intermediate-use sourcing wedges, and unit costs enter with $-\theta$. The final term is the log-derivative of the sourcing-share denominator in equation (19). The direct and unit-cost terms are measured relative to the sourcing-share-weighted average across competing origins in the same destination-sector-use cell. The intermediate-use sourcing wedge enters the direct term only for intermediate use, but it can also change general-use flows through unit costs and expenditure. Total trade adds the two uses, $\mathrm{d}X_{ijs} = \mathrm{d}X^G_{ijs} + \mathrm{d}X^M_{ijs}$, so its response is the use-share-weighted combination of equation (49), with $s^u_{ijs} \equiv \frac{X^u_{ijs}}{X_{ijs}}$ and $s^u_{ijs}\,\mathrm{d}\ln X^u_{ijs} \equiv \frac{\mathrm{d}X^u_{ijs}}{X_{ijs}}$.

Substituting equation (49) into Proposition 3.1 separates $\mathrm{d}\widehat{\beta}$ into direct, unit-cost, and expenditure contributions. The numerator weights realized flows X_{ijs}, whereas $\mathcal{V}_{\tilde{z}} \equiv \sum_{ijs} \mu_{ijs}\tilde{z}^2_{ijs}$ uses fitted flows. The within conditions (47) therefore impose orthogonality under fitted-flow weights. For any exporter-importer array a_{ij} and destination-sector array b_{js}, writing $e_{ijs} \equiv X_{ijs} - \mu_{ijs}$ gives

$$\sum_{ijs} X_{ijs}\tilde{z}_{ijs}(a_{ij} + b_{js}) = \sum_{ijs} e_{ijs}\tilde{z}_{ijs}(a_{ij} + b_{js}).$$

Thus, exporter-importer and destination-sector components affect $\widehat{\beta}$ only through the difference between realized and fitted flows, and vanish under an exact fit. The score conditions alone do not remove them. In particular, changes in destination-sector expenditure are not differenced out of the estimate.

The Unit-Cost System. The direct terms in equation (49) are functions of primitives, while unit costs solve a world input-output system:

$$\mathrm{d}\ln \boldsymbol{c} = (\mathbf{I} - A)^{-1}\left(F^{\text{input}} + F^{\text{wage}}\right).$$

Proposition D.1 in Appendix D defines the matrix and the two right-hand-side components and proves the result. Expenditure responds through absorption and factor-market clearing.

Where Each Shock Enters. For a perturbation, let D^u_{ijs} denote the direct component of equation (49) before the sourcing-share normalization.

Lemma 3.2. *If $D^u_{ijs} = D^u_{js}$ for every origin $i \in \mathcal{O}^u_{js}$ within a destination-sector-use cell, then the direct component cancels from that cell's flow response. It therefore has no direct effect on $\widehat{\beta}$ under any weighting scheme.*

Proof. Because the sourcing shares sum to one, $D^u_{ijs} - \sum_{\ell \in \mathcal{O}^u_{js}} \pi^u_{\ell js} D^u_{\ell js} = D^u_{js}(1 - \sum_{\ell \in \mathcal{O}^u_{js}} \pi^u_{\ell js}) = 0$, so equation (49) gives zero direct flow response cell by cell. □

A productivity change common across origins satisfies Lemma 3.2. A general-use trade-cost change can instead vary bilaterally, affect both uses, and change delivered input costs. The offshoring shock changes the additional intermediate-use sourcing wedge. This wedge enters the direct component only for intermediate use; it affects general-use flows through unit costs and expenditure. None of these perturbations has a fixed-sign effect on the coefficient because the sign also depends on the values of $\tilde{z}$ associated with the induced flow changes.

Equation (49) identifies the three flow components and the within-transformed regressor used to measure their contributions. Section 4 quantifies those components.

4 Decomposing Changes in Comparative Advantage

This section decomposes the change in skill-based comparative advantage using the model developed in Section 3. I describe the data and the calibration of the 1980 economy and the three shocks through 2014, report the benchmark Shapley decomposition and robustness checks, and then allocate the change from each shock across channels using exact counterfactual flows.

4.1 Data

The quantitative analysis constructs two benchmark input–output matrices. The 1980 matrix combines the Long-Run World Input-Output Database with the 1980 manufacturing trade data used in Section 2. The 2014 matrix combines the 2014 table from the 2016 release of WIOD with the empirical 2015 manufacturing trade wave used in that section (Timmer et al., 2015).[21] In both matrices, off-diagonal manufacturing flows come from Comtrade. I infer diagonal manufacturing flows from WIOD gross output and take all service-sector flows and the input–output structure from WIOD. The WIOD Socio-Economic Accounts provide country-sector factor-payment benchmarks, and the Barro-Lee Educational Attainment Dataset provides high- and low-skilled labor endowments (Barro and Lee, 2013).

The resulting model contains 24 named economies and the rest of the world, denoted by `ROW`, for a total of 25 economies, whereas the main empirical PPML in Section 2 spans 143 countries. The model has 401 sectors: 390 four-digit SIC87dd manufacturing sectors and 11 nonmanufacturing sectors. Its equilibrium includes domestic and foreign flows in both manufacturing and services. The regression used for the decomposition is narrower: it retains only cross-border manufacturing flows among the 24 named economies.

4.2 Calibration and Shocks

Externally assigned parameters I set the trade elasticity to $\theta = 4$. I set $\varepsilon = 1.4$ in the benchmark. This parameter governs how strongly tasks shift from low-skilled labor to capital when capital services become cheaper relative to labor. Because ε is defined for the capital–labor task-share odds, this value corresponds to a conventional substitution elasticity of 2.4. This value lies within the range of the automation-specific evidence. Eden and Gaggl (2018) report a calibrated elasticity between ICT capital and routine labor ranging from 2.14 to 3.27, while Adachi (2025) estimates a robot–worker elasticity of about 2 when it is common across occupations and about 2.7 for production occupations. As a benchmark for a quantitative automation model, Leduc and Liu (2024) use an elasticity of 3. I therefore use $\varepsilon = 1.4$ as the main specification and report $\varepsilon = 1.0$ as a more conservative sensitivity check. Automation-specific estimates are the relevant comparison because ε governs task assignment between low-skilled workers and machines, rather than substitution between aggregate labor and capital.

The 1980 Economy. I take 1980 as the benchmark year and solve the model in changes using the exact hat algebra of Section 3.4 (Dekle et al., 2008). The benchmark accounts fix the intermediate share α_{is}^{M},

[21] The 2015 trade wave is the centered average of 2014–2016 flows. The model calibration and shocks end in 2014; no separate 2015 model shock is inferred.

high-skill share α_{is}^H, task share α_{is}^T, and capital share of task payments Γ_{is}^K. The intermediate-use blocks determine the input bundle $\gamma_{i,rs}$ and the intermediate sourcing shares π_{ijr}^M. Final-consumption flows provide the prior for ν_{ir}, final consumption plus gross fixed capital formation provide the prior for π_{ijr}^G, and the 1997 capital-flow tables in Ding (2026) provide the prior for $\kappa_{i,rs}$. These values are jointly reconciled to product absorption and the model-implied intermediate, capital, and final-use margins. Endowments H_i and L_i are the Barro-Lee populations aged 25–64 with and without higher education. The deficit share d_i is net imports relative to world factor income.

Automation shock The shocks run from 1980 to 2014, and Table 1 summarizes the calibrated shocks. I calibrate the automation shock using observed NBER-CES equipment-price changes relative to aggregate manufacturing prices.[22] For manufacturing sector r, let ρ_r denote this relative price change. Because a change in λ_r common across origins implies $\widehat{P}_r = \widehat{\lambda}_r^{-1/\theta}$ at fixed costs, I set

$$\widehat{\lambda}_{ir} = \rho_r^{-\theta} \tag{50}$$

in equipment sectors, with $\widehat{\lambda}_{ir} = 1$ elsewhere. All other prices and allocations are determined in equilibrium.

Because the same ρ_r applies to every origin within an equipment sector, Lemma 3.2 implies that its direct component cancels from the flow response. The shock can still change β through unit costs and expenditure. The within-sector mechanism is task reassignment: as the relative price of capital services changes, tasks shift between capital and low-skilled labor. The signs of these endogenous responses are ambiguous. Previous work connects falling equipment prices to skill demand through capital-skill complementarity (Greenwood et al., 1997; Krusell et al., 2000; Burstein et al., 2013).

Trade cost and offshoring shocks I infer the trade and offshoring shocks from the base year and 2014 sourcing shares. For either sourcing system and each cell in the inversion support, define the share change normalized by the domestic share

$$\widetilde{\pi}_{ijr}^u \equiv \frac{\widehat{\pi}_{ijr}^u}{\widehat{\pi}_{jjr}^u}, \qquad u \in \{G, M\}. \tag{51}$$

I invert only cells whose relevant endpoint shares are at least 10^{-6}.[23] Following Head and Ries (2001), I infer the following symmetric iceberg trade-cost shock

$$\widehat{\tau}_{ijr} = \left(\widetilde{\pi}_{ijr}^G \widetilde{\pi}_{jir}^G\right)^{-\frac{1}{2\theta}}. \tag{52}$$

The intermediate-use wedge change is

$$\widehat{\chi}_{ijr} = \left(\frac{\widetilde{\pi}_{ijr}^M}{\widetilde{\pi}_{ijr}^G}\right)^{-\frac{1}{\theta}}, \qquad i \neq j, \tag{53}$$

[22] The construction aggregates SIC87 industries to SIC87dd using nominal and real shipments, with 1980 shipment weights. It covers all 84 equipment sectors in SIC87dd 3510–3599 and 3600–3699, retains both price increases and decreases, and applies each sectoral change to all 25 economies.

[23] For the Head–Ries inversion, both bilateral general-use shares and both countries' domestic general-use shares must meet this cutoff at both endpoints. Conditional on this support, the directed offshoring inversion for $i \to j$ also requires π_{ijr}^M and π_{jjr}^M to meet the cutoff at both endpoints. I neither floor nor impute unsupported cells; their corresponding shock hats remain one.

Table 1: Summary Statistics for the Calibrated Shocks, 1980–2014

Shock notation	Shock	p_{10}	p_{50}	p_{90}
$\rho_r = \widehat{\lambda}_{ir}^{-\frac{1}{\theta}}$	Automation	0.40	0.98	1.28
$\widehat{\tau}_{ijr}$	Trade costs	0.30	0.66	1.25
$\widehat{\tau}_{ijr}^{\text{CHN}}$	China trade costs	0.24	0.47	0.91
$\widehat{\tau}_{ijr}^{\text{non-CHN}}$	Non-China trade costs	0.30	0.67	1.26
$\widehat{\chi}_{ijr}$	Offshoring	0.56	1.03	2.09
$\widehat{\chi}_{ijr}^{\text{adv}}$	Offshoring to advanced	0.58	1.04	2.13
$\widehat{\chi}_{ijr}^{\text{dev}}$	Offshoring to developing	0.52	0.99	1.96
$\frac{\widehat{H}_i}{\widehat{L}_i}$	Endowment	2.99	4.54	7.77

Notes: This table shows the calibrated shocks from 1980 to 2014. Automation shocks are the relative equipment-price changes $\rho_r = \widehat{\lambda}_{ir}^{-\frac{1}{\theta}}$ for 84 equipment sectors. Trade-cost and offshoring percentiles exclude diagonal and unit cells. The indented China and Non-China rows show the exporter-based multiplicative partition of the total trade-cost shock. The indented advanced and developing rows show the origin-based multiplicative partition of the total offshoring shock. Advanced origins are the 14 Western European economies, Australia, Canada, Japan, and the United States. Endowment shocks are $\widehat{\left(\frac{H_i}{L_i}\right)} = \frac{\widehat{H}_i}{\widehat{L}_i}$.

with $\widehat{\chi}_{jjr} = 1$.

Other shocks Endowment changes $\widehat{H}_i$ and $\widehat{L}_i$ are measured from the same source as the base-year endowments. The deficit shock replaces each economy's 1980 deficit share d_i with its measured 2014 share, where the deficit share is net imports relative to world factor income. It therefore shifts final expenditure across economies without directly changing productive capacity. The benchmark decomposition holds endowments and deficit shares at their 1980 values; the robustness analysis adds the endowment and deficit shocks as separate blocks. Section 5 applies the measured endowment changes but keeps deficit shares fixed at their 1980 values.

4.3 Decomposition

With this calibration, I decompose the change in the coefficient on skill-based comparative advantage from 1980 to 2015, with the model shocks running to 2014. The three baseline shock blocks are automation, trade costs, and offshoring. Starting from the 1980 benchmark equilibrium, I solve all 2^3 combinations of the shocks, including the no-shock equilibrium. Each counterfactual keeps all 25 economies and 401 sectors in equilibrium.

For each counterfactual, I estimate the same PPML specification as in Panel 3i of Figure 3 on total flows generated by the model, the sum of general-use and intermediate-use flows. The estimation sample contains the 24 named economies as exporters and destinations, excluding domestic flows and `ROW`, and 390 manufacturing sectors. Every model regression holds the exporter-sector skill interaction at its 1980 value, and the baseline specification is unweighted. The robustness analysis below reports two four-block partitions of the shocks, a six-block design that adds endowment and deficit changes, the weighted variant, the $\varepsilon = 1.0$

sensitivity, and a shorter calibration window (1995–2014).

Panel 3i reports the corresponding empirical series. Its coefficient falls from 1.38 in 1980 to -0.23 in 2015, a decline of 1.61. I use this empirical change to scale the model contributions. By construction, the model baseline coincides with its empirical 1980 endpoint because the calibrated cross-border flows are the Comtrade flows. Therefore, the model-data gap arises entirely at the 2015 endpoint.

