The demographic origins of premature deindustrialization

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Preliminary and incomplete, please do not circulate

February 2026

Abstract

This paper examines whether accelerated demographic transitions—by shrinking the young-adult (25–34) population share earlier—contribute to premature deindustrialization and lower output per capita. Using a country–year panel and instrumenting young-adult shares with birth rates lagged 25–34 years, I show that larger young-adult cohorts predict higher manufacturing employment and a larger manufacturing-employment "hump," while earlier aging shifts employment toward services at lower income levels. Harmonized IPUMS International census microdata from more than 80 countries combined with consumption data indicate that manufacturing work and durable goods spending are concentrated among younger workers and households, while both low- and high-skill services employment rise with age and feature steeper wage–age profiles. A multi-sector overlapping-generations model with age-varying task productivity rationalizes these facts and implies sizable aggregate effects: shifting from the oldest to the youngest demographic trajectory in the cross-country distribution raises peak manufacturing employment by 2.3 percentage points and cumulative output per capita by 17.1 percentage points. Employment per capita explains 10.5 points of the gap; life-cycle reallocation of labor and its interaction with durables explain the remaining 6.6 points.

*I thank Nezih Guner, Sebastian Fanelli, Federico Kochen and Josep Pijoan-Mas for their guidance and comments, as well as all the participants of the CEMFI Macroeconomics Workshop. This project received the support of a fellowship from the "la Caixa" Foundation (ID 100010434) fellowship code LCF/BQ/DR23/12000010.

1 Introduction

Manufacturing-intensive development has become more difficult for many low- and middle-income countries. In many cases, manufacturing employment peaks at a lower level and at an earlier stage of development than it did for early industrializers—a pattern Rodrik (2016) terms *premature deindustrialization*. This raises a positive question about the determinants of cross-country differences in structural transformation, and a normative one because sectoral reallocation shapes long-run income. Historically, manufacturing has been a locus of rapid productivity growth and convergence; truncating the manufacturing-intensive phase can therefore have important consequences for output per capita.

A noteworthy feature of recent development episodes is that the transition away from manufacturing is occurring alongside rapid demographic change. Fertility now declines at much lower income levels in today's middle- and low-income economies than it did among early industrializers, with some countries reaching (or approaching) below-replacement fertility before substantial industrialization has taken place. As a result, population aging accelerates and young cohorts shrink during the stage when manufacturing employment would historically have been expanding. This paper asks whether faster demographic transitions can account for muted and early manufacturing peaks, and what this implies for output per capita.

Existing explanations of premature deindustrialization emphasize trade, relative prices, and non-homothetic demand. This paper highlights a distinct margin: the population's age structure. I show that variation in the young-adult share over time and across countries predicts employment reallocation across sectors—including within non-agriculture—and is strongly associated with both the height of the manufacturing hump and the income level at which it peaks. The mechanism operates through life-cycle differences in labor supply and consumption demand between sectors. Manufacturing employment is disproportionately youth-intensive, while the propensity to work in both low- and high-skilled services rises with age. On the demand side, accumulation of manufacturing-produced durables is front-loaded early in adulthood, raising manufacturing demand when cohorts are young and shifting expenditure toward services as populations age.

The paper begins by documenting the empirical relationships between age composition and sectoral allocations, at both the aggregate and individual levels. I show that a one percentage point increase in the young-adult share (ages 25–34) robustly predicts a 0.6–1 pp. increase in the manufacturing/industry shares of employment, conditional on income among other controls and using the birth rate 25–34 years earlier as an instrument for age structure. Young adult shares in the years leading up to a country's industrial employment peak are strongly associated with both the height of the hump and the income level at which it occurs.

Micro evidence from IPUMS supports a life-cycle labor-supply interpretation for these aggregate

relationships. Conditional on non-agricultural employment and robust controls, workers around age 20 are close to twice as likely to be employed in manufacturing as workers in their early sixties, while the propensity to work in both low- and high-skilled services rises with age. Wage–age profiles are also steeper for service sector workers.[1] This is consistent with services placing relatively greater weight on tasks and skills that accumulate with experience and do not deteriorate with age, whereas manufacturing relies more on abilities that peak earlier in the life cycle. The evidence is also supports a life-cycle consumption-demand interpretation. Using Eurostat data covering EU countries and neighboring middle-income economies, I show the share of manufacturing-produced durables in total consumption is 27 percent (or 4 percentage points) higher for households with a primary earner that is under 30 than for those with a primary earner that is 60 or older.

I then develop a quantitative framework to interpret these facts and to study the implications of counterfactual demographic trajectories. The model is a calibrated, open-economy overlapping-generations economy with four sectors—agriculture, manufacturing, low-skill services, and high-skill services—that nests standard drivers of structural transformation, including non-homothetic CES preferences and sector-specific productivity growth, while allowing international trade to shape equilibrium relative prices and sectoral incentives. Demographics affect structural transformation through two complementary life-cycle channels. On the supply side, workers' comparative advantage over tasks evolves with age, sectors differ in task intensity, and mobility frictions generate imperfect sorting across sectors over the life cycle. On the demand side, households accumulate a slowly depreciating consumer durable produced in manufacturing. The framework maps demographic trajectories into equilibrium sectoral allocations, manufacturing-peak outcomes, and output per capita along the development path.

To quantify the mechanism, I run demographic counterfactuals for 1970-2009 in which the economy's initial conditions and all non-demographic parameters are held fixed while the population-by-age profile is replaced with trajectories drawn from the cross-country distribution of age structures. I consider four trajectories spanning the 10th to 90th percentile of the young-adult share distribution: youngest (approximately p10), young (p25), old (p75), and oldest (p90). This exercise isolates how changes in age structure reshape sectoral allocations, trade patterns, and aggregate income. Manufacturing under the youngest's demographic trajectory trajectory peaks 2.3 percentage points higher and 8 years later than under the oldest's, with the young and old trajectories in between.[2] The normative implications of this are sizeable: cumulative output per capita rises by 93.6% under the youngest's demographic trajectory and by 76.5% under the oldest's, a 17.1 percentage-point gap. A channel decomposition shows employment per capita explains 10.5 percentage points of this gap, the remaining 6.6 percentage points is due to life-cycle reallocation mechanisms.

[1] Because older workers who remain in manufacturing are likely positively selected, these service–manufacturing differences in life-cycle wage growth should be interpreted as conservative.

[2] This differential is more modest than what we find in the data, but it reflects the preliminary nature of the calibration.

This paper contributes to three strands of work. First, I document that faster demographic transitions are systematically associated with lower and earlier industrial employment peaks, and I provide two life-cycle mechanism—disciplined by harmonized microdata on sector choice and expenditure—that rationalizes this link, contributing to the premature deindustrialization literature (Rodrik, 2016, 2013). Second, I introduce population age structure as a driver of reallocation within non-agriculture by shifting both effective labor supply and expenditure composition, and I quantify these forces in a multi-sector overlapping-generations framework, complementing quantitative models of structural transformation that emphasize non-homothetic demand, relative prices, productivity, and trade (e.g. Kongsamut et al. 2001; Ngai and Pissarides 2007; Acemoglu and Guerrieri 2008; Comin et al. 2021). Third, I extend the macro-demographics literature by moving beyond agriculture exit and advanced-economy aging to focus on post-agricultural reallocation between manufacturing and services, and by integrating life-cycle labor-supply and durable-demand channels into a framework designed for cross-country demographic counterfactuals (Bloom and Williamson, 1998; Bloom et al., 2003; Porzio et al., 2022; Cravino et al., 2022).

The remainder of the paper is organized as follows. Section 2 establishes the macro and micro facts that motivate the model's life-cycle channels. Section 3 develops the model. Section 4 outlines the calibration while Section 5 reports quantitative results from demographic counterfactuals that hold non-demographic primitives fixed. Section 6 concludes.

2 Empirical Evidence

Manufacturing employment follows a hump-shaped path with development, but the hump has become markedly lower and shifted to lower income levels in countries that industrialized later—a pattern commonly referred to as *premature deindustrialization* (e.g. Rodrik, 2016). Figure 1 illustrates this regularity in the data: manufacturing employment rises with income but peaks earlier and at lower levels for low- and middle-income economies. Appendix B.1 reproduces the graph for the share of employment in services, as well as low-skilled services specifically, to show a linear increase that is steeper for middle-income and even more so for low-income economies, a well-established trajectory with the premature deindustrialization literature. This paper focuses on a distinct and increasingly salient margin—demographic timing— which may help account for the left-shift and compression of the manufacturing hump.

Compared with historical industrializers, today's low- and middle-income economies (LMICs) experience fertility decline and population aging much earlier along the development path. If manufacturing employment is disproportionately young-adult intensive and if the demand for manufacturing-intensive durables is front-loaded early in adulthood, then an earlier shrinkage of young cohorts can mechani-

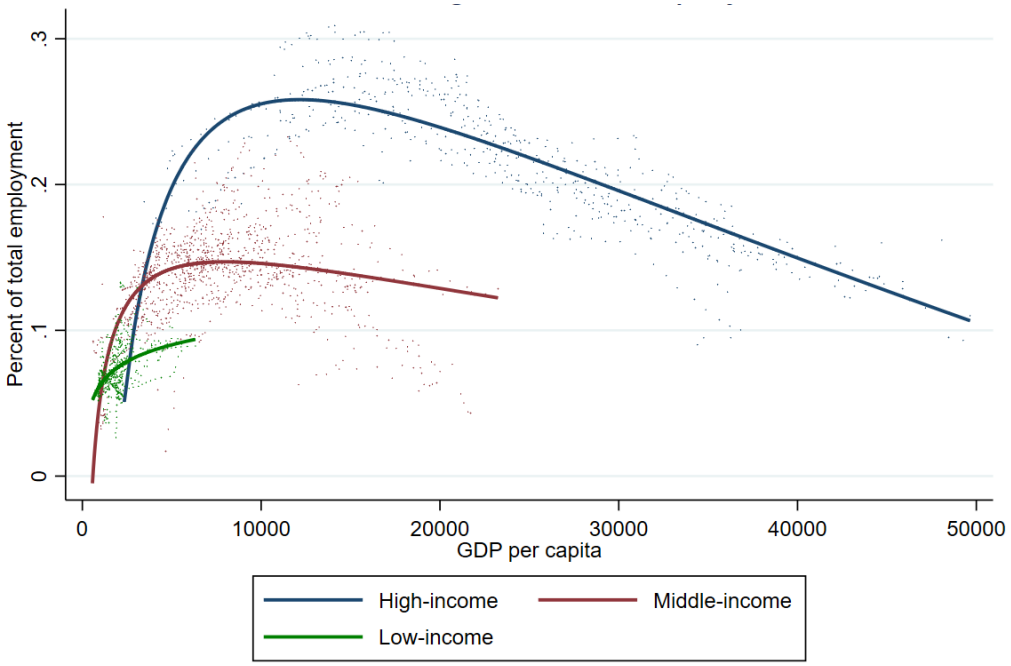


Figure 1: Manufacturing employment and premature deindustrialization. *Notes:* Each dot is a country–year observation. Curves plot fitted values from income-group-specific regressions of the manufacturing employment share on log GDP per capita (2010 income-group classification).

cally compress the manufacturing hump and shift labor and demand toward services while countries are still relatively poor.

This section assembles empirical evidence in two layers. First, I document macro reduced-form facts linking demographic timing and cohort composition to sectoral employment shares and to the height and location (in GDP terms) of the manufacturing hump. Second, I document life-cycle moments that discipline the paper's mechanisms: age structure affects labor supply per capita, sectoral sorting over the life cycle, and consumption composition. Because the model's key margin is reallocation within the non-agricultural economy, I emphasize the manufacturing–services trade-off both in the aggregate and in the micro data.

2.1 Data and measurement

I combine harmonized census microdata with long-run cross-country aggregates.

Micro data (IPUMS). The core micro source is *IPUMS International*, which provides harmonized census samples for over 80 countries and between 2 and 10 census waves since 1960, totaling more than one billion individual observations. IPUMS records age (or year of birth), gender, schooling, rural/urban status, migration status, and industry of employment; for 14 countries in the sample there is data for wage or earnings income. These data allow me to (i) measure how sectoral employment varies over the life cycle and (ii) construct sectoral wage–age profiles that discipline life-cycle comparative

advantage. Appendix A describes the micro data and harmonization in more detail.

Cross-country aggregates. My baseline cross-country panel uses sectoral employment shares from the World Bank's *World Development Indicators* (WDI), which provides substantially broader country coverage than alternative historical sectoral datasets. I use these series to construct employment shares in agriculture, industry, and services, and (because the paper focuses on post-agricultural reallocation) the industry and services shares within non-agriculture. Where available, I report robustness exercises using the Groningen Growth and Development Centre (GGDC) sectoral databases (ETD and 10S) in the Appendix, including narrower sector definitions. Demographic measures (including age shares and total fertility rates) are constructed from the UN World Population Prospects (WPP), focusing on the young-adult share (ages 25–34) in total population. Long-run data on births per thousand are drawn from Delventhal et al. (2024), which provide coverage for early industrializers and broad coverage for LMICs. GDP per capita series are drawn from Maddison and the Penn World Tables. CPI data used to deflate wages across census waves are taken from the IMF, except for Venezuela, for which CPI data are drawn from the St. Louis Fed. Unless stated otherwise, countries are classified as high-, middle-, and low-income based on their 2010 GDP per capita.

Key demographic and sectoral objects. Let $young_{it}$ denote the share of the total population aged 25–34 in country i and year t. Let $s_{j,it}$ denote sector j's employment share in total employment for $j \in \{\text{Agriculture}, \text{Industry}, \text{Services}\}$. To isolate the manufacturing–services margin after the agricultural transition, I also report shares within non-agriculture: the industry share within non-agriculture is constructed as $s^{NA}_{I,it} \equiv I_{it}/(I_{it} + S_{it})$, with $s^{NA}_{S,it} = 1 - s^{NA}_{I,it}$.

2.2 Macro evidence: demographic timing and the manufacturing hump

Fact 1: Demographic transitions occur earlier along the development path in LMICs. Fertility falls at much lower income levels in today's low- and middle-income economies than it did for historical industrializers: within-country estimates imply that a $1,000 increase in real GDP per capita is associated with about 3.1 fewer births per thousand in low-income economies, 1.5 fewer in middle-income economies, and about 0.5 fewer in high-income economies. To quantify this pattern, I estimate, separately by 2010 income group, within-country (country fixed-effects) regressions of fertility outcomes on GDP per capita:

$$B_{it} = \alpha_i + \beta\, GDPpc_{it} + \varepsilon_{it}, \tag{1}$$

where B_{it} is either births per thousand or the total fertility rate (TFR), and $GDPpc_{it}$ denotes GDP per capita. Figure 2 plots births per thousand[3] against GDP per capita by income group.

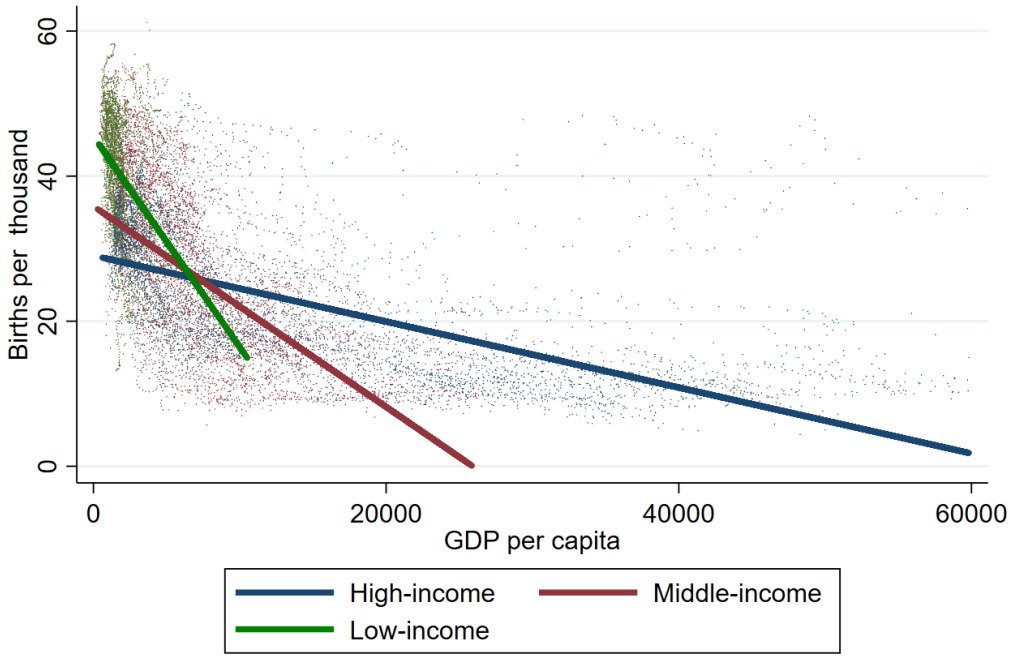


Figure 2: Births per thousand by GDP per capita (by 2010 income group).

Two descriptive patterns underscore the speed of the transition and its implications for cohort size. First, many low- and middle-income economies have already reached (or are near) below-replacement fertility (Appendix Table 8). Second, the income level at which the young share peaks is substantially lower in low- and middle-income economies: the peak young share among the working-age population occurs at a mean GDP per capita of $30,566 in high-income economies versus $9,531 in middle-income and $4,635 in low-income economies.[4] Taken together, Fact 1 implies that many developing economies begin to age at income levels at which historical industrializers were still expanding manufacturing employment. The next facts show that this timing shift is empirically linked to sectoral reallocation and to the manufacturing hump.

Fact 2: Age structure predicts sectoral employment shares within countries. There is a strong relationship between age structure and sectoral employment. Within countries, larger young-adult cohorts predict systematically higher industry employment and lower services employment conditional on development: in 2SLS, a one-percentage-point larger young-adult share is associated with a 0.62–0.66 percentage point higher industry share in total employment, and with an almost one percentage point higher industry share within non-agriculture (and an equal and opposite decline in services). I establish this pattern in a panel that combines annual WDI employment shares with WPP

[3]Births-per-thousand series extend farther back for historical industrializers than TFR series, capturing earlier stages of the transition. Appendix Figure 9 reproduces the binned relationship using TFR.

[4]I compute peaks using WPP historical series over the sample window; countries whose young adult share has not yet peaked in this window are excluded. Group means are descriptive and reflect this selection bias.

cohort-size measures.

Let $s_{j,it}$ denote the employment share of sector $j \in \{\text{Agriculture}, \text{Industry}, \text{Services}\}$ for country i in year t. I estimate:

$$s_{j,it} = \beta\, young_{it} + \alpha_i + \gamma_t + \lambda \log GDPpc_{it} + \delta\, FLFP_{it} + \psi\, LsecComp_{it} + \varepsilon_{it}, \tag{2}$$

where $young_{it}$ is the population share aged 25–34. Country fixed effects α_i absorb time-invariant cross-country differences, and year fixed effects γ_t absorb global shocks. The control $\log GDPpc_{it}$ conditions on the level of development. I additionally control for $FLFP_{it}$ (female labor force participation) and $LsecComp_{it}$ (lower secondary school completion) from the WDI to absorb time-varying changes in female labor supply and human capital that may co-move with demographic change and independently affect sectoral allocation. In Panel B specifications I additionally include $(\log GDPpc_{it})^2$ to allow for nonlinearities in the relationship between development and sectoral shares. The estimating sample for specifications that include the education control contains 1,606 country–year observations spanning 124 countries and 26 years.

Table 1: Young-adult cohort size (25–34) and sectoral employment shares (WDI)

	Agriculture		Industry		Services	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Panel A: Controls include $\log GDPpc$						
Young-adult share (25–34)	0.021	-0.493^{**}	0.854^{***}	0.661^{***}	-0.875^{***}	-0.167
	(0.072)	(0.224)	(0.105)	(0.169)	(0.128)	(0.199)
$\log GDPpc$	-0.002	0.001	0.026^{***}	0.027^{***}	-0.024^{***}	-0.028^{***}
	(0.006)	(0.007)	(0.005)	(0.005)	(0.006)	(0.006)
Female LF participation	0.208^{***}	0.213^{***}	-0.159^{***}	-0.157^{***}	-0.049^{**}	-0.056^{**}
	(0.028)	(0.029)	(0.021)	(0.021)	(0.023)	(0.024)
Lower secondary completion	-0.075^{***}	-0.068^{***}	0.060^{***}	0.062^{***}	0.015	0.005
	(0.011)	(0.011)	(0.009)	(0.009)	(0.010)	(0.010)
Panel B: Controls include $\log GDPpc$ *and* $(\log GDPpc)^2$						
Young-adult share (25–34)	-0.180^{**}	-0.182	0.906^{***}	0.615^{***}	-0.726^{***}	-0.433^{**}
	(0.071)	(0.177)	(0.104)	(0.152)	(0.121)	(0.170)
$\log GDPpc$	-0.317^{***}	-0.317^{***}	0.108^{***}	0.074^{**}	0.209^{***}	0.243^{***}
	(0.031)	(0.038)	(0.032)	(0.035)	(0.034)	(0.039)
$(\log GDPpc)^2$	0.018^{***}	0.018^{***}	-0.005^{**}	-0.003	-0.013^{***}	-0.015^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female LF participation	0.115^{***}	0.115^{***}	-0.135^{***}	-0.143^{***}	0.019	0.028
	(0.029)	(0.029)	(0.023)	(0.023)	(0.023)	(0.023)
Lower secondary completion	-0.056^{***}	-0.056^{***}	0.055^{***}	0.061^{***}	0.001	-0.005
	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)
Observations	1,606	1,606	1,606	1,606	1,606	1,606
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are WDI employment shares in agriculture, industry, and services. The key regressor is the share of the total population aged 25–34. 2SLS instruments the young-adult share with the mean crude birth rate (births per 1,000 population) lagged 25–34 years. Female labour force participation and lower secondary completion are rescaled to fractions on $(0, 1)$. All specifications include country and year fixed effects. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A key identification concern is that the contemporaneous cohort share may respond to sectoral conditions (for example through selective migration). To isolate predetermined variation in cohort

size, I instrument $young_{it}$ with the mean crude birth rate (births per 1,000 population) lagged 25–34 years. By construction, this instrument shifts the size of the cohort reaching ages 25–34 in year t.

Table 1 reports estimates for sectoral shares in total employment; Table 2 reports shares within non-agriculture. The core results are stark on the post-agricultural margin: within non-agriculture, Panel A implies an approximately one-for-one reallocation from services to industry, with 2SLS coefficients of 0.98 for industry and −0.98 for services (Table 2). Panel B yields a similar conclusion: the 2SLS coefficient for industry is 0.945 with an equal and opposite decline in services. In total employment, the 2SLS coefficients imply that a larger young-adult share raises industry employment and reduces both agriculture and services employment. The first stage is strong in both panels.[5]

Table 2: Young-adult cohort size (25–34) and industry–services shares within non-agriculture (WDI)

	Industry share (non-ag)		Services share (non-ag)	
	OLS	2SLS	OLS	2SLS
Panel A: Controls include $\log GDPpc$				
Young-adult share (25–34)	0.979^{***}	0.984^{***}	-0.979^{***}	-0.984^{***}
	(0.113)	(0.228)	(0.113)	(0.228)
$\log GDPpc$	0.032^{***}	0.032^{***}	-0.032^{***}	-0.032^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
Female LF participation	-0.080^{***}	-0.080^{***}	0.080^{***}	0.080^{***}
	(0.029)	(0.030)	(0.029)	(0.030)
Lower secondary completion	0.050^{***}	0.050^{***}	-0.050^{***}	-0.050^{***}
	(0.011)	(0.012)	(0.011)	(0.012)
Panel B: Controls include $\log GDPpc$ *and* $(\log GDPpc)^2$				
Young-adult share (25–34)	1.009^{***}	0.945^{***}	-1.009^{***}	-0.945^{***}
	(0.113)	(0.192)	(0.113)	(0.192)
$\log GDPpc$	0.079^{*}	0.072	-0.079^{*}	−0.072
	(0.045)	(0.054)	(0.045)	(0.054)
$(\log GDPpc)^2$	−0.003	−0.002	0.003	0.002
	(0.002)	(0.003)	(0.002)	(0.003)
Female LF participation	-0.066^{**}	-0.068^{**}	0.066^{**}	0.068^{**}
	(0.029)	(0.029)	(0.029)	(0.029)
Lower secondary completion	0.047^{***}	0.048^{***}	-0.047^{***}	-0.048^{***}
	(0.012)	(0.012)	(0.012)	(0.012)
Observations	1,606	1,606	1,606	1,606
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Dependent variables are industry and services employment shares within non-agriculture, constructed as industry (services) employment divided by industry + services employment. The key regressor is the share of the total population aged 25–34. 2SLS instruments the young-adult share with the mean crude birth rate lagged 25–34 years. Female labor force participation and lower secondary completion are rescaled to fractions on $(0, 1)$. All specifications include country and year fixed effects. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A remaining interpretational concern is that WDI "industry" bundles manufacturing with mining, utilities, and construction. Appendix D.1 addresses this directly using GGDC employment data: when "industry" is replaced by manufacturing, the relationship only increases: the 2SLS coefficient on the young-adult share is 1.484 on total employment (Appendix Table 10) and 1.711 on non-agricultural employment (Appendix Table 11). Furthermore, Appendix Table 12 measures the coefficients on in-

[5]Kleibergen–Paap rk Wald $F = 102.095$ in Panel A and $F = 147.613$ in Panel B.

dustry excluding manufacturing industry (other industry) and on its three components individually (mining, utilities and construction). Only utilities have a positive and statistically significant coefficient, but it is an over an order of magnitude smaller than the coefficient on manufacturing. The 2SLS coefficients on construction and other industry are negative. I use WDI as the baseline source for calibration because of its broader cross-country coverage.

Appendix D.2 shows that the industry–services reallocation is not sensitive to alternative young-cohort definitions (ages 20–34). Appendix D.3 provides additional diagnostics and timing evidence for the instrument. It reports a partial first stage and a "lag fingerprint" exercise in which predictive content is concentrated in the lag window that matches the age range of the endogenous regressor. It also reports lead–lag timing plots for the OLS and reduced-form relationships at horizons $h \in \{-20, -15, -10, -5, 0, 5, 10\}$.

Fact 3: Young adult (25-34) shares predict the height and development level of the industry hump. A central theme in the premature deindustrialization literature is that late industrializers tend to reach a lower peak in industrial employment at a lower level of development. This fact links two objects: (i) the height of the industrial-employment "hump" and (ii) income per capita at the peak. This section documents that both margins are systematically related to demographic composition in the run-up to the peak. Countries that approach their industrial-employment peak with larger young cohorts reach higher peaks and do so at higher income levels. Quantitatively, a one-percentage-point larger pre-peak young-cohort share is associated with a 1.1–1.5 percentage point higher peak industrial employment share (Table 3) and with 20–29 percentage points higher GDP per capita at the peak (Table 4), depending on whether the demographic measure is averaged over 5, 10, or 15 pre-peak years.

For each country i, let t_i^{peak} denote the year in which the industrial employment share reaches its maximum (the "raw" peak), and let s_i^{peak} denote the corresponding peak industrial employment share. The key regressor is the size of the young cohort in the run-up to the peak, measured as the average young-cohort population share over the L years preceding the peak year, $\overline{\text{Young}}_i^{(-L)}$, with $L \in \{5, 10, 15\}$. For a baseline sample of 85 countries with a peak within the data window, I estimate:

$$s_i^{\text{peak}} = \beta\, \overline{\text{Young}}_i^{(-L)} + \lambda_1 \Delta \ln(\text{GDPpc})_i^{(-L)} + \lambda_2 \overline{\ln(\text{GDPpc})}_i^{(-L)} + \lambda_3 \left(\overline{\ln(\text{GDPpc})}_i^{(-L)}\right)^2 + \lambda_4\, t_i^{\text{peak}} + \delta_{d(i)} + \varepsilon_i, \tag{3}$$

where $\delta_{d(i)}$ are decade fixed effects.

The magnitudes are economically large. In column (1), a one percentage point larger young-cohort share in the five years preceding the peak is associated with a 1.085 percentage point higher peak industrial employment share. The association is similar—and slightly larger—when the demographic measure is averaged over longer pre-peak windows: 1.274 percentage points for the ten-year average

Table 3: Peak Industrial Employment and Pre-Peak Demographics

	(1) 5-year pre-peak average	(2) 10-year pre-peak average	(3) 15-year pre-peak average
Young adult (25-34) share (average)	1.085***	1.274***	1.535***
	(0.312)	(0.406)	(0.503)
GDP per capita growth	-0.008	-0.015	0.000
	(0.061)	(0.036)	(0.027)
Log GDP per capita (average)	0.204	0.216*	0.257**
	(0.132)	(0.121)	(0.108)
(Log GDP per capita)^2 (average)	-0.009	-0.010	-0.013**
	(0.007)	(0.007)	(0.006)
Peak year	-0.006*	-0.006**	-0.006**
	(0.003)	(0.003)	(0.003)
Decade FE	Yes	Yes	Yes
Observations	85	85	85
Adj. R^2	0.486	0.488	0.499

Notes: Unit of observation is a country. The dependent variable is the country's peak industrial employment share (raw peak). The key regressor is the average young-cohort share over the L years preceding the peak ($L \in \{5, 10, 15\}$). "GDP per capita growth" is the log change in GDP per capita over the same pre-peak window; level controls are the average of log GDP per capita and its square. The young adult share (25-34) is measured as a decimal (0–1). All specifications include decade fixed effects (absorbed) and the peak year; regressions are estimated without a constant. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

and 1.535 percentage points for the fifteen-year average (columns (2)–(3)). Evaluated at the cross-country variation in cohort size, these estimates imply that a one-standard-deviation higher pre-peak young-cohort share is associated with an increase in peak industrial employment of roughly 3.5–4.2 percentage points (about 0.6 standard deviations), a sizeable shift in the height of the industrialization hump.

The premature deindustrialization literature also emphasizes that many countries reach their manufacturing peaks at lower levels of development. I therefore estimate:

$$\ln(\text{GDPpc})_i^{\text{peak}} = \beta\, \overline{\text{Young}}_i^{(-k)} + \lambda_1 \Delta \ln(\text{GDPpc})_i^{(-k)} + \lambda_2\, t_i^{\text{peak}} + \delta_{d(i)} + \varepsilon_i, \tag{4}$$

where $\ln(\text{GDPpc})_i^{\text{peak}}$ is log GDP per capita in the peak year.