Decomposition method To make the results independent of decomposition order, I use the Shapley decomposition. Let $\mathcal{B}$ denote the set of shock blocks, let $\widehat{\beta}(S)$ denote the PPML estimate on the counterfactual in which the subset $S \subseteq \mathcal{B}$ is applied, and let $v(S) = \widehat{\beta}(S) - \widehat{\beta}(\varnothing)$ be the change in the estimated coefficient. The Shapley contribution of shock b is

$$\phi_b = \sum_{S \subseteq \mathcal{B} \setminus \{b\}} \frac{|S|!\,(|\mathcal{B}| - |S| - 1)!}{|\mathcal{B}|!} \left[v(S \cup \{b\}) - v(S) \right]. \tag{54}$$

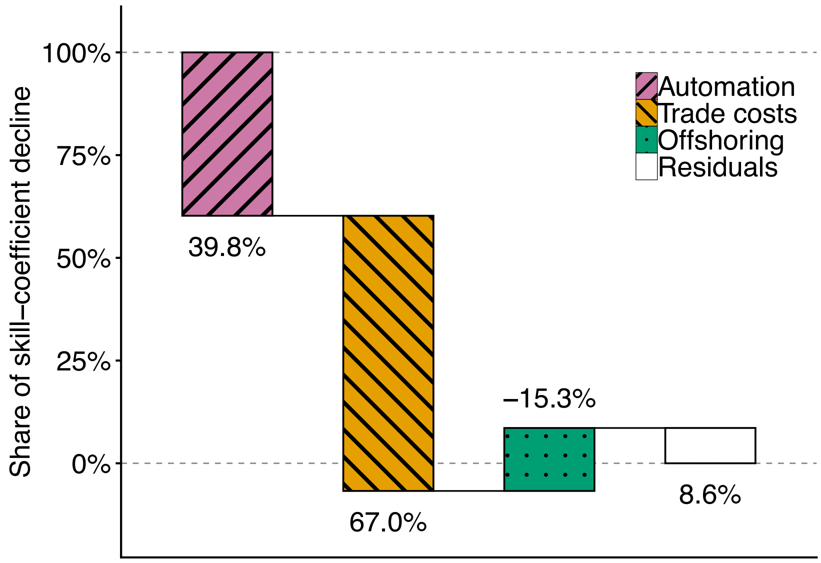
This averages the marginal contribution of each shock over all orderings and allocates the model's interaction effects across the blocks. The benchmark takes $\mathcal{B}$ to be the three blocks above; the finer partitions below enlarge $\mathcal{B}$ and leave the definition unchanged. I divide each ϕ_b by the empirical change $\Delta\widehat{\beta}^{\text{emp}} = \widehat{\beta}^{\text{emp}}_{2015} - \widehat{\beta}^{\text{emp}}_{\text{base}}$. The residual is $\Delta\widehat{\beta}^{\text{emp}} - v(\mathcal{B})$, the part of the empirical decline not generated by the model shocks.

Decomposition results Figure 4 reports the benchmark decomposition results. The empirical coefficient falls from 1.38 in 1980 to -0.23 in 2015, a decline of 1.61. Inferred trade costs account for 67.0 percent of this decline, the largest contribution, and automation for 39.8 percent, the second largest. Offshoring contributes -15.3 percent and therefore offsets part of the decline. The three shocks generate 91.4 percent of the empirical change; the remaining 8.6 percent is the residual model-data gap.

Figure 5 shows six specifications of the decomposition. Panel (a) replaces the combined trade-cost block with separate China and non-China blocks. The China block is the change in trade costs for exports from China, and the non-China block comprises all other trade-cost changes. Here, the four elements are automation, China trade costs, non-China trade costs, and offshoring. Panel (b) instead splits offshoring by the origins of intermediate inputs into advanced and developing components; advanced origins are the 14 Western European economies, Australia, Canada, Japan, and the United States. The four elements are automation, combined trade costs, offshoring to advanced economies, and offshoring to developing economies. Panel (c) adds endowment and deficit changes to panel (a)'s four elements. Panels (d) and (e) return to the three-block design and change the regression weights and the task-assignment elasticity, respectively. Panel (f) changes the calibration window to 1995–2014. Unless noted otherwise, each panel is unweighted, uses the three-block design, covers 1980–2014, and sets $\varepsilon = 1.4$.

Across the five 1980–2014 specifications in panels (a)–(e), combined trade costs remain the largest contribution, automation remains the second largest, and offshoring continues to offset part of the decline. Lowering the task-assignment elasticity from $\varepsilon = 1.4$ to $\varepsilon = 1.0$ reduces automation's share of the comparative-advantage decline from 39.8 to 31.7 percent. Panel (b) identifies the source of the offshoring offset: offshoring to advanced economies accounts for -13.5 percent of the decline, compared with -1.3 percent for offshoring to developing economies, so the offset comes almost entirely from sourcing among advanced

Figure 4: Decomposition of the Change in the Importance of Skill Abundance in Comparative Advantage



Notes: This figure shows the exact Shapley decomposition of the PPML coefficient's decline from 1.38 in 1980 to -0.23 in 2015 using the model sample and holding the skill interaction fixed at its 1980 value. The counterfactuals start from the 1980 benchmark equilibrium, apply the 1980–2014 shocks, and set $\varepsilon = 1.4$. The PPML outcome is the sum of model-generated general-use and intermediate-use cross-border flows among 24 named economies and 390 manufacturing sectors. The regression uses no weights. Each colored bar shows a shock's Shapley contribution divided by the empirical decline. The residual is the model-data gap, so the bars sum to 100 percent. A negative share offsets the empirical decline. Shares are rounded to one decimal, so the components need not sum to the displayed totals.

economies. In panel (f), however, offshoring contributes 5.7 percent of the empirical decline rather than offsetting it. This shorter-window specification is not used in the mechanism or macroeconomic analyses.

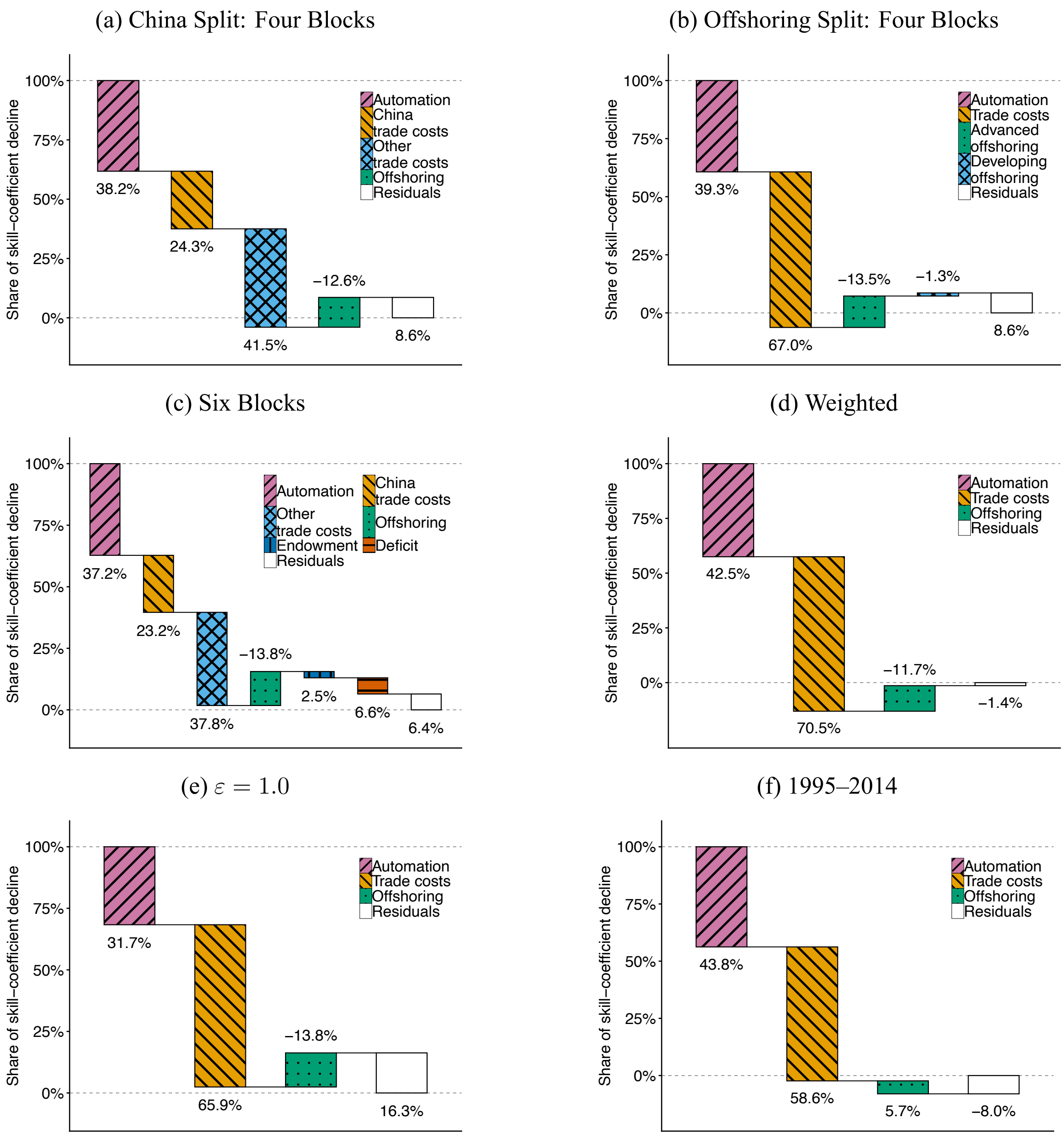
4.4 Channel Accounting

Figures 4 and 5 show that trade costs and automation contribute to the change in comparative advantage documented in Section 2, while offshoring partly offsets it. To understand how these shocks contribute to the decline in $\widehat{\beta}_t$, I use equation (49) to separate the trade flow response into direct, unit-cost, and expenditure channels. I measure the same three channels exactly for each finite calibrated change by constructing model trade flows at the 2014 endpoint for every subset of these channels and re-estimating PPML. Let 0 denote the 1980 baseline, and let $k \in \{\tau, \lambda, \chi\}$ denote the counterfactual that applies only one of the trade-cost, automation, or offshoring shocks. For use $u \in \{G, M\}$ and channel $p \in \mathcal{P} \equiv \{d, c, e\}$, define

$$\zeta^{u,k}_{d,ijs} = \begin{cases} \widehat{\tau}^{-\theta}_{ijs}, & k = \tau, \\ \widehat{\lambda}_{is}, & k = \lambda, \\ 1, & k = \chi,\ u = G, \\ \widehat{\chi}^{-\theta}_{ijs}, & k = \chi,\ u = M, \end{cases}$$

$$\zeta^{u,k}_{c,ijs} = (\widehat{c}^{k}_{is})^{-\theta}, \qquad \zeta^{u,k}_{e,ijs} = \widehat{E}^{u,k}_{js},$$

Figure 5: Decomposition of the Change in the Importance of Skill Abundance: Robustness



Notes: This figure shows six robustness checks for the exact Shapley decomposition of the PPML coefficient's decline. Except where noted in the panel title, each panel covers 1980–2014, uses the unweighted three-block design with automation, trade costs, and offshoring, and sets $\varepsilon = 1.4$. Panel (a) splits trade costs into China and non-China components. Panel (b) splits offshoring by the origins of intermediate inputs into advanced and developing components. Advanced origins are the 14 Western European economies, Australia, Canada, Japan, and the United States. Panel (c) adds endowment and deficit changes to panel (a)'s four blocks. Panel (d) weights observations by exporter-sector total exports in 2015, held fixed across destinations and counterfactuals. Panel (e) sets $\varepsilon = 1.0$. Panel (f) applies the benchmark specification to 1995–2014. Each colored bar shows a block's Shapley contribution divided by the corresponding empirical decline. The residual is the model-data gap.

where $\widehat{E}^{u,k}_{js} = E^{u,k}_{js,1}/E^{u}_{js,0}$. The notation keeps the products below compact: the unit-cost factor does not vary with destination j or use u, and the expenditure factor does not vary with origin i. The resulting endpoint trade flow satisfies

$$X^{u,k}_{ijs,1} = X^{u}_{ijs,0}\frac{\zeta^{u,k}_{d,ijs}\zeta^{u,k}_{c,ijs}}{\sum_{\ell}\pi^{u}_{\ell js,0}\zeta^{u,k}_{d,\ell js}\zeta^{u,k}_{c,\ell js}}\zeta^{u,k}_{e,ijs}. \tag{55}$$

The denominator makes the sourcing shares sum to one and is not a fourth channel.

For any subset $S \subseteq \mathcal{P}$, construct the synthetic use-specific flow

$$X^{u,k}_{ijs}(S) = X^{u}_{ijs,0}\frac{\prod_{p\in S\cap\{d,c\}}\zeta^{u,k}_{p,ijs}}{\sum_{\ell}\pi^{u}_{\ell js,0}\prod_{p\in S\cap\{d,c\}}\zeta^{u,k}_{p,\ell js}}\prod_{p\in S\cap\{e\}}\zeta^{u,k}_{p,ijs}. \tag{56}$$

Total trade is formed only after constructing the two use-specific flows:

$$X^{k}_{ijs}(S) = X^{G,k}_{ijs}(S) + X^{M,k}_{ijs}(S). \tag{57}$$

Re-estimating PPML on each of the eight flow matrices gives $\widehat{\beta}^{k}(S)$. Define $v^{k}(S) \equiv \widehat{\beta}^{k}(S) - \widehat{\beta}^{k}(\varnothing)$. Applying equation (54) with $\mathcal{B} = \mathcal{P}$ and $v = v^{k}$ defines the channel contribution ϕ^{k}_{p}. The three contributions add exactly to the change from the corresponding shock reported in Table 2:

$$\phi^{k}_{d} + \phi^{k}_{c} + \phi^{k}_{e} = \widehat{\beta}^{k}(\mathcal{P}) - \widehat{\beta}^{k}(\varnothing). \tag{58}$$

Trade Costs. Table 2 reports the exact channel changes and their shares of each shock's total.[24] For trade costs, the direct channel is market access, $\widehat{\tau}^{-\theta}_{ijs}$. Its -0.98 entry is negative because the Shapley-weighted average along the paths of the flow-weighted interaction between the normalized direct reallocation and the within-transformed regressor $\widetilde{z}$ is negative. Under fitted-flow weights, $\widetilde{z}$ is orthogonal to every exporter-importer and destination-sector array. Those components therefore affect the entry only through the difference between realized and fitted flows described in Section 3.5; apart from that difference, the variation in trade costs remaining after exporter-importer and destination-sector effects are removed drives the direct channel. This channel accounts for 86.6 percent of the exact trade-cost change. The Shapley-weighted average of the flow-weighted interaction is also negative for the -0.19 unit-cost entry, which reinforces the decline, and positive for the $+0.04$ expenditure entry, which partly offsets it. Table B.1 shows that the unit-cost Shapley entry is $+0.32$ for the China block and -0.32 for the non-China block. The opposite signs show that the joint negative unit-cost entry is not a China-block result; the two block entries need not add to the joint entry.

[24] Corollary D.2 and Lemma D.3 in Appendix D.2 show that each unscaled $\Delta\widehat{\beta}$ entry is a Shapley-weighted integral of an exact channel derivative along the synthetic paths used for the accounting. I describe its sign and magnitude using the Shapley-weighted average along these paths of the X-weighted interaction between a channel's flow response and the within-transformed regressor in equation (80). At the baseline, the derivative reproduces equation (49); the paths are accounting devices, not equilibrium transitions. The percentage column rescales each channel entry by the corresponding shock's exact total.

Automation. Automation's direct contribution is zero along every path associated with a channel subset: its productivity factor is common across origins and therefore satisfies Lemma 3.2 and cancels exactly. The Shapley-weighted averages of the flow-weighted interactions are negative for both the -0.60 unit-cost entry and the -0.19 expenditure entry. One component of the unit-cost response is task reassignment: equipment productivity changes capital-service prices relative to low-skilled wages. The unit-cost entry also includes differences in equipment exposure, input-output propagation, and factor-price responses. The expenditure entry works through changes in destination-sector expenditure. The structural zero in this decomposition does not imply a zero technology term in the welfare decomposition; the two terms answer different questions.

Offshoring. The direct offshoring entry is small and slightly negative. Unlike automation's zero, it is a quantitative outcome of the calibrated accounting, not a structural identity. The intermediate-use wedge enters the direct channel only for intermediate flows. The $+0.20$ unit-cost and $+0.10$ expenditure entries include the general-equilibrium response, and their Shapley-weighted averages of the flow-weighted interactions are positive; the expenditure entry operates through changes in expenditure. Together, the three channels sum to $+0.29$, the exact change from the offshoring shock.

These are endpoint accounting results under the maintained calibration and inversion assumptions.[25]

5 Trade, Automation, and the Skill Premium

I next examine how lower trade costs and automation affect skill premia and welfare as skill supplies expand. Katz and Murphy (1992) and Berman et al. (1994) separate changes in relative skill demand into between- and within-industry components. Berman et al. (1994) interpret the predominance of within-industry upgrading over between-industry employment reallocation as evidence favoring labor-saving technological change over trade-related product-demand shifts. Feenstra and Hanson (1996, 1999) show that offshoring can also raise skill demand within industries. This within-between decomposition differs from the product-price and factor-content approaches that connect trade to factor prices (Deardorff and Staiger, 1988; Leamer, 2000; Krugman, 2000; Adão et al., 2022); Krugman (2008) further emphasizes that specialization can occur within broadly defined industries.

Even holding the intermediate-use wedge fixed, a decline in general-use trade costs can change delivered equipment and input prices and reassign tasks from low-skilled labor to capital. The conventional within-between decomposition is therefore descriptive rather than an identification strategy in this environment: within-industry skill upgrading need not reveal whether the primitive shock was technological or a decline in trade costs.

All counterfactuals in this section include the measured changes in high- and low-skilled labor supplies.[26] I compare endowment changes alone, automation at 1980 trade costs, the observed trade-cost decline without

[25] They do not identify independent causal effects and impose neither the sign of a baseline-local Ψ_p^k nor a pointwise sign restriction.

[26] Both labor types move freely across sectors within each country in the model, so the exercise compares endpoint equilibria rather than transition dynamics with mobility frictions; see Caliendo et al. (2019).

Table 2: Exact Channel Decomposition of Each Shock's Effect on $\widehat{\beta}$

Channel	$\Delta\widehat{\beta}$	Percent (%)
Trade costs		
Market access ($\widehat{\tau}^{-\theta}$)	-0.98	86.6
Unit cost ($\widehat{c}^{-\theta}$)	-0.19	17.1
Expenditure	0.04	-3.7
Total (exact one-shock $\Delta\widehat{\beta}$)	-1.14	100.0
Automation		
Direct productivity term in $\widehat{\beta}$	—	—
Unit cost ($\widehat{c}^{-\theta}$)	-0.60	75.9
Expenditure	-0.19	24.1
Total (exact one-shock $\Delta\widehat{\beta}$)	-0.79	100.0
Offshoring		
Direct wedge ($\widehat{\chi}^{-\theta}$)	-0.005	-1.5
Unit cost ($\widehat{c}^{-\theta}$)	0.20	68.3
Expenditure	0.10	33.3
Total (exact one-shock $\Delta\widehat{\beta}$)	0.29	100.0

Notes: This table shows the exact decomposition of the change generated by each shock in the PPML coefficient from 1980 to 2014 into the direct, unit-cost, and expenditure factors in equation (55). Each factor subset defines a normalized synthetic flow matrix through equations (56) and (57) and has a separate PPML estimate. The channel entries sum to the change generated by each shock, as shown in equation (58). Percentages divide each entry by the corresponding exact total. The unit-cost factor combines input-cost propagation and factor-price responses. The expenditure factor allows general and intermediate expenditure to move separately. Automation has no direct contribution by construction.

automation, and the two shocks jointly. Intermediate-use wedges and deficit shares remain at their 1980 values. Section 5.2 then compares the automation effect under 1980 and 2014 trade costs. For outcome $Y \in \{\mathrm{SP}, W\}$, let

$$y_i^Y(a,t) \equiv 100 \ln Q_i^Y(a,t), \qquad a,t \in \{0,1\},$$

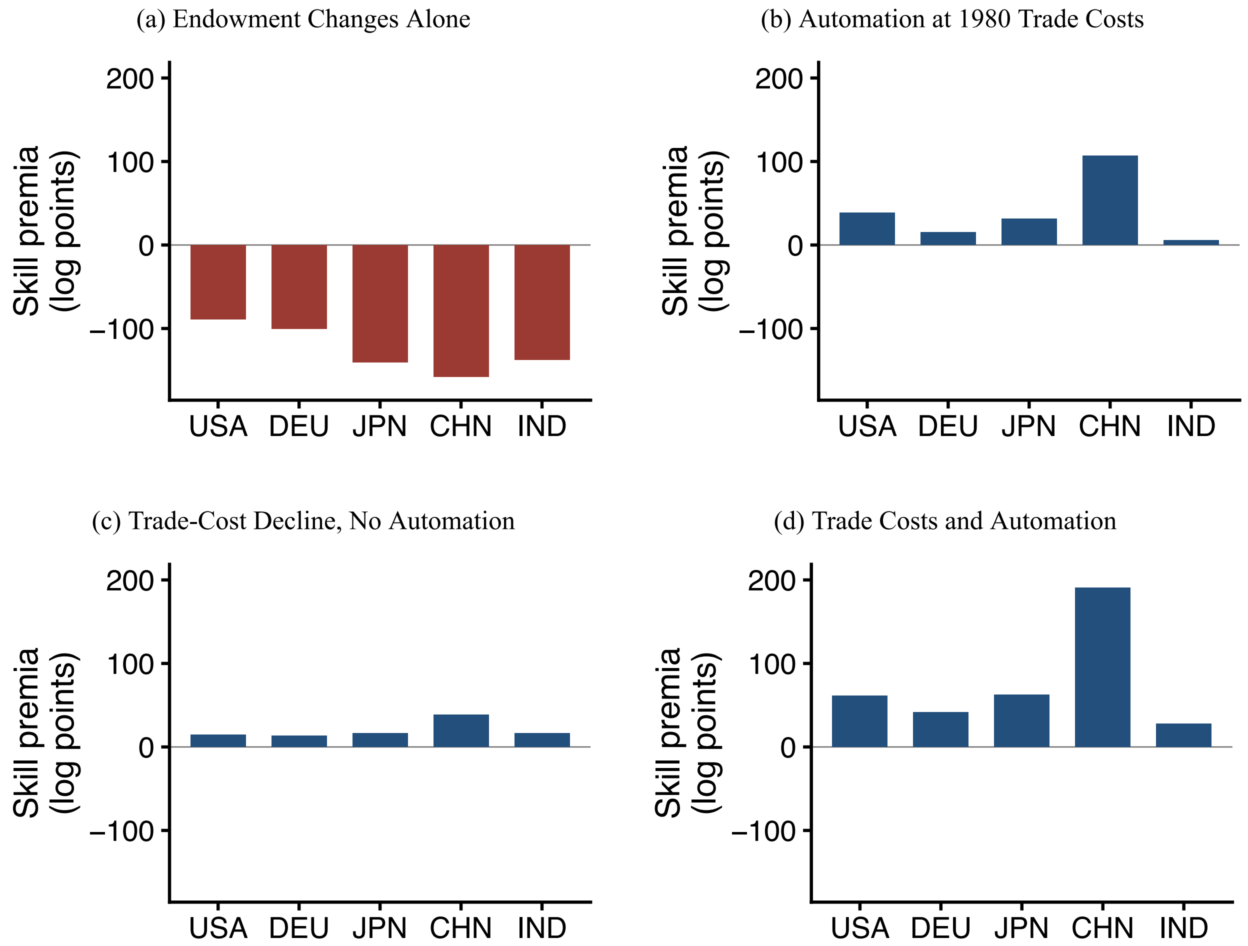
where Q_i^{SP} is the skill-premium hat, Q_i^W is the welfare hat, a indicates automation, and t the trade-cost environment. Appendix B.2 gives the full definitions and the comparisons used in the tables and figures.

5.1 Trade and Technology in the Race for Skills

The skill premium can be organized as a race between shifts in the supply of skill and shifts in its relative demand, a perspective associated with Tinbergen (1974) and developed systematically by Goldin and Katz (2008). Acemoglu and Restrepo (2018, 2022b) recast technological change in terms of task assignment: automation expands the set of tasks performed by capital and can displace workers from tasks they previously performed.

Figure 6 reports the race between skill supply, trade costs, and automation. The measured growth of

Figure 6: The Race for Skills: Endowments, Trade Costs, and Automation



Notes: This figure shows skill-premium changes from endowments, trade costs, and automation, measured in log points. Panel (a) shows the 1980–2014 endowment changes relative to the 1980 equilibrium. Panels (b)–(d) show, respectively, automation at 1980 trade costs, the trade-cost decline without automation, and both shocks relative to the endowment-only equilibrium. All counterfactuals apply the measured endowment changes and hold intermediate-use wedges and deficit shares at their 1980 values. The model has 25 economies and 401 sectors; the figure shows five economies on a common vertical axis.

relative skill supplies alone lowers the skill premium in all 25 economies, by 137.41 log points at the median. Against that baseline, automation at 1980 trade costs raises the premium in every economy by 15.44 log points at the median, and the trade-cost decline without automation raises it by 18.86 log points at the median. Applying both shocks raises the premium by 59.47 log points at the median. In China, the joint increase of 190.80 log points more than offsets the 157.96-log-point supply-driven decline; in the United States, the joint increase of 61.54 log points leaves 27.09 log points of the 88.64-log-point decline. These counterfactuals isolate the effects of measured skill supplies, trade costs, and equipment productivity; they are not a complete accounting of the historical skill-premium path. Other shifts in relative skill demand, including the secular component emphasized by Katz and Murphy (1992), remain outside the exercise.

Factor-market clearing separates the local skill-premium response into relative supply, sectoral reallocation, and task reassignment. Let b_{is}^{H} and b_{is}^{L} denote the high- and low-skilled wage-bill shares in the current equilibrium, let $\Gamma^K_{is} \equiv 1 - \Gamma^L_{is}$, and let w^K_{is} denote the capital-service price. Then

$$\mathrm{d}\ln\left(\frac{w^H_i}{w^L_i}\right) = \mathrm{d}\ln\left(\frac{L_i}{H_i}\right) + \underbrace{\sum_s (b^H_{is} - b^L_{is})\,\mathrm{d}\ln R_{is}}_{\text{sectoral reallocation}} - \underbrace{\sum_s b^L_{is}\,\mathrm{d}\ln\Gamma^L_{is}}_{\text{task reassignment}}, \tag{59}$$

$$\mathrm{d}\ln\Gamma^L_{is} = -\varepsilon\Gamma^K_{is}\left(\mathrm{d}\ln w^L_i - \mathrm{d}\ln w^K_{is}\right). \tag{60}$$

Automation reassigns tasks from low-skilled labor to capital when equipment productivity lowers the capital-service price relative to the low-skilled wage. Lower trade costs can induce the same reassignment by changing the delivered prices of equipment and intermediate inputs and the associated equilibrium wage response.

This task-displacement mechanism differs from the capital-skill-complementarity channel in Burstein et al. (2013). Here, cheaper capital raises relative skill demand by taking over tasks previously assigned to low-skilled labor, not by directly complementing high-skilled labor.