The association between cohort size and income at the peak is also economically large. A one percentage point larger pre-peak young-cohort share is associated with 0.179–0.251 higher log GDP per capita at the peak, corresponding to approximately 20–29 percent higher GDP per capita. In standard-deviation terms, a one-standard-deviation larger young-cohort share is associated with about 0.58–0.69 log points higher GDP per capita in the peak year (roughly 78–99 percent), or almost two thirds of a standard deviation of log GDP per capita at peak.

Appendix E provides additional robustness. Appendix E.1 replicates the analysis with GGDC data to isolate the manufacturing peak specifically, beyond the broader industry characterisation. One percentage point increase in the young-adult (25-34) share is associated with 1.8–2.6 higher manufacturing peak at 25 to 35 percent higher GDP per capita. Similarly to Fact 2, narrowing

Table 4: Income at the Industrial Employment Peak and Pre-Peak Demographics

	(1) 5-year pre-peak average	(2) 10-year pre-peak average	(3) 15-year pre-peak average
Young adult (25-34) share (average)	17.915***	22.512***	25.114***
	(2.042)	(2.407)	(3.175)
GDP per capita growth	-0.465	0.551	0.565***
	(0.595)	(0.334)	(0.176)
Peak year	0.028	0.009	-0.014
	(0.029)	(0.028)	(0.028)
Decade FE	Yes	Yes	Yes
Observations	85	85	85
Adj. R^2	0.382	0.485	0.578

Notes: Unit of observation is a country. The dependent variable is log GDP per capita in the country's peak industrial-employment year. The key regressor is the average young-cohort share over the k years preceding the peak ($k \in \{5, 10, 15\}$). "GDP per capita growth" is the log change in GDP per capita over the same pre-peak window. The young adult share (25-34) is measured as a decimal (0–1). All specifications include decade fixed effects (absorbed) and the peak year; regressions are estimated without a constant. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

the definition to manufacturing only sharpens the coefficients. Appendix E.2 further addresses the concern that pre-peak demographics are still centered on each country's peak year by constructing predetermined demographic measures based on GDP-band averages; the relationship remains positive and statistically significant, and the coefficients on the young adult share are, in fact, moderately larger. Appendix E.3 replicates the analysis with alternative peak definitions (smoothing and local-hump criteria). Appendix E.3 also measures the peak of industrial employment relative to non-agricultural employment.

Taken together, Facts 1–3 imply that countries that become older earlier, due to earlier fertility decline, exhibit lower industry/manufacturing employment shares and reach systematically smaller peaks at lower income levels.

2.3 Micro evidence: life-cycle mechanisms that discipline the model

Fact 4: Demographics predict labor force per capita. Labor supply per capita moves almost one-for-one with the working-age share: the estimated slope in the aggregate data is between 0.76 and 0.83 (95 percent confidence interval), so a one percentage point increase in the working-age share raises labor force per capita by roughly 0.8 percentage points. Figure 3 illustrates this relationship by plotting the outcome of regressing the labor force per capita on the share of the population that is working age (20-64) plus country fixed effects.[6]

This fact is central for mapping demographics into output per capita. Along the development path, aging changes not only where workers are employed (manufacturing versus services) but also how many workers there are per person. Because sectoral employment shares are defined over employment while

[6]Scatter observations are net of country fixed effects.

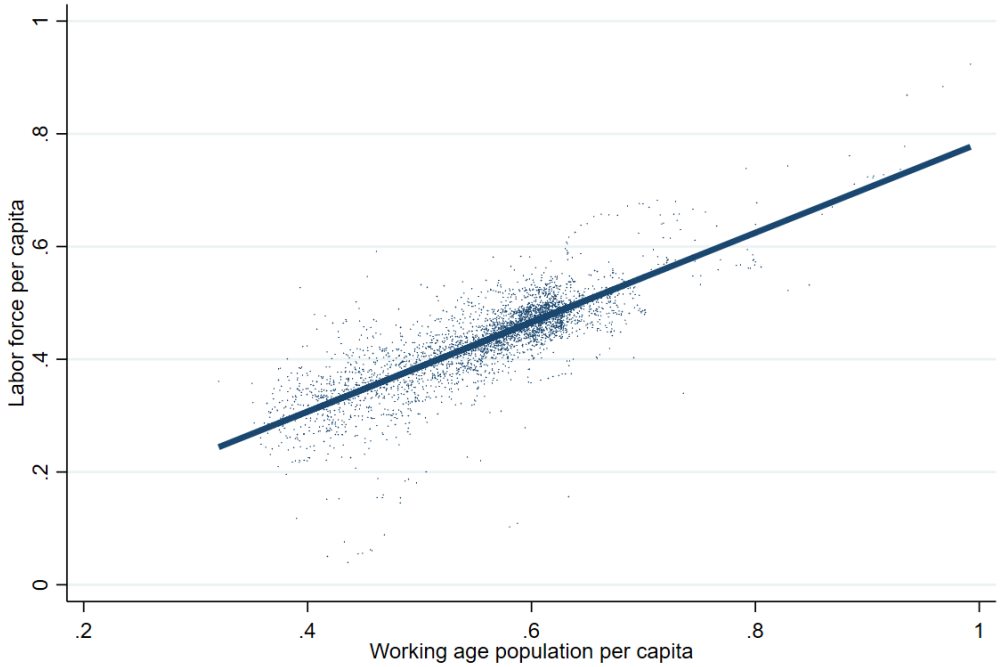


Figure 3: Labor force per capita and the working-age share.

the paper's outcomes are in per-capita terms, shifts in the labor-force-to-population ratio directly affect aggregate output per capita even holding sectoral productivities fixed. This motivates the model's partition of cohorts into workers and retirees and the emphasis on the working-age share as a sufficient statistic for effective labor supply per capita.[7]

Fact 5: Manufacturing employment is youth-intensive within countries, and wage growth over the life cycle is steeper in services. Micro data show that manufacturing draws disproportionately from young adults, while services employment rises with age, consistent with an age-dependent labor-supply channel. Identifying this age gradient requires addressing the age–period–cohort (APC) identification problem: since cohort = year − age, one cannot include unrestricted fixed effects for all three dimensions simultaneously. For the sectoral sorting regressions, I control for cohort effects nonparametrically and absorb period variation with a parsimonious proxy; for the wage profiles below, I follow the Heckman–Lochner–Taber restriction. Appendix F reports extensive sensitivity analysis under alternative APC strategies.

Sectoral sorting by age. Using IPUMS microdata, I estimate conditional sector-selection regressions for manufacturing, low-skill services, and high-skill services as shares of non-agricultural employment. The baseline specification is

$$s_n^j \;=\; \sum_{a\neq 50} \alpha_a \,\mathbf{1}[\text{age}_n = a] \;+\; X_n\beta \;+\; \gamma_1 \ln \text{GDP}_{ct} \;+\; \gamma_2 (\ln \text{GDP}_{ct})^2 \;+\; \mu_{c,b} \;+\; \varepsilon_n, \tag{5}$$

[7] In the model, all working-age individuals supply a unit of labor inelastically, so the labor force per capita is equivalent to employment per capita.

where n indexes individuals, s_n^j is the propensity of individual n to work in sector j among non-agricultural workers in country c at time t, X_n includes indicators for male, foreign-born, years of schooling, and urban residence, $\ln \text{GDP}_{ct}$ is log real GDP per capita from the Maddison Project Database entered as a quadratic, and $\mu_{c,b}$ are country $\times$ five-year birth-cohort fixed effects with cohort bins $b = 5\lfloor \text{byear}/5 \rfloor$. The omitted age category is 50; the sample includes ages 20–70.

The country×cohort fixed effects $\mu_{c,b}$ absorb all time-invariant heterogeneity across birth cohorts within each country, including differences in cohort-level education, labor-market entry conditions, and institutional environment. This is the main defense against confounding by cohort composition—the concern that, for example, younger cohorts enter with more education and different sectoral propensities. With these fixed effects in place, the age coefficients $\{\alpha_a\}$ are identified from within-cohort variation: the same birth cohort observed at different ages across successive census waves.

The quadratic in $\ln \text{GDP}_{ct}$ serves as a proxy for aggregate period effects—economy-wide forces that shift all workers' sectoral propensities in a given country-year, such as trade liberalization, technological change, or macroeconomic conditions. Because the specification already includes country×cohort fixed effects, it cannot simultaneously include unrestricted country×year fixed effects without absorbing the variation used to identify age effects. The GDP proxy is a parsimonious alternative: in developing countries, log GDP per capita and its square capture the dominant source of time variation in sectoral composition—the movement along the structural transformation path. The identifying assumption is that, conditional on $\mu_{c,b}$ and the GDP quadratic, residual period shocks are uncorrelated with the age dummies.[8]

Figure 4 plots the estimated age coefficients for all countries in the sample.

Manufacturing is sharply youth-intensive: the estimated age coefficient at age 20 is 0.12 relative to the base (age 50), falling to −0.05 by age 64. The pattern is reversed for services: for low-skill services the age coefficient is −0.06 at age 20 and +0.05 at age 64, while for high-skill services it is −0.06 at age 20, rising toward zero by age 60.[9] The implied differences are economically large: a worker around age 20 is close to twice as likely to be employed in manufacturing than a worker at age 70, conditional on non-agricultural employment.

The country×cohort fixed effects in this specification address the threat of confounding the age profile by birth-cohort composition directly and nonparametrically. The cost is that period effects

[8]The regression is estimated with `reghdfe` using analytic weights equal to employment in each cell and standard errors clustered by country. Appendix F reports results under alternative APC strategies: country-specific linear time trends in place of the GDP proxy, unrestricted country×year fixed effects without cohort controls, and the polynomial-age identification strategy of Porzio et al. (2022). The qualitative patterns are robust across all specifications.

[9]The high-skill services gradient is attenuated relative to specifications without cohort fixed effects, because much of the cross-sectional HSS variation reflects between-cohort differences in educational attainment. The within-cohort age profile for HSS is correspondingly flatter but remains upward-sloping over the prime working years.

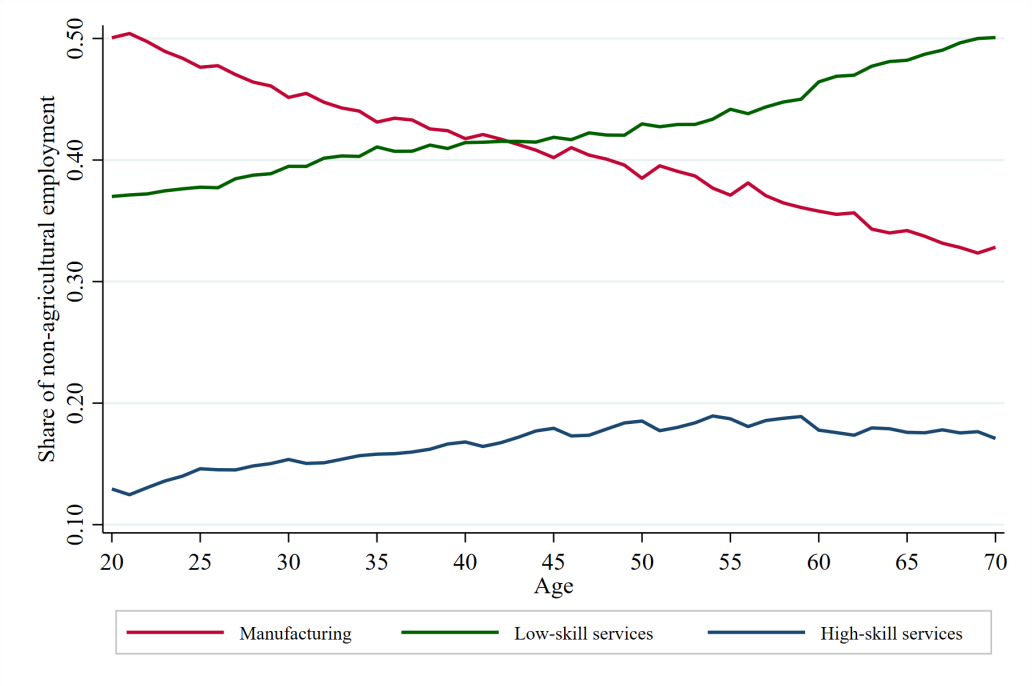


Figure 4: Life-cycle sectoral sorting within non-agricultural employment. Notes: Estimated age coefficients $\{\hat{\alpha}_a\}$ from equation (5), with country × 5-year birth-cohort fixed effects and a quadratic in log GDP per capita as period proxy. Age 50 is the omitted category. All countries in the IPUMS sample.

must be absorbed parametrically rather than with unrestricted year fixed effects—but in the structural transformation context, a quadratic in log GDP captures the first-order source of time variation in sectoral shares. To guarantee the robustness of these results, Appendix F reports extensive sensitivity analysis. Alternative specifications replace the GDP proxy with country-specific linear time trends, adopt the Porzio et al. (2022) polynomial-age identification strategy that absorbs period effects non-parametrically at the cost of restricting the age profile to a smooth function, and include a conventional specification with unrestricted country×year fixed effects but no cohort controls. All specifications are reported for subsamples of non-high-income countries and middle-income countries only, and where applicable for sectoral propensities defined over both non-agricultural and total employment. The patterns are robust throughout.

Within-cohort versus between-cohort reallocation. The within-cohort identification strategy is further supported by a direct decomposition of aggregate sectoral changes into within-cohort and between-cohort components, following Porzio et al. (2022). For each country with two or more census waves, I track birth cohorts over time and decompose changes in non-agricultural sectoral shares into a within-cohort component—workers switching sectors as they age—and a between-cohort component—younger cohorts entering with different sectoral allocations. Critically, within-cohort changes are age effects: they capture how a given birth cohort's sectoral composition shifts as its members grow older, holding cohort identity fixed.

Across all countries, the median within-cohort share of the change in manufacturing's share of

non-agricultural employment is approximately 1.0 (detailed results in Appendix F.6), meaning that essentially all of the observed reallocation occurs within cohorts rather than through cohort replacement.[10] This stands in sharp contrast to the agricultural margin: Porzio et al. (2022) find that roughly half of structural transformation out of agriculture is between-cohort, driven by new cohorts entering with less agricultural employment. The non-agricultural margin is fundamentally different: sorting between manufacturing and services is overwhelmingly a within-cohort, life-cycle phenomenon. This contrast further motivates the paper's focus on the non-agricultural composition margin when documenting age-dependent sectoral propensities. Together, the sorting regressions and the within-cohort decomposition are consistent with age-related comparative advantage across sectors: as workers age, their relative productivity shifts away from manufacturing and toward services, generating life-cycle reallocation within the non-agricultural labor force.

Sectoral wage profiles. Sectoral wage profiles provide independent support for this interpretation. If comparative advantage in services increases with age, then the return to experience should be steeper in services than in manufacturing. In the subset of IPUMS countries with harmonized earnings measures, I construct wage–age profiles by 5-year age bins separately for manufacturing and services and normalize each profile to an age 20–24 baseline. To account for time and cohort effects, I follow Lagakos et al. (2018) and estimate a flexible wage equation in repeated cross-sections with age-group dummies, year effects, cohort effects, and controls for years of schooling, imposing the Heckman–Lochner–Taber (HLT) restriction; the resulting cross-country average wage–age profiles are plotted in Figure 5.[11] The HLT restriction—that age-related wage growth is approximately zero in the final ten working years—provides an economically grounded way to break the age–period–cohort collinearity for wages: late-career workers' wage changes within a cohort identify time effects, and the remaining variation identifies the age profile. For sectoral employment propensities, no equally compelling economic restriction is available, which motivates the cohort-fixed-effects approach used above for the sorting regressions.[12]

For ages 45–59, the age–wage profile for the service sector is around 35 percent higher on average than that for the manufacturing sector; in all countries bar Brazil, it is at least 25 percent higher. For low-skilled services only, the age–wage profile is 19–20 percent higher than the manufacturing profile.

[10] The within-cohort share can exceed one when the between-cohort component works in the opposite direction—for instance, when younger cohorts enter with *higher* manufacturing propensities even as all cohorts gradually leave manufacturing with age. See Appendix F.6 for details.

[11] The wage analysis is limited to 9 of the 14 countries with harmonized earnings data, as at least two census waves are required to recover time effects. This subset closely matches that used by Lagakos et al. (2018). Venezuela is excluded due to inconsistencies in earnings measurement across waves. Appendix A lists the countries in the earnings subsample.

[12] The HLT restriction exploits the empirical regularity that wage growth flattens at older ages. No analogous regularity holds for sectoral employment shares, which may continue to shift throughout the working life.

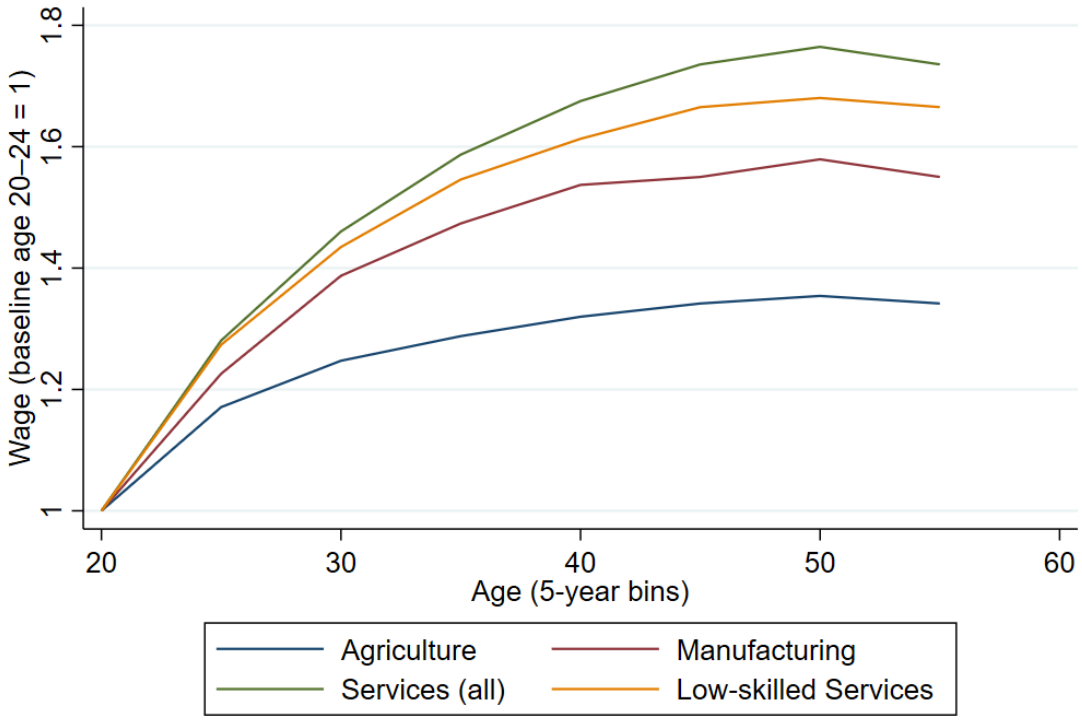


Figure 5: Wage–age profiles by sector, IPUMS 9-country earnings subsample. Notes: Wages are normalized to 20–24 within each country–year; ages are 5-year bins.

Because manufacturing employment diminishes sharply with age, older manufacturing workers are likely positively selected, so these service–manufacturing differences in life-cycle wage growth should be interpreted as conservative. Appendix G.2 reports additional robustness based on simpler cross-sectional profiles, while Appendix G.3 shows that omitting education controls widens the gap further.

These life-cycle moments discipline the model's labor-supply mechanism by pinning down the strength of age-dependent comparative advantage—that is, the age profile of task efficiency. They provide an external validation of the O*NET-based sectoral task intensities.

Fact 6: Life-cycle expenditure shifts away from manufacturing-intensive durables with age. The final mechanism operates through the demand side: expenditure composition changes systematically over the life cycle. Early in adulthood, households are in a stock-building phase and devote a larger share of expenditure to durables, which are almost exclusively manufacturing goods.[13] Prior work has emphasized rising services expenditure with age (e.g. Cravino et al. 2022 for the United States). In the cross-country data used here, the dominant life-cycle margin operates through the durable–non-durable split: durable expenditure declines sharply with age, while the sectoral composition of non-durable expenditure varies little.

I document these patterns using Eurostat data on the structure of household consumption expenditure by COICOP purpose and age of the household reference person.[14] The share of manufacturing-

[13] In the COICOP breakdown of consumption categories used, every type of good classified as durable was also independently classified as being a manufacturing good.

[14] The data covers all 27 EU member states as well as Kosovo, North Macedonia, Montenegro, Norway, Serbia, Türkiye,

produced durables in total consumption is 27 percent—around 4 percentage points higher for households with a reference person below age 30 than for those with a reference person aged 60 or above. The durable share for households with a reference person aged 30–44 is only slightly lower than for the youngest group, while it is around 1.5 percentage points lower for households with a reference person aged 45–59. Excluding durables, the sectoral composition of non-durable consumption varies little with age; if anything, older households allocate a slightly larger share of non-durable expenditure to agricultural goods rather than services. Restricting the sample to observations classified as middle-income or controlling for GDP per capita has only marginal effects on these estimates.

This evidence motivates the durable-stock demand mechanism in the model and clarifies which consumption moments discipline its calibration.

Summary. The macro evidence (Facts 1–3) shows that demographic transitions are accelerated in LMICs and that cohort composition predicts both sectoral allocation within countries and the height and location of the manufacturing (industrial) hump. The micro evidence (Facts 4–6) pins down the key channels: aging reduces labor supply per capita, shifts labor supply away from youth-intensive manufacturing toward services, and shifts demand away from manufacturing-intensive durables. The quantitative framework uses these moments to map demographic trajectories into equilibrium sectoral allocations and output per capita.

3 Model

This section develops a multi-sector overlapping-generations open-economy model in which demographic change affects structural transformation through (i) life-cycle labor supply (age-dependent comparative advantage with mobility frictions) and (ii) life-cycle demand (cohort-specific durable accumulation). The model is designed for quantitative counterfactuals: the time path of cohort sizes is taken from the data and can be replaced by alternative demographic histories.

The economy produces four sectoral domestic varieties: agriculture (A), manufacturing (M), low-skill services (L), and high-skill services (H). Agriculture, manufacturing, and high-skill services are traded internationally, while low-skill services are non-traded. Trade is introduced in reduced form through Armington aggregation on the absorption side and a constant-elasticity foreign demand schedule for domestic varieties. Households consume sectoral absorption composites (which coincide with domestic varieties in the non-traded sector).

and the United Kingdom, observed approximately every five years from 1988 onward, though some countries are missing early waves. The sample includes a non-trivial number of middle-income economies, particularly in the earlier years.

3.1 Demographics

Time is discrete, $t = 0, 1, 2, \ldots$. Individuals live for a maximum of A periods and are indexed by age $a \in \{20, \ldots, A = 89\}$. Let $\pi_t(a)$ denote the measure of individuals of age a at time t. The sequence $\{\pi_t(a)\}_{t,a}$ is taken directly from the data. Cohorts age deterministically. Entrants satisfy $\pi_{t+1}(20)$ from the data, and for $a = 20, \ldots, A-1$,

$$\pi_{t+1}(a+1) = s_t(a)\,\pi_t(a). \tag{6}$$

Given $\{\pi_t(a)\}$, set $s_t(a) \equiv \pi_{t+1}(a+1)/\pi_t(a)$ whenever $\pi_t(a) > 0$.

Counterfactual demographic experiments replace the observed path $\{\pi_t(a)\}$ with an alternative path (e.g. holding fertility fixed, accelerating aging, or imposing another country's age structure), while keeping preferences and technologies unchanged. In each experiment, the implied survival rates $\{s_t(a)\}$[15] are recomputed from the counterfactual $\{\pi_t(a)\}$ using (6).

Ages are partitioned into workers and retirees. Let $\bar{a} = 64$ denote an exogenous retirement age. Individuals with $a \leq \bar{a}$ are workers and supply one unit of time inelastically; individuals with $a > \bar{a}$ are retired and supply no labor.

3.2 Endowments and human capital

Each entering worker draws an idiosyncratic human-capital type at labor-market entry ($a = 20$). Let b denote the birth-cohort index (year of birth). Entrants draw a unit-interval index $u \in [0, 1]$,

$$u \sim \text{Beta}(\alpha_b, \beta_b), \qquad \alpha_b > 0,\ \beta_b > 0, \tag{7}$$

and this index is mapped into the productivity-relevant human-capital level

$$h \equiv h_{\min} + (h_{\max} - h_{\min})u \in [h_{\min}, h_{\max}],$$

which is held fixed over the life cycle. Thus, an age-a individual observed at time t belongs to birth cohort $b = t - a$ and has human-capital density $f_b(h) \equiv f_{t-a}(h)$ supported on $[h_{\min}, h_{\max}]$. Since labor-market entry occurs at age $a_0 = 20$, entrants at time t correspond to birth cohort $b = t - a_0$. The mean of the cohort distribution in u is $\mu_b \equiv \mathbb{E}[u \mid b] = \alpha_b/(\alpha_b + \beta_b)$, so average human capital $\mathbb{E}[h \mid b] = h_{\min} + (h_{\max} - h_{\min})\mu_b$ increases across cohorts when μ_b rises.

Human capital affects productivity only in high-skill services, as specified below. In all other sectors, individual productivity depends solely on age-specific task efficiencies.

[15] Note $\{s_t(a)\}$ is referred to as survival for simplicity, in practice it covers both survival and net immigration for that age group.

3.3 Preferences: non-durables (CLM) and durables

Within-period preferences. Individuals derive utility from consuming non-durable absorption composites from four sectors—agriculture, manufacturing, low-skill services, and high-skill services—and from services provided by a cohort-specific durable stock. Let $c_{j,t}(a)$ denote age-a per-capita non-durable consumption of the sector-j absorption composite at time t, where $j \in \{A, M, L, H\}$.

Following Comin et al. (2021), non-durable preferences can be written in terms of a (nonhomothetic CES) index of real non-durable consumption. Let $\mathcal{C}_t(a) > 0$ denote the cohort-specific per-capita index and let $(\sigma, \{\iota_j, \Omega_j\}_j)$ denote the identifiable parameters of the demand system, normalized so that manufacturing is the base sector, $\iota_M = 1$, while $\sum_j \Omega_j = 1$. For each cohort (t, a), the index $\mathcal{C}_t(a)$ is defined implicitly by

$$\sum_{j \in \{A,M,L,H\}} \Omega_j^{1/\sigma} \left(\frac{c_{j,t}(a)}{\mathcal{C}_t(a)^{\iota_j}} \right)^{\frac{\sigma-1}{\sigma}} = 1, \tag{8}$$

where $\sigma > 0$ governs the elasticity of substitution and ι_j governs the strength of income (scale) effects across sectors. When ι_j is constant across j, the system collapses to homothetic CES.

These preferences deliver Hicksian demands and a per-capita expenditure function. Let $E_t(a)$ denote the minimum per-capita non-durable expenditure required to attain $\mathcal{C}_t(a)$ at household (absorption) prices $p_t^Q \equiv \{p_{j,t}^Q\}_j$. Then the Hicksian demand for good j is

$$c_{j,t}(a) = \Omega_j \left(\frac{p_{j,t}^Q}{E_t(a)} \right)^{-\sigma} \mathcal{C}_t(a)^{(1-\sigma)\iota_j}, \tag{9}$$

and the associated expenditure function is

$$E_t(a) = \left[\sum_{j \in \{A,M,L,H\}} \Omega_j \, \mathcal{C}_t(a)^{(1-\sigma)\iota_j} \, (p_{j,t}^Q)^{\,1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{10}$$

Durable services. In addition to non-durables, each cohort holds a cohort-specific durable stock $D_t(a) \geq 0$ that provides within-period utility services. Per-period utility for an age-a cohort at time t is

$$u_t(a) = \log \mathcal{C}_t(a) + \varphi \log\big(1 + D_t(a)\big), \tag{11}$$

where $\varphi > 0$ governs the strength of utility from durable services.

Dynastic pooling and budget constraint. A representative dynasty fully insures all cohorts alive at a given date by pooling labor income and choosing cohort-specific allocations of the non-durable index $\{\mathcal{C}_t(a)\}_{a=20}^{A}$ and durable purchases $\{x_t(a)\}_{a=20}^{A}$ to maximize expected discounted utility.[16]

$$\max_{\{\mathcal{C}_t(a),\, x_t(a)\}_{t,a}} \sum_{t=0}^{\infty} \beta^t \sum_{a=20}^{A} \pi_t(a)\, u_t(a), \tag{12}$$

[16] Expectations are taken over idiosyncratic sector taste shocks that are realized each period.

where $\beta \in (0,1)$ and per-period utility $u_t(a)$ is given by (11). The dynasty takes prices, wages, and demographic paths as given.

Throughout, $E_t(a)$ and $x_t(a)$ are per-capita objects for an age-a member at time t, so cohort totals are obtained by multiplying by $\pi_t(a)$. Durable purchases are purchases of the manufacturing absorption composite and are priced at $p^Q_{M,t}$. The dynasty's pooled resource constraint is therefore

$$\sum_{a=20}^{A} \pi_t(a)\, E_t(a) \;+\; p^Q_{M,t} \sum_{a=20}^{A} \pi_t(a)\, x_t(a) \;\le \sum_{j\in\{A,M,L,H\}} w_{j,t}\, N_{j,t}, \tag{13}$$

where $\sum_j w_{j,t} N_{j,t}$ denotes the aggregate wage bill (with sectoral effective labor inputs $\{N_{j,t}\}$ defined below). Let $\lambda_t \ge 0$ denote the Lagrange multiplier on (13). The shadow value λ_t scales the dynasty's valuation of wage income in the labor allocation problem, ensuring that wages affect sectoral employment under full insurance.

Dynasty optimality condition for non-durables. For each t and each age a with $\pi_t(a) > 0$, the optimal allocation of $\mathcal{C}_t(a)$ satisfies

$$\frac{1}{\mathcal{C}_t(a)} = \lambda_t \frac{\partial}{\partial \mathcal{C}} E\big(\mathcal{C}_t(a); p^Q_t\big). \tag{14}$$

3.4 Durable accumulation

Durables are acquired through purchases of the manufacturing absorption composite. Let $x_t(a) \ge 0$ denote per-capita manufacturing purchases made by the dynasty on behalf of cohort (t,a) at the beginning of period t. Each unit of $x_t(a)$ is converted one-for-one into a durable good owned by that cohort and immediately available for consumption in period t.