The high-skilled share of labor payments within sector s is

$$s^H_{is} \equiv \frac{\alpha^H_{is}}{\alpha^H_{is} + \alpha^T_{is}\Gamma^L_{is}}. \tag{61}$$

Because α^H_{is} and α^T_{is} are fixed, a decline in Γ^L_{is} raises s^H_{is} within the sector. A conventional within-between accounting exercise would record this task reassignment as within-industry skill upgrading. It could therefore classify the effect of lower trade costs as technological change even though the primitive shock is a decline in trade costs.

This task-reassignment margin differs from the worker-sorting margin in Adão (2026). Here, workers are homogeneous within each skill type, and the set of tasks assigned to low-skilled labor changes within a country-sector cell. There, workers within demographic groups differ in sector-specific skills and sort across sectors according to comparative advantage, changing sectoral employment, average wages, and within-group wage dispersion.

To implement the decomposition for finite counterfactuals, I use the exact factor-market identity. Let a superscript 0 denote the 1980 equilibrium and define the base-year high- and low-skilled wage-bill shares

$$b^{H,0}_{is} \equiv \frac{\alpha^H_{is} R^0_{is}}{w^{H,0}_i H^0_i}, \qquad b^{L,0}_{is} \equiv \frac{\alpha^T_{is}\Gamma^{L,0}_{is} R^0_{is}}{w^{L,0}_i L^0_i}. \tag{62}$$

Here R_{is} is gross sectoral revenue and Γ^L_{is} is the share of sector s's tasks assigned to low-skilled labor. For each cell (a,t), let $r^{a,t}_{is} \equiv \widehat{R}_{is}(a,t)$ and $g^{a,t}_{is} \equiv \widehat{\Gamma}^L_{is}(a,t) = \Gamma^L_{is}(a,t)/\Gamma^{L,0}_{is}$. The factor-market conditions (42) then imply the exact identity

$$Q^{\mathrm{SP}}_i(a,t) = \frac{\widehat{L}_i}{\widehat{H}_i} \cdot \frac{\sum_s b^{H,0}_{is} r^{a,t}_{is}}{\sum_s b^{L,0}_{is} g^{a,t}_{is} r^{a,t}_{is}}. \tag{63}$$

Appendix B.3 defines the exact two-element Shapley allocation of the remaining finite change in equation (63) between sectoral revenue and task assignment. For the endowment panel, Table 3 reports these components for $(a,t) = (0,0)$. For each shock panel $(a,t) \in \{(1,0),(0,1),(1,1)\}$, it reports $100[C^k_i(a,t) - C^k_i(0,0)]$ for $k \in \{R,\Gamma\}$; the common supply term therefore cancels. This construction compares two cell-level decompositions, both anchored at 1980; it does not re-anchor the Shapley decomposition at the endowment-only equilibrium.

Table 3 quantifies this result. Its sectoral-reallocation component is the model's between-industry output-mix margin, not a literal Stolper-Samuelson effect. At 1980 trade costs, task reassignment contributes 26.43 log points to automation's 23.94-log-point mean effect, while sectoral reallocation contributes -2.49. For the trade-cost decline without automation, task reassignment contributes 30.20 log points and sectoral reallocation contributes -6.00, for a total of 24.20. Applying both shocks yields 74.61 through task reassignment and -9.10 through sectoral reallocation. Task reassignment therefore accounts for the positive mean skill-premium effects of both primitive shocks, while sectoral reallocation offsets them. In this environment, the conventional within-between decomposition is descriptive rather than identifying: lower general-use trade costs produce the within-industry skill upgrading commonly attributed to technology even though the intermediate-use wedge is fixed.

5.2 Trade and Automation as Complements

This subsection asks whether the same equipment-productivity shock has larger skill-premium and welfare effects when trade costs are lower. Define the interaction

$$\text{INT}_i^Y \equiv y_i^Y(1,1) - y_i^Y(0,1) - y_i^Y(1,0) + y_i^Y(0,0). \tag{64}$$

A positive value means that lower trade costs amplify the effect of the fixed automation shock; zero means that its effect is independent of the trade-cost environment.

Panel (a) of Figure 7 compares automation's effect on the skill premium under 1980 and 2014 trade costs. Every economy lies above the 45-degree line. The interaction averages 17.37 log points across the 25 economies and has a median of 14.52; it equals 45.25 in China and 8.36 in the United States. The factor-market decomposition assigns 17.98 log points to task reassignment and -0.61 to sectoral reallocation. Task reassignment accounts for the positive mean interaction, while sectoral reallocation offsets it.

Welfare is representative-household real income,

$$W_i \equiv \frac{I_i}{P_i^C}, \qquad I_i = w_i^H H_i + w_i^L L_i + d_i V^W, \qquad \widehat{P}_i^C = \exp\left(\sum_r \nu_{ir,1980} \ln \widehat{P}_{ir}^G\right). \tag{65}$$

In the exact-change representation, the price system determines the sourcing channel. With trade elasticity θ, the delivered-price hats satisfy

$$\widehat{P}_{ir}^u = \widehat{c}_{ir} \left(\frac{\widehat{\pi}_{iir}^u}{\widehat{\lambda}_{ir}}\right)^{1/\theta}, \qquad u \in \{G, M\}. \tag{66}$$

Here π_{iir}^G and π_{iir}^M are domestic expenditure shares in the general- and intermediate-use sourcing systems. The calibrated automation shock is common across origins within each affected equipment sector. Lower trade costs change the sourcing shares and production networks, altering how this common equipment-productivity improvement affects each economy. This changes capital-service prices, task assignment, and the consumption price index, so the welfare effect of the same technology shock depends on the trade-cost environment.

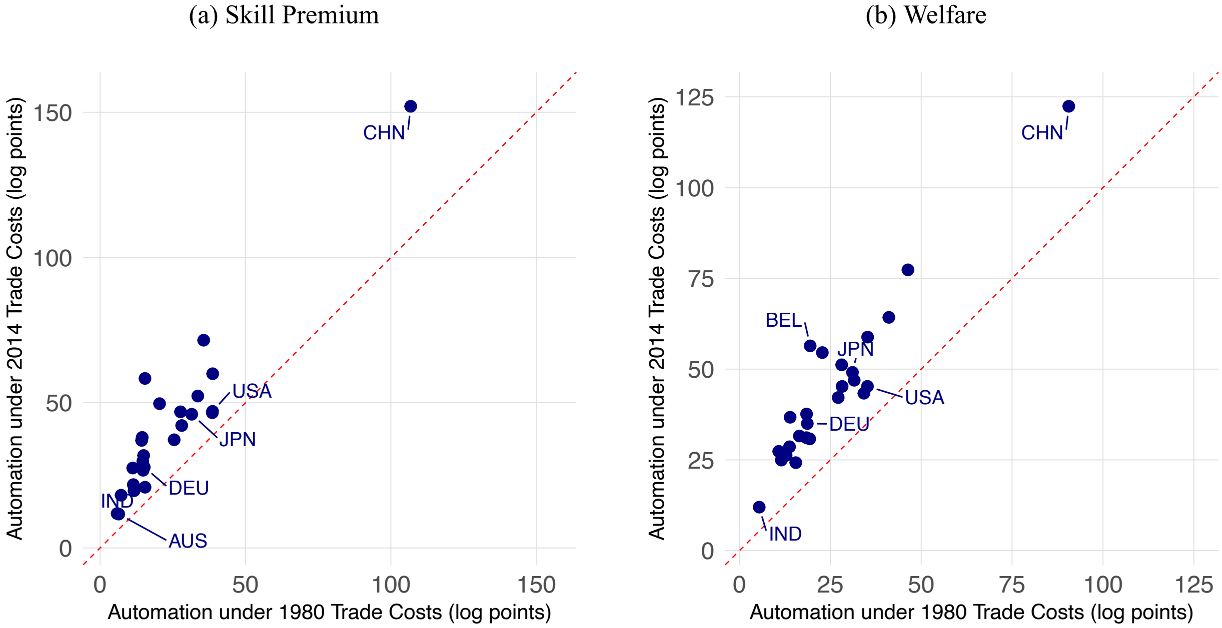
Panel (b) of Figure 7 shows the welfare results. Lower trade costs amplify automation's welfare effect

Table 3: Sectoral Reallocation and Task Reassignment in the Skill-Premium Response

	(Log points)			
Country	Supply	Sectoral reallocation	Task reassignment	Total
Panel A. Endowment changes				
USA	-105.21	-1.88	18.45	-88.64
DEU	-110.93	-1.31	12.22	-100.02
JPN	-164.69	-1.16	25.52	-140.33
CHN	-160.79	-0.72	3.55	-157.96
IND	-151.40	1.26	12.73	-137.41
Mean (25)	-153.12	-1.34	15.81	-138.65
Panel B. Automation at 1980 trade costs				
USA	—	-2.80	41.47	38.67
DEU	—	-1.41	16.60	15.19
JPN	—	-0.33	31.84	31.51
CHN	—	6.32	100.49	106.81
IND	—	-0.04	5.92	5.88
Mean (25)	—	-2.49	26.43	23.94
Panel C. Trade-cost changes without automation				
USA	—	0.29	14.22	14.51
DEU	—	-3.23	16.74	13.51
JPN	—	-0.78	17.25	16.47
CHN	—	6.44	32.30	38.74
IND	—	-0.58	16.78	16.20
Mean (25)	—	-6.00	30.20	24.20
Panel D. Both shocks				
USA	—	-3.98	65.52	61.54
DEU	—	-6.03	47.35	41.32
JPN	—	-2.16	64.66	62.50
CHN	—	17.31	173.49	190.80
IND	—	-1.74	29.77	28.03
Mean (25)	—	-9.10	74.61	65.51

Notes: This table shows the supply, sectoral-reallocation, and task-reassignment components of the 1980–2014 skill-premium response. Entries are log points (100 times the log change). Country rows show the United States, Germany, Japan, China, and India. Mean (25) is the unweighted mean across all 25 model economies, including ROW. Supply is the direct relative-supply term $\ln\left(\frac{\widehat{L}_i}{\widehat{H}_i}\right)$ from factor-market clearing. Sectoral Reallocation and Task Reassignment show the exact two-element Shapley split of the remainder between $\widehat{R}_{is}$ and $\widehat{\Gamma}^L_{is}$ at base-year wage-bill shares, as in equation (59). The rounding convention ensures that the displayed components sum to Total. Panel A shows the measured 1980–2014 endowment changes relative to the 1980 equilibrium. Panels B–D show the specified shocks relative to the endowment-only equilibrium; their supply terms are zero. Panel B holds trade costs at their 1980 values; Panel C excludes automation; and Panel D applies both shocks. Intermediate-use wedges and deficit shares remain at their 1980 values.

Figure 7: Trade Costs Amplify the Effects of Automation



Notes: This figure shows automation's effects on the skill premium and welfare. The horizontal axis shows the effect at 1980 trade costs, $y_i^Y(1,0) - y_i^Y(0,0)$, and the vertical axis shows the effect at 2014 trade costs, $y_i^Y(1,1) - y_i^Y(0,1)$. Points above the 45-degree line have $\text{INT}_i^Y > 0$. Both panels include all 25 model economies, including ROW. Values are log points.

in all 25 economies. The interaction averages 18.27 log points and has a median of 16.34; it equals 31.81 in China and 10.04 in the United States. Burstein and Vogel (2017) show that trade can affect skill premia through reallocation across sectors and firms, while Bustos (2011) and Lileeva and Trefler (2010) show that market access can induce firms to adopt technology. Here, the equipment-productivity shock is held fixed and only the trade-cost environment changes. A positive interaction therefore means that integration increases the skill-premium or welfare effect of a given automation shock; it does not mean that integration causes more automation.

Appendix B.5 provides an autarky benchmark. Closing the economy reduces automation's skill-premium and welfare effects in every economy, confirming that trade amplifies rather than creates the effects of automation.

6 Conclusion

Has the emergence of China and other developing countries made previous patterns of comparative advantage more prominent? Or has the 21st century, with new technologies such as automation, reversed these patterns, rendering them less relevant? This paper shows that the positive association between skill abundance and skill-intensive specialization weakened and ultimately reversed.

First, on the empirical side, a country's skill abundance was a source of comparative advantage in skill-intensive sectors during the 1980s. The relationship weakened in the 1990s, was statistically insignificant in 2000 and 2005, and was significantly negative in 2010 and 2015. The decline is robust across alternative specifications and when both countries' skill abundance and sectors' skill intensity are held fixed at common benchmark years.

Second, on the quantitative side, I embed task assignment in a multi-sector trade model with input-output linkages and use it to measure the roles of automation, trade costs, and offshoring. Combined trade-cost declines make the largest contribution to the decline in skill-based comparative advantage, automation makes the second-largest contribution, and offshoring offsets part of the decline. Market access accounts for most of the trade-cost contribution. Automation works through production costs, factor prices, and expenditure, with task reassignment as its within-sector mechanism. Task reassignment also accounts for the positive skill-premium effects of automation and its interaction with lower trade costs, while sectoral reallocation offsets them. Lower trade costs amplify automation's effects on skill premia and welfare in all 25 economies.

These results qualify the conventional interpretation of within-between evidence. In this environment, within-between accounting is not an identifying strategy for separating trade from technology: a decline in general-use trade costs can generate within-industry skill upgrading through task reassignment even when the intermediate-use wedge is fixed. The incidence of automation is not determined by technology alone. The international trading environment determines how strongly equipment productivity reassigns tasks, changes relative wages, and raises real income.

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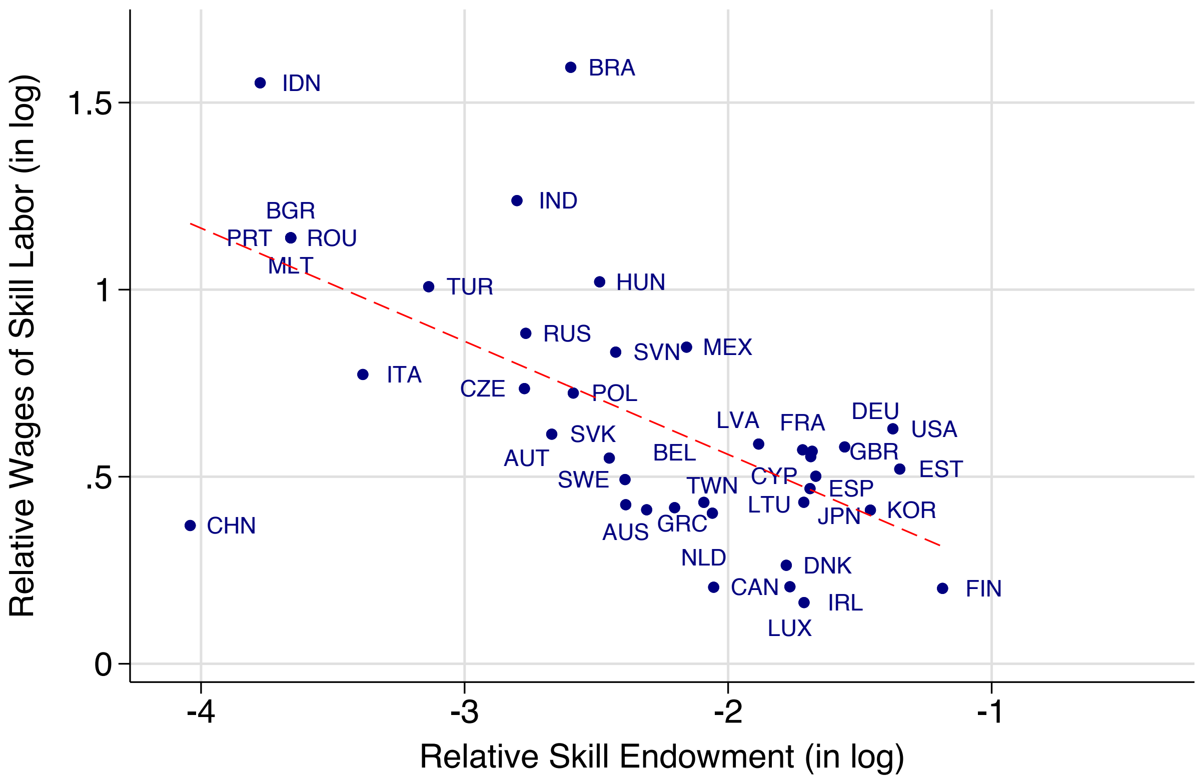
Online Appendix for *Does Skill Abundance Still Matter? The Evolution of Comparative Advantage in the 21st Century*

A Additional Empirical Results

A.1 Additional Figures for Section 2

Relative Skill Endowments and Relative Wages of Skilled Labor. Figure A.1 shows relative skill endowments and relative wages of skilled labor across countries in 1995, with both variables measured in logarithms. The data come from the WIOD Socio Economic Accounts (Timmer et al., 2015). The estimated slope is negative (-0.30), consistent with equation (3).

Figure A.1: Relative Skill Endowments and Relative Wages of Skilled Labor



Notes: This figure shows log relative skill endowments and log relative wages of skilled labor across countries in 1995. Each dot is a country, and the line is the OLS fit. The source is the WIOD Socio Economic Accounts.

B Additional Quantitative Results

B.1 Mechanism Accounting Detail

Table B.1 repeats the exact channel accounting of Table 2 for the China and non-China trade-cost blocks separately over 1980–2014. It reports both the effect of changing each factor separately from its baseline value and the exact Shapley allocation.

Table B.1: Exact Channel Decomposition of the Trade-Cost Effect on $\widehat{\beta}$

	China		Non-China		Joint	
Channel	Alone	Shapley	Alone	Shapley	Alone	Shapley
Panel A. Change in $\widehat{\beta}$						
Market access ($\widehat{\tau}^{-\theta}$)	-1.13	-0.99	-1.14	-0.99	-0.88	-0.98
Unit cost ($\widehat{c}^{-\theta}$)	0.15	0.32	-0.53	-0.32	-0.24	-0.19
Expenditure	0.01	0.02	0.23	0.10	0.23	0.04
Interaction	0.31	—	0.23	—	-0.24	—
Total (exact $\Delta\widehat{\beta}$)	-0.66	-0.66	-1.21	-1.21	-1.14	-1.14
Panel B. Percent of the exact $\Delta\widehat{\beta}$						
Market access ($\widehat{\tau}^{-\theta}$)	172.2	150.4	94.5	81.7	77.9	86.6
Unit cost ($\widehat{c}^{-\theta}$)	-23.4	-47.9	43.5	26.7	21.5	17.1
Expenditure	-1.1	-2.5	-19.4	-8.3	-20.6	-3.7
Interaction	-47.7	—	-18.7	—	21.2	—
Total (exact $\Delta\widehat{\beta}$)	100.0	100.0	100.0	100.0	100.0	100.0

Notes: This table shows the channel decomposition of the China and non-China trade-cost blocks separately. For each block and use $u \in \{G, M\}$, every subset of the direct factor $\widehat{\tau}_{ijs}^{-\theta}$, unit-cost factor $\widehat{c}_{is}^{-\theta}$, and expenditure factor $\widehat{E}_{js}^{u}$ defines the normalized synthetic flow in equation (56). The Alone column turns on one factor from the 1980 baseline and equals $\widehat{\beta}(\{p\}) - \widehat{\beta}(\emptyset)$. The Interaction row equals the exact change minus the sum of the three Alone effects. Shapley assigns this interaction to the three channels, so the table has no separate interaction entry. The entries in each block sum to the exact block change. Percentages divide each entry by the corresponding block change.

B.2 Counterfactual Definitions and Full Country Results

Let $q = (a, t) \in \{0, 1\}^2$, where $a = 1$ applies the measured 1980–2014 equipment-productivity shock and $a = 0$ does not, while $t = 0$ holds trade costs at their 1980 values and $t = 1$ applies the measured trade-cost decline. Every cell applies the measured changes $(\widehat{H}_i, \widehat{L}_i)$ to the 1980 equilibrium. Intermediate-use wedges and deficit shares remain at their 1980 values. For outcome $Y \in \{\text{SP}, W\}$, define

$$Q_i^{\text{SP}}(a,t) \equiv \frac{\widehat{w}_i^H(a,t)}{\widehat{w}_i^L(a,t)}, \qquad Q_i^W(a,t) \equiv \widehat{W}_i(a,t), \qquad y_i^Y(a,t) \equiv 100 \ln Q_i^Y(a,t).$$

The five comparisons used in Section 5 are

$$E_i^Y \equiv y_i^Y(0,0), \qquad A_{i,1980}^Y \equiv y_i^Y(1,0) - y_i^Y(0,0), \qquad \mathrm{TC}_i^Y \equiv y_i^Y(0,1) - y_i^Y(0,0),$$
$$J_i^Y \equiv y_i^Y(1,1) - y_i^Y(0,0), \qquad A_{i,2014}^Y \equiv y_i^Y(1,1) - y_i^Y(0,1).$$

The interaction in equation (64) is $\mathrm{INT}_i^Y = A_{i,2014}^Y - A_{i,1980}^Y$. Table B.2 reports the country-level values used to construct Figure 7. For each outcome it gives automation's effect at 1980 trade costs, its effect at 2014 trade costs, and their difference. The table includes all 25 model economies and the unweighted mean, median, 10th percentile, and 90th percentile.

Table B.2: Automation Effects at 1980 and 2014 Trade Costs, All Economies (1980–2014)

	Skill premium (Log points)			Welfare (Log points)		
Country	1980 trade costs	2014 trade costs	Interaction	1980 trade costs	2014 trade costs	Interaction
AUS	6.41	11.66	5.25	11.52	24.94	13.42
AUT	11.23	27.52	16.29	16.48	31.58	15.10
BEL	15.44	58.36	42.92	19.46	56.40	36.95
BRA	38.59	46.56	7.97	34.23	43.36	9.12
CAN	20.46	49.68	29.22	22.80	54.55	31.75
CHN	106.81	152.06	45.25	90.59	122.40	31.81
DEU	15.19	27.81	12.62	18.67	35.01	16.34
DNK	14.49	38.05	23.57	13.94	36.74	22.80
ESP	11.44	21.80	10.36	12.84	26.23	13.40
FIN	11.70	19.71	8.01	15.50	24.23	8.73
FRA	28.08	42.15	14.08	27.16	42.17	15.00
GBR	25.48	37.25	11.77	28.24	45.23	16.99
GRC	7.24	18.16	10.92	13.78	28.61	14.83
IND	5.88	11.83	5.96	5.44	11.97	6.53
IRL	15.47	20.91	5.44	28.12	51.19	23.06
ITA	14.80	26.75	11.95	18.40	31.12	12.71
JPN	31.51	46.03	14.52	31.09	49.10	18.01
KOR	38.72	59.98	21.26	46.35	77.34	30.99
MEX	14.98	31.82	16.84	10.81	27.34	16.53
NLD	14.29	37.03	22.74	18.47	37.63	19.16
PRT	35.62	71.52	35.90	35.26	58.82	23.56
SWE	14.69	29.83	15.14	19.33	30.78	11.46
TWN	27.67	46.87	19.20	41.10	64.25	23.15
USA	38.67	47.03	8.36	35.21	45.26	10.04
ROW	33.60	52.31	18.71	31.57	46.93	15.35
Mean	23.94	41.31	17.37	25.86	44.13	18.27
Median	15.44	37.25	14.52	19.46	42.17	16.34
P10	8.84	18.78	6.76	12.05	25.46	9.49
P90	38.64	59.33	33.23	38.76	62.08	31.45

Notes: This table shows automation's effects on the skill premium and welfare at 1980 and 2014 trade costs, in log points (100 times the log change). The 1980-trade-cost columns show $100\ln[Q_i^Y(1,0)/Q_i^Y(0,0)]$; the 2014-trade-cost columns show $100\ln[Q_i^Y(1,1)/Q_i^Y(0,1)]$. The interaction equals the latter minus the former, or $100\ln\{Q_i^Y(1,1)Q_i^Y(0,0)/[Q_i^Y(0,1)Q_i^Y(1,0)]\}$. All cells apply the measured endowment changes; intermediate-use wedges, deficits, and other primitives remain at their 1980 values. Summary rows show unweighted statistics across the 25 economies, including ROW. P10 and P90 use linear interpolation. Country rows satisfy the interaction identity up to rounding. Because each statistic is computed by column, summary rows need not satisfy the identity.

B.3 Decomposition of the Skill-Premium Response

Divide the counterfactual factor-market clearing conditions (42) by their base-year counterparts:

$$\widehat{w}_i^H\widehat{H}_i=\sum_s b_{is}^{H,0}\widehat{R}_{is},\qquad \widehat{w}_i^L\widehat{L}_i=\sum_s b_{is}^{L,0}\widehat{\Gamma}_{is}^L\widehat{R}_{is}.$$

The shares in equation (62) sum to one. Taking the ratio and moving the endowment hats to the right-hand side gives equation (63). For the finite changes reported in the table, define

$$v_i(r,g)\equiv\ln\left(\sum_s b_{is}^{H,0}r_{is}\right)-\ln\left(\sum_s b_{is}^{L,0}g_{is}r_{is}\right),\qquad v_i(\mathbf{1},\mathbf{1})=0. \tag{67}$$

The exact two-element Shapley values of revenue and task assignment are

$$\begin{aligned}C_i^R(a,t)&\equiv\frac{1}{2}v_i(r^{a,t},\mathbf{1})+\frac{1}{2}\left[v_i(r^{a,t},g^{a,t})-v_i(\mathbf{1},g^{a,t})\right],\\ C_i^\Gamma(a,t)&\equiv\frac{1}{2}v_i(\mathbf{1},g^{a,t})+\frac{1}{2}\left[v_i(r^{a,t},g^{a,t})-v_i(r^{a,t},\mathbf{1})\right].\end{aligned} \tag{68}$$

Their sum is $v_i(r^{a,t},g^{a,t})$, so equation (63) becomes

$$\ln Q_i^{\mathrm{SP}}(a,t)=\ln\left(\frac{\widehat{L}_i}{\widehat{H}_i}\right)+C_i^R(a,t)+C_i^\Gamma(a,t). \tag{69}$$

Taking log differentials of the factor-market conditions along a differentiable path gives

$$\mathrm{d}\ln w_i^H+\mathrm{d}\ln H_i=\sum_s b_{is}^H\,\mathrm{d}\ln R_{is},\qquad \mathrm{d}\ln w_i^L+\mathrm{d}\ln L_i=\sum_s b_{is}^L\left(\mathrm{d}\ln R_{is}+\mathrm{d}\ln\Gamma_{is}^L\right).$$

Subtracting the second expression from the first gives equation (59).

The decomposition is anchored at the 1980 equilibrium. In each shock row, the table subtracts the endowment cell's sectoral-reallocation and task-reassignment components from the corresponding components of the shocked cell; all components are measured relative to the 1980 equilibrium. The interaction component is

$$C_i^{k,\mathrm{int}}\equiv C_i^k(1,1)-C_i^k(1,0)-C_i^k(0,1)+C_i^k(0,0),\qquad k\in\{R,\Gamma\},$$

and its supply term is zero. This construction preserves exact adding-up while using the same base-year wage-bill shares in every comparison.