The cohort-specific durable stock evolves according to

$$D_t(a) = (1-\delta_D) D_{t-1}(a-1) + x_t(a), \qquad a = 21, \ldots, A, \tag{15}$$

where $\delta_D \in (0,1)$ is the depreciation rate. Entering cohorts satisfy

$$D_t(20) = x_t(20). \tag{16}$$

There is no market for used durables and no inter-cohort transfers: durable goods cannot be sold, transferred, or reallocated across cohorts.

Optimal durable purchases. For each cohort age $a = 20, \ldots, A-1$, optimal durable purchases satisfy the Euler equation

$$\lambda_t\, p^Q_{M,t} = \frac{\varphi}{1 + D_t(a)} + \beta\, s_t(a)\, (1-\delta_D)\, \lambda_{t+1}\, p^Q_{M,t+1}. \tag{17}$$

For the terminal age $a = A$, the optimality condition is

$$\lambda_t \, p^Q_{M,t} = \frac{\varphi}{1 + D_t(A)}, \tag{18}$$

unless the non-negativity constraint binds. When $x_t(a) \geq 0$ binds, (17) (and (18) for $a = A$) holds with weak inequality and complementary slackness.

3.5 Technology and sectoral productivity

There are four production sectors $j \in \{A, M, L, H\}$. In each sector, competitive firms produce the domestic variety using effective labor:

$$Y_{j,t} = A_{j,t} \, N_{j,t}, \tag{19}$$

where $A_{j,t} > 0$ is sector-specific labor-augmenting productivity and $N_{j,t}$ denotes sector-j effective labor (measured in efficiency units). Let $w_{j,t}$ denote the wage paid per unit of effective labor in sector j.

Productivity follows sector-specific growth paths,

$$A_{j,t+1} = (1 + g_{j,t}) A_{j,t}, \tag{20}$$

where $g_{j,t} > -1$ is the sector-j growth rate. Consistent with sectoral evidence, productivity growth is fastest in agriculture and slowest in services. In the quantitative analysis, the paths $\{g_{j,t}\}$ are disciplined by sector-level data using model-consistent accounting identities.

3.6 Age-dependent tasks and sectoral efficiency

Task endowments. Working individuals possess age-dependent efficiency in three task bundles: physical (P), fluid-cognitive (F), and crystallized/interpersonal (C).[17] Let $z_k(a) > 0$ denote the efficiency of an age-a worker in task $k \in \{P, F, C\}$. I assume

$$z_P(a) \text{ and } z_F(a) \text{ decline with } a, \qquad z_C(a) \text{ increases with } a. \tag{21}$$

Sectoral task intensities. In non-agricultural sectors $j \in \{M, L, H\}$, task endowments are mapped into sector-specific efficiency units. Let $\theta_{j,k} \geq 0$ denote the intensity of task k in sector j, with $\sum_k \theta_{j,k} = 1$. The task-intensity parameters $\{\theta_{j,k}\}$ are measured using O*NET task requirements:

[17] A large literature documents that many measures of fluid cognition and some physical capacities decline with age, whereas crystallized abilities related to accumulated knowledge and experience tend to remain stable longer or improve. See, for example, (Horn and Cattell, 1967; Salthouse, 2004; Skirbekk, 2004).

occupation-level task measures are grouped into the three bundles and aggregated to the sector level using occupational employment weights.[18]

Define the task-based efficiency of an age-a worker in sector $j \in \{M, L, H\}$ as

$$\tilde{z}_j(a) = \left(\sum_{k \in \{P,F,C\}} \theta_{j,k} \, z_k(a)^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \tag{22}$$

where $\rho > 0$ governs within-worker substitutability across task bundles.

Human capital and sector-specific productivity. High-skill services additionally value individual human capital. For an individual of age a with human-capital draw h, sector-specific efficiency is given by

$$z_j(a, h) = \begin{cases} \tilde{z}_j(a), & \text{if } j \in \{M, L\}, \\ h^{\chi} \tilde{z}_H(a), & \text{if } j = H, \end{cases} \tag{23}$$

where $\chi > 0$ governs the strength of human capital in high-skill services. Agriculture uses the simplest labor specification:

$$z_A(a, h) = 1 \qquad \text{for all } a \leq \bar{a}, \tag{24}$$

so agricultural productivity does not depend on task composition or human capital.

Reduced-form implementation. Equations (20)–(22) provide a task-based interpretation of sectoral efficiency. In the quantitative implementation used for the preliminary exercises, I treat the implied age profiles $\{\tilde{z}_j(a)\}_{j \in \{M,L,H\}}$ as reduced-form objects disciplined directly from micro evidence on life-cycle wages and sector choice (Section 4.7). This allows the preliminary analysis to embed empirically realistic life-cycle sorting without committing to a specific decomposition into task endowments $\{z_k(a)\}$, task intensities $\{\theta_{j,k}\}$, and the within-worker substitution parameter ρ. In the full calibration roadmap, I will discipline $\theta_{j,k}$ using O*NET and jointly estimate the underlying task profiles and mobility parameters so that the model matches both wage and sorting moments.

3.7 labor supply and sector choice

Birth. New entrants at age $a_0 = 20$ begin their working life without a pre-determined occupational history. Their initial sectoral allocation is determined by the same dynamic sector-choice problem that governs subsequent transitions.

[18] O*NET provides harmonized descriptors of task requirements by occupation, widely used in task-based analyses of labor markets (e.g. Autor et al. 2003).

Idiosyncratic tastes and switching costs. At the beginning of each period t, each working individual of age $a \leq \bar{a}$ with human capital h observes a vector of sector-specific idiosyncratic taste shocks $\{\varepsilon_{j,t}(a,h)\}_{j\in\{A,M,L,H\}}$ and then chooses a sector $s_t(a,h) \in \{A,M,L,H\}$. Let $j^- \equiv s_{t-1}(a-1,h)$ denote the sector chosen in the previous period. Moving from j^- to j entails a fixed switching cost $\kappa(j^-,j) \geq 0$ (with $\kappa(j,j)=0$) and delivers the contemporaneous taste shock $\varepsilon_{j,t}(a,h)$. [19]

Under full dynastic insurance, wages affect sectoral allocation through the shadow value of resources λ_t from the dynasty's pooled budget constraint (13). The dynasty-valued per-period return relevant for the sectoral choice problem is therefore

$$r_{j,t}(a,h \,|\, j^-) \equiv \lambda_t \, w_{j,t} \, z_j(a,h) \;-\; \kappa(j^-,j) \;+\; \varepsilon_{j,t}(a,h). \tag{25}$$

Individuals are forward-looking until retirement. Let $V_t(a,h,j^-)$ denote the value for a worker of age $a \leq \bar{a}$ with human capital h and previous sector j^-. Then

$$V_t(a,h,j^-) = \mathbb{E}_\varepsilon\left[\max_{j\in\{A,M,L,H\}} \left\{r_{j,t}(a,h \,|\, j^-) + \beta \, s_t(a) \, V_{t+1}(a+1,h,j)\right\}\right], \tag{26}$$

with terminal condition $V_t(\bar{a}+1,h,j^-)=0$. I assume $\{\varepsilon_{j,t}(a,h)\}_j$ are i.i.d. Type-I extreme value with scale $\xi > 0$, which for the choice-specific index

$$\Upsilon_{j,t}(a,h \mid j^-) \equiv \lambda_t w_{j,t} z_j(a,h) - \kappa(j^-,j) + \beta \, s_t(a) \, V_{t+1}(a+1,h,j), \tag{27}$$

implies the following multinomial logit choice probabilities:

$$\Pr\big(s_t(a,h) = j \,\big|\, j^-\big) = \frac{\exp(\Upsilon_{j,t}(a,h \mid j^-)/\xi)}{\sum_{m\in\{A,M,L,H\}} \exp(\Upsilon_{m,t}(a,h \mid j^-)/\xi)}. \tag{28}$$

Aggregating these probabilities over h and over the distribution of previous-sector states j^- yields sectoral labor supplies by age and time.

Aggregation and the law of motion for previous sector. Because switching costs depend on the previous sector, aggregate labor supply requires tracking the distribution of lagged-sector states. Let $\eta_{m,t}(a,h)$ denote the fraction of age-a workers with type h at time t whose previous-period sector is $m \in \{A,M,L,H\}$; by definition, $\sum_m \eta_{m,t}(a,h) = 1$ for all (t,a,h) with $a \leq \bar{a}$.

Define the choice probabilities implied by (28) as

$$P_{m\to j,t}(a,h) \equiv \Pr\big(s_t(a,h) = j \,\big|\, j^- = m\big), \qquad j,m \in \{A,M,L,H\}.$$

At labor-market entry, individuals have no predetermined lagged sector. Their initial sectoral allocation is determined endogenously by the choice probabilities $P_{m\to j,t}(a,h)$ evaluated without switching

[19] Switching costs are asymmetric to capture rural–urban mobility frictions in reduced form: $\kappa(A,j) > 0$ for $j \neq A$, while $\kappa(j,A) = 0$ for all j.

costs. Accordingly, the entry distribution over sectors reflects optimal choice rather than a mechanically imposed initial condition. For continuing workers, the lagged-sector distribution evolves according to the Markov law of motion (for $a = 20, \ldots, \bar{a} - 1$):

$$\eta_{j,t+1}(a+1,h) = \sum_{m \in \{A,M,L,H\}} \eta_{m,t}(a,h)\, P_{m \to j,t}(a,h). \tag{29}$$

The current-period sectoral choice shares are then

$$\ell_{j,t}(a,h) = \sum_{m \in \{A,M,L,H\}} \eta_{m,t}(a,h)\, P_{m \to j,t}(a,h). \tag{30}$$

These objects are the inputs into aggregate effective labor in (43).

3.8 Trade, firms, and prices

Tradable sectors, prices, and the real exchange rate. Let $\mathcal{T} \equiv \{A, M, H\}$ denote the set of tradable sectors. For each $j \in \mathcal{T}$, distinguish between the producer price $p^d_{j,t}$ (received by domestic firms for the domestic variety) and the absorption price $p^Q_{j,t}$ (the unit-expenditure price of the Armington composite that households purchase). For the non-traded sector, $p^Q_{L,t} = p^d_{L,t}$.

Manufacturing is the producer-side numeraire:

$$p^d_{M,t} \equiv 1 \qquad \text{for all } t. \tag{31}$$

World prices $p^*_{j,t}$ are taken as exogenous and denominated in a foreign numeraire (e.g. foreign currency or the foreign manufacturing good). Let e_t denote the real exchange rate, defined as the price of one unit of the foreign numeraire in units of the domestic manufacturing good. The domestic (import) price of sector-j imports is therefore $e_t\, \tau_j p^*_{j,t}$, where $\tau_j \geq 1$ is an iceberg trade cost.

Armington aggregation for absorption. For each tradable sector $j \in \mathcal{T}$, domestic absorption $Q_{j,t}$ is a CES aggregate of domestic use of the domestic variety, denoted $Y^{\text{abs}}_{j,t}$, and imports $m_{j,t}$:

$$Q_{j,t} = \left[\omega_j^{1/\eta} \left(Y^{\text{abs}}_{j,t} \right)^{\frac{\eta-1}{\eta}} + (1-\omega_j)^{1/\eta} \left(m_{j,t} \right)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \qquad \eta > 1,\ \omega_j \in (0,1). \tag{32}$$

Cost minimization in (32) implies the absorption price index

$$p^Q_{j,t} = \left[\omega_j (p^d_{j,t})^{1-\eta} + (1-\omega_j) \big(e_t\, \tau_j p^*_{j,t} \big)^{1-\eta} \right]^{\frac{1}{1-\eta}}, \qquad j \in \mathcal{T}, \tag{33}$$

as well as the associated conditional demands

$$Y^{\text{abs}}_{j,t} = \omega_j \left(\frac{p^d_{j,t}}{p^Q_{j,t}} \right)^{-\eta} Q_{j,t}, \tag{34}$$

$$m_{j,t} = (1-\omega_j) \left(\frac{e_t\, \tau_j p^*_{j,t}}{p^Q_{j,t}} \right)^{-\eta} Q_{j,t}, \tag{35}$$

for each $j \in \mathcal{T}$.

Equations (34)–(35) imply that changes in domestic absorption $Q_{j,t}$ are allocated between the domestic variety and imports according to home bias ω_j, the Armington elasticity η, and the relative price $p^d_{j,t}/(e_t \tau_j p^*_{j,t})$. Hence, even in a small open economy, shifts in domestic preferences (including age-composition-driven shifts in durable demand) can affect domestic production and employment when varieties are imperfect substitutes and/or home bias is strong. [20] The extent of this "home-market" channel is therefore an equilibrium object disciplined by $(\omega_j, \eta, \tau_j, \varepsilon)$.

Competitive firms and zero profits. In each sector $j \in \{A, M, L, H\}$, a representative competitive firm produces the domestic variety using effective labor according to (19). Firms take producer prices and wages as given and choose effective labor to maximize profits,

$$\max_{N_{j,t} \geq 0} \quad p^d_{j,t} A_{j,t} N_{j,t} - w_{j,t} N_{j,t}.$$

Under perfect competition and constant returns to scale, zero profits imply

$$w_{j,t} = p^d_{j,t} A_{j,t}, \qquad j \in \{A, M, L, H\}, \tag{36}$$

with $p^d_{M,t} \equiv 1$ from (31). Thus, wages paid per efficiency unit reflect producer prices and sector-specific productivity.

Foreign demand and exports. In each tradable sector $j \in \mathcal{T}$, the domestic variety can be sold abroad. Foreign demand is assumed to be constant-elasticity in the foreign-currency price of the domestic variety. Since the producer price is denominated in domestic manufacturing units, the corresponding foreign-currency price is $p^d_{j,t}/e_t$. Exports therefore satisfy

$$X_{j,t} = \Xi_{j,t} \left(\frac{p^d_{j,t}}{e_t} \right)^{-\varepsilon}, \qquad \Xi_{j,t} > 0,\ \varepsilon > 0,\ j \in \mathcal{T}, \tag{37}$$

where $\Xi_{j,t}$ is a sector-time demand shifter and ε governs the price elasticity of export demand. Domestic production in sector j is allocated between domestic absorption of the domestic variety and exports:

$$Y_{j,t} = Y^{\text{abs}}_{j,t} + X_{j,t}, \qquad j \in \mathcal{T}. \tag{38}$$

Balanced trade and the exchange-rate closure. The economy does not borrow internationally. The trade account therefore balances each period at border prices. Expressed in the foreign numeraire, balanced trade requires

$$\sum_{j \in \mathcal{T}} \tau_j p^*_{j,t}\, m_{j,t} = \sum_{j \in \mathcal{T}} \frac{p^d_{j,t}}{e_t}\, X_{j,t}. \tag{39}$$

[20] This is the case in the baseline calibration.

Equation (39) pins down the real exchange rate e_t period by period, given domestic producer prices, import quantities, and export quantities.[21]

Special cases. The closed-economy benchmark is nested by shutting down trade (e.g. $\tau_j \to \infty$ or $\omega_j \to 1$ and $\Xi_{j,t} \equiv 0$ for all $j \in \mathcal{T}$), which implies $p^Q_{j,t} = p^d_{j,t}$ and $m_{j,t} = X_{j,t} = 0$. In this case e_t is irrelevant and can be normalized. As $\eta \to \infty$, domestic and imported varieties become close substitutes in absorption; as $\varepsilon \to \infty$, export demand becomes approximately perfectly elastic.

3.9 Market clearing and equilibrium

Goods markets: absorption and domestic varieties. Households consume sectoral absorption composites. Composite absorption clears as

$$Q_{j,t} = \sum_{a=20}^{A} \pi_t(a)\, c_{j,t}(a) \qquad \text{for } j \in \{A, H\}, \tag{40}$$

while for manufacturing the absorption identity additionally includes durable purchases:

$$Q_{M,t} = \sum_{a=20}^{A} \pi_t(a)\, c_{M,t}(a) + \sum_{a=20}^{A} \pi_t(a)\, x_t(a). \tag{41}$$

For the non-traded sector, absorption equals the domestic variety, and market clearing is

$$Y_{L,t} = \sum_{a=20}^{A} \pi_t(a)\, c_{L,t}(a). \tag{42}$$

In tradable sectors, domestic-variety market clearing is given by (38).

Labor markets. Let $\ell_{j,t}(a,h)$ denote the fraction of age-a workers with human-capital type h who choose sector j at time t, as implied by (28) and the law of motion for the lagged-sector distribution. Effective labor supplied to sector j is

$$N_{j,t} = \sum_{a \le \bar{a}} \pi_t(a) \int_{h_{\min}}^{h_{\max}} \ell_{j,t}(a,h)\, z_j(a,h)\, f_{t-a}(h)\, dh, \tag{43}$$

where $z_j(a,h)$ is sector-specific efficiency and $f_{t-a}(h)$ is the human-capital density of the entry cohort to which age-a workers at time t belong, supported on $[h_{\min}, h_{\max}]$.

Equilibrium. Let $\mathcal{T} \equiv \{A, M, H\}$ and normalize the producer price of manufacturing to one, $p^d_{M,t} \equiv 1$ for all t. The non-traded sector satisfies $p^Q_{L,t} = p^d_{L,t}$.

Given exogenous sequences $\{\pi_t(a)\}_{t,a}$ (and $\{s_t(a)\}_{t,a}$), $\{A_{j,t}\}_{j,t}$, $\{z_k(a)\}_{k,a}$, $\{f_b(h)\}_b$, world prices $\{p^*_{j,t}\}_{j\in\mathcal{T},t}$ (foreign numeraire), parameters $(\beta, \sigma, \{\Omega_j, \iota_j\}_j, \varphi, \delta_D, \rho, \{\theta_{j,k}\}_{j,k}, \chi, \kappa, \xi, \{\omega_j, \tau_j\}_{j\in\mathcal{T}}, \eta, \varepsilon)$,

[21] Equivalently, multiplying (39) by e_t yields the trade-balance condition in domestic manufacturing units: $\sum_{j\in\mathcal{T}} e_t \tau_j p^*_{j,t} m_{j,t} = \sum_{j\in\mathcal{T}} p^d_{j,t} X_{j,t}$.

initial conditions for predetermined states $\{D_{-1}(a)\}_{a=20}^{A}$ and $\{\eta_{m,0}(a,h)\}_{m,a\leq\bar{a},h}$, and foreign-demand shifters $\{\Xi_{j,t}\}_{j\in\mathcal{T},t}$, an equilibrium is a collection of sequences $\{p_{j,t}^{d}\}_{j,t}$, $\{p_{j,t}^{Q}\}_{j,t}$, $\{w_{j,t}\}_{j,t}$, $\{\lambda_t\}_t$, and $\{e_t\}_t$, together with the allocations implied by household and worker optimality, and decision rules for the dynasty and workers, such that for every t:

1. **Prices, wages, and production.** Wages satisfy $w_{j,t} = p_{j,t}^{d} A_{j,t}$ for all j and output satisfies $Y_{j,t} = A_{j,t} N_{j,t}$.

2. **Households.** Given absorption prices $\{p_{j,t}^{Q}\}_j$ and wages $\{w_{j,t}\}_j$, the dynasty solves (12) subject to (13) and (15)–(16), with $x_t(a) \geq 0$. Optimality implies (14) and (17)–(18). Given $\mathcal{C}_t(a)$ and $\{p_{j,t}^{Q}\}_j$, the CLM system (8)–(10) implies $\{E_t(a), c_{j,t}(a)\}_j$.

3. **Workers and effective labor.** Given $\{w_{j,t}\}_j$ and λ_t, workers solve (26), implying logit choice probabilities (28). The lagged-sector distribution follows (29), and current choice shares satisfy (30). Effective labor satisfies (43).

4. **Armington absorption prices and trade demands (tradables).** For each $j \in \mathcal{T}$, absorption prices satisfy (33), which depends on the real exchange rate e_t through the domestic import price $e_t \tau_j p_{j,t}^{*}$. Given $Q_{j,t}$, conditional demands for domestic absorption and imports satisfy (34)–(35).

5. **Market clearing, exports, and trade balance.** Composite absorption equals household demand: (40) for $j \in \{A, H\}$ and (41) for manufacturing. The non-traded sector clears as in (42). Exports satisfy (37) and the domestic-variety market clears in tradables via (38). The real exchange rate e_t adjusts so that balanced trade holds each period as in (39).

4 Calibration

To obtain preliminary quantitative insights, I run the model with a deliberately parsimonious calibration that disciplines the main exogenous processes and initial conditions directly from data and pins down the remaining preference and friction parameters using a combination of established estimates from the literature and transparent moment matching. Micro data from IPUMS International discipline cohort human-capital profiles (via years of schooling), the return to schooling used to map schooling into the skill intensity of high-skill services, and reduced-form life-cycle profiles of wages and sectoral propensities that anchor age-varying comparative advantage. Sectoral productivity paths are constructed from GGDC sectoral accounts as real value added per worker, while household expenditure data discipline the age profile of durable spending used to initialize durable holdings for cohorts alive at the start of the simulation. Trade elasticities are set to standard values and trade shifters

are disciplined using import penetration and export-demand series. For this calibration, inputs are computed throughout as cross-country averages over the set of countries 32 with overlapping coverage in IPUMS International and the GGDC databases, which emphasizes empirical regularities common across countries and reduces sensitivity to country-specific measurement and classification differences.

A model period is one year. Workers enter at age $a_0 = 20$, retire at age $\bar{a}$ and die after $A = 89$. There are no children - per capita output and any other per capita variables are measured over the 20-89 population. The model is solved between 1970 and 2009, with backward and forward simulation windows outside that period.[22]

4.1 Demographic inputs: population-by-age path $\pi_t(a)$

A key input to the quantitative analysis is the full age distribution of the population over time. Let $\pi_t(a)$ denote the measure of individuals of (single-year) age a at date t. The entire sequence $\{\pi_t(a)\}_{t,a}$ is taken directly from the UN *World Population Prospects* (WPP) population-by-age data and is treated as predetermined with respect to the model. In particular, fertility, mortality, and migration are not endogenized: the equilibrium is solved conditional on the WPP demographic path, so economic outcomes do not feed back into cohort sizes.

In each year, the WPP series pins down both the level and composition of the population. Given $\{\pi_t(a)\}$, the model-implied survival rates[23] are computed residually from the cohort accounting identity $\pi_{t+1}(a+1) = s_t(a)\,\pi_t(a)$, i.e.

$$s_t(a) \equiv \frac{\pi_{t+1}(a+1)}{\pi_t(a)} \qquad \text{whenever } \pi_t(a) > 0.$$

This ensures that the model exactly reproduces the observed evolution of cohort sizes. Counterfactual demographic experiments are implemented by replacing the baseline WPP path $\{\pi_t(a)\}_{t,a}$ with an alternative path (e.g. a different timing of aging or another country's age structure), while holding preferences and technologies fixed; the corresponding survival rates are recomputed using the same accounting identity.

4.2 Cohort human capital and skill intensity

Entrants draw a cohort-specific skill level that remains fixed over the life cycle. I discipline the evolution of cohort skill using IPUMS micro data on years of schooling. For each country c and birth cohort b, I compute the weighted mean and standard deviation of schooling $(\mu_{s,c}(b), \sigma_{s,c}(b))$ and form

[22] The quantitative implementation solves the equilibrium on an extended horizon to avoid boundary effects; section 4.9 describes the treatment of cohorts already alive at the start of the sample and cohorts alive near the end.

[23] Note $\{s_t(a)\}$ is referred to as survival for simplicity, in practice it covers both survival and net immigration for a given age group.

cross-country averages

$$\mu_s(b) = \frac{1}{|\mathcal{C}|}\sum_{c\in\mathcal{C}} \mu_{s,c}(b), \qquad \sigma_s(b) = \frac{1}{|\mathcal{C}|}\sum_{c\in\mathcal{C}} \sigma_{s,c}(b),$$

where $\mathcal{C}$ denotes the common country set.[24] Schooling is bounded on $[s_{\min}, s_{\max}] = [0, 20]$ and normalized as $u = (s - s_{\min})/(s_{\max} - s_{\min}) \in [0, 1]$, implying

$$\mu_u(b) = \frac{\mu_s(b) - s_{\min}}{s_{\max} - s_{\min}}, \qquad \sigma_u(b) = \frac{\sigma_s(b)}{s_{\max} - s_{\min}}.$$

For each cohort I match $(\mu_u(b), \sigma_u(b))$ with a Beta distribution $u \sim \text{Beta}(\alpha_b, \beta_b)$ using

$$\kappa_b = \frac{\mu_u(b)\,[1 - \mu_u(b)]}{\sigma_u(b)^2} - 1, \qquad \alpha_b = \mu_u(b)\kappa_b, \qquad \beta_b = [1 - \mu_u(b)]\,\kappa_b.$$

The productivity-relevant human-capital type in the model is an affine transformation of the unit-interval index u,

$$h = h_{\min} + (h_{\max} - h_{\min})u \in [h_{\min}, h_{\max}],$$

so the cohort density $f_b(h)$ is the distribution induced by $u \sim \text{Beta}(\alpha_b, \beta_b)$ under this mapping. Birth cohorts are mapped into entry years via $t = b + a_0$ (equivalently, entrants at date t are from birth cohort $b = t - a_0$), and the implied cohort distributions are discretized on the model skill grid to obtain the entrant mass function $p_t(h)$.

Skill affects productivity only in high-skill services through h^χ. To discipline χ with a moment that corresponds to the model's sector-specific mechanism, I estimate Mincer regressions in the high-skill services subsample (equivalently, using sector-by-schooling interactions in the full sample) and compute a cross-country average within-H return r_H. Given the mapping

$$h(s) = h_{\min} + (h_{\max} - h_{\min})\frac{s - s_{\min}}{s_{\max} - s_{\min}},$$

I choose χ so that the model-implied within-H earnings gradient matches r_H for a representative schooling contrast (s_0, s_1):

$$\chi = \frac{r_H(s_1 - s_0)}{\log(h(s_1)/h(s_0))}.$$

I set $h_{\min} = 0.2$ and $h_{\max} = 1.9$ in the baseline implementation and obtain $\chi = 1.25$ (from $r_H = 0.078$).

4.3 Non-durable demand parameters and base-year taste shifters

Non-durable consumption follows the non-homothetic CES system in Comin et al. (2021). I set the elasticity of substitution to $\sigma = 0.5$ and normalize manufacturing so that $\iota_M = 1$. For agriculture I set $\iota_A = 0.05$. To assign values to $iota_L$ and $iota_H$, I use the sub-sector level estimates in Comin et al.

[24] The baseline assigns equal weight to each country.

(2021) mapping *community, social and personal services* to low-skill services and *finance, insurance and real estate* to high-skill services, yielding

$$\iota = (\iota_A, \iota_M, \iota_L, \iota_H) = (0.05,\ 1.0,\ 0.85,\ 2.3).$$

The remaining taste shifters Ω_j are chosen to match initial expenditure shares. For each country in $\mathcal{C}$ I construct sectoral consumption shares in the base year and map data categories into the four model sectors (A, M, L, H). Averaging across countries yields target shares $(\bar{s}_A, \bar{s}_M, \bar{s}_L, \bar{s}_H)$, and I choose Ω so that the model reproduces these shares given (σ, ι). Normalizing $\sum_j \Omega_j = 1$ gives

$$\Omega = (0.35,\ 0.30,\ 0.23,\ 0.12).$$

4.4 Durables

Durables deliver utility through the service flow from a stock that depreciates over time. I set the annual discount factor to $\beta = 0.96$, consistent with medium- and large-scale DSGE calibrations such as the FRB/EDO model (Chung et al., 2010). The depreciation rate is $\delta_D = 0.10$, consistent with Petrella and Santoro (2010); Chung et al. (2010). The utility weight on durables is set to $\varphi = 0.49$, following Barsky et al. (2016).

To initialize durable holdings for cohorts already alive when the simulation begins, I use an age profile of durable expenditure shares. Let $s_x(a)$ denote the share of total household expenditure devoted to durables at age a, measured from household expenditure data and treated as time-invariant for this preliminary calibration. I normalize total expenditure to a constant level E in model units and set purchases to $x(a) = E\, s_x(a)$.

The model's timing implies that entrants have zero inherited durables but can purchase in their entry period, so $D_t(20) = x_t(20)$. Consistent with this convention, I construct an end-of-period stock-by-age profile recursively as

$$D_{\text{init}}(a_0) = x(a_0), \qquad D_{\text{init}}(a) = (1 - \delta_D) D_{\text{init}}(a-1) + x(a) \quad \text{for } a > a_0.$$

The resulting $D_{\text{init}}(a)$ pins down the initial condition for the predetermined durable-stock state for cohorts alive at the beginning of the (extended) simulation horizon; later entering cohorts inherit zero durables by construction.

4.5 Sector productivity paths

Production is linear in effective labor, $Y_{j,t} = A_{j,t}N_{j,t}$. I measure sector productivity as labor productivity (real value added per worker),[25]

$$A_{j,c,t} \propto \frac{\text{RealVA}_{j,c,t}}{\text{Emp}_{j,c,t}},$$

using the GGDC Economic Transformation Database and 10-Sector Database. Sector definitions are harmonized to the model's four sectors. For each sector and year I compute the cross-country log average,

$$\log A_{j,t} = \frac{1}{|\mathcal{C}|} \sum_{c \in \mathcal{C}} \log A_{j,c,t},$$

and normalize by setting $A_{M,1970} = 1$. Where both databases overlap, I prioritize the ETD; outside the data window, growth rates are held at endpoint averages.

4.6 Mobility frictions

Sectoral reallocation is subject to fixed switching costs. Let κ_{mj} denote the cost of moving from last period's sector m to the current sector j, as it enters the worker return $r_{j,t}(a, h \mid m) = \lambda_t w_{j,t} z_j(a, h) - \kappa_{mj} + \varepsilon_{j,t}(a, h)$ in equation (24). I normalize the logit taste-shock scale to $\xi = 1$, so that κ_{mj} is measured in the same dynasty-valued payoff units as $\lambda_t w_{j,t} z_j(a, h)$.

Magnitude from the literature. To discipline the scale of mobility frictions, I draw on external evidence expressed in annual wage equivalents. Artuç et al. (2015) estimate mobility costs on the order of three to four annual wages in developing economies (and around three annual wages in developed economies), while Dix-Carneiro (2014) reports sector-switching costs between roughly 1.4 and 2.7 annual wages in a detailed country case study.