High-skilled and low-skilled labor receive $\alpha_{is}^H R_{is}$ and $\alpha_{is}^T\Gamma_{is}^L R_{is}$. The high-skilled share of labor payments is therefore given by equation (61). With α_{is}^H and α_{is}^T fixed, a decline in Γ_{is}^L raises the high-skilled share within the sector.

B.4 Welfare Accounting

This subsection gives the detailed accounting for the welfare calculations in Section 5.2. Cobb-Douglas production shares, final-expenditure shares ν, and bundle weights are fixed, while sourcing shares remain endogenous. For country j, define the domestic input-output matrix and cumulative input-output weight vector

$$\mathcal{A}_{j,sr} \equiv \alpha^T_{js}\Gamma^K_{js}\kappa_{j,rs} + \alpha^M_{js}\gamma_{j,rs}, \qquad \boldsymbol{\ell}'_j \equiv \boldsymbol{\nu}'_j(\mathbf{I}_S - \mathcal{A}_j)^{-1}.$$

Here $\boldsymbol{\ell}_j$ is lowercase ell and $\mathbf{I}_S$ is the $S \times S$ identity matrix. Define the cumulative cost shares for skilled and low-skilled labor, factor-income shares, deficit share of absorption, and domestic-share weights by

$$\begin{aligned}
&\bar{\alpha}^H_j \equiv \sum_s \ell_{js}\alpha^H_{js}, && \bar{\alpha}^L_j \equiv \sum_s \ell_{js}\alpha^T_{js}\Gamma^L_{js}, && \\
&\varsigma^H_j \equiv \frac{w^H_j H_j}{I_j}, && \varsigma^L_j \equiv \frac{w^L_j L_j}{I_j}, && \delta_j \equiv \frac{D_j}{I_j}, \\
&m^G_{jr} \equiv \nu_{jr} + \sum_s \ell_{js}\alpha^T_{js}\Gamma^K_{js}\kappa_{j,rs}, && m^M_{jr} \equiv \sum_s \ell_{js}\alpha^M_{js}\gamma_{j,rs}. &&
\end{aligned} \tag{70}$$

Because absorption is factor income plus the transfer, $\varsigma^H_j + \varsigma^L_j = 1 - \delta_j$.

Proposition B.1. *(i) For any counterfactual in the system described in Section 3.4, delivered prices satisfy equation (66), and the welfare change is given exactly by*

$$\ln \widehat{W}_j = \ln \widehat{I}_j - \sum_r \nu_{jr} \ln \widehat{P}^G_{jr}, \tag{71}$$

with $\widehat{I}_j$ from equation (39). The welfare change is homogeneous of degree zero in the nominal hats. When the deficit share is fixed within an environment, the change depends on the counterfactual through the skill-premium hat, the endowment hats, world factor income relative to the low-skilled wage, the two domestic-share hats, and the own-country productivity hats. If d'_j changes, it enters as an additional argument through equation (39).

(ii) Along a differentiable equilibrium path at fixed deficit shares, with all weights evaluated at the current equilibrium,

$$\begin{aligned}
\mathrm{d}\ln W_j = &\underbrace{\left(\varsigma^H_j - \bar{\alpha}^H_j\right)\mathrm{d}\ln\left(\frac{w^H_j}{w^L_j}\right)}_{\textit{skill-premium term}} + \underbrace{\varsigma^H_j\,\mathrm{d}\ln H_j + \varsigma^L_j\,\mathrm{d}\ln L_j}_{\textit{endowment terms}} + \underbrace{\delta_j\left[\mathrm{d}\ln V^W - \mathrm{d}\ln w^L_j\right]}_{\textit{indexation term}} \\
&\underbrace{-\frac{1}{\theta}\sum_r\left[m^G_{jr}\,\mathrm{d}\ln\pi^G_{jjr} + m^M_{jr}\,\mathrm{d}\ln\pi^M_{jjr}\right]}_{\textit{gains-from-trade term}} + \underbrace{\frac{1}{\theta}\sum_r\left(m^G_{jr} + m^M_{jr}\right)\mathrm{d}\ln\lambda_{jr}}_{\textit{technology term}}.
\end{aligned} \tag{72}$$

The proof is in Appendix C.

Corollary B.2. *(i) The coefficient $\varsigma^H_j - \bar{\alpha}^H_j$ equals the skilled cost content of country j's sectoral net exports after accounting for the input-output linkages represented by $\mathcal{A}_j$, as a share of absorption. The two factor coefficients satisfy $(\varsigma^H_j - \bar{\alpha}^H_j) + (\varsigma^L_j - \bar{\alpha}^L_j) = -\delta_j$. In a closed economy every sector's net exports are zero, so $\varsigma^H_j = \bar{\alpha}^H_j$ and the local skill-premium term vanishes.*

(ii) In a closed economy the domestic shares equal one and the transfer is zero along any equilibrium path. The gains-from-trade and indexation terms therefore vanish, and equation (72) *reduces to the endowment and technology terms. The proof is in Appendix* C*.*

The skilled cost-content representation relates the coefficient on the local skill premium to the factor-content literature (Deardorff and Staiger, 1988; Adão et al., 2022). Here, the relevant quantity is the model-specific cost content of sectoral net exports after accounting for the input-output linkages represented by $\mathcal{A}_j$.

Table B.3 decomposes each finite welfare change using exact Shapley values for the factor groups in Proposition B.1, with deficit shares held fixed. The panels report endowments, automation at 1980 trade costs, the trade-cost changes without automation, and both shocks; offshoring does not enter. Each country-level row sums to the exact welfare change. The endowment terms account for the direct welfare gain from factor accumulation, the technology term accounts for most of automation's welfare change, and changes in domestic sourcing shares account for most of the trade-cost change. The joint panel records the interaction among these components. The technology term in the welfare decomposition is distinct from the direct channel in the $\widehat{\beta}$ decomposition.

Table B.3: Exact Decomposition of the Welfare Response (1980–2014)

Country	(Log points) Endowments	Skill premium	Gains from trade	Technology	Indexation	Total
Panel A. Endowment changes alone						
USA	30.6	-1.1	0.6	—	-0.0	30.0
DEU	33.2	-0.2	1.0	—	0.5	34.5
JPN	8.1	-3.5	2.5	—	-0.0	7.1
CHN	81.2	-3.3	-0.4	—	-0.0	77.4
IND	105.9	-3.7	-0.9	—	0.5	101.7
Median (25)	43.6	-1.9	0.6	—	0.3	39.7
Panel B. Automation, given endowment changes						
USA	—	-0.2	0.4	35.0	-0.0	35.2
DEU	—	-0.2	2.1	15.9	0.9	18.7
JPN	—	-0.4	1.7	29.4	0.4	31.1
CHN	—	-1.2	-4.5	96.3	0.0	90.6
IND	—	-0.0	0.7	4.5	0.3	5.4
Median (25)	—	-0.2	1.7	17.8	0.5	19.5
Panel C. Trade costs, given endowment changes						
USA	—	0.0	17.9	—	-0.1	17.9
DEU	—	-0.2	37.0	—	0.1	36.9
JPN	—	-0.2	27.0	—	0.2	27.0
CHN	—	0.1	42.2	—	0.0	42.3
IND	—	-0.1	17.2	—	0.2	17.3
Median (25)	—	-0.2	38.6	—	-0.0	39.0
Panel D. Both shocks, given endowment changes						
USA	—	-0.2	24.6	38.9	-0.1	63.1
DEU	—	-0.8	52.2	19.2	1.3	71.9
JPN	—	-0.9	42.1	34.2	0.6	76.1
CHN	—	-4.1	44.7	124.0	0.0	164.7
IND	—	-0.2	23.4	5.5	0.7	29.3
Median (25)	—	-0.8	52.1	29.7	0.2	71.9

Notes: This table shows the exact Shapley decomposition of the log change in real income into the terms in equation (72). Entries are log points (100 times the log change). The decomposition uses the finite factor groups in the exact hat form of Proposition B.1(i). The endowment terms change $(\widehat{H}_j, \widehat{L}_j)$. The skill-premium term changes $\widehat{w}_j^H/\widehat{w}_j^L$. The gains-from-trade term changes the domestic sourcing shares $\widehat{\pi}_{jjr}^G$ and $\widehat{\pi}_{jjr}^M$. The technology term changes $\widehat{\lambda}_{jr}$. The indexation term changes world factor income $\widehat{V}^W$ relative to $\widehat{w}_j^L$. Deficit shares remain fixed within each comparison. The components sum to the exact log welfare change for each country. The Median (25) row shows each column's median and therefore need not sum to the total. An unchanged factor group contributes zero. The technology term is zero when the automation shock is absent. Panel A shows the measured 1980–2014 endowment changes alone. Panel B adds automation. Panel C adds the trade-cost changes. Panel D adds both shocks. Panels B–D show changes relative to Panel A.

B.5 Open Economy, Zero Deficits, and Autarky

The historical comparison in Section 5.2 changes trade costs from their 1980 to their 2014 values. This subsection instead evaluates the measured automation shock in three benchmark environments. Each environment applies the measured endowment changes in both the no-shock and automation cells. The open economy holds the observed 1980 deficit shares fixed; the zero-deficit open economy sets every deficit share to zero in both cells; and autarky imposes $\pi^{G\prime}_{jjr} = \pi^{M\prime}_{jjr} = 1$ and zero transfers. Each reported effect is the log double difference within its own environment, so the common endowment change cancels.

Equation (66) isolates the price component of the difference. In autarky the domestic shares remain one, so an economy cannot reallocate expenditure across origins as the automation shock changes delivered costs. Corollary B.2 makes the local skill-premium coefficient vanish at a closed-economy equilibrium. Some Shapley orderings include intermediate coalition states in which the skill-premium term is nonzero, so the finite contribution need not be exactly zero. Table B.5 allocates the welfare gap between the open economy and autarky across the same factor groups.

Table B.4 reports all economies. The median automation effect on the skill premium falls from 15.4 log points under trade to 11.6 under autarky, and the median welfare effect falls from 19.5 to 14.4. The open-economy effect exceeds the autarky effect in every economy for both outcomes. The zero-deficit results remain within 0.1 log points of the observed-deficit results for the skill premium and 0.5 log points for welfare at the median, so fixed 1980 deficits do not account for the difference between the open and closed economies. Across the 25 model economies, including ROW, the median of the economy-level proportional reductions from trade to autarky is about 25 percent for automation's skill-premium effect and 22 percent for its welfare effect. The median welfare gap is 5.1 log points. Across countries, the median ratio of the gains-from-trade component to the welfare gap is 30.3 percent. Automation raises both outcomes under autarky as well, so trade amplifies its effects rather than creating them.

Table B.4: Automation Under Trade and Under Autarky, All Economies, 1980–2014

	Skill premium (Log points)			Welfare (Log points)		
Country	Trade	Trade, $d = 0$	Autarky	Trade	Trade, $d = 0$	Autarky
AUS	6.4	6.2	4.5	11.5	11.0	6.4
AUT	11.2	10.9	6.6	16.5	14.5	9.5
BEL	15.4	14.9	5.3	19.5	16.2	7.0
BRA	38.6	38.5	36.9	34.2	34.2	32.9
CAN	20.5	20.5	10.5	22.8	22.7	12.0
CHN	106.8	106.8	97.5	90.6	90.5	86.9
DEU	15.2	15.1	12.2	18.7	18.0	14.7
DNK	14.5	14.3	6.4	13.9	13.4	7.6
ESP	11.4	11.5	8.6	12.8	12.4	9.6
FIN	11.7	11.6	7.6	15.5	14.2	9.5
FRA	28.1	28.0	23.7	27.2	26.7	22.8
GBR	25.5	25.5	22.2	28.2	28.2	24.5
GRC	7.2	5.0	2.4	13.8	8.2	4.3
IND	5.9	5.8	5.2	5.4	5.1	4.2
IRL	15.5	16.3	9.1	28.1	27.8	17.3
ITA	14.8	14.7	11.6	18.4	17.3	14.4
JPN	31.5	31.6	26.8	31.1	31.2	26.7
KOR	38.7	40.3	28.5	46.4	49.7	39.5
MEX	15.0	15.0	13.0	10.8	12.0	10.6
NLD	14.3	14.2	5.7	18.5	18.1	9.6
PRT	35.6	36.9	27.2	35.3	35.8	30.0
SWE	14.7	14.7	9.8	19.3	19.1	14.0
TWN	27.7	27.0	14.2	41.1	39.3	22.1
USA	38.7	38.6	36.5	35.2	35.2	33.0
ROW	33.6	33.2	29.9	31.6	31.6	28.9

Notes: This table shows the 1980–2014 effects of automation on the skill premium $\frac{\widehat{w}_i^H}{\widehat{w}_i^L}$ and real income $\widehat{W}_i$ under three trade regimes. Entries are log points (100 times the log change). All three regimes apply the measured endowment changes $(\widehat{H}_i, \widehat{L}_i)$ in both the no-shock and automation cells. The common endowment change therefore cancels, so each column isolates automation. Trade shows the open economy with the observed 1980 deficits and compares the automation cell with the endowment-only cell. Its entries equal the automation totals in Tables 3 and B.3. Trade, $d = 0$ shows the same open economy with every deficit share set to zero and uses its own zero-deficit endowment baseline. Autarky shows the per-country closed economy with zero transfers and the low-skilled wage as the numeraire and compares it with the closed economy without automation. Within each regime, trade costs and intermediate-use wedges remain at their 1980 values. Deficit shares remain at their observed 1980 values under Trade and at zero under Trade, $d = 0$ and autarky. Thus, only the equipment-price shock changes between the no-shock and automation cells.