Parsimonious structure and unit conversion. Guided by this evidence, I impose a parsimonious structure. Remaining in the same sector is costless: $\kappa_{jj} = 0$ for all j. Exiting agriculture entails a cost of 3.7 annual wages: for $j \in \{M, L, H\}$,

$$\kappa_{Aj} = 3.7 \times \lambda_{1970} w_{M,1970}.$$

[25] Sectoral productivity paths $A_{j,t}$ are constructed from sectoral real value added per headcount worker in GGDC. Because production uses effective labor in efficiency units, this proxy should be interpreted as a reduced-form labor-productivity shifter that may partly reflect workforce composition (age/skill) in the underlying data. In the demographic counterfactuals reported below, $\{A_{j,t}\}$ is held fixed across scenarios; hence any composition component embedded in $A_{j,t}$ is common across experiments and is unlikely to materially affect the relative comparisons in this preliminary calibration. A fuller calibration will explore quality-adjusted alternatives.

Switching across non-agricultural sectors entails a cost of 2.0 annual wages: for distinct $m, j \in \{M, L, H\}$,

$$\kappa_{mj} = 2.0 \times \lambda_{1970} w_{M,1970}.$$

Finally, switching into agriculture is frictionless, $\kappa_{mA} = 0$ for $m \in \{M, L, H\}$. The base-year term $\lambda_{1970} w_{M,1970}$ provides a transparent conversion from "wage-year" magnitudes in the empirical literature into the payoff units of the worker problem in equation (24).

Time variation in wage-equivalent terms. Since κ_{mj} is held fixed in base-year payoff units, its magnitude in contemporaneous wage-equivalent terms can drift with growth. Relative to a contemporaneous manufacturing wage payoff, for example,

$$\frac{\kappa_{Aj}}{\lambda_t w_{M,t}} = 3.7 \times \frac{\lambda_{1970} w_{M,1970}}{\lambda_t w_{M,t}}.$$

In the preliminary exercises I view this feature as acceptable—and potentially realistic—because institutional change, transport improvements, and falling information frictions can reduce effective mobility barriers over time. Moreover, this time variation applies quasi-symmetrically across demographic scenarios. Concretely, in the quantitative exercises presented, switching costs κ_{ij} are normalized in units of 1970 utility. Their contemporaneous strength in wage-equivalent terms therefore scales with $\kappa_{ij}/(\lambda_t \bar{w}_t)$, where λ_t denotes the dynasty's shadow value of income and $\bar{w}_t$ is a wage index. In the quantitative exercises, aggregate output per worker, $Y_{pw,t} \equiv Y_t/Emp_t$, is proportional to the average wage in this labor-only environment and thus provides a transparent gauge of how the wage component of $\lambda_t \bar{w}_t$ evolves under alternative demographic paths. Across the full-model demographic counterfactuals, $Y_{pw,2009}/Y_{pw,1970}$ lies in a tight range—1.854 under the oldest path simulated and 1.912 under the youngest—so a cost fixed in base-year units falls to roughly 0.52–0.54 of its initial share of the average wage by 2009 and differs by only about 3% across these endpoint counter-factuals. This implies that the base-year normalization generates only modest cross-scenario variation in the effective tightness of mobility frictions. That said, in the full calibration, I will allow for richer scaling (e.g. costs proportional to a wage trend or to contemporaneous $\lambda_t w_{M,t}$) and discipline such scaling using transition-rate evidence when available.

4.7 Life-cycle comparative advantage

Life-cycle comparative advantage is captured by the sectoral efficiency term $z_j(a, h)$ introduced in Section 3.6. In the quantitative implementation I parameterize

$$z_A(a, h) \equiv 1, \qquad z_M(a, h) = \tilde{z}_M(a), \qquad z_L(a, h) = \tilde{z}_L(a), \qquad z_H(a, h) = h^{\chi} \tilde{z}_H(a),$$

so that age-specific comparative advantage operates through $\tilde{z}_j(a)$ in the non-agricultural sectors, while human capital affects productivity only in high-skill services through h^{χ}.

Micro evidence. Using harmonized IPUMS micro data, I estimate sectoral propensities by single year of age for the four model sectors $j \in \{A, M, L, H\}$. The estimates control for schooling, gender, rural–urban residence, and foreign-born status. The resulting age profiles therefore reflect residual age–sector sorting patterns conditional on observables. Importantly, the propensities are unconditional across sectors (i.e. not conditioned on non-agricultural employment), so that sectoral shares sum to one at each age.

Reduced-form construction. The propensity profiles identify relative sectoral attractiveness by age but do not separately identify productivity from wages or mobility frictions. I therefore adopt a symmetric reduced-form mapping from propensities to age-specific age–sector return shifters.

Let $s_j(a)$ denote the estimated propensity to work in sector j at age a, with $\sum_j s_j(a) = 1$. For each age, define the centered log-share

$$u_j(a) \equiv \log s_j(a) - \frac{1}{4} \sum_{k \in \{A,M,L,H\}} \log s_k(a).$$

This multilateral normalization removes the age-specific common component and avoids privileging any sector as a reference category. I then construct raw efficiency indices

$$z_j^{\text{raw}}(a) = \exp(\xi_z \, u_j(a)) \, .$$

In the preliminary calibration I set $\xi_z = 1$, so that relative efficiency differences mirror observed log-share differences without additional amplification.

Normalization and scope. Because $s_j(a)$ identifies only relative sectoral incentives at a given age, I normalize each constructed profile to have unit mean over working ages A_w:

$$\tilde{z}_j^{\text{data}}(a) \equiv \frac{z_j^{\text{raw}}(a)}{\frac{1}{|A_w|} \sum_{a \in A_w} z_j^{\text{raw}}(a)}, \qquad j \in \{A, M, L, H\}.$$

This normalization ensures that average sector productivity differences are governed by the exogenous $A_{j,t}$ paths (Section 4.5), while $\tilde{z}_j^{\text{data}}(a)$ affects only life-cycle reallocation patterns.

In the quantitative implementation I impose $z_A(a, h) \equiv 1$ and use the constructed profiles only for the non-agricultural sectors: $z_M(a, h) = \tilde{z}_M(a)$, $z_L(a, h) = \tilde{z}_L(a)$, and $z_H(a, h) = h^{\chi} \tilde{z}_H(a)$. The multilateral centering step is applied using all four sectors only as a convenient normalization; the resulting agricultural profile is not interpreted as an age-dependent productivity shifter. This reflects the view that age patterns in agricultural employment primarily capture constraints and non-pecuniary factors (and are influenced by mobility frictions), whereas sector-average productivity differences are already captured by $A_{j,t}$.

Relationship to mobility frictions. The constructed $\tilde{z}_j(a)$ profiles are based on observed sorting patterns and therefore may embed components that, in the structural model, could alternatively be attributed to mobility frictions or to other non-wage determinants of sectoral choice. In the preliminary calibration I do not attempt to separately identify these forces. Instead, I discipline the level of switching costs κ using external evidence (Section 4.6), and interpret $\tilde{z}_j(a)$ as reduced-form age-dependent return shifters that discipline the life-cycle component of incentives within non-agriculture. In the full calibration strategy (Section 4.10), I replace this reduced-form step with a task-based construction of $z_j(a, h)$ and jointly estimate the underlying task profiles and mobility parameters so that the model matches both sorting and wage moments.

4.8 Trade

I set the Armington elasticity between domestic and imported varieties to $\eta = 2$, consistent with the low-to-moderate trade elasticities commonly used in international business-cycle models (Backus et al., 1994; Ruhl, 2008). I set the export demand elasticity to $\varepsilon = 2$, following small open economy frameworks with CES foreign demand for home varieties (Galí and Monacelli, 2005).

Home bias parameters are disciplined using import penetration. Let s_j^{imp} denote the mean import expenditure share in sector $j \in \{A, M, H\}$. Under the Armington aggregator, the import share at the baseline relative price is approximately $1 - \omega_j$, so I set $\omega_j = 1 - s_j^{\text{imp}}$. Using sample averages yields $\omega_A = 0.90$, $\omega_M = 0.79$, and $\omega_H = 0.94$. For this preliminary calibration I normalize iceberg trade costs and world prices to unity, $\tau_j = 1$ and $p_{j,t}^* = 1$, and let the endogenous real exchange rate adjust to satisfy balanced trade period by period. Foreign demand shifters $\Xi_{t,j}$ are constructed from annual export-demand series and mapped into the model's tradable sectors, so that the level and time variation of $\Xi_{t,j}$ reproduce observed export patterns up to the equilibrium relative price term $(p_{t,j}^d / e_t)^{-\varepsilon}$.

Trade costs and identification. In the Armington system, imports enter only through the domestic import price $p_{j,t}^{imp} = e_t \tau_j p_{j,t}^*$. With limited information on trade prices and trade-cost wedges at the sectoral level, τ_j and ω_j are not separately identified from import penetration: different combinations of τ_j and ω_j can generate similar baseline import shares given η. For the preliminary calibration I therefore normalize iceberg trade costs to unity, $\tau_j = 1$, and interpret ω_j as a reduced-form openness wedge that matches import penetration under this normalization. I assess the robustness of the quantitative results to alternative degrees of tradability and home bias by varying (ω_j, η) and, in sensitivity checks, allowing $\tau_{j,t}$ to vary over time.

4.9 Simulation window and boundary conditions

Solving the model over the observed data window requires specifying economic conditions for (i) ages of cohorts already alive in the first observed year and (ii) future years needed to evaluate continuation values for cohorts alive near the end of the sample. To address this, the quantitative implementation extends the simulation window backward and forward in time. In the baseline implementation, the extended window starts $y_{\min} = y_0 - y_{\text{Burn}}$ (1900 when $y_0 = 1970$ and $y_{\text{Burn}} = 70$). Initial conditions are imposed at $y_{\min}$ for predetermined states: cohorts alive at $y_{\min}$ are assigned the age profile $D_{\text{init}}(a)$ constructed above, and (for simplicity) the lagged-sector state at entry is initialized in agriculture. Prior to the first year with comprehensive sectoral data, exogenous aggregates (demographics, productivity growth rates, and cohort human-capital trends) are held fixed assuming steady state so that early cohorts face a well-defined pre-sample environment. The pre-sample extension described here concerns only exogenous processes; durables, sectoral allocations, and prices are solved endogenously in equilibrium over the entire extended horizon. After the last observed year, exogenous processes are extrapolated using constant growth rates and demographic projections, and the economy is simulated sufficiently far into the future so that cohorts relevant for the last observed years complete their life cycles. Calibration targets are computed only over the data window.

4.10 Formal calibration strategy (roadmap)

The quantitative results reported in this version rely on the simplified preliminary calibration in Section 4. This subsection lays out the roadmap for a full calibration designed to discipline the model's life-cycle labor-supply and demand channels at a higher level of empirical rigor. The strategy is explicitly cross-country: I estimate a common vector of structural parameters using harmonized moments constructed for each country, while allowing exogenous paths and initial conditions to vary by country. This approach highlights the widespread implications of demographic change while exploiting the rich micro evidence available for a large set of individual countries.

Country-specific exogenous inputs. For each country c, I treat the following objects as data-imposed inputs to the equilibrium computation. First, the demographic path $\{\pi_{c,t}(a)\}_{t,a}$ is taken from population-by-age data; survival rates are computed using the model's accounting identity. Second, sectoral productivity paths $\{A_{c,j,t}\}_{j,t}$ are disciplined using sectoral value added and employment data, mapped to the model's four sectors. Third, the entrant (entry-year) human-capital distribution is constructed from IPUMS International schooling data by birth cohort and mapped into entry years using $t = b + a_0$ (equivalently, $b = t - a_0$), yielding $\{p_{c,t}(h)\}_t$. These inputs vary across countries and anchor the model's counterfactual suitability: demographic counterfactuals replace $\pi_{c,t}(a)$ holding

other exogenous processes fixed.

Task technology and the structural construction of $z_j(a,h)$. In the full calibration, life-cycle comparative advantage is disciplined using the model's task-based mapping rather than reduced-form age profiles. Workers possess age-dependent efficiency in three task bundles $k \in \{P, F, C\}$ (physical, fluid-cognitive, and crystallized/interpersonal). I parameterize the task-efficiency profiles $\{z_k(a)\}_a$ flexibly (e.g. splines over age).

Sectoral task intensities $\theta_{j,k}$ for $j \in \{M, L, H\}$ are disciplined externally using O*NET. Occupation-level task requirements are first mapped into the three bundles (P, F, C) and then aggregated to sectors using employment weights. IPUMS International harmonized micro data provide sector and occupation codes (and sampling weights) that permit a consistent mapping from occupations to sectors across countries. In the baseline, I construct a cross-country average set of sectoral task intensities (pooling countries with harmonized occupation coverage), and I assess robustness to allowing $\theta_{j,k}$ to vary by country.

Given $(\theta_{j,k}, z_k(a), \rho)$, sector-specific efficiency in non-agriculture is constructed using the CES task aggregator:

$$\tilde{z}_j(a) = \left(\sum_{k \in \{P,F,C\}} \theta_{j,k}\, z_k(a)^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \qquad j \in \{M, L, H\},$$

where $\rho > 0$ governs within-worker substitutability across task bundles. Human capital affects productivity only in high-skill services, so

$$z_j(a,h) = \begin{cases} \tilde{z}_j(a), & j \in \{M, L\}, \\ h^{\chi} \tilde{z}_H(a), & j = H, \\ 1, & j = A, \end{cases}$$

with $\chi > 0$ governing the strength of human capital in high-skill services. The parameters (ρ, χ) are estimated jointly with the age profiles $\{z_k(a)\}_k$ and mobility frictions to match micro life-cycle evidence on wage growth and sectoral sorting.

Externally disciplined elasticities and normalizations. A subset of parameters are disciplined externally to reduce the dimension of the internally estimated parameter vector and to leverage well-identified empirical inputs. These include (i) the non-durable demand system parameters governing substitution and income effects, disciplined using sectoral expenditure shares and relative prices in consumption data; (ii) trade elasticities in the open-economy extension, disciplined using standard trade-elasticity evidence; and (iii) the depreciation rate for durables, disciplined using standard durable-depreciation evidence. In the discrete-choice labor block, the taste-shock scale is normalized (and switching costs are interpreted relative to this normalization).

Internal estimation by simulated method of moments. The remaining preference and friction parameters are estimated internally by simulated method of moments (SMM), exploiting both micro life-cycle moments and macro demographic sensitivities. Let ϑ denote the vector of parameters estimated by SMM. In the baseline, ϑ includes: (i) parameters governing the task-efficiency profiles $\{z_k(a)\}$; (ii) the within-worker task-substitution parameter ρ; (iii) the human-capital elasticity χ (jointly with the cohort skill mapping when needed); (iv) parameters governing sectoral mobility costs $\kappa(m, j)$; and (v) durable preference parameters governing intertemporal tradeoffs and the utility weight on durables. For each candidate ϑ, I solve the equilibrium for each country c given its exogenous paths, compute model counterparts to the empirical moments, and minimize a weighted distance:

$$\hat{\vartheta} \in \arg\min_{\vartheta} \left(\hat{m}^{\text{data}} - \hat{m}^{\text{model}}(\vartheta)\right)' W \left(\hat{m}^{\text{data}} - \hat{m}^{\text{model}}(\vartheta)\right),$$

where moments are stacked across countries and W is initially diagonal using empirical standard errors where available.

Micro Data. IPUMS International is the primary source of micro moments. The baseline moment set includes: (i) age profiles of sectoral employment conditional on non-agricultural work, constructed from harmonized industry codes and controlling for observables; (ii) sectoral wage–age profiles (or differences in life-cycle wage growth between manufacturing and services), constructed from harmonized earnings measures and regression designs that purge cohort and year effects; (iii) cohort schooling distributions by birth cohort, used to construct entrant skill distributions and their evolution; and (iv) moments on skill composition and wage premia that discipline the interaction of h and high-skill services through χ. These micro moments are complemented with macro targets designed to identify the general-equilibrium strength of the demographic channel, including country–year semi-elasticities linking cohort composition to manufacturing versus services employment and cross-country relationships between pre-peak cohort composition and manufacturing-peak outcomes. Durable parameters are disciplined using both aggregate and life-cycle moments on durable spending and holdings, including the age gradient of durable expenditure shares and the average durable share in manufacturing absorption.

Cross-country pooling, heterogeneity, and robustness. The baseline estimation pools information across countries by imposing a common structural parameter vector ϑ, while allowing country-specific exogenous processes (demographics, productivity, and entrant skill distributions) and country-specific base-year taste shifters to vary. This design uses cross-country variation to strengthen identification and to emphasize empirical regularities that are not specific to a single country. Robustness exercises include re-estimating on subsamples (e.g. by income group or region), leave-one-out procedures, alternative weighting matrices, and alternative constructions of key IPUMS moments (e.g.

alternative industry mappings, alternative wage measures, and alternative control sets). Standard errors for micro moments are obtained using survey-weighted sampling variation and, where appropriate, block bootstrap procedures at the country–sample level; standard errors for macro regression targets follow the corresponding panel and cross-sectional specifications.

5 Preliminary quantitative results

This section reports a set of preliminary quantitative exercises that illustrate the strength of the model's demographic mechanisms. The simulations use the preliminary calibration described in Section 4 and are not the outcome of an internally estimated parameter vector (no moment targeting or SMM is imposed). The goal is instead diagnostic: to isolate the role of age structure in shaping (i) manufacturing employment over time and (ii) living standards, and to assess whether the model reproduces the qualitative reduced-form relationships documented in the empirical section.

5.1 Design of the counterfactuals

I run the model on the 1970–2009 window under a baseline demographic path given by the cross-country average age distribution. I then replace only the demographic structure $\pi_t(a)$ with four country-specific paths that span the cross-country distribution of age structures. The trajectories correspond approximately to the 10th percentile (youngest), 25th (young), 75th (old), and 90th (oldest) of the young-adult share distribution, and are chosen because they exhibit pronounced demographic dynamics over a period with high-quality annual age distributions. All remaining primitives and parameters (preferences, productivity paths, trade objects, cohort human capital, mobility frictions, and life-cycle comparative advantage) are held fixed at their baseline cross-country averages. Differences across scenarios therefore reflect only the demographic channel. Figure 6 plots the evolution of the young adult (25–34) share for the four trajectories over the period, to illustrate the size of these differences in the four counter-factual demographic trajectories.[26] The youngest trajectory (p10) maintains a high and rising young-adult share through the 1990s and remains only slightly below peak in 2009. The young trajectory (p25) peaks around 1990 and then declines. The old trajectory (p75) peaks around 1988 and at a lower level. The oldest trajectory (p90) peaks around 1975 and falls steadily, reaching 0.16 by 2009.

Throughout, I distinguish headcount employment from effective labor in efficiency units. Let $L_{j,t}$ denote the number of employed individuals (headcount) in sector $j \in \{A, M, L, H\}$ and let $L_t \equiv \sum_j L_{j,t}$. Let $N_{j,t}$ denote effective labor (the efficiency units that enter production). All manufacturing

[26] The share is over the total model-consistent population (i.e. 20-89).

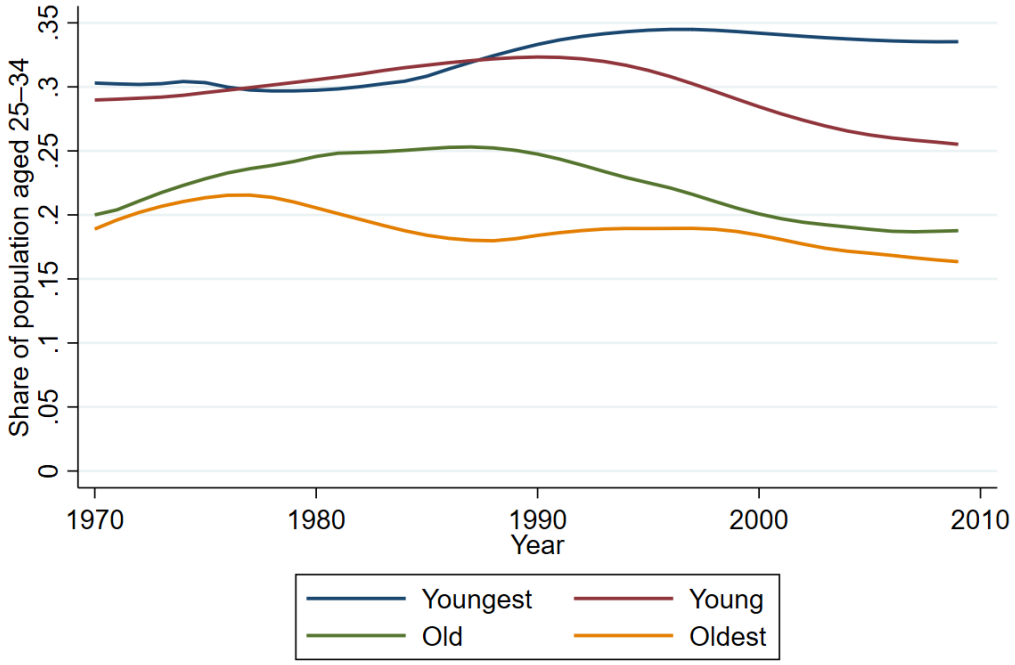


Figure 6: Young-adult (25–34) share of the model population (ages 20–89) under each counterfactual demographic trajectory, 1970–2009.

employment shares and peaks reported below are headcount objects, defined as

$$s_{M,t} \equiv \frac{L_{M,t}}{L_t}.$$

Likewise, output per worker is measured in headcount terms as $Y_{pw,t} \equiv Y_t/L_t$, while output per capita is $Y_{pc,t} \equiv Y_t/Pop_t$, where Pop_t denotes population aged 20–89. The model also implies output per efficiency unit, $Y_t/\sum_j N_{j,t}$, which can move differently because average efficiency varies endogenously with cohort composition; I reserve that accounting object for model diagnostics and report living-standard measures in headcount terms to maintain a transparent link to standard empirical definitions.

Because manufacturing is tradable, a demographic shift that increases durable-driven manufacturing absorption can be accommodated through higher imports rather than higher domestic production. To quantify the relative importance of the demand-side durable channel versus the supply-side life-cycle sorting channel, I therefore compute three restricted variants in addition to the full model. In a *supply-only* variant I shut down durable accumulation (setting the utility weight on durables to zero so that durable purchases are identically zero), so that demographic effects operate only through the labor-supply block (age-dependent comparative advantage with mobility frictions). In a *demand-only* variant I eliminate life-cycle comparative advantage by flattening the sector-specific age–sector return shifters, so that demographics affect outcomes only through life-cycle demand for durables and general-equilibrium prices and trade. A third *neither* variant imposes both restrictions. Comparing these economies to the full model isolates the contributions of each channel (and their interaction) to manufacturing peaks, import penetration, and living standards.

5.2 Manufacturing employment, manufacturing peaks, and manufacturing import penetration

Table 5 summarizes manufacturing outcomes across the four demographic trajectories. Two patterns emerge.

First, younger age structures generate systematically higher manufacturing employment. Under the youngest trajectory (p10), manufacturing peaks at 43.8% of headcount employment (in 2006) and averages 41.9% over 1970–2009. Under the oldest trajectory (p90), the manufacturing peak is lower at 41.5% (in 1998) and mean manufacturing employment falls to 40.1%. Intermediate demographic paths lie between these endpoints: the young trajectory (p25) peaks at 42.9% (1999) with a mean of 41.7%, while the old trajectory (p75) peaks at 41.9% (1999) with a mean of 40.8%.[27] Because all non-demographic primitives and parameters are held fixed across runs, these differences are attributable to demographic composition alone: younger trajectories place more weight on ages with higher manufacturing propensity and higher manufacturing-relative efficiency, and (through the durable channel) generate a stronger manufacturing-absorption impulse early in the life cycle.

Second, demographic aging is accompanied by higher manufacturing import penetration. I summarize openness in manufacturing using the value import share of manufacturing absorption,

$$s^{imp}_{M,t} \equiv \frac{p^m_{M,t}\, m_{M,t}}{p^Q_{M,t}\, Q_{M,t}},$$

where $m_{M,t}$ denotes manufacturing imports, $Q_{M,t}$ denotes manufacturing absorption (including durable purchases), $p^m_{M,t}$ is the domestic import price, and $p^Q_{M,t}$ is the Armington unit-expenditure price. Mean manufacturing import penetration rises from 20.9% under the youngest trajectory to 22.9% under the oldest, with the young and old trajectories in between (21.2% and 22.2%, respectively). The same pattern holds at the manufacturing peak: $s^{imp}_{M,t^{\text{peak}}}$ is 20.3% under the youngest and 22.6% under the oldest.

Because manufacturing is tradable, demographic composition can affect domestic manufacturing employment without a one-for-one change in absorption: equilibrium imports adjust so that absorption is met at prevailing relative prices. In this calibration, the cross-trajectory gradient in import penetration is primarily a supply-side and relative-price phenomenon rather than a durables-demand effect. For example, the oldest trajectory's mean manufacturing import share exceeds the youngest's by 2.00 percentage points, of which 0.96 pp arises even when both life-cycle channels are shut down and an additional 0.97 pp reflects the life-cycle sorting add-on.[28] Accordingly, higher import penetration

[27] The shares of manufacturing employment are higher than what we see in the data, especially for mean values. This reflects the preliminary nature of the calibration, which has not yet targeted empirical moments; the formal calibration described in Section 4.10 is underway.

[28] The durables-demand add-on is only 0.03 pp.

under older demographics should be interpreted mainly as reflecting weaker domestic manufacturing supply (and induced relative-price adjustment), not stronger durable-driven absorption.

Table 5: Demographic counterfactuals: manufacturing headcount employment, import penetration, and output (full model, 1970–2009)

Scenario	$\frac{Y_{pw,2009}}{Y_{pw,1970}}$	$\frac{Y_{pc,2009}}{Y_{pc,1970}}$	Peak $s_{M,t}$ (%)	Year of peak	Mean $s_{M,t}$ (%)	Mean $s^{imp}_{M,t}$ (%)	$s^{imp}_{M,t^{\text{peak}}}$ (%)
Youngest (p10)	1.912	1.936	43.8	2006	41.9	20.9	20.3
Young (p25)	1.893	1.848	42.9	1999	41.7	21.2	21.3
Old (p75)	1.870	1.840	41.9	1999	40.8	22.2	22.0
Oldest (p90)	1.854	1.765	41.5	1998	40.1	22.9	22.6

Notes: $s_{M,t}$ is manufacturing *headcount* employment as a share of total headcount employment, $s_{M,t} \equiv L_{M,t}/L_t$. $Y_{pw,t}$ denotes output per worker in headcount terms, $Y_{pw,t} \equiv Y_t/L_t$, and $Y_{pc,t}$ denotes output per capita, $Y_{pc,t} \equiv Y_t/Pop_t$, where Pop_t is population aged 20–89. The manufacturing import share is the value of imports as a share of manufacturing absorption, $s^{imp}_{M,t} \equiv p^m_{M,t} m_{M,t}/(p^Q_{M,t} Q_{M,t})$. Each row replaces only the demographic structure $\pi_t(a)$; all other primitives and parameters are held fixed at their baseline values.

5.3 Output per worker, employment-to-population, and output per capita

Table 5 also reports implications for output per worker and output per capita. Output per worker grows faster under younger demographic structures: between 1970 and 2009, Y_{pw} rises by 91.2% under the youngest trajectory ($Y_{pw,2009}/Y_{pw,1970} = 1.912$) and by 85.4% under the oldest (1.854), with the young and old trajectories in between (89.3% and 87.0%, respectively). These differences reflect the model's life-cycle comparative-advantage channel operating through effective labor: younger trajectories place more mass on ages with relatively high manufacturing-relative efficiency and higher manufacturing propensity, raising equilibrium exposure to a sector with moderately fast productivity growth (especially relative to low-skilled services).

The implications for output per capita are larger. Output per capita increases by 93.6% under the youngest trajectory ($Y_{pc,2009}/Y_{pc,1970} = 1.936$) but by 76.5% under the oldest (1.765), a gap of 17.1 percentage points in cumulative growth. This larger response reflects the additional role of headcount labor supply per person. Because sectoral outputs $Y_{j,t}$ are measured in different physical units, aggregate output is computed in value terms using domestic producer prices in the manufacturing numeraire:

$$Y_t \equiv \sum_j p^d_{j,t} Y_{j,t}, \qquad p^d_{M,t} \equiv 1.$$

Under zero profits, this coincides with the aggregate wage bill and is therefore the model-consistent notion of GDP (value added) in common units. Output per worker and output per capita are then defined as $Y_{pw,t} \equiv Y_t/L_t$ and $Y_{pc,t} \equiv Y_t/Pop_t$, where L_t is total headcount employment and Pop_t is the population aged 20–89. In these counterfactuals, the employment-to-population ratio evolves differently across demographic paths because the retirement threshold is fixed and only cohort sizes shift. Concretely, under the youngest trajectory the employment-to-population ratio rises from 0.943 in 1970 to 0.954 in 2009 (a 1.2% increase), while under the oldest trajectory it falls from 0.813 to 0.774

(a 4.8% decline). A log decomposition of the youngest–oldest difference in cumulative Y_{pc} growth implies that 66.6% of the gap is accounted for by differences in the employment-to-population ratio and 33.4% by differences in output per worker.[29] Thus, demographic change affects living standards not only through the number of employed workers per person, but also through equilibrium changes in output per employed worker, which are quantitatively material.

5.4 Life-cycle supply and demand decompositions

To isolate how demographics operate through the model's two life-cycle mechanisms, I compute the restricted variants described above in addition to the full model. Two diagnostics are informative.

First, the durable channel is the main force raising the level of manufacturing employment in this preliminary calibration, but contributes little to explaining cross-country differences. When durables are shut down (supply-only), all four demographic trajectories peak in 1980 at employment shares below 35%. When life-cycle sorting is instead shut down but durables are retained (demand-only), manufacturing peaks much later and at substantially higher levels, between 43.1% and 43.8% across the four trajectories (in 2005–2006). This illustrates that life-cycle demand for durables has the strongest effect on the overall level of manufacturing absorption, while demographic sensitivity of domestic manufacturing employment depends on how that absorption is mapped into production in general equilibrium.

Second, life-cycle sorting is central for import penetration and productivity. Holding durables shut down, introducing sorting reduces the mean manufacturing import share by 1.49–2.46 percentage points across trajectories (relative to the "neither" economy) and raises cumulative output-per-worker growth by 10.96–13.75 percentage points, reflecting a more efficient allocation of cohorts across sectors given their age-dependent productivities.

To make the interaction between channels transparent, Table 6 decomposes the difference between the youngest and oldest trajectories. For any outcome O, let ΔO^v denote the youngest–oldest gap under variant $v \in \{N, S, D, F\}$, where N denotes the economy with neither channel, S the supply-only economy, D the demand-only economy, and F the full model. The decomposition writes

$$\Delta O^F = \Delta O^N + \underbrace{\left(\Delta O^S - \Delta O^N\right)}_{\text{supply add-on}} + \underbrace{\left(\Delta O^D - \Delta O^N\right)}_{\text{demand add-on}} + \underbrace{\left(\Delta O^F - \Delta O^S - \Delta O^D + \Delta O^N\right)}_{\text{interaction}},$$

so that the interaction term captures complementarity between the labor-supply and durables-demand channels in generating demographic sensitivity.

[29] Two decompositions are reported. The 66.6% figure is the share of the youngest–oldest log difference in cumulative Y_{pc} growth attributable to $\log(L/Pop)$ using the identity $Y_{pc} = Y_{pw} \cdot (L/Pop)$ in the full model. Table 6 instead decomposes the percentage-point gap in cumulative growth across model variants and includes an interaction term. The two accounting exercises therefore yield similar but not identical shares.

Table 6: Youngest–oldest differences: decomposition into supply, demand, and interaction

Outcome (youngest minus oldest)	Δ full	baseline (neither)	supply add-on	demand add-on	interaction
Peak manufacturing share (pp)	2.31	-1.00	1.37	0.40	1.54
Mean manufacturing share (pp)	1.81	-0.93	1.66	0.44	0.65
Mean manufacturing import share (pp)	-2.00	-0.96	-0.97	-0.03	-0.04
Manufacturing import share at peak (pp)	-2.26	-0.96	-0.85	-0.09	-0.37
Output per worker growth 1970–2009 (pp)	5.80	0.24	2.80	0.15	2.62
Output per capita growth 1970–2009 (pp)	17.06	10.51	3.49	0.60	2.46
Peak year (years)	8	0	0	0	8

Notes: "Supply-only" shuts down durables (durable purchases are identically zero) but retains age-dependent comparative advantage and mobility frictions. "Demand-only" flattens life-cycle comparative advantage (constant age–sector return shifters) but retains durable accumulation. "Neither" applies both restrictions. The interaction term is defined residually as $\Delta O^F - \Delta O^S - \Delta O^D + \Delta O^N$.

This decomposition underscores that while the employment-to-population ratio remains first-order for living standards, life-cycle reallocation is also quantitatively material. In the full model, cumulative output-per-capita growth under the youngest trajectory exceeds that under the oldest by 17.06 percentage points. Of this gap, 10.51 percentage points (61.6%) arise already in the baseline economy with neither life-cycle channel and reflect differences in headcount employment-to-population driven by cohort composition. The supply add-on contributes an additional 3.49 percentage points by raising output per worker and lowering import penetration, and the interaction term adds a further 2.46 percentage points. Together, life-cycle sorting and its interaction with the durable channel account for 5.95 percentage points (34.9%) of the youngest–oldest difference in cumulative output-per-capita growth (with the remaining 0.6 percentage points being attributed to durables exclusively), and they are central for matching the sign and magnitude of the youngest–oldest difference in peak manufacturing employment.

6 Conclusion

This paper studies how demographic transitions shape structural change and aggregate income in an open economy when productivity and demand vary systematically over the life cycle. The central mechanism is that changes in the age structure do not merely scale the size of the workforce; they also reweight the economy toward ages with different comparative advantage and different propensities to accumulate durables. These life-cycle forces alter sectoral labor allocations and the degree to which domestic absorption is met by domestic production versus imports, thereby affecting both structural change and productivity.

In quantitative demographic counterfactuals that hold fixed all non-demographic features of the economy, replacing the population-by-age profile with trajectories spanning the youngest to oldest ends of the cross-country age-structure distribution generates meaningful variation in manufacturing and income outcomes. Peak manufacturing employment ranges from 41.5% (oldest) to 43.8% (youngest), and the timing of the peak shifts across trajectories (1998 under the oldest and 1999 under the young

and old versus 2006 under the youngest). These reallocations coincide with systematic movements in trade shares: average manufacturing import penetration is 22.9% under the oldest trajectory but 20.9% under the youngest (22.6% versus 20.3% at the manufacturing peak). Over the same period, output per capita grows by 93.6% under the youngest trajectory and by 76.5% under the oldest, while output per worker grows by 91.2% and 85.4%, respectively.

A channel decomposition clarifies that these demographic effects are not reducible to a standard employment per capita logic. When I remove both life-cycle reallocation mechanisms—age-dependent sorting across sectors and durable accumulation that shifts expenditure shares over the life cycle—the youngest–oldest difference in per-capita growth falls from 17.1 to 10.5 percentage points. The remaining 6.6 percentage points reflects reallocation forces that operate through life-cycle comparative advantage and life-cycle demand, with a quantitatively important role for their interaction. The evidence is particularly stark for productivity: the youngest–oldest gap in output-per-worker growth is 5.80 percentage points in the full model but only 0.24 points once life-cycle reallocation is shut down. In other words, while employment-to-population ratio is central for per-capita income, the model's life-cycle channels are also quantitatively very important. They are also essential for understanding how demographics map into specialization, import penetration, and productivity growth.

Taken together, these results imply that demographic transitions can meaningfully influence the path of industrialization even in an open economy. Accounting for life-cycle reallocation changes the magnitude—and, for manufacturing outcomes, can change the qualitative predictions—relative to a framework in which demographics matter only through employment per capita. A natural next step is to further discipline the strength of life-cycle comparative advantage and sectoral mobility frictions. This will allow the model to deliver fully disciplined counterfactuals on how demographic timing reshapes manufacturing peaks and output per capita along the development path.

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Appendix

A IPUMS International Microdata

A.1 Data source and scope

The paper's micro evidence uses **IPUMS International**, a harmonized collection of census (and some survey) microdata that integrates variables across countries and over time. As described in the paper, the extract used here covers over 80 countries, with 2–10 census waves since 1960, totaling more than one billion individual observations.[30]

IPUMS International provides anonymized individual-level records with harmonized ("integrated") variables such as age, sex, educational attainment, urban/rural location, nativity/migration status, and industry/occupation. The integrated coding is designed to make cross-country and over-time analysis feasible while preserving documentation about comparability and the underlying country-specific source variables.

A.2 Unit of observation, weights, and repeated cross-sections

- **Unit of observation:** An individual person record in a census micro-sample.
- **Repeated cross-sections:** The analysis uses repeated census cross-sections by country and year; individuals are not followed over time.
- **Population weights:** All descriptive profiles and collapses use the IPUMS person weight (`PERWT`), which scales sample observations to represent the full population.

A.3 Core IPUMS variables used

This subsection summarizes the IPUMS variables used in the paper's micro moments (sector sorting and wage–age profiles). Variable definitions follow the IPUMS International documentation.

Demographics

- `AGE`: Age in years as of the person's last birthday prior to (or on) the enumeration date. Used to construct age fixed effects, age bins, and birth-year cohorts (`byear = YEAR - AGE`).
- `SEX`: Sex of the respondent (coded 1 = Male, 2 = Female in the harmonized scheme). Used to construct the indicator `male`.

[30] See Section 2.1 of the main text.

- `URBAN`: Urban–rural residence status. Definitions vary across countries (population thresholds versus administrative classifications), and IPUMS provides comparability notes by country and year. Used to construct an urban indicator.
- `NATIVITY`: Indicates whether a person is native-born or foreign-born. Used to construct a foreign-born indicator.

labor-market status and employment relationships

- `EMPSTAT`: Employment (activity) status. The first digit distinguishes employed, unemployed, and inactive individuals in a fully comparable manner. Used to define employment and labor-force participation.
- `CLASSWK`: Class of worker (employee, self-employed, etc.). Used to construct indicators for self-employment and non-employee status.

Industry and occupation

- `INDGEN`: Industry, general recode. This harmonized recode maps country-specific industry classifications into twelve broad groups designed to be comparable across samples and roughly aligned with ISIC categories. Used to construct sector indicators (manufacturing, low-skill services, high-skill services, and agriculture).
- `OCCISCO`: Occupation, harmonized to ISCO major groups. Used in robustness exercises and for constructing occupation-group indicators.

Education

- `EDATTAIN` / `EDATTAIND`: harmonized educational attainment (general and detailed versions). Used to construct a continuous years-of-schooling variable.

Educational attainment categories are mapped into approximate years of schooling using a 6–3–3+postsecondary structure, generating values of 0, 2, 4, 5, 6, 9, 12, 13,14, and 16 years depending on attainment. For some robustness exercises, schooling is aggregated into three groups:

- Low: < 9 years
- Medium: 9–12 years
- High: > 12 years

Earnings and hours

- `INCWAGE`: Wage and salary income over the reference period (weekly, monthly, or annual depending on sample), reported in local currency and not inflation-adjusted.
- `INCEARN`: Total earned income (wages plus self-employment income).
- `HRSWORK1`: Total hours worked per week at all jobs.
- `HRSMAIN`: Hours worked in the main job.
- `HRSUSUAL2`: Usual hours worked per week (interval-coded).

Because income reference periods, currency units, and hours concepts differ across samples, wage profiles are normalized within country–year (e.g. to the 20–24 age group) in the empirical analysis.

A.4 Sector definitions constructed from `INDGEN`

Sector indicators are constructed by collapsing harmonized `INDGEN` codes into broad groups:

- **Agriculture:** `INDGEN == 10`.
- **Manufacturing:** `INDGEN == 30`.
- **Industry (broad):** `INDGEN {20, 30, 40, 50, 130}`.
- **Low-skill services:** `INDGEN {60, 70, 80, 110, 114, 120}`.
- **High-skill services:** `INDGEN {90, 100, 111, 112, 113}`.

The main life-cycle regressions restrict the sample to non-agricultural workers and estimate propensities to work in manufacturing, low-skill services, and high-skill services.

A.5 Earnings subsample

Wage information is available only for a subset of IPUMS country–years. The earnings subsample includes:

- Brazil (1980, 1991, 2000, 2010)
- Canada (1971, 1981, 1991, 2001, 2011)
- Dominican Republic (1981)

- Germany (1970)
- Indonesia (1976, 1995)
- Israel (1983, 1995, 2008)
- Italy (2011–2020)
- Jamaica (1982, 1991, 2001)
- Mexico (1960, 1970, 1990, 1995, 2000, 2005–2020)
- Panama (1970, 1990, 2000, 2010)
- Trinidad and Tobago (2000)
- United States (1960, 1970, 1980, 1990, 2000, 2005, 2010, 2015, 2020)
- Uruguay (2006)
- Venezuela (1981, 1990, 2001)

The main wage-profile specification uses countries with more than one earnings wave, excluding Venezuela due to inconsistencies in earnings measurement across waves.

Hourly wages are constructed by combining labor income measures (`INCWAGE` or `INCEARN`) with hours variables (`HRSWORK1`, `HRSMAIN`, or `HRSUSUAL2`) when available.

A.6 Comparability considerations

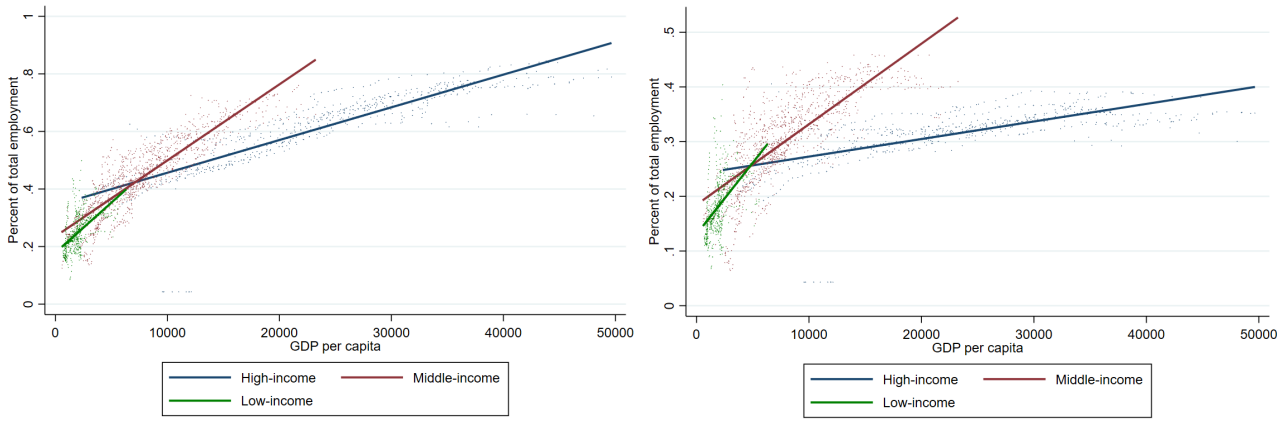
IPUMS documentation highlights several relevant comparability issues:

- **Industry coding:** `INDGEN` ensures broad comparability but cannot preserve all country-specific detail.
- **Hours worked:** Measures differ in whether they refer to actual or usual hours and whether secondary jobs are included.
- **Earnings:** Income is reported in contemporaneous local currency and is not inflation-adjusted.
- **Age reporting:** In some samples age is interval-coded and harmonized to midpoints.

These features motivate the use of broad harmonized sector categories and within-country-year normalization of wage profiles, as well as transparent trimming and missing-value handling in the earnings analysis.

B Additional evidence for the motivating puzzle

B.1 Services absorption and functional-form robustness



(a) Services share

(b) Low-skilled services share

Figure 7: Services absorption along the development path. Employment shares are plotted against GDP per capita by 2010 income group.

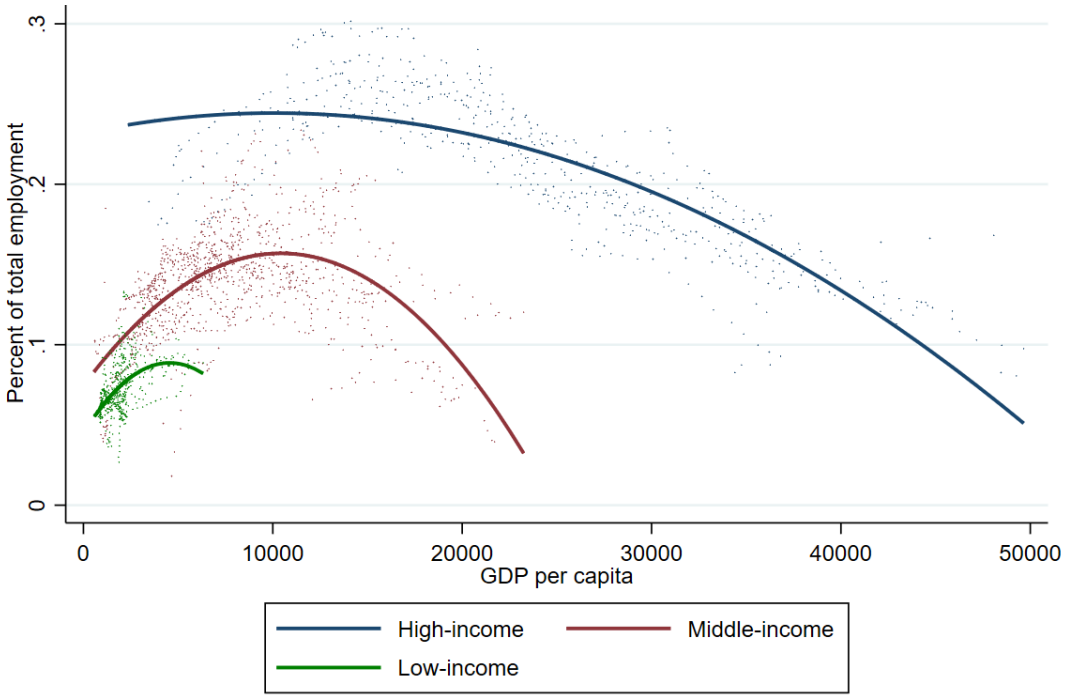


Figure 8: Functional-form robustness: manufacturing hump in income levels. Same object as Figure 1, but the fitted curves are obtained from a quadratic in income levels.

C Additional evidence on the speed of demographic transition

C.1 Fertility–income gradients by income group

Figure 9 plots the same binned relationship as Figure 2, but using total fertility rates (TFR) rather than births per thousand. Appendix Table 7 summarizes the corresponding within-country regression slopes from equation (1) by 2010 income group, reported as the change in fertility associated with a $10,000 increase in GDP per capita.

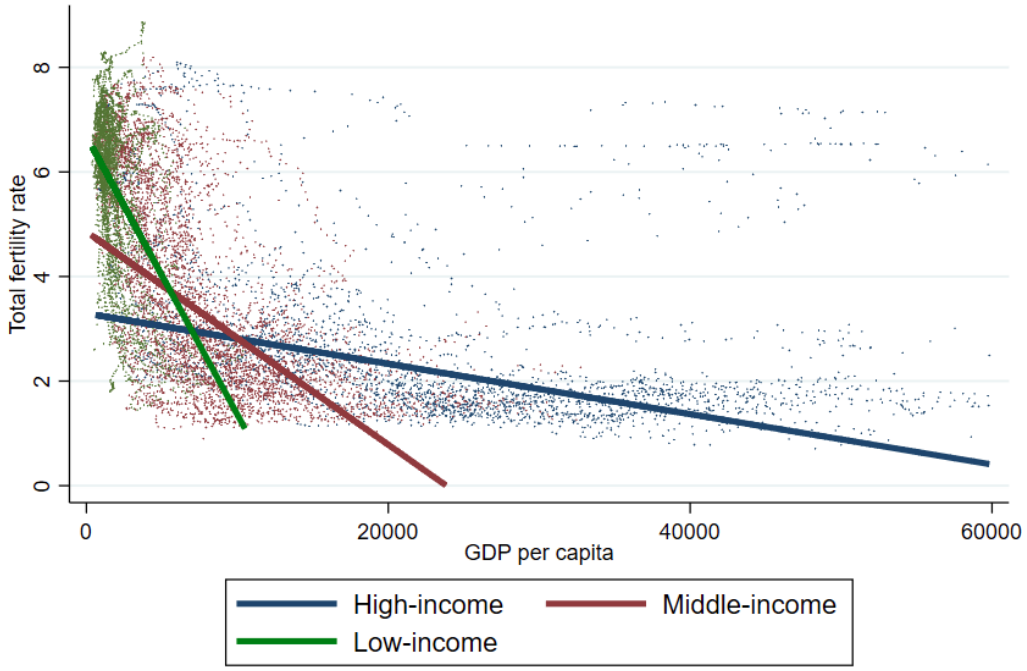


Figure 9: Total fertility rate (TFR) by GDP per capita (by 2010 income group).

Table 7: Fertility–income gradients by 2010 income group.

Income group	TFR (Δ per $10k GDP pc)	Births per thousand (Δ per $10k GDP pc)
Low-income	−5.30	−31.40
Middle-income	−2.00	−14.50
High-income	−0.50	−4.75
High-income ($GDPpc < 40{,}000$)	−0.76	−7.05

Notes: Entries report the within-country slope coefficient β from equation (1), scaled to reflect the change in the outcome associated with a $10,000 increase in GDP per capita, estimated separately by 2010 income group. The last row restricts the high-income sample to observations with GDP per capita below $40,000.

C.2 Below-replacement fertility in recent data

Table 8 lists LMICs below replacement; Table 9 reports peak young-adult share by 2010 income group. Countries whose young-adult share has not peaked are excluded, resulting group means reflect

this right-censoring.

Table 8: Low- and middle-income economies with sub-replacement fertility (2024).

Low & Middle-Income sub-replacement			Low & Middle-Income sub-replacement			Low & Middle-Income sub-replacement		
Country	TFR	GDP pc	Country	TFR	GDP pc	Country	TFR	GDP pc
Ukraine	0.99	7,749	Hungary	1.49	29,452	Tunisia	1.82	10,914
China	1.01	19,238	Bosnia Herzegovina	1.49	12,143	Mexico	1.89	16,235
Chile	1.14	22,741	Serbia	1.50	17,098	Philippines	1.89	8,371
Thailand	1.20	16,421	Argentina	1.50	18,292	Vietnam	1.89	8,050
Lithuania	1.21	30,863	Cape Verde	1.51	7,203	Sri Lanka	1.95	10,705
Belarus	1.22	18,700	Malaysia	1.54	26,629	Nepal	1.96	3,014
Mauritius	1.23	20,643	Brazil	1.61	14,640	India	1.96	7,766
Poland	1.30	32,468	Turkey	1.62	27,362	Peru	1.96	12,763
Costa Rica	1.32	15,497	Colombia	1.63	14,469	Venezuela, RB	2.08	5,267
Albania	1.34	12,978	Azerbaijan	1.67	17,683	Myanmar	2.10	5,177
Latvia	1.34	27,220	Iran, Islamic Rep.	1.68	18,473	Panama	2.11	23,557
Jamaica	1.35	7,482	Barbados	1.71	11,546	Seychelles	2.11	31,055
Estonia	1.36	30,067	Romania	1.71	26,198	Indonesia	2.11	12,802
St. Lucia	1.39	10,452	Armenia	1.72	13,838	Bangladesh	2.14	4,926
Uruguay	1.40	20,182	Moldova	1.73	6,675	South Africa	2.20	11,416
Cuba	1.45	7,649	Bulgaria	1.75	20,592	Nicaragua	2.21	5,093
Russian Federation	1.46	25,437	El Salvador	1.77	9,219	Morocco	2.21	8,400
Macedonia, FYR	1.47	14,051	Korea, Dem. Rep.	1.78	1,569	Dominican Republic	2.22	17,714
Croatia	1.47	26,987	Georgia	1.80	14,360	Lebanon	2.23	10,341
Dominica	1.48	8,880	Ecuador	1.81	10,124	Guatemala	2.29	7,969

Notes: Income group classification based on 2010 GDP per capita. Replacement fertility estimated at 2.3-2.33 for LMICs.

Table 9: Peak Young-adult (25-34) share by income group

	Panel A: Share of Total Population			
Income Group	Max Share Young	Mean Year	Mean GDP per Capita (USD)	Countries
High Income	0.192	1991	30,566	41
Middle Income	0.178	1996	9,531	49
Low Income	0.176	2014	4,635	12

	Panel B: Share of Working-Age Population			
Income Group	Max Share Young	Mean Year	Mean GDP per Capita (USD)	Countries
High Income	0.298	1989	27,828	41
Middle Income	0.292	1988	7,137	55
Low Income	0.293	1995	2,149	39

Notes: Income group classification based on 2010 GDP per capita. Working-age defined as 20-64.

D Robustness of Fact 2

This appendix complements Fact 2 by reporting additional robustness results and diagnostics for the cohort-size instrument based on lagged birth rates.

D.1 Industry versus manufacturing in WDI: GGDC validation

A potential concern with the baseline WDI results in Fact 2 is measurement: the WDI "industry" category bundles manufacturing with mining, utilities, and construction. Because construction is non-tradable and plausibly responsive to demographic-driven demand for housing and infrastructure, the positive relationship between young-adult cohort size and WDI industry employment could, in principle, reflect a construction boom rather than changes in tradable manufacturing employment.

To address this concern directly, I replicate the baseline OLS and 2SLS specifications using GGDC sectoral employment data, which separately identifies manufacturing and the non-manufacturing industry subsectors. Appendix Table 10 shows that the core reallocation pattern is present when "industry" is replaced by manufacturing: the coefficient on the young-adult share is 0.872 in OLS and 1.484 in 2SLS for manufacturing, larger than the baseline especially in the IV specification. Table 11 replicates the analysis for non-agricultural employment. Similarly to the WDI analysis in the main text, the coefficient is higher at 1.711.

Table 10: Fact 2 Robustness: Young-adult cohort size (25–34) and sectoral employment shares (GGDC)

	Agriculture		Manufacturing		Services	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Independent variables						
Young-adult share (25–34)	-0.931^{***}	-1.011^{***}	0.872^{***}	1.484^{***}	-0.469^{***}	-2.476^{***}
	(0.076)	(0.149)	(0.056)	(0.091)	(0.078)	(0.174)
$\log GDP$ per capita	-0.051^{***}	-0.040^{***}	0.001	0.012^{***}	0.060^{***}	0.016^{***}
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
Summary statistics						
Observations	2,733	1,924	2,733	1,924	2,733	1,924
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are employment shares in total employment. OLS includes country and year fixed effects. 2SLS instruments the young-adult share with births per 1,000 25-34 years earlier; $\log GDP$ pc is included as an exogenous control. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Instrument strength (2SLS): Anderson LM = 647.578 (p= 0.000); Cragg–Donald $F = 926.908$; Stock–Yogo 10% critical value = 16.38.

Furthermore, to quantify the role of non-manufacturing industry—and, in particular, to isolate construction from manufacturing—Appendix Table 12 reports coefficients for mining, construction, and utilities, as well as their aggregate (*other industry*, defined as mining + construction + utilities, i.e., industry excluding manufacturing).

The results show that the cohort-size relationship is not driven by non-manufacturing industry. In 2SLS, the construction coefficient is significant but negative, opposite in sign to the manufacturing

Table 11: Fact 2 Robustness: Young-adult cohort size (25–34) and non-agricultural employment (GGDC)

	Manuf. (NA)		Services (NA)	
	OLS	2SLS	OLS	2SLS
Young-adult share (25–34)	0.754^{***}	1.711^{***}	-0.846^{***}	-2.233^{***}
	(0.061)	(0.125)	(0.075)	(0.161)
$\log GDP$ pc	-0.020^{***}	-0.012^{***}	0.013^{***}	-0.004
	(0.002)	(0.003)	(0.002)	(0.004)
Observations	2,733	1,924	2,733	1,924
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Dependent variables are employment shares within non-agriculture (NA). OLS includes country and year fixed effects. 2SLS instruments the young-adult share with births per 1,000 25-34 years earlier; $\log GDP$ pc is included as an exogenous control. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Instrument strength (2SLS): Anderson LM = 647.578 (p= 0.000); Cragg–Donald $F = 926.908$; Stock–Yogo 10% critical value = 16.38.

coefficient of 1.484 in Appendix Table 10. Utilities is the only non-manufacturing subsector with a positive coefficient in both OLS and 2SLS, but these magnitudes are more than an order of magnitude smaller than the corresponding manufacturing coefficients. Moreover, for the aggregate of mining, construction, and utilities, the 2SLS coefficient is negative, small, and statistically insignificant. Taken together, these estimates indicate that the WDI "industry" coefficients in Fact 2 are capturing manufacturing rather than being driven by construction or other non-manufacturing components.

Table 12: Fact 2 Robustness: Young-adult (25–34) share and other industry employment (GGDC)

	Mining		Construction		Utilities		Other industry	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Young-adult share (25–34)	-0.030^{***}	0.086^{***}	0.196^{***}	-0.123^{***}	0.006^{*}	0.014^{**}	0.171^{***}	-0.023
	(0.009)	(0.020)	(0.022)	(0.043)	(0.003)	(0.006)	(0.025)	(0.047)
$\log GDP$ pc	0.000	0.000	0.011^{***}	0.014^{***}	0.001^{***}	0.001^{***}	0.012^{***}	0.016^{***}
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	2,733	1,924	2,733	1,924	2,733	1,924	2,733	1,924
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are GGDC employment shares in mining, construction, and utilities, and *other industry* (defined as mining + construction + utilities, i.e., industry excluding manufacturing). The key regressor is the share of the total population aged 25–34. OLS includes country and year fixed effects. 2SLS instruments the young-adult share with births per thousand 25–34 years earlier and includes $\log GDP$ per capita as an exogenous control. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Instrument strength (2SLS): Anderson LM = 647.578 (p= 0.000); Cragg–Donald $F = 926.908$; Stock–Yogo 10% critical value = 16.38.

D.2 Broader young adult definition

Tables 13–14 replicate the baseline panel specifications using an alternative definition of the young-adult cohort (ages 20–34 rather than 25–34). Coefficients for industry and services are very similar to those in the main specification, if slightly weaker - it is workers aged 25-34 that appear to matter most for the sectoral composition of employment.