Table B.5: What Trade Adds to Automation's Welfare Effect (1980–2014)

	(Log points)				
Country	Gap	Gains from trade	Skill-premium terms	Deficit indexation	Technology terms
USA	2.2	0.4	0.0	-0.0	1.8
DEU	4.0	2.1	-0.2	0.9	1.2
JPN	4.4	1.7	-0.3	0.4	2.6
CHN	3.7	-4.5	-0.3	0.0	8.5
IND	1.2	0.7	-0.0	0.3	0.2
Median (25)	5.1	1.7	-0.2	0.5	2.8

Notes: This table shows the exact Shapley decomposition of the difference between automation's welfare effects under trade and autarky from 1980 to 2014. Entries are log points (100 times the log change). Both environments apply the measured endowment changes in their no-shock and automation cells, so the common change cancels and each effect isolates automation. The gap equals the open-economy welfare effect minus the autarky effect. Country rows satisfy the four-term identity up to rounding; the Median (25) row shows each column's median and therefore need not sum to the total. Each component is the difference between its open-economy and autarky Shapley values for the finite factor groups in Proposition B.1(i), grouped as in equation (72). The gains-from-trade term changes the domestic sourcing shares $\widehat{\pi}^G_{jjr}$ and $\widehat{\pi}^M_{jjr}$. The skill-premium term changes $\widehat{w}^H_j/\widehat{w}^L_j$. The indexation term changes world factor income $\widehat{V}^W$ relative to $\widehat{w}^L_j$. The technology term changes the Fréchet scales $\widehat{\lambda}_{jr}$. The open-economy decomposition uses the endowment-only equilibrium as its baseline. The autarky decomposition uses its own no-shock equilibrium, income shares, and task assignment.

C Proofs

C.1 Proofs of Main-Text Results

Proof of Proposition 3.1. Stack $\vartheta = (\beta, f, g)$, and let the row of the design matrix D for each observation contain z_{is} followed by the indicators for (i, j) and (j, s), so that $\mu = \exp(\mathsf{D}\vartheta)$ and equation (46) is $\mathsf{D}^\top(X - \mu) = 0$. The two indicator blocks share the importer index. Imposing one normalization per importer for the balanced panel, or equivalently using a generalized inverse, leaves the column span and fitted values unchanged.

Differentiating the moment conditions gives $-\mathsf{D}^\top \operatorname{diag}(\mu)\mathsf{D}\, \mathrm{d}\vartheta + \mathsf{D}^\top \mathrm{d}X = 0$, the normal equations for a weighted least-squares regression of $\frac{\mathrm{d}X}{\mu}$ on D with weights μ. In the inner product $\langle u, v\rangle_\mu \equiv \sum_{ijs} \mu_{ijs} u_{ijs} v_{ijs}$, the array $\widetilde{z}$ defined by the conditions in equation (47) is exactly the residual from projecting z on the span of the indicator columns, so Frisch-Waugh-Lovell gives

$$\mathrm{d}\widehat{\beta} = \frac{\left\langle \widetilde{z}, \frac{\mathrm{d}X}{\mu} \right\rangle_\mu}{\langle \widetilde{z}, \widetilde{z}\rangle_\mu} = \frac{\sum_{ijs} \widetilde{z}_{ijs}\, \mathrm{d}X_{ijs}}{\sum_{ijs} \mu_{ijs} \widetilde{z}_{ijs}^2},$$

which is equation (48). This projection depends only on the span, not on its parameterization, so $\widetilde{z}$ and $\mathrm{d}\widehat{\beta}$ are unique even though $\mathrm{d}(f, g)$ is not. When the flow support is locally fixed, $\mathrm{d}X_{ijs} = 0$ off the support; substituting $\mathrm{d}X_{ijs} = X_{ijs}\, \mathrm{d}\ln X_{ijs}$ on the support gives the second display of the proposition. $\square$

C.2 Proofs of Appendix Results

Proof of Proposition B.1. For domestic sourcing, both frictions equal one: $\widehat{\tau}_{jjr} = \widehat{\chi}_{jjr} = 1$. Setting $i = j$ in equation (37) gives $\widehat{\pi}^u_{jjr} = \widehat{\lambda}_{jr}(\widehat{c}_{jr}/\widehat{P}^u_{jr})^{-\theta}$ for $u \in \{G, M\}$; solving this equality for the price term gives equation (66). Conditional on own unit costs and productivity, foreign productivity, general-use trade costs, and intermediate-use wedges affect country j's prices through the domestic shares in this identity. The consumption deflator with fixed final-expenditure shares is $\ln \widehat{P}^C_j = \sum_r \nu_{jr} \ln \widehat{P}^G_{jr}$, and absorption changes by equation (39), which together prove equation (71). The system of cost equations solved jointly with equation (66) has a unique solution given the specified hats: each row of the log-cost map's Jacobian satisfies $\alpha^T_{js}\Gamma^{K\prime}_{js} + \alpha^M_{js} \leq 1 - \alpha^H_{js} < 1$, so the map is a contraction. Scaling the nominal hats $(\widehat{w}^H_j, \widehat{w}^L_j, \widehat{V}^W)$ by a common factor scales $\widehat{c}_{jr}$, $\widehat{P}^u_{jr}$, and $\widehat{I}_j$ by that factor. The system in equations (31)–(34) is homogeneous of degree one in nominal prices, and the task shares in equation (31) depend only on the ratio $\frac{\widehat{w}^L_i}{\widehat{w}^K_{is}}$. Therefore, $\ln \widehat{W}_j$ is unchanged. For comparisons with fixed deficits, this establishes the claimed dependence. If d'_j changes, equation (39) introduces an additional dependence on the counterfactual deficit share. This completes part (i).

For part (ii), differentiate equation (66) and substitute the result into the bundle prices. The task-price envelope is $\mathrm{d}\ln w_{js}^T = \Gamma_{js}^L \,\mathrm{d}\ln w_j^L + \Gamma_{js}^K \,\mathrm{d}\ln w_{js}^K$, where the boundary term vanishes because the two task costs are equal at the assignment boundary. Combining these expressions with the unit-cost differential gives the domestic cost system

$$\begin{aligned}\mathrm{d}\ln c_{js} = &\sum_r \mathcal{A}_{j,sr}\,\mathrm{d}\ln c_{jr} + \alpha_{js}^H\,\mathrm{d}\ln w_j^H + \alpha_{js}^T\Gamma_{js}^L\,\mathrm{d}\ln w_j^L \\ &+ \frac{\alpha_{js}^T\Gamma_{js}^K}{\theta}\sum_r \kappa_{j,rs}\left[\mathrm{d}\ln \pi_{jjr}^G - \mathrm{d}\ln\lambda_{jr}\right] + \frac{\alpha_{js}^M}{\theta}\sum_r \gamma_{j,rs}\left[\mathrm{d}\ln\pi_{jjr}^M - \mathrm{d}\ln\lambda_{jr}\right].\end{aligned}$$

Row s of $\mathcal{A}_j$ sums to $\alpha_{js}^T\Gamma_{js}^K + \alpha_{js}^M < 1$, so $(\mathbf{I}_S - \mathcal{A}_j)^{-1}$ exists and is nonnegative.

Premultiply the solved system by $\boldsymbol{\nu}_j'$, the transpose of the final-expenditure-share vector ν_{jr} in equation (24). Because $\boldsymbol{\nu}_j'(\mathbf{I}_S - \mathcal{A}_j)^{-1} = \boldsymbol{\ell}_j'$, the consumption-price expression

$$\mathrm{d}\ln P_j^C = \sum_r \nu_{jr}\left(\mathrm{d}\ln c_{jr} + \frac{1}{\theta}\left[\mathrm{d}\ln\pi_{jjr}^G - \mathrm{d}\ln\lambda_{jr}\right]\right)$$

collects the domestic-share terms with weights

$$m_{jr}^G = \nu_{jr} + \sum_s \ell_{js}\alpha_{js}^T\Gamma_{js}^K\kappa_{j,rs}, \qquad\qquad m_{jr}^M = \sum_s \ell_{js}\alpha_{js}^M\gamma_{j,rs}.$$

The $\mathrm{d}\ln\lambda_{jr}$ terms have total weight

$$\nu_{jr} + \sum_s \ell_{js}\mathcal{A}_{j,sr} = m_{jr}^G + m_{jr}^M,$$

because $\mathcal{A}_{j,sr} = \alpha_{js}^T\Gamma_{js}^K\kappa_{j,rs} + \alpha_{js}^M\gamma_{j,rs}$. Hence

$$\begin{aligned}\mathrm{d}\ln P_j^C = &\ \bar\alpha_j^H\,\mathrm{d}\ln w_j^H + \bar\alpha_j^L\,\mathrm{d}\ln w_j^L \\ &+ \frac{1}{\theta}\sum_r\left\{m_{jr}^G\left[\mathrm{d}\ln\pi_{jjr}^G - \mathrm{d}\ln\lambda_{jr}\right] + m_{jr}^M\left[\mathrm{d}\ln\pi_{jjr}^M - \mathrm{d}\ln\lambda_{jr}\right]\right\}.\end{aligned}$$

The row sums satisfy

$$(\mathbf{I}_S - \mathcal{A}_j)\mathbf{1} = \alpha_j^H + \alpha_j^T\Gamma_j^L,$$

so $\bar\alpha_j^H + \bar\alpha_j^L = 1$. Differentiating $I_j = w_j^H H_j + w_j^L L_j + d_j V^W$ at a fixed deficit share d_j and dividing by I_j gives

$$\mathrm{d}\ln I_j = \varsigma_j^H\left(\mathrm{d}\ln w_j^H + \mathrm{d}\ln H_j\right) + \varsigma_j^L\left(\mathrm{d}\ln w_j^L + \mathrm{d}\ln L_j\right) + \delta_j\,\mathrm{d}\ln V^W,$$

since $\delta_j = \frac{d_j V^W}{I_j}$. Subtract the consumption-price change. Because $\varsigma_j^H + \varsigma_j^L = 1 - \delta_j$ and $\bar\alpha_j^L = 1 - \bar\alpha_j^H$, the low-skilled coefficient satisfies $\varsigma_j^L - \bar\alpha_j^L = -(\varsigma_j^H - \bar\alpha_j^H) - \delta_j$, so the two wage terms collect into $(\varsigma_j^H - \bar\alpha_j^H)\,\mathrm{d}\ln\left(\frac{w_j^H}{w_j^L}\right) - \delta_j\,\mathrm{d}\ln w_j^L$. The second wage term combines with $\delta_j\,\mathrm{d}\ln V^W$ to form the indexation term; separating the price sum into its domestic-share and productivity components gives the gains-from-trade and technology terms. This proves equation (72). Under balanced trade with fixed endowments, $\delta_j = \mathrm{d}\ln H_j = \mathrm{d}\ln L_j = 0$ and only the skill-premium, gains-from-trade, and technology terms remain. □

Proof of Corollary B.2. Country j's expenditure on sector r, summed across origins, is $\nu_{jr}I_j + \sum_s \mathcal{A}_{j,sr}R_{js}$:

final expenditure plus the equipment and intermediate demands of equation (40), whose revenue weights are the entries of $\mathcal{A}_j$. Sectoral net exports

$$\mathrm{NX}_{jr} \equiv R_{jr} - \nu_{jr} I_j - \sum_s \mathcal{A}_{j,sr} R_{js}$$

therefore satisfy $\boldsymbol{R}_j = (\mathbf{I}_S - \mathcal{A}_j')^{-1}(\boldsymbol{\nu}_j I_j + \mathbf{NX}_j)$, where $\mathcal{A}_j'$ is the transpose of $\mathcal{A}_j$ and $(\mathbf{I}_S - \mathcal{A}_j')^{-1}\boldsymbol{\nu}_j = \boldsymbol{\ell}_j$. Substituting into factor-market clearing $w_j^H H_j = \sum_s \alpha_{js}^H R_{js}$ and dividing by I_j gives

$$\varsigma_j^H - \bar{\alpha}_j^H = \frac{1}{I_j} \sum_s \alpha_{js}^H \left[(\mathbf{I}_S - \mathcal{A}_j')^{-1} \mathbf{NX}_j \right]_s,$$

the skilled cost content of net exports after accounting for the input-output linkages represented by $\mathcal{A}_j$, as a share of absorption. Applying the same substitution to the low-skilled cost shares $\alpha_{js}^T \Gamma_{js}^L$, adding the skilled and low-skilled expressions, and using $\bar{\alpha}_j^H + \bar{\alpha}_j^L = 1$ gives $(\varsigma_j^H - \bar{\alpha}_j^H) + (\varsigma_j^L - \bar{\alpha}_j^L) = \frac{V_j - I_j}{I_j} = -\delta_j$. In a closed economy goods-market clearing sets $\mathrm{NX}_{jr} = 0$ sector by sector, so $\varsigma_j^H = \bar{\alpha}_j^H$ and the skill-premium term of equation (72) vanishes; the domestic shares equal one along any closed-economy path, so $\mathrm{d}\ln \pi_{jjr}^G = \mathrm{d}\ln \pi_{jjr}^M = 0$ and the gains-from-trade term vanishes as well; and a closed economy has zero net imports, so equation (30) gives $D_j = 0$, $\delta_j = 0$, and the indexation term vanishes. $\square$

D Theory Appendix

D.1 Unit-Cost Response

Each producer's cost affects the delivered prices faced by its buyers, so unit costs are jointly determined. Proposition D.1 gives this system for arbitrary perturbations and separates the input-cost component from the wage component.