Table 13: Fact 2 Robustness: Young cohort size (20–34) and sectoral employment shares

	Agriculture		Industry		Services	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Panel A: Controls include $\log GDPpc$						
Young cohort share (20–34)	-0.606^{***}	-0.652^{***}	0.713^{***}	0.428^{***}	-0.107	0.224^{**}
	(0.094)	(0.184)	(0.045)	(0.085)	(0.076)	(0.101)
$\log GDPpc$	-0.042^{***}	-0.045^{***}	0.015^{***}	0.015^{***}	0.027^{***}	0.030^{***}
	(0.003)	(0.004)	(0.001)	(0.001)	(0.002)	(0.003)
Panel B: Controls include $\log GDPpc$ *and* $(\log GDPpc)^2$						
Young cohort share (20–34)	0.063	0.134	0.491^{***}	0.271^{***}	-0.555^{***}	-0.405^{***}
	(0.088)	(0.100)	(0.039)	(0.044)	(0.070)	(0.083)
$\log GDPpc$	-0.096^{***}	-0.093^{***}	-0.004	-0.004	0.100^{***}	0.097^{***}
	(0.005)	(0.006)	(0.002)	(0.002)	(0.004)	(0.004)
$(\log GDPpc)^2$	0.006^{***}	0.006^{***}	0.001^{***}	0.001^{***}	-0.007^{***}	-0.007^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,638					
Country FE	Yes					
Year FE	Yes					

Notes: Dependent variables are WDI employment shares in agriculture, industry, and services. The key regressor is the is the share of the total population aged 20–34. 2SLS instruments the young-adult share with the mean crude birth rate (births per 1,000 population) lagged 20–34 years. All specifications include country and year fixed effects. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 14: Fact 2 Robustness: Young cohort size (20–34) and industry–services shares within non-agriculture

	Industry share (non-ag)		Services share (non-ag)	
	OLS	2SLS	OLS	2SLS
Panel A: Controls include $\log GDPpc$				
Young cohort share (20–34)	0.731^{***}	0.758^{***}	-0.731^{***}	-0.758^{***}
	(0.058)	(0.118)	(0.058)	(0.118)
$\log GDPpc$	0.034^{***}	0.033^{***}	-0.034^{***}	-0.033^{***}
	(0.003)	(0.004)	(0.003)	(0.004)
Panel B: Controls include $\log GDPpc$ *and* $(\log GDPpc)^2$				
Young cohort share (20–34)	0.755^{***}	0.846^{***}	-0.755^{***}	-0.846^{***}
	(0.058)	(0.100)	(0.058)	(0.100)
$\log GDPpc$	0.012^{**}	0.014^{**}	-0.012^{**}	-0.014^{**}
	(0.006)	(0.007)	(0.006)	(0.007)
$(\log GDPpc)^2$	0.001^{***}	0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,638			
Country FE	Yes			
Year FE	Yes			

Notes: Dependent variables are industry and services employment shares within non-agriculture, constructed as industry (services) employment divided by industry + services employment. The key regressor share of the total population aged 20–34. 2SLS instruments this share with the mean crude birth rate lagged 20–34 years. All specifications include country and year fixed effects. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

D.3 Instrument diagnostics

Because cohort shares can also reflect migration and mortality in addition to fertility, Figures 10 and 11 provide direct evidence on instrument relevance in the estimation sample. Figure 10 plots the partial (residualised) first-stage relationship between the lagged birth-rate instrument and the 25–34 young-adult share after absorbing country and year fixed effects and GDP controls. Figure 11 presents a "lag fingerprint" by estimating the first stage with alternative birth-rate lag windows, showing that predictive power is concentrated in the lag window that matches the age range of the endogenous

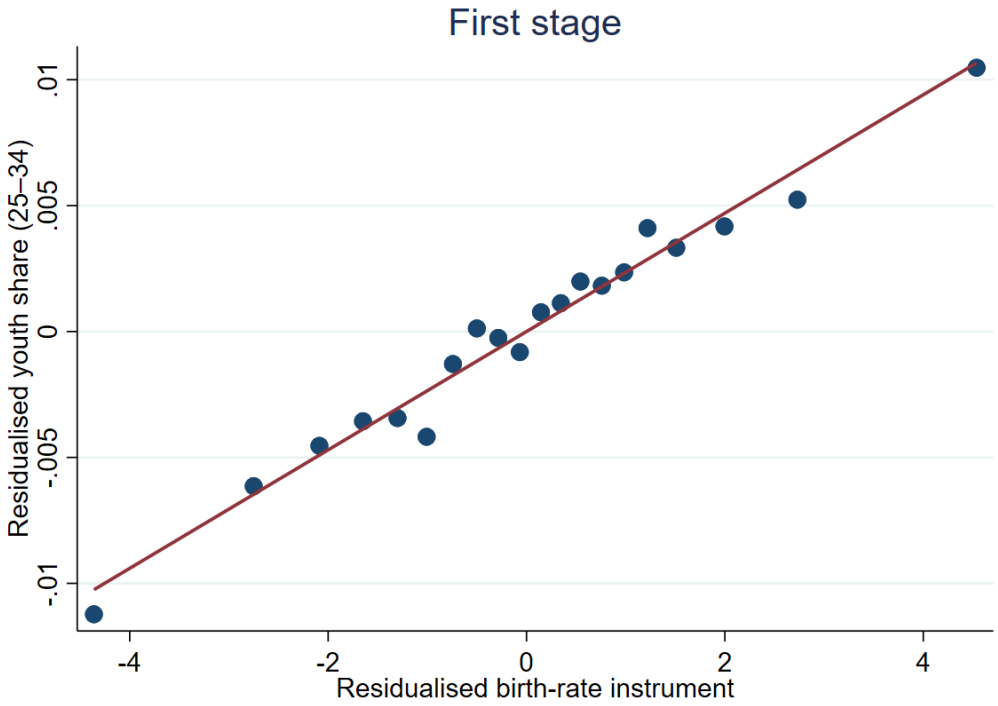


Figure 10: First stage (partial): lagged birth rates and the 25–34 population share.

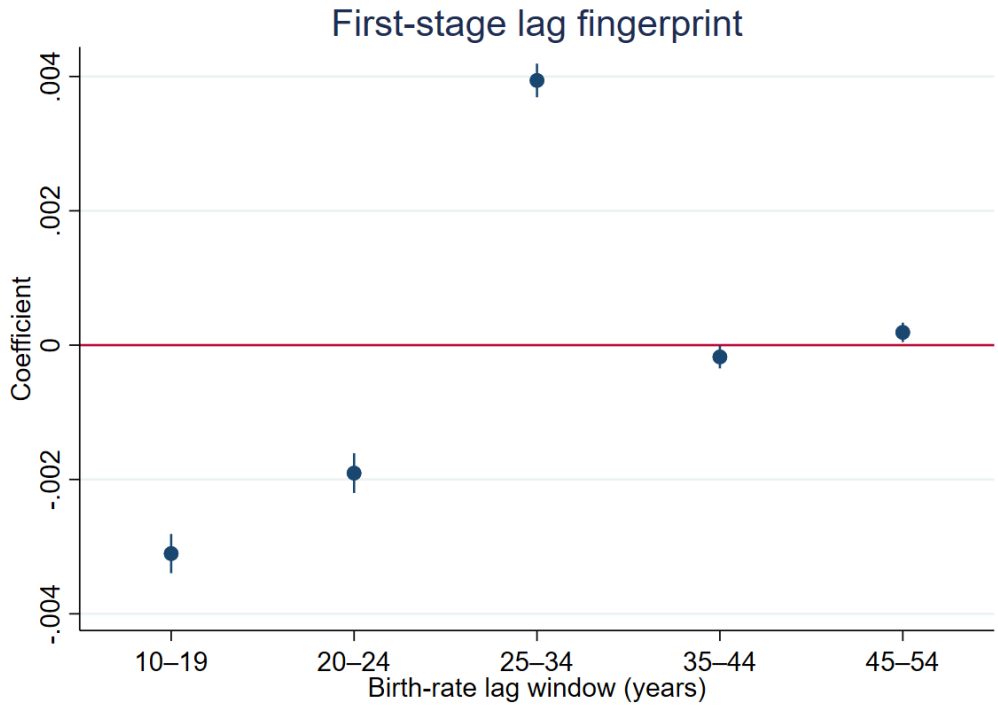
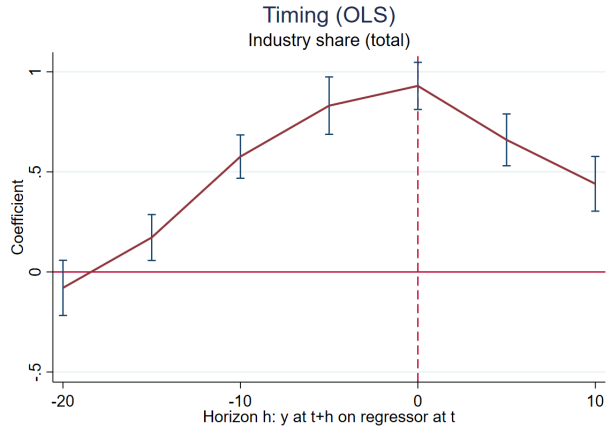


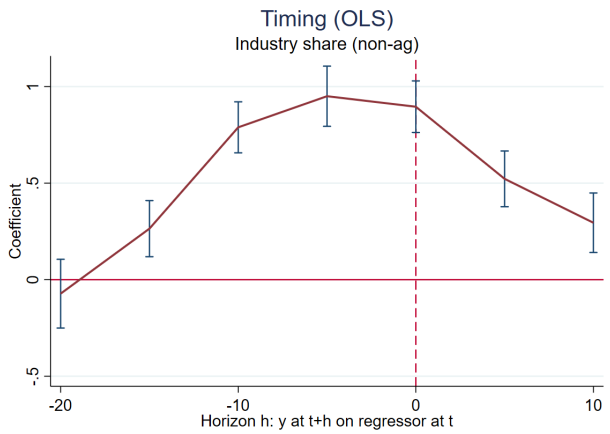
Figure 11: First-stage "lag fingerprint": predictive content of alternative birth-rate lag windows.

regressor.

Finally, Figures 12 and 13 report lead–lag coefficients from regressions of industry shares at $t+h$ on the young-adult share at t (OLS) and on the birth-rate instrument at t (reduced form), for horizons $h \in \{-20, -15, -10, -5, 0, 5, 10\}$. These timing plots summarize how the association varies across



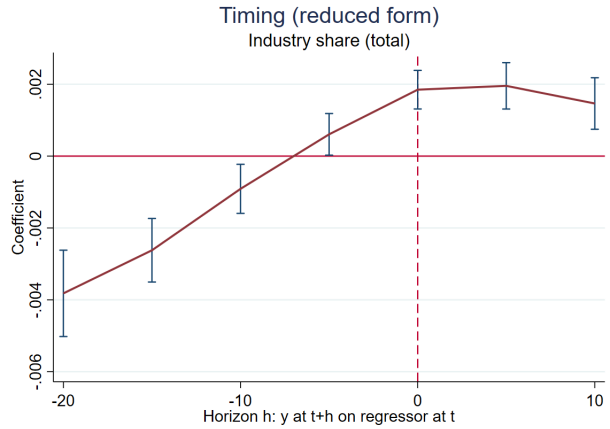
(a) Industry share (total employment)



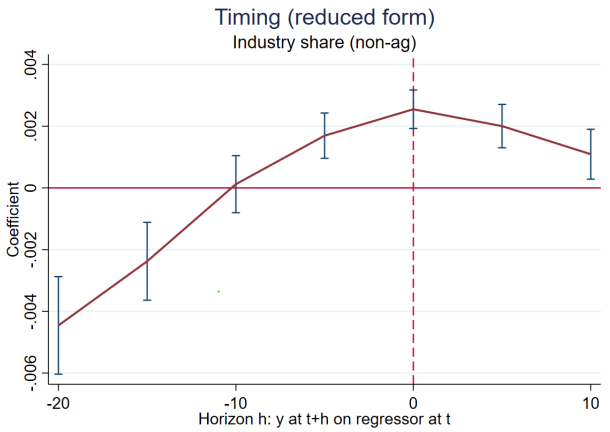
(b) Industry share (within non-agriculture)

Figure 12: Timing evidence (OLS): coefficients from regressions of industry shares at $t+h$ on the young-adult share at t for horizons $h \in \{-20, -15, -10, -5, 0, 5, 10\}$.

horizons and provide a transparent view of the temporal pattern implied by the cohort-size channel.



(a) Reduced form: industry share (total employment)



(b) Reduced form: industry share (within non-agriculture)

Figure 13: Timing evidence (reduced form): coefficients from regressions of industry shares at $t+h$ on the lagged birth-rate instrument at t for horizons $h \in \{-20, -15, -10, -5, 0, 5, 10\}$.

E Robustness of Fact 3

This appendix reports robustness checks for Fact 3 along four dimensions: GGDC data that isolates the narrower manufacturing peak, predetermined demographic measures constructed from GDP-band averages, alternative peak definitions, and alternative measurement of industrial employment.

E.1 Industry versus manufacturing in WDI: GGDC validation

Similarly to Fact 2, a potential concern with the baseline WDI results in Fact 2 is measurement: the WDI "industry" category bundles manufacturing with mining, utilities, and construction.

Table 15: Fact 3 Robustness: Young adult (25-34) shares and peak manufacturing employment

	Peak manufacturing employment share		
	5 years pre-peak	10 years pre-peak	15 years pre-peak
	(1)	(2)	(3)
Independent variables			
Young-adult (25-34) share (average)	1.842***	2.172***	2.563***
	(0.501)	(0.601)	(0.841)
GDP growth around peak	0.030	0.024	0.029
	(0.025)	(0.021)	(0.022)
log GDP pc (average)	0.026	0.091	0.128
	(0.096)	(0.143)	(0.141)
$(\log GDPpc)^2$ (average)	0.001	−0.004	−0.007
	(0.006)	(0.009)	(0.009)
Summary statistics			
Observations	38	36	32
Adj. R^2	0.724	0.695	0.677
Decade FE	Yes	Yes	Yes

Notes: Cross-country regressions relating the manufacturing "hump" to pre-peak cohort composition. The dependent variable is the peak manufacturing employment share. The key regressor is the average young-adult (25–34) share in the k years preceding the peak. All specifications absorb decade fixed effects. "GDP growth around peak" is the growth term used in the baseline specification; log GDP pc controls include a quadratic in the average level around the peak. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 16: Fact 3 Robustness: Young-adult (25-34) shares and income at peak manufacturing employment

	Dependent variable: log GDP pc at peak manufacturing employment		
	5 years pre-peak	10 years pre-peak	15 years pre-peak
	(1)	(2)	(3)
Independent variables			
Young-adult (25-34) share (average)	26.012***	21.958**	30.813***
	(8.925)	(8.648)	(10.927)
GDP growth around peak	0.400	0.733**	0.709**
	(0.552)	(0.352)	(0.332)
Year of peak	0.067	0.059	0.033
	(0.058)	(0.051)	(0.053)
Summary statistics			
Observations	38	36	32
Adj. R^2	0.144	0.318	0.506
Decade FE	Yes	Yes	Yes

Notes: Cross-country regressions relating the the manufacturing "hump" to pre-peak cohort composition. The dependent variable is $\log GDP$ per capita in the year the manufacturing employment share reaches its maximum for Table 16. The key regressor is the average young-adult (25-34) share in the k years preceding the peak. All specifications absorb decade fixed effects as well as controlling for the year the peak took place. "GDP growth around peak" is the growth term used in the baseline specification. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 15 replicates the analysis with GGDC data that isolates the manufacturing peak specifically. Similarly to Fact 2, the coefficients remain positive and statistically significant, and increase moderately in size: a one percentage point increase in the young adult share is associated with a 1.8–2.6 percentage point increase in peak size depending on the L window, while a one standard deviation increase in the young adult share is associated with a 4.0–4.3 percentage point increase.

The pattern is similar for the level of GDP per capita at which manufacturing peaks. A one percentage point increase in the young adult share is associated with 0.22-0.31 higher log GDP points. A one-standard-deviation increase in the pre-peak young adult (25-34) share raises GDP per capita at the peak by 54–77 per cent. Relative to the cross-country dispersion in $\ln GDPpc$ at the peak, these effects are sizable (about 0.39–0.52 standard deviations).

E.2 Predetermined demographic measures from GDP-band averages

Table 17: Fact 3 Robustness: Predetermined Demographic Measures from GDP-Band Averages

	(1) GDP band 1	(2) GDP band 2
Panel A: Peak industrial employment share (raw peak)		
Young-adult (25–34) share (GDP-band average)	2.198***	2.058***
	(0.666)	(0.650)
GDP per capita growth (10-year)	-0.040	-0.047
	(0.033)	(0.034)
Log GDP per capita (10-year average)	0.184	0.217
	(0.140)	(0.179)
(Log GDP per capita)^2 (10-year average)	-0.008	-0.010
	(0.008)	(0.010)
Peak year	-0.005*	-0.006**
	(0.003)	(0.003)
Decade FE	Yes	Yes
Observations	84	80
Adj. R^2	0.506	0.496
Panel B: Peak industrial employment share / non-agricultural employment (raw peak)		
Young-adult (25–34) share (GDP-band average)	2.083***	2.045***
	(0.632)	(0.575)
GDP per capita growth (10-year)	-0.010	-0.017
	(0.034)	(0.037)
Log GDP per capita (10-year average)	0.114	0.065
	(0.113)	(0.153)
(Log GDP per capita)^2 (10-year average)	-0.007	-0.004
	(0.007)	(0.009)
Peak year	0.003	0.002
	(0.004)	(0.004)
Decade FE	Yes	Yes
Observations	78	71
Adj. R^2	0.083	0.104
Panel C: Log GDP per capita at peak (raw peak year)		
Young-adult (25–34) share (GDP-band average)	29.912***	20.620***
	(9.085)	(6.181)
GDP per capita growth (10-year)	0.260	0.208
	(0.429)	(0.443)
Peak year	0.025	0.015
	(0.035)	(0.037)
Decade FE	Yes	Yes
Observations	84	80
Adj. R^2	0.320	0.183

Notes: "Young-adult (25–34) share (GDP-band average)" averages each country's young-adult share over all years in which real GDP per capita falls within a common income band (band 1: 1,000–20,000; band 2: 2,000–15,000, in the units of real GDP per capita used in the data). Because these measures are computed without reference to the country-specific peak year, they are predetermined with respect to the peak outcomes. All specifications include decade fixed effects (absorbed) and are estimated without a constant. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A remaining concern is that pre-peak demographic measures, while dated relative to the peak year, still reference a window centered on each country's peak. To address this, I construct predetermined demographic measures that do not condition on t_i^{peak}. Specifically, I average each country's young-

cohort share across all years in which real GDP per capita falls within a common income band, and I use this country-level average as the demographic regressor. Because these measures are computed without reference to the country-specific peak year, they are predetermined with respect to the peak outcomes.

Table 17 shows that the relationship between demographics and both (i) peak industrial employment and (ii) log GDP per capita at the peak remains positive and statistically significant under predetermined GDP-band demographic measures. Not only that, they are moderately larger than in the baseline specification.

E.3 Alternative peak definitions

Table 18: Fact 3 Robustness: Peak Height under Alternative Peak Definitions

	(1)	(2)	(3)
	5-year pre-peak average	10-year pre-peak average	15-year pre-peak average
Panel A: MA5-smoothed peak			
Young-adult (25–34) share (average)	0.943***	1.082***	1.322***
	(0.234)	(0.326)	(0.397)
GDP per capita growth	0.056	0.009	0.020
	(0.059)	(0.040)	(0.026)
Log GDP per capita (average)	0.175*	0.212**	0.252**
	(0.097)	(0.104)	(0.097)
(Log GDP per capita)^2 (average)	-0.008	-0.010*	-0.013**
	(0.005)	(0.006)	(0.005)
Peak year	0.004	0.004	0.004
	(0.003)	(0.004)	(0.004)
Decade FE	Yes	Yes	Yes
Observations	65	65	65
Adj. R^2	0.564	0.543	0.553
Panel B: Local-hump peak			
Young-adult (25–34) share (average)	0.661*	0.694	0.667
	(0.379)	(0.436)	(0.486)
GDP per capita growth	0.098	0.043	0.025
	(0.070)	(0.044)	(0.030)
Log GDP per capita (average)	0.216	0.211	0.218
	(0.149)	(0.137)	(0.134)
(Log GDP per capita)^2 (average)	-0.009	-0.009	-0.010
	(0.008)	(0.008)	(0.008)
Peak year	-0.001	-0.000	-0.000
	(0.004)	(0.004)	(0.004)
Decade FE	Yes	Yes	Yes
Observations	58	58	58
Adj. R^2	0.541	0.512	0.505

Notes: The dependent variable is the peak industrial employment share. Panel A defines the peak as the maximum of a 5-year moving-average series (MA5). Panel B defines the peak as a local maximum that is preceded by at least five years of rising industrial employment share and followed by at least five years of decline (local-hump criterion). All specifications match Table 3 in controls and fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 18 re-estimates the peak-height regressions using (i) a 5-year moving-average series to define the peak year and peak height and (ii) a local-hump criterion that requires a sustained rise before, and decline after, the local maximum. The positive relationship between pre-peak demographics and peak industrial employment is preserved under MA5 smoothing and remains positive under the local-hump definition.

Table 19 shows that the relationship between pre-peak demographics and income at the peak is

also robust to these alternative peak-year definitions.

Table 19: Fact 3 Robustness: Income at the Peak under Alternative Peak Definitions

	(1)	(2)	(3)
	5-year pre-peak average	10-year pre-peak average	15-year pre-peak average
Panel A: MA5-smoothed peak year			
Young-adult (25–34) share (average)	17.929***	21.560***	23.468***
	(2.015)	(2.332)	(2.873)
GDP per capita growth	0.120	0.794*	0.716***
	(0.713)	(0.458)	(0.252)
Peak year	-0.028	-0.025	-0.026
	(0.057)	(0.047)	(0.040)
Decade FE	Yes	Yes	Yes
Observations	65	65	65
Adj. R^2	0.322	0.448	0.562
Panel B: Local-hump peak year			
Young-adult (25–34) share (average)	20.536***	22.617***	22.714***
	(2.603)	(3.003)	(3.630)
GDP per capita growth	0.882	1.286***	0.739***
	(0.584)	(0.424)	(0.221)
Peak year	-0.055	-0.046	-0.045
	(0.045)	(0.040)	(0.033)
Decade FE	Yes	Yes	Yes
Observations	58	58	58
Adj. R^2	0.339	0.458	0.485

Notes: The dependent variable is log GDP per capita in the peak year implied by each peak definition. Panels correspond to alternative peak-year definitions; specifications otherwise match Table 4. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 20: Fact 3 Robustness: Peak Height Measured Relative to Non-Agricultural Employment

	(1)	(2)	(3)
	5-year pre-peak average	10-year pre-peak average	15-year pre-peak average
Young-adult (25–34) share (average)	0.983**	1.092**	1.270**
	(0.376)	(0.498)	(0.608)
GDP per capita growth	0.025	0.027	0.023
	(0.065)	(0.037)	(0.024)
Log GDP per capita (average)	0.061	0.082	0.128
	(0.121)	(0.120)	(0.119)
(Log GDP per capita)^2 (average)	-0.004	-0.005	-0.008
	(0.007)	(0.007)	(0.007)
Peak year	0.000	-0.000	-0.001
	(0.003)	(0.003)	(0.003)
Decade FE	Yes	Yes	Yes
Observations	79	79	79
Adj. R^2	0.051	0.036	0.042

Notes: The dependent variable is the peak industrial employment share measured relative to non-agricultural employment (raw peak). All specifications match Table 3 in controls and fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 20 replaces the baseline peak industrial employment share with industrial employment relative to non-agricultural employment. The estimated relationship between the pre-peak young-cohort share and peak industrial employment remains positive, significant and of a similar magnitude.

F Robustness of Fact 5: age–sector propensity profiles

This appendix reports sensitivity analysis for the life-cycle sectoral sorting profiles documented in Fact 5. The baseline specification in the main text (equation 5) includes country × five-year birth-cohort fixed effects and absorbs period variation with a quadratic in log GDP per capita. The age

profile is identified from within-cohort variation: the same birth cohort observed at different ages across successive census waves.

The core challenge is the age–period–cohort (APC) identification problem. Because cohort = year − age, one cannot simultaneously include unrestricted fixed effects for all three dimensions. Different approaches to handling this collinearity involve different trade-offs between the flexibility of cohort and period controls and the assumptions imposed on the age profile. Below I report results under five alternative approaches that vary the treatment of cohort and period effects. In the regression-based specifications (Sections F.1–F.5), the individual-level controls are the same throughout: indicators for male, foreign-born, years of schooling, and urban residence, with analytic weights equal to cell-level employment and standard errors clustered by country. The final subsection reports a decomposition exercise that operates on cohort-level pseudo-panel data rather than individual-level regressions.

Throughout this appendix, solid lines denote shares of non-agricultural employment and dashed lines denote shares of total employment (including agriculture). Figures are reported for three income-group samples: all countries, non-high-income countries, and middle-income countries. Income groups are defined using 2010 GDP per capita relative to the United States (Maddison data): high-income if the ratio exceeds 0.45, middle-income if between 0.10 and 0.45, and low-income otherwise.

F.1 Baseline specification: country × cohort FE + log GDP per capita

This is the specification used in the main text (equation 5), reported here for the full set of income-group subsamples and for both definitions of the dependent variable (non-agricultural and total employment shares). The regression is

$$s_n^j \;=\; \sum_{a \neq 50} \alpha_a \, \mathbf{1}[\text{age}_n = a] \;+\; X_n'\beta \;+\; \gamma_1 \ln \text{GDP}_{ct} \;+\; \gamma_2 (\ln \text{GDP}_{ct})^2 \;+\; \mu_{c,b} \;+\; \varepsilon_n,$$

where $\mu_{c,b}$ are country × five-year birth-cohort fixed effects and $\ln \text{GDP}_{ct}$ is log real GDP per capita from the Maddison Project Database. The country×cohort fixed effects absorb all permanent differences across birth cohorts within each country—including cohort-level education, labor-market entry conditions, and institutional environment—so the age coefficients $\{\alpha_a\}$ are identified purely from within-cohort variation across census waves. Period variation is absorbed by the quadratic in log GDP per capita, which captures the dominant source of time variation in sectoral composition in developing countries: movement along the structural transformation path.

The identifying assumption is that, conditional on the country×cohort fixed effects and the GDP quadratic, residual period effects are orthogonal to the age dummies. This would be violated if country-year shocks that are not well proxied by GDP (e.g., sudden trade liberalizations or sector-specific policy changes) differentially affect workers of different ages. The quadratic functional form is flexible enough

to capture the nonlinear relationship between development level and sectoral shares documented in the structural transformation literature, but it cannot absorb idiosyncratic country-year shocks. The next subsection addresses this concern by replacing the GDP proxy with country-specific linear time trends.

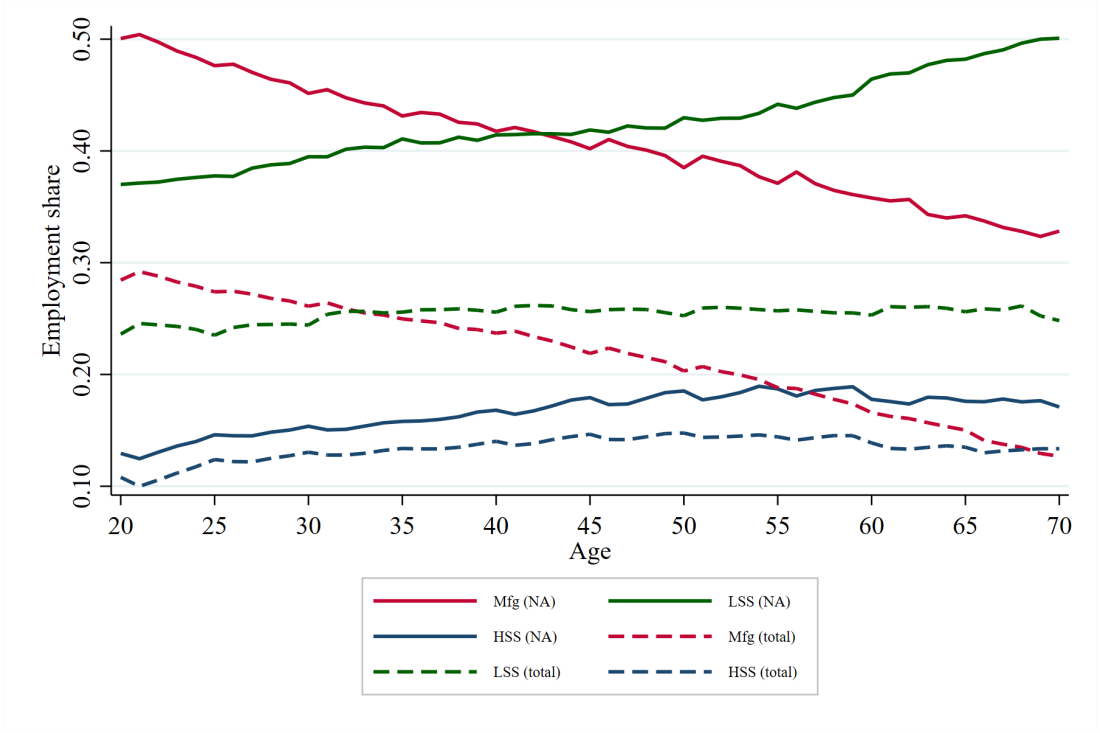


Figure 14: Cohort FE + log GDP p.c. — All countries.

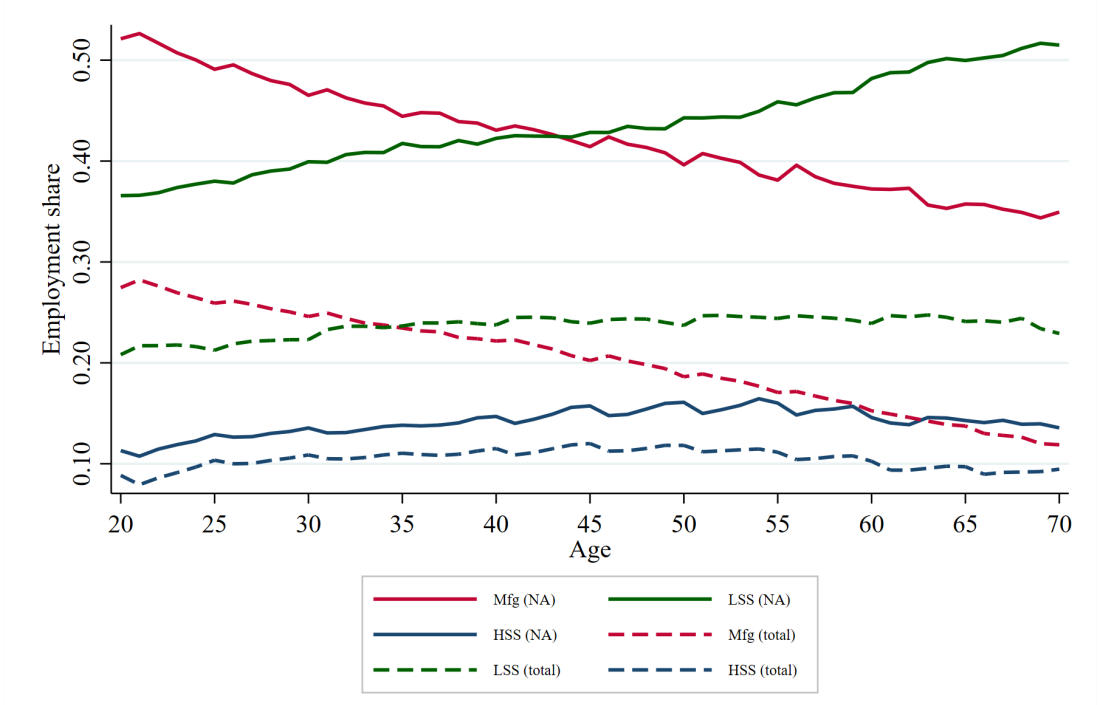


Figure 15: Cohort FE + log GDP p.c. — Non-high-income countries.

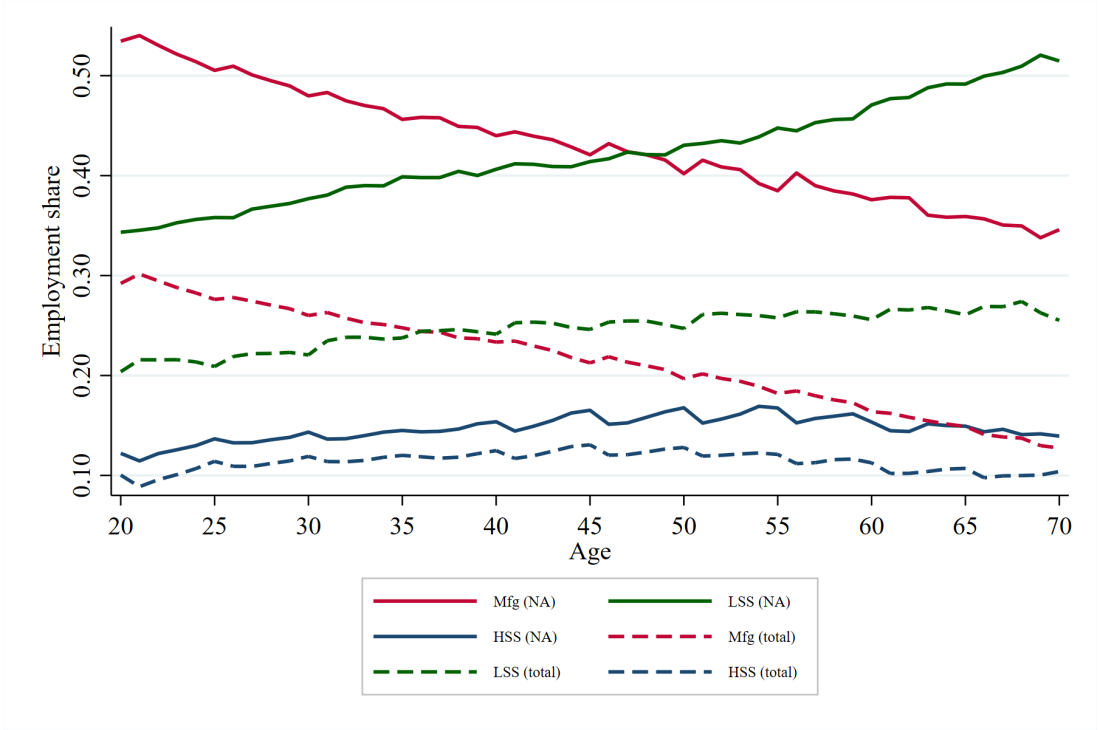


Figure 16: Cohort FE + log GDP p.c. — Middle-income countries.

F.2 Country × cohort FE + country-specific linear trends

This specification replaces the GDP period proxy with country-specific linear time trends:

$$s_n^j = \sum_{a \neq 50} \alpha_a \, \mathbf{1}[\text{age}_n = a] + X_n'\beta + \mu_{c,b} + \lambda_c \cdot t + \varepsilon_n.$$

The country-specific linear trends $\lambda_c \cdot t$ absorb any secular period variation that evolves linearly within each country, such as gradual trade opening, steady technological progress, or long-run shifts in industrial policy. This approach is less parametric than the GDP quadratic (it does not impose a common functional form across countries) but more restrictive than unrestricted country×year fixed effects (it cannot absorb nonlinear or transitory country-year shocks). Age effects are again identified from within-cohort variation, now net of the country-specific linear period trend.

The identifying assumption is that period effects are approximately linear within each country over the sample period. Nonlinear period shocks (e.g., a sudden financial crisis or trade reform) would not be absorbed and could contaminate the age coefficients. Nevertheless, this specification provides a useful robustness check because it relaxes the baseline's reliance on a common GDP functional form while retaining the core feature of nonparametric cohort controls.

The profiles under country-specific trends are strikingly close to the baseline across all income groups. The manufacturing age gradient is virtually unchanged, and the services gradient is preserved with only minor attenuation at the tails. This indicates that the baseline results are not sensitive to the specific functional form used to absorb period variation: whether one uses a quadratic in log GDP

or country-specific linear trends, within-cohort aging accounts for essentially all of the estimated age gradient.

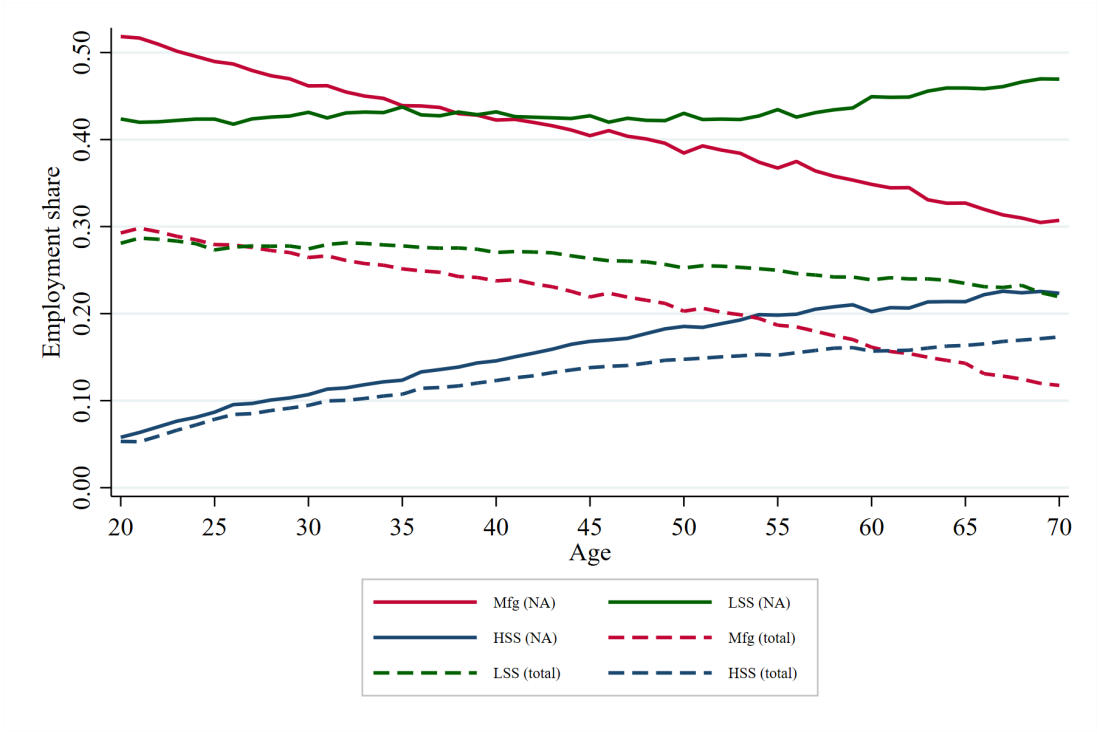


Figure 17: Cohort FE + country trends — All countries.

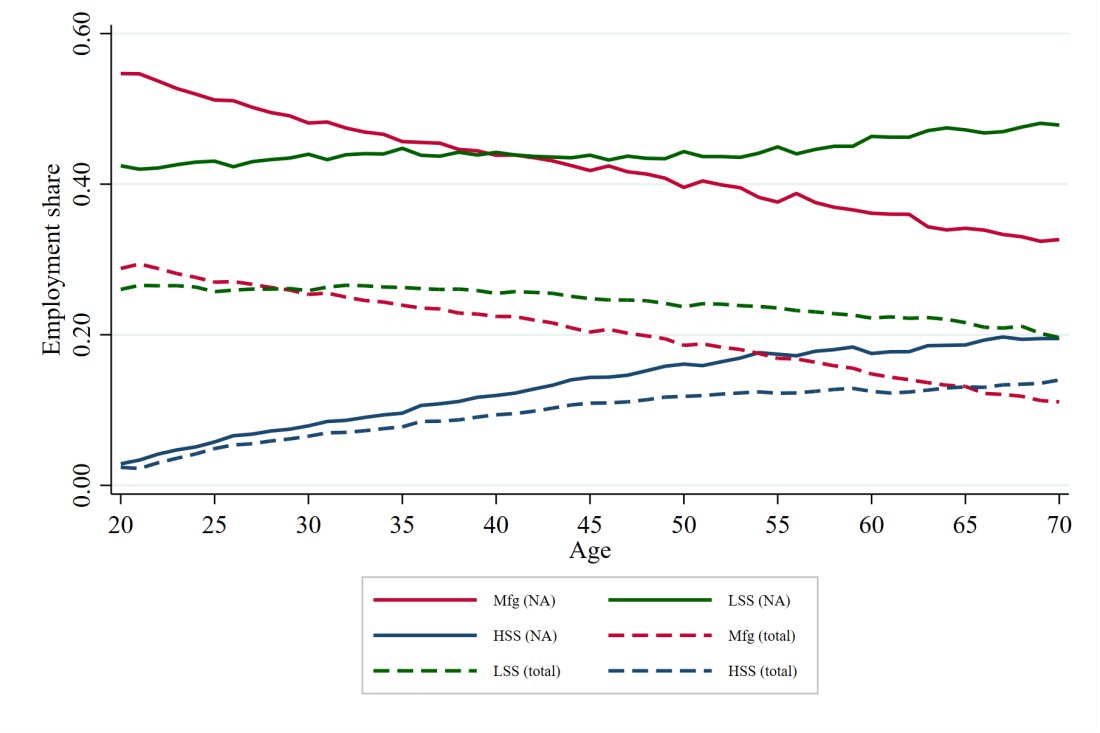


Figure 18: Cohort FE + country trends — Non-high-income countries.

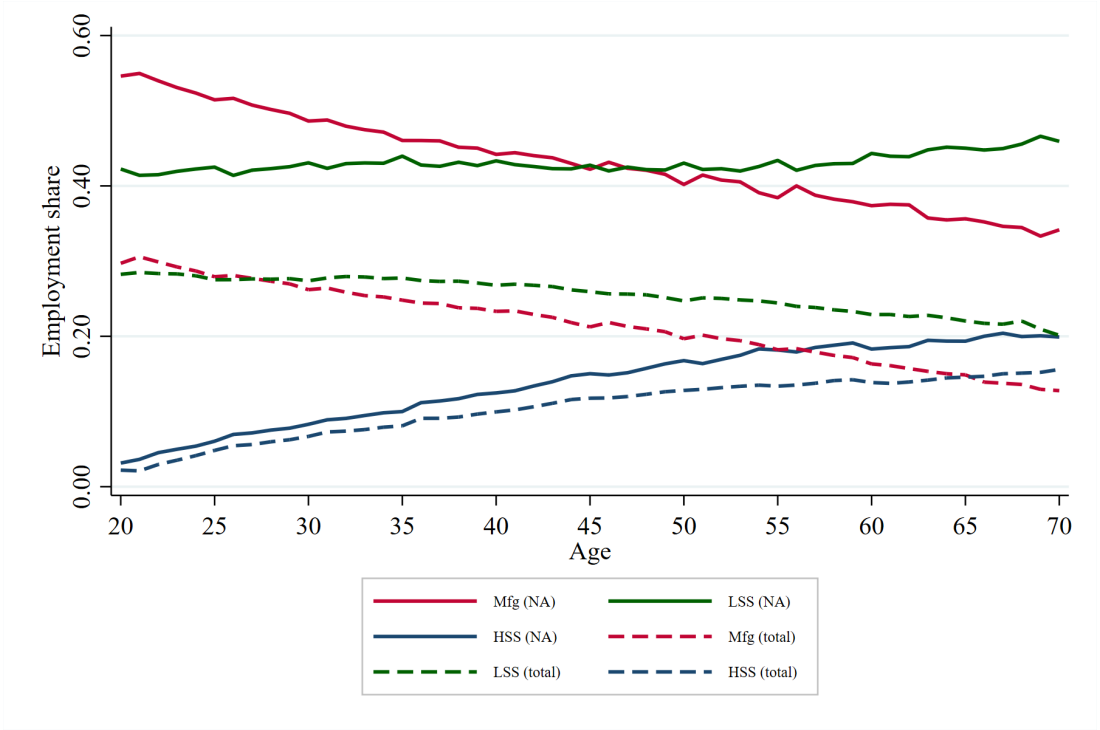


Figure 19: Cohort FE + country trends — Middle-income countries.

F.3 PRS polynomial identification: quintic specification

This specification adapts the identification strategy of Porzio et al. (2022) (PRS). Unlike the baseline, it includes both country × five-year birth-cohort fixed effects and unrestricted year fixed effects, thereby absorbing period variation nonparametrically (no GDP proxy is needed). However, including both cohort FE and year FE alongside unrestricted age dummies would be infeasible due to the APC collinearity. Identification is achieved by restricting the age function to a smooth polynomial with no linear term, centered at age $\bar{a} = 23$:

$$s_n^j = \sum_{k=2}^{5} \beta_k \left(\frac{a_n - \bar{a}}{\bar{a}} \right)^k + X_n'\gamma + \mu_{c,b} + \delta_t + \varepsilon_n,$$

where $\mu_{c,b}$ are country × five-year birth-cohort fixed effects and δ_t are year fixed effects. The age function $f(a) = \sum_{k=2}^{5} \beta_k [(a - \bar{a})/\bar{a}]^k$ enters as explicit regressors (the four polynomial terms from quadratic through quintic), while cohort and year effects are absorbed. The absence of a linear term means the age function is flat at $\bar{a}$: age effects are approximately zero for young workers entering the labor market. This restriction is motivated by the PRS argument that at young ages workers have not yet accumulated sector-specific human capital, so mobility frictions do not generate age-dependent sectoral propensities. The polynomial is mechanically zero at $\bar{a}$ by construction, and the remaining curvature parameters ($k = 2, \ldots, 5$) are identified from within-cohort variation after absorbing both cohort and year effects. The plotted age profile evaluates the estimated polynomial at each integer age and normalizes to zero at age 50 (the reference age used in all other specifications) to facilitate

visual comparison.

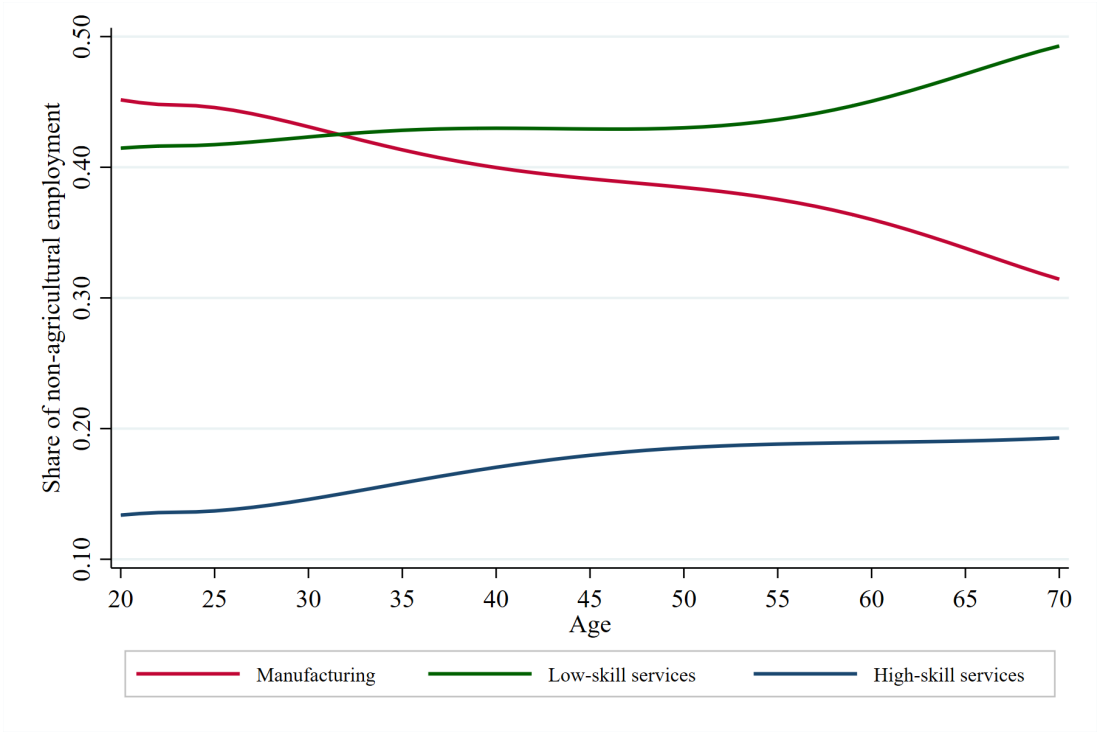


Figure 20: PRS quintic polynomial — All countries.

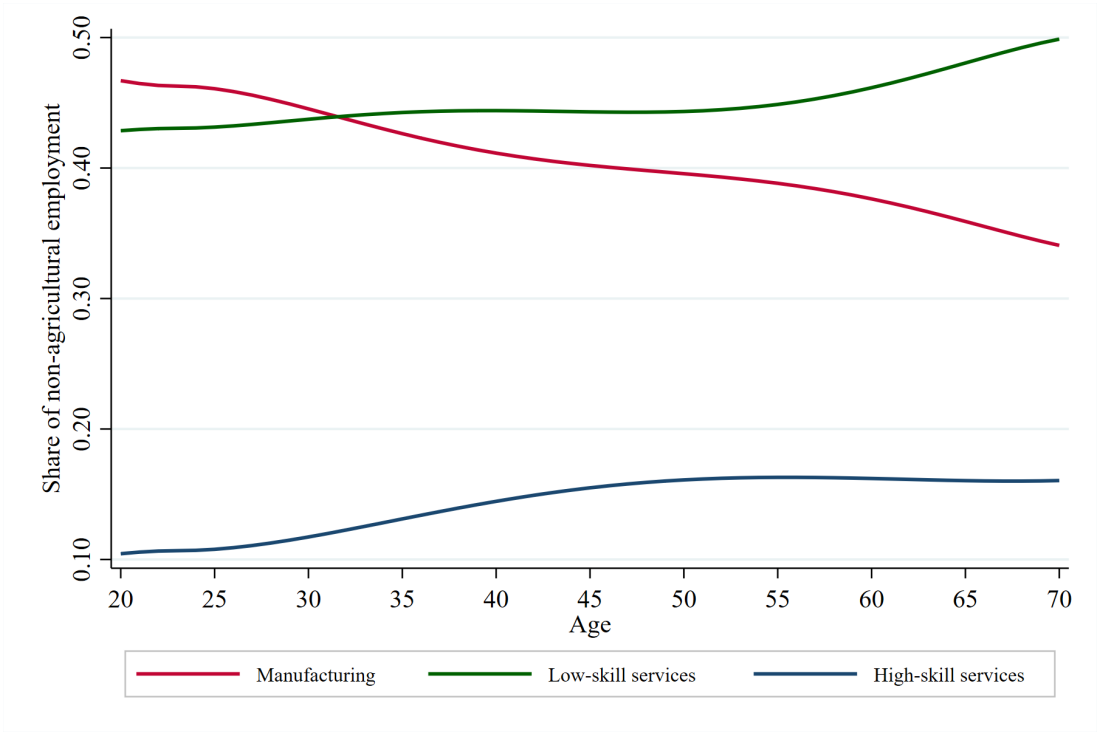


Figure 21: PRS quintic polynomial — Non-high-income countries.

The identifying assumption is twofold: (i) the age profile is well approximated by a smooth polynomial, and (ii) age effects are negligible at $\bar{a}$. The first assumption rules out discrete jumps or kinks in sectoral propensities by age. The second assumption is made only up to $\bar{a} = 23$, younger than in PRS, to avoid an age where young workers may already have sector-relevant preferences or training. This

specification is the only one that absorbs both cohort and period effects nonparametrically, making it a valuable robustness check.

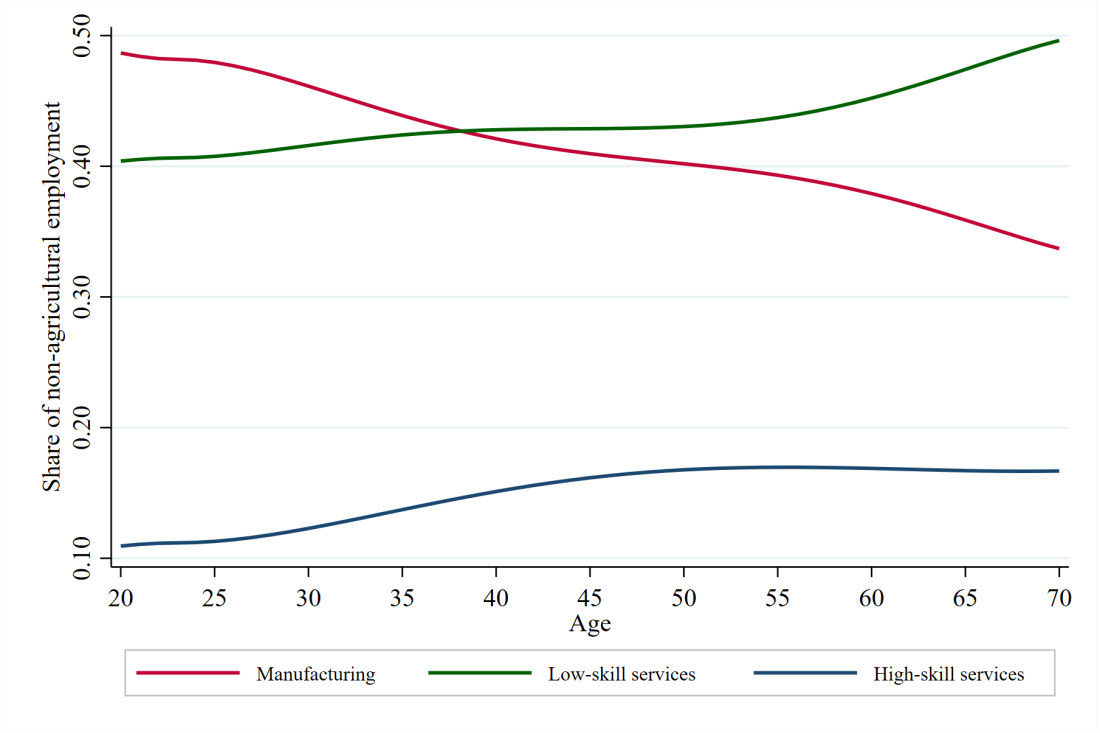


Figure 22: PRS quintic polynomial — Middle-income countries.

F.4 PRS identification with five-year age bins

As a nonparametric alternative to the polynomial restriction, this specification replaces the age polynomial with five-year age-group dummies (reference group: ages 50–54), while retaining country × five-year birth-cohort fixed effects and unrestricted year fixed effects:

$$s_n^j = \sum_{g \neq 50} \alpha_g \, \mathbf{1}[\text{agebin}_n = g] + X_n'\beta + \mu_{c,b} + \delta_t + \varepsilon_n,$$

where the age bins $g \in \{20, 25, 30, \ldots, 65, 70\}$ are defined as $g = 5\lfloor \text{age}/5 \rfloor$, the reference bin is $g = 50$ (ages 50–54), $\mu_{c,b}$ are country × five-year birth-cohort fixed effects, and δ_t are year fixed effects. With five-year age bins and five-year cohort bins, the exact linear dependence age = year − cohort no longer holds at the bin level (because multiple single-year ages map to each age bin and multiple single-year cohorts map to each cohort bin), substantially weakening the collinearity and permitting estimation. This approach imposes no functional form on the age profile; identification relies on the discretization of age into five-year groups, which introduces sufficient variation to distinguish age bins from the cohort×year structure.

The key assumption is that within each five-year age bin, age effects are approximately constant. This is less restrictive than the polynomial assumption but coarser than single-year dummies, trading resolution for identification.

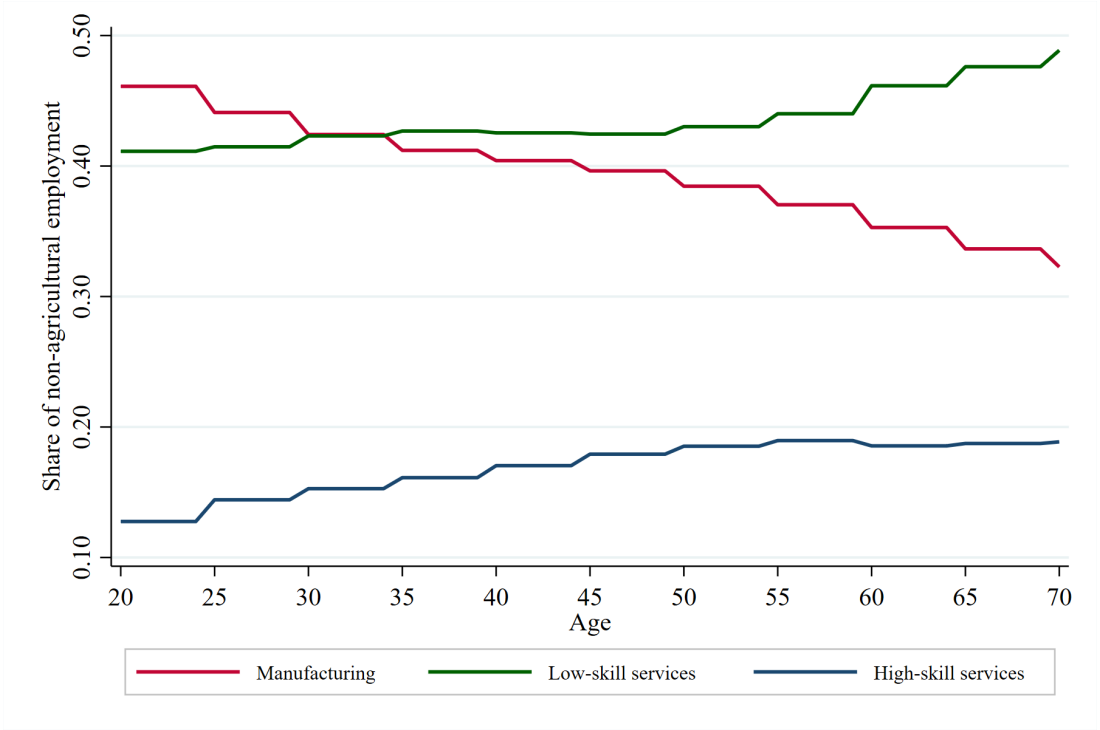


Figure 23: PRS five-year age bins — All countries.

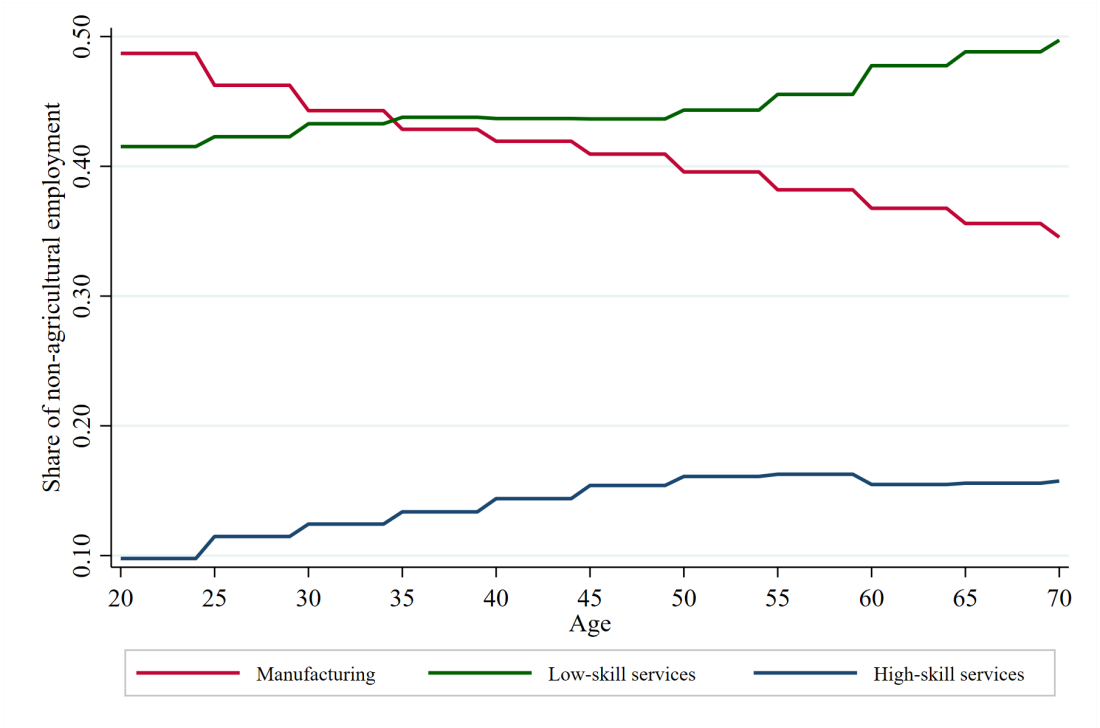


Figure 24: PRS five-year age bins — Non-high-income countries.

The step-function profiles trace out the same qualitative pattern as the polynomial specifications, confirming that the results are not sensitive to the functional form of the age profile. Manufacturing propensity declines monotonically across age bins, while low-skill services rises. The coarser resolution prevents detecting fine-grained age variation but validates the overall gradient.