Proposition D.1. *Hold α_{js}^H, α_{js}^T, α_{js}^M, $\kappa_{j,rs}$, and $\gamma_{j,rs}$ fixed, and evaluate the task and sourcing shares at the current equilibrium. Define the wage component by*

$$F_{js}^{\text{wage}} \equiv \alpha_{js}^H \,\mathrm{d}\ln w_j^H + \alpha_{js}^T \Gamma_{js}^L \,\mathrm{d}\ln w_j^L, \tag{73}$$

and the world input-output cost matrix A by

$$A_{(js),(ir)} \equiv \alpha_{js}^T \Gamma_{js}^K \kappa_{j,rs} \pi_{ijr}^G + \alpha_{js}^M \gamma_{j,rs} \pi_{ijr}^M, \tag{74}$$

where country i supplies inputs to country j. Define the input-cost component by

$$\begin{aligned} F_{js}^{\text{input}} \equiv\ & \alpha_{js}^T \Gamma_{js}^K \sum_r \kappa_{j,rs} \sum_i \pi_{ijr}^G \left(\mathrm{d}\ln \tau_{ijr} - \frac{1}{\theta} \mathrm{d}\ln \lambda_{ir} \right) \\ & + \alpha_{js}^M \sum_r \gamma_{j,rs} \sum_i \pi_{ijr}^M \left(\mathrm{d}\ln \tau_{ijr} + \mathrm{d}\ln \chi_{ijr} - \frac{1}{\theta} \mathrm{d}\ln \lambda_{ir} \right). \end{aligned}$$

If $\alpha_{js}^H + \alpha_{js}^T \Gamma_{js}^L > 0$ in every country-sector cell, then $\mathbf{I} - A$ is invertible with nonnegative inverse and

$$\mathrm{d}\ln \boldsymbol{c} = (\mathbf{I} - A)^{-1} \left(F^{\text{input}} + F^{\text{wage}} \right), \tag{75}$$

where $\mathbf{I}$ *is the identity matrix on country-sector cells. The system is homogeneous under a common scaling of nominal prices: a common infinitesimal proportional increase in all nominal prices raises each entry of* $\mathrm{d}\ln\mathbf{c}$ *by that amount and leaves the coefficient derivative in equation* (48) *unchanged.*

Proof. Away from the measure-zero tie set, the cost of a task changes with the low-skilled wage on labor tasks and with the capital-service price on capital tasks. Integrating across tasks gives

$$\mathrm{d}\ln w_{js}^{T} = \Gamma_{js}^{L}\,\mathrm{d}\ln w_{j}^{L} + \Gamma_{js}^{K}\,\mathrm{d}\ln w_{js}^{K}. \tag{76}$$

The two task costs are equal at the assignment boundary, which removes the boundary term, so derivatives of the task shares themselves do not appear.

Differentiating the price aggregators in equation (19) and using the price index $P_{jr}^{u} = \mathcal{C}_r(\Phi_{jr}^{u})^{-\frac{1}{\theta}}$ of equation (20) gives

$$\begin{aligned}
\mathrm{d}\ln P_{jr}^{G} &= \sum_{i} \pi_{ijr}^{G}\left(\mathrm{d}\ln c_{ir} + \mathrm{d}\ln\tau_{ijr} - \tfrac{1}{\theta}\mathrm{d}\ln\lambda_{ir}\right), \\
\mathrm{d}\ln P_{jr}^{M} &= \sum_{i} \pi_{ijr}^{M}\left(\mathrm{d}\ln c_{ir} + \mathrm{d}\ln\tau_{ijr} + \mathrm{d}\ln\chi_{ijr} - \tfrac{1}{\theta}\mathrm{d}\ln\lambda_{ir}\right).
\end{aligned} \tag{77}$$

A productivity gain at an origin therefore lowers the delivered costs faced by its buyers by $\frac{1}{\theta}\mathrm{d}\ln\lambda$.

The bundle prices in equation (16) satisfy

$$\mathrm{d}\ln w_{js}^{K} = \sum_{r} \kappa_{j,rs}\,\mathrm{d}\ln P_{jr}^{G}, \qquad \mathrm{d}\ln w_{js}^{M} = \sum_{r} \gamma_{j,rs}\,\mathrm{d}\ln P_{jr}^{M},$$

where w_{js}^{K} and w_{js}^{M} are the capital-service and intermediate-bundle unit costs. Substituting these expressions and equation (76) into the differential of the unit cost (17), $\mathrm{d}\ln c_{js} = \alpha_{js}^{H}\mathrm{d}\ln w_{j}^{H} + \alpha_{js}^{T}\mathrm{d}\ln w_{js}^{T} + \alpha_{js}^{M}\mathrm{d}\ln w_{js}^{M}$, gives

$$\begin{aligned}
\mathrm{d}\ln c_{js} = F_{js}^{\text{wage}} &+ \alpha_{js}^{T}\Gamma_{js}^{K}\sum_{r}\kappa_{j,rs}\sum_{i}\pi_{ijr}^{G}\left(\mathrm{d}\ln c_{ir} + \mathrm{d}\ln\tau_{ijr} - \frac{1}{\theta}\mathrm{d}\ln\lambda_{ir}\right) \\
&+ \alpha_{js}^{M}\sum_{r}\gamma_{j,rs}\sum_{i}\pi_{ijr}^{M}\left(\mathrm{d}\ln c_{ir} + \mathrm{d}\ln\tau_{ijr} + \mathrm{d}\ln\chi_{ijr} - \frac{1}{\theta}\mathrm{d}\ln\lambda_{ir}\right).
\end{aligned} \tag{78}$$

The wage component is given by equation (73), and the remaining input-cost terms form F^{input}. Collecting the terms in $\mathrm{d}\ln c_{ir}$ gives the matrix A of equation (74). The matrix A is nonnegative, and because the bundle weights and the sourcing shares each sum to one, row (j,s) sums to

$$\alpha_{js}^{T}\Gamma_{js}^{K} + \alpha_{js}^{M} = 1 - \left(\alpha_{js}^{H} + \alpha_{js}^{T}\Gamma_{js}^{L}\right) < 1,$$

where the strict inequality follows from the proposition's assumption. Hence $\|A\|_{\infty} < 1$ and

$$(\mathbf{I} - A)^{-1} = \sum_{m=0}^{\infty} A^{m}$$

exists and is nonnegative, so solving the system yields equation (75).

To verify homogeneity, a common nominal scaling raises unit costs and expenditures uniformly while leaving task and sourcing shares unchanged. It therefore scales all bilateral flows uniformly, and that common scale is absorbed by the PPML fixed effects, leaving $\widehat{\beta}$ unchanged. □

The inverse matrix $(\mathbf{I} - A)^{-1}$ sums the effect of each component over successive input-cost rounds. Section 4.4 evaluates the corresponding finite changes.

The domestic cost matrix in the proof of Proposition B.1 satisfies $\mathcal{A}_{j,sr} = \sum_i A_{(js),(ir)}$. Both matrices record the weight of sector r's delivered price in sector s's unit cost. The world matrix keeps suppliers' costs in separate country-sector columns. The domestic system instead eliminates foreign costs through the domestic-share identity (66).

D.2 Channel Accounting

Section 4.4 defines the synthetic states used below.

Extend equation (56) to a continuous state $\boldsymbol{r} = (r_d, r_c, r_e) \in [0,1]^3$ by raising each factor $\zeta_p^{u,k}$ to r_p. Write $X_{ijs}^{u,k}(\boldsymbol{r})$ for the resulting use-specific flow and $X_{ijs}^{k}(\boldsymbol{r}) = \sum_u X_{ijs}^{u,k}(\boldsymbol{r})$ for total trade. The current sourcing and use shares are

$$\pi_{ijs}^{u,k}(\boldsymbol{r}) \equiv \frac{\pi_{ijs,0}^{u}(\zeta_{d,ijs}^{u,k})^{r_d}(\zeta_{c,ijs}^{u,k})^{r_c}}{\sum_{\ell} \pi_{\ell js,0}^{u}(\zeta_{d,\ell js}^{u,k})^{r_d}(\zeta_{c,\ell js}^{u,k})^{r_c}}, \qquad s_{ijs}^{u,k}(\boldsymbol{r}) \equiv \frac{X_{ijs}^{u,k}(\boldsymbol{r})}{X_{ijs}^{k}(\boldsymbol{r})}.$$

For any route-level array v, define the state-specific sourcing-normalization operator

$$\mathcal{R}_{\boldsymbol{r}}^{u,k}[v]_{ijs} \equiv v_{ijs} - \sum_{\ell} \pi_{\ell js}^{u,k}(\boldsymbol{r}) v_{\ell js}. \tag{79}$$

Corollary D.2. *Suppose the factors are positive and each use-specific synthetic flow has fixed support and remains positive on that support; let* $\operatorname{supp}(X^k)$ *denote the support of total trade, which is the union of the use-specific supports. At the current state* $\boldsymbol{r}$*, suppose the PPML conditions of Proposition 3.1 hold on a fixed estimation sample, with* $\mathcal{V}_{\tilde{z}}^{k}(\boldsymbol{r}) \equiv \sum_{ijs} \mu_{ijs}^{k}(\boldsymbol{r})[\tilde{z}_{ijs}^{k}(\boldsymbol{r})]^2 > 0$*. For a differentiable perturbation of* $\boldsymbol{r}$*, define*

$$\xi_{d,ijs}^{k}(\boldsymbol{r}) \equiv \sum_{u\in\{G,M\}} s_{ijs}^{u,k}(\boldsymbol{r})\mathcal{R}_{\boldsymbol{r}}^{u,k}[\ln \zeta_d^{u,k}]_{ijs},$$
$$\xi_{c,ijs}^{k}(\boldsymbol{r}) \equiv \sum_{u\in\{G,M\}} s_{ijs}^{u,k}(\boldsymbol{r})\mathcal{R}_{\boldsymbol{r}}^{u,k}[\ln \zeta_c^{u,k}]_{ijs},$$
$$\xi_{e,ijs}^{k}(\boldsymbol{r}) \equiv \sum_{u\in\{G,M\}} s_{ijs}^{u,k}(\boldsymbol{r}) \ln \zeta_{e,ijs}^{u,k}.$$

Then, for each $p \in \mathcal{P}$ *and* $(i,j,s) \in \operatorname{supp}(X^k)$*,*

$$\frac{\partial \ln X_{ijs}^{k}(\boldsymbol{r})}{\partial r_p} = \xi_{p,ijs}^{k}(\boldsymbol{r}),$$

and the exact differential of the PPML coefficient is

$$\mathrm{d}\widehat{\beta}^{k}(\boldsymbol{r}) = \sum_{p\in\mathcal{P}} \Psi_p^{k}(\boldsymbol{r})\,\mathrm{d}r_p, \qquad \Psi_p^{k}(\boldsymbol{r}) \equiv \frac{\partial \widehat{\beta}^{k}(\boldsymbol{r})}{\partial r_p} = \frac{\sum_{(i,j,s)\in\operatorname{supp}(X^k)} X_{ijs}^{k}(\boldsymbol{r})\tilde{z}_{ijs}^{k}(\boldsymbol{r})\xi_{p,ijs}^{k}(\boldsymbol{r})}{\mathcal{V}_{\tilde{z}}^{k}(\boldsymbol{r})}. \tag{80}$$

All flows on the positive support, fitted values, residualized regressors, sourcing shares, and use shares in *equation (80) are evaluated at the current state; no residual term appears. The direct log factor is*

$$\ln \zeta_{d,ijs}^{u,k} = \begin{cases} -\theta \ln \widehat{\tau}_{ijs}, & k = \tau, \\ \ln \widehat{\lambda}_{is}, & k = \lambda, \\ 0, & k = \chi,\ u = G, \\ -\theta \ln \widehat{\chi}_{ijs}, & k = \chi,\ u = M. \end{cases}$$

By construction, $\ln \zeta_c^{u,k} = -\theta \ln \widehat{c}_{is}^k$ *and* $\ln \zeta_e^{u,k} = \ln \widehat{E}_{js}^{u,k}$.

Proof. On the positive support for each use, log-differentiating the normalized synthetic-flow identity gives

$$\begin{aligned} \frac{\partial \ln X^{u,k}}{\partial r_p} &= \mathcal{R}_{\boldsymbol{r}}^{u,k}[\ln \zeta_p^{u,k}], && p \in \{d, c\}, \\ \frac{\partial \ln X^{u,k}}{\partial r_e} &= \ln \zeta_e^{u,k}. \end{aligned}$$

Weighting by use shares at the current state gives $\partial \ln X^k / \partial r_p = \xi_p^k$; applying Proposition 3.1 at the current state yields equation (80). □

Lemma D.3. *Suppose the conditions of Corollary D.2 hold on every segment defined below. Suppose also that the estimation sample is fixed and that the PPML estimate is finite and continuously differentiable on every segment. For* $p \in \mathcal{P}$ *and* $S \subseteq \mathcal{P} \setminus \{p\}$, *define*

$$r_q^{S,p}(t) = \begin{cases} 1, & q \in S, \\ t, & q = p, \\ 0, & q \notin S \cup \{p\}, \end{cases} \qquad t \in [0, 1].$$

Let $\Psi_p^{k,S}(t) \equiv \Psi_p^k(\boldsymbol{r}^{S,p}(t))$, *with all quantities evaluated at the corresponding state. Then*

$$\widehat{\beta}^k(S \cup \{p\}) - \widehat{\beta}^k(S) = \int_0^1 \Psi_p^{k,S}(t)\, \mathrm{d}t, \tag{81}$$

and the exact channel Shapley value satisfies

$$\phi_p^k = \sum_{S \subseteq \mathcal{P} \setminus \{p\}} \frac{|S|!\,(3 - |S| - 1)!}{3!} \int_0^1 \Psi_p^{k,S}(t)\, \mathrm{d}t. \tag{82}$$

Proof. The path connects the synthetic flow for S to the synthetic flow for $S \cup \{p\}$, and Corollary D.2 gives $\frac{\mathrm{d}}{\mathrm{d}t}\widehat{\beta}^k(\boldsymbol{r}^{S,p}(t)) = \Psi_p^{k,S}(t)$. The fundamental theorem of calculus proves equation (81); substituting it into equation (54) with $\mathcal{B} = \mathcal{P}$ proves equation (82). □