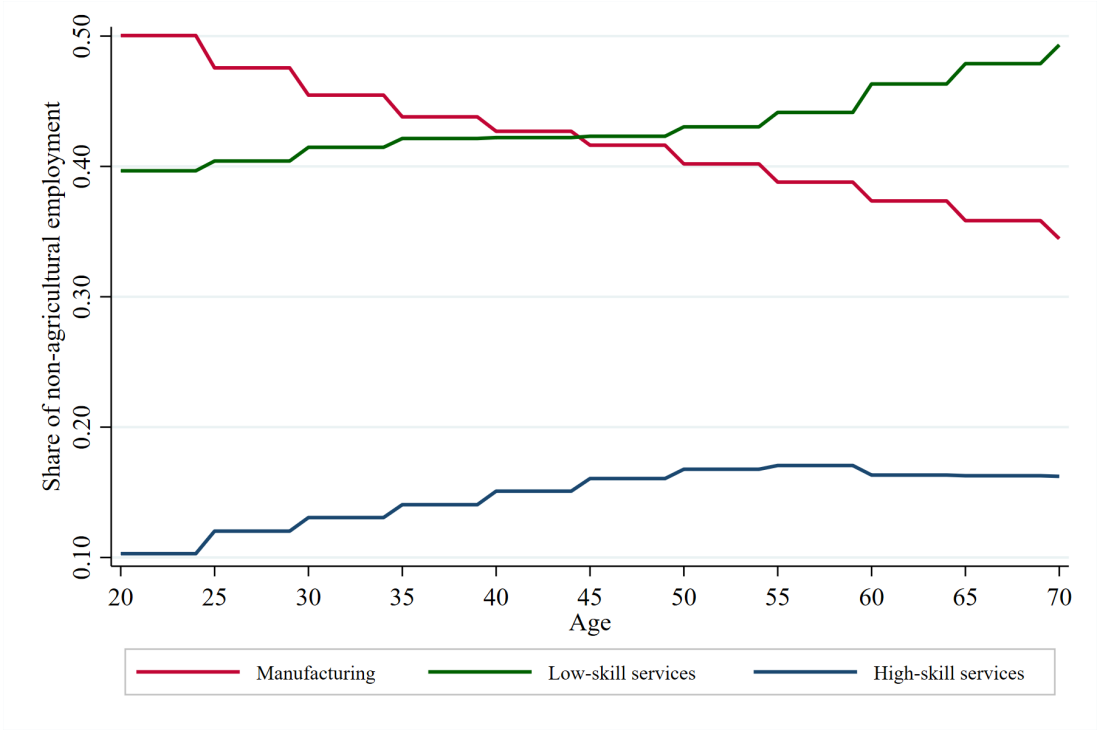


Figure 25: PRS five-year age bins — Middle-income countries.

F.5 Country × year fixed effects (no cohort controls)

For comparison, this specification reports results from a more conventional approach that includes unrestricted country×year fixed effects but no birth-cohort controls:

$$s_n^j = \sum_{a \neq 50} \alpha_a \, \mathbf{1}[\text{age}_n = a] + X_n'\beta + \delta_{ct} + \varepsilon_n,$$

where δ_{ct} are country×year fixed effects. This absorbs all country-year-specific variation nonparametrically—including aggregate period shocks, country-specific trends, and any interaction of the two—but does not control for birth-cohort differences. The age coefficients $\{\alpha_a\}$ are identified from cross-sectional variation in age within each country-year, which conflates life-cycle effects with between-cohort composition differences. For instance, if younger cohorts have more education and are therefore more likely to work in services regardless of age, the estimated manufacturing coefficient at age 20 would be biased upward (too youth-intensive) because it captures both the genuine age effect and the cohort-composition effect. No log GDP proxy is included, as the country×year fixed effects absorb all period variation.

This specification represents the strongest possible control for period effects but the weakest possible control for cohort effects.

That said, the manufacturing profile in the baseline specification maintains over 80 percent of the difference exhibited here between the propensity of 20 year-olds and 64-year olds to work in manufacturing (17 percentage points vs. 21 percentage points), implying that age effects are the main driver of the composition of employment in the sector.

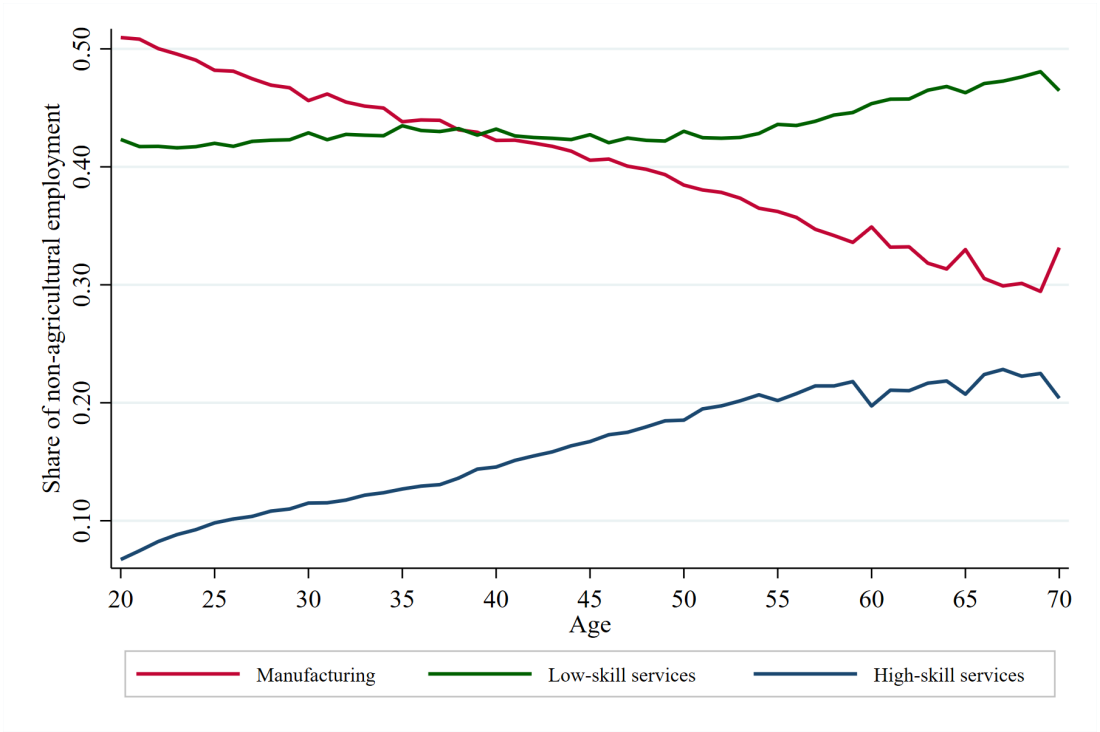


Figure 26: Country×year FE (no cohort controls) — All countries.

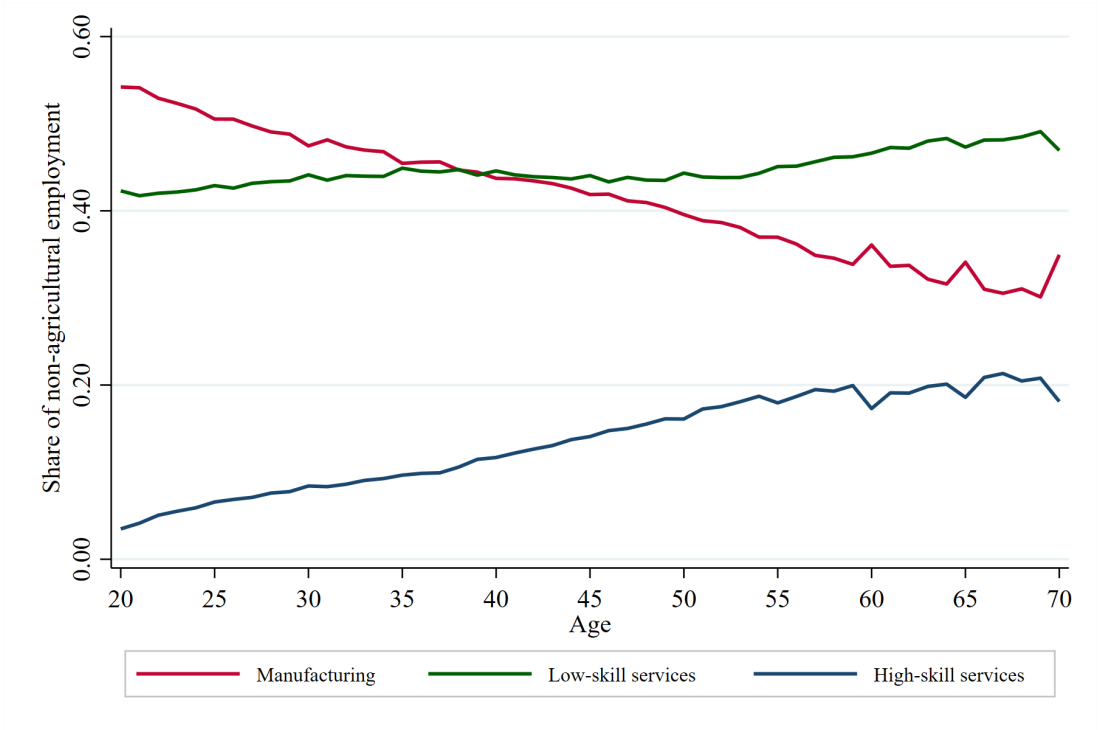


Figure 27: Country×year FE (no cohort controls) — Non-high-income countries.

Moreover, the differential for low-skilled services without controlling for cohorts is equivalent to the baseline (11 percentage points in both cases). Only for high-skilled services are age effects substantially overstated in specifications that do not control for cohort effects - in that case the differential is over 2 times higher in this specification than the baseline. Nevertheless, the qualitative pattern is the same. The direction of the age gradient for manufacturing and services is preserved under all specifications

reported in this appendix.

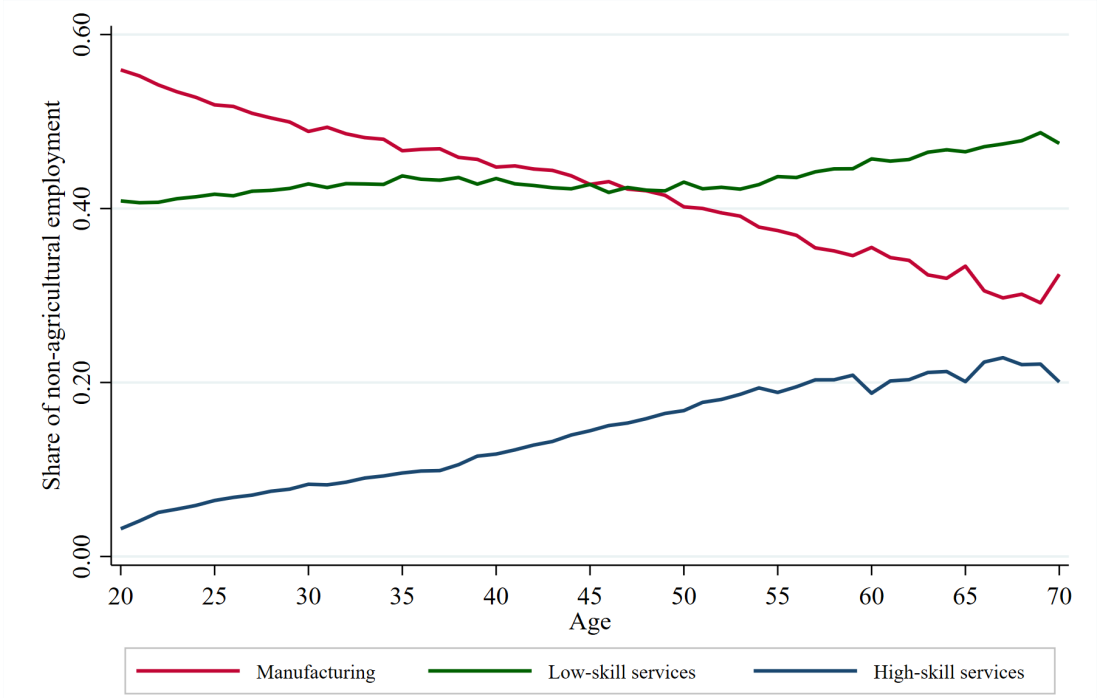


Figure 28: Country×year FE (no cohort controls) — Middle-income countries.

F.6 Within-cohort versus between-cohort decomposition

Figure 29 reports the within-cohort share of aggregate changes in each sector's share of non-agricultural employment, following the decomposition methodology of Porzio et al. (2022). For each country with two or more census waves, I collapse the microdata to pseudo-panel cells at the single-year birth-cohort × survey-year level within each country and compute log sectoral employment shares at the cell level.[31] For each country and sector separately, I estimate

$$\ln s^{j}_{b,t} = \beta_2\left(\tfrac{a-\bar{a}}{\bar{a}}\right)^2 + \beta_3\left(\tfrac{a-\bar{a}}{\bar{a}}\right)^3 + \delta_t + \mu_b + \varepsilon_{b,t},$$

where $s^{j}_{b,t}$ is sector j's share of non-agricultural employment for birth cohort b in year t, $a = t - b$ is age, $\bar{a} = 23$ is the reference age, δ_t are year fixed effects, and μ_b are single-year birth-cohort fixed effects. The regression is estimated country-by-country using `areg` with single-year birth cohorts as the absorbed factor. The age polynomial has no linear term, following the PRS restriction that age effects are approximately zero at $\bar{a}$. The within-cohort component of sectoral change is identified as the change in estimated year effects $(\hat{\delta}_{t'} - \hat{\delta}_t)$ between successive census waves; the between-cohort

[31] The use of single-year birth cohorts (rather than the five-year bins used in the regression-based specifications) follows the original PRS methodology and maximizes the number of cohort×year cells available for the decomposition. Log shares are used because the decomposition is multiplicative: the log of the aggregate share can be expressed as a weighted sum of cohort-level log shares, which decomposes additively into year and cohort components.

component is the residual, reflecting differences in cohort fixed effects between entering and exiting cohorts.

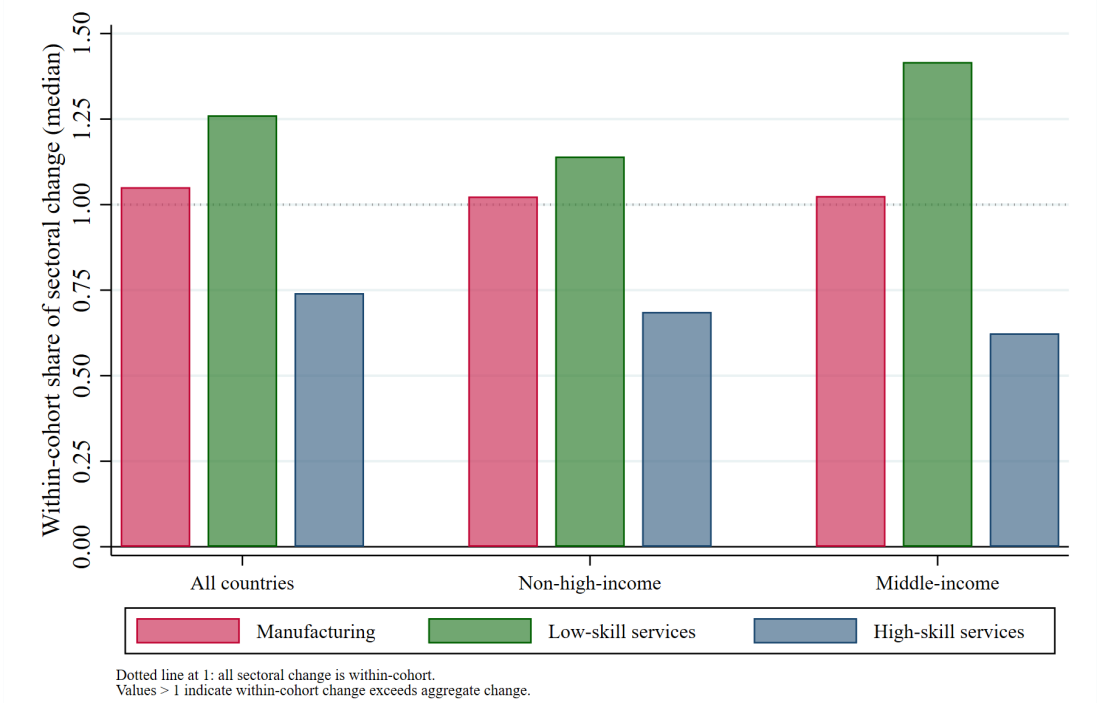


Figure 29: Within-cohort share of sectoral change (median across countries). Dotted line at 1: all change is within-cohort. Values above 1 indicate within-cohort change exceeds aggregate change.

Across all income-group samples, the median within-cohort share for manufacturing is approximately 1.0, confirming that reallocation between manufacturing and services within non-agricultural employment is overwhelmingly a within-cohort phenomenon. Low-skill and high-skill services display within-cohort shares that are also near or above unity. The fact that low-skilled services exhibits the highest within cohort effects, and high-skilled services the lowest is consistent with the fact that for low-skilled services the specification in Appendix F.5 is equivalent to the baseline (and in manufacturing it is only slightly steeper) while for high-skilled services not controlling for cohort effects substantially overstates age effects. These results complement the regression-based evidence: the age gradient in Fact 5 reflects genuine life-cycle sorting, not between-cohort compositional shifts.

G Robustness of Fact 5: wage–age profiles

This appendix provides additional detail for the wage–age evidence discussed in Fact 5. Appendix G.1 outlines the main specification. Appendix G.2 constructs wage age profiles under a simplified specification of repeated cross-sections, without assumptions but consequently failing to control for time and cohort effects. Appendix G.3 repeats the exercise from the core specification albeit without controlling for education. Wage information is available only for a subset of IPUMS country–years,

and coverage varies by country.

G.1 Details on the baseline specification

Following Lagakos et al. (2018), I identify age, time, and cohort effects from repeated cross-sections by estimating a flexible Mincer equation for log wages that controls for years of schooling and includes age-group dummies, calendar-year effects, and birth-cohort effects. Because these components are otherwise collinear, the Heckman–Lochner–Taber (HLT) restriction assumes that age-related wage growth is approximately zero in the final ten working years, so wage changes for late-career workers within a fixed cohort identify time effects. Given the recovered time effects, the remaining variation identifies cohort effects and the full age profile. The resulting cross-country average wage–age profiles are plotted in Figure 5 in the main text. This is the main specification, as it allows age effects to be cleanly isolated while permitting period effects and long-run growth to be country-specific.

G.2 Simple specification: constructing wage–age profiles by sector

For each country–year with earnings data, I also construct simple wage profiles separately by year for agriculture manufacturing and services.

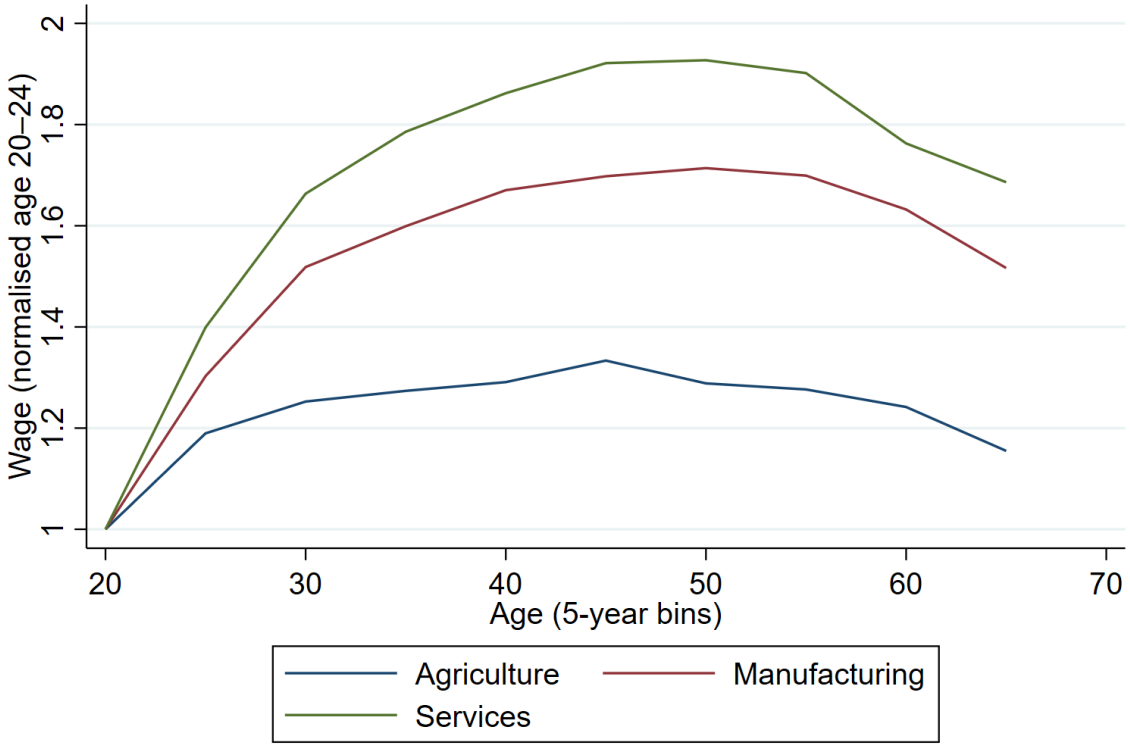


Figure 30: Wage–age profiles by sector, IPUMS earnings 14-country subsample. Notes: 5-year age bins, normalized to the 20–24 age group within country–year; lines averaged across available years within each country using sample weights.

Similarly to the main specification, I use 5-year age bins and normalize each sector's profile to

the 20–24 age group within the same country–year, and then average across available years within a country (weighting by sample weights). Figure 30 plots the resulting average cross-country wage–age curves. The key summary statistic used in the text is the difference in peak life-cycle wage growth between services and manufacturing. For each country, define

$$\Delta_{j,i}^{\max} \equiv \max_{a \in \mathcal{A}} \left(100 \times \left[\frac{\bar{w}_{j,i}(a)}{\bar{w}_{j,i}(20\text{–}24)} - 1 \right] \right), \qquad j \in \{\text{Agr}, \text{Mfg}, \text{Serv}\},$$

where $\bar{w}_{j,i}(a)$ is the mean wage in age bin a for sector j in country i (after aggregating across years). The object of interest is $\Delta_{\text{Serv},i}^{\max} - \Delta_{\text{Mfg},i}^{\max}$, which captures how much larger peak wage growth is in services relative to manufacturing within a country.

G.3 Wage-age profiles without controlling for education

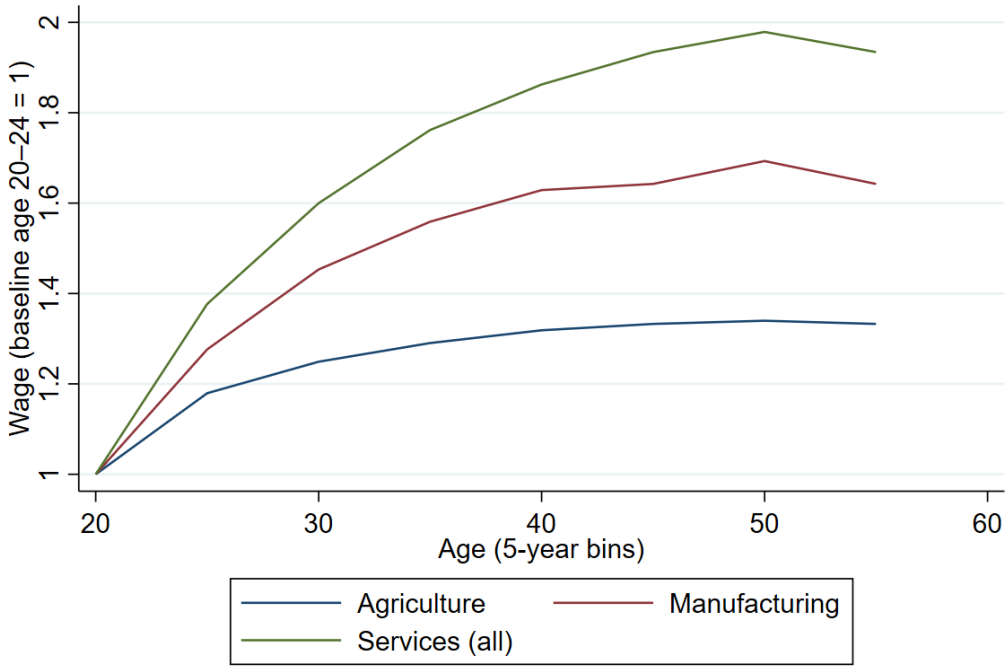


Figure 31: Wage–age profiles by sector, IPUMS earnings 9-country subsample, with HLT method in Lagakos et al. (2018), without controlling for years of schooling

Figure 31 plots the results of the main specification albeit without controlling for years of schooling. As you can see, this only widens the gap between the age-wage curves of services and manufacturing, supporting the patterns described in Fact 5 and task-based comparative advantage interpretation.[32]

[32]Selection into services by age and education can overturn the naive aggregate-cohort logic and thus make the no-education-control profiles diverge even more.

H Durable consumption categories (COICOP)

This appendix lists the COICOP consumption categories classified as durables in the household-expenditure data. In the main specification, semi-durables are included as durables; hence the durable aggregate used in the paper includes all items in both columns of Table 21. Categories are defined using the raw `coicop_key` labels in the source data.

Table 21: COICOP categories classified as durables (baseline: durables + semi-durables).

Durable goods	**Semi-durable goods (treated as durable)**
• motor cars • motor cycles • bicycles • purchase of vehicles • furniture and furnishings • household appliances • major household appliances whether electric or not • small electric household appliances • major tools and equipment • tools and equipment for house and garden • audio-visual, photographic and information processing equipment • equipment for the reception, recording and reproduction of sound and picture • information processing equipment • photographic and cinematographic equipment and optical instruments • telephone and telefax equipment • musical instruments and major durables for indoor recreation • major durables for outdoor recreation • other major durables for recreation and culture • medical products, appliances and equipment • therapeutic appliances and equipment • jewellery, clocks and watches • electrical appliances for personal care • furniture and furnishings, carpets and other floor coverings	• clothing • garments • clothing materials • other articles of clothing and clothing accessories • footwear • shoes and other footwear • clothing and footwear • household textiles • carpets and other floor coverings • books • games, toys and hobbies

I Equilibrium conditions and numerical solution

This appendix collects the equilibrium conditions and summarizes the numerical procedure used to compute equilibrium transition paths under alternative demographic scenarios. Table 22 lists the equilibrium conditions. The first set corresponds to optimality conditions for durables and non-durables for the representative dynasty. The second set contains worker sector-choice conditions and the law of motion for the distribution of lagged-sectors. The third set collects firms' optimality and pricing conditions, the Armington absorption block and foreign demand for exports. The final set includes market-clearing for (i) absorption composites and domestic varieties by sector, (ii) effective labor aggregation, and (iii) period-by-period balanced trade. Manufacturing is the producer-side numeraire. Algorithm I.2 describes the nested fixed-point iteration used in the quantitative implementation.

I.1 Equilibrium conditions

Table 22: Equilibrium conditions (open economy)

(i) Competitive production firms

$\mathrm{Y}_{j,t} = A_{j,t}\, N_{j,t} \qquad \forall(j,t),$

$w_{j,t} = p^d_{j,t}\, A_{j,t} \qquad \forall(j,t),$

$p^d_{M,t} \equiv 1 \qquad \forall t.$

(ii) Retail/absorption (Armington) and international trade

$\mathrm{p}^Q_{L,t} = p^d_{L,t} \qquad \forall t,$

$p^m_{j,t} = \tau_j\, e_t\, p^*_{j,t} \qquad \forall(j \in \mathcal{T}, t),$

$Q_{j,t} = \left[\omega_j^{1/\eta}\,(Y^{abs}_{j,t})^{\frac{\eta-1}{\eta}} + (1-\omega_j)^{1/\eta}\,(m_{j,t})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \qquad \forall(j \in \mathcal{T}, t),$

$p^Q_{j,t} = \left[\omega_j\,(p^d_{j,t})^{1-\eta} + (1-\omega_j)\,(p^m_{j,t})^{1-\eta}\right]^{\frac{1}{1-\eta}} \qquad \forall(j \in \mathcal{T}, t),$

$Y^{abs}_{j,t} = \omega_j\left(\frac{p^d_{j,t}}{p^Q_{j,t}}\right)^{-\eta} Q_{j,t}, \qquad m_{j,t} = (1-\omega_j)\left(\frac{p^m_{j,t}}{p^Q_{j,t}}\right)^{-\eta} Q_{j,t} \qquad \forall(j \in \mathcal{T}, t),$

$X_{j,t} = \Xi_{j,t}\left(\frac{p^d_{j,t}}{e_t}\right)^{-\varepsilon} \qquad \forall(j \in \mathcal{T}, t),$

$Y_{j,t} = Y^{abs}_{j,t} + X_{j,t} \qquad \forall(j \in \mathcal{T}, t),$

$\sum_{j\in\mathcal{T}} p^m_{j,t} m_{j,t} = \sum_{j\in\mathcal{T}} p^d_{j,t} X_{j,t} \qquad \forall t.$

(iii) Dynasty: non-durables (CLM) and durables

$\sum_{j\in\{A,M,L,H\}} \Omega_j^{1/\sigma}\left(\frac{c_{j,t}(a)}{C_t(a)^{\iota_j}}\right)^{\frac{\sigma-1}{\sigma}} = 1 \qquad \forall(t,a),$

$E_t(a) = \left[\sum_{j\in\{A,M,L,H\}} \Omega_j\, C_t(a)^{(1-\sigma)\iota_j}\,(p^Q_{j,t})^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \qquad \forall(t,a),$

$c_{j,t}(a) = \Omega_j\left(\frac{p^Q_{j,t}}{E_t(a)}\right)^{-\sigma} C_t(a)^{(1-\sigma)\iota_j} \qquad \forall(j,t,a),$

$\frac{1}{C_t(a)} = \lambda_t\, \frac{\partial E_t(a)}{\partial C_t(a)} \qquad \forall(t,a),$

$\sum_{a=20}^{A} \pi_t(a)\, E_t(a) + p^Q_{M,t} \sum_{a=20}^{A} \pi_t(a)\, x_t(a) = \sum_{j\in\{A,M,L,H\}} w_{j,t} N_{j,t} \qquad \forall t,$

$D_t(20) = x_t(20), \qquad D_t(a) = (1-\delta_D) D_{t-1}(a-1) + x_t(a) \quad (a \geq 2) \qquad \forall t,$

$\lambda_t p^Q_{M,t} = \frac{\varphi}{1+D_t(a)} + \beta\, s_t(a)\,(1-\delta_D)\,\lambda_{t+1} p^Q_{M,t+1} \qquad \forall(t, a \leq A-1),$

$\lambda_t p^Q_{M,t} = \frac{\varphi}{1+D_t(A)} \qquad \forall t,$

$x_t(a) \geq 0$ for all (t,a) (with weak inequality and complementary slackness in the previous two equations if this binds).

(iv) Worker sector choice and mobility frictions

$\Upsilon_{j,t}(a,h \mid j^-) \equiv \lambda_t w_{j,t} z_j(a,h) - \kappa(j^-,j) + \beta s_t(a) V_{t+1}(a+1,h,j) \qquad \forall(t, a \leq \bar{a}, h, j^-, j),$

$V_t(a,h,j^-) = \xi \log\Big(\sum_{j\in\{A,M,L,H\}} \exp\big(\Upsilon_{j,t}(a,h \mid j^-)/\xi\big)\Big), \qquad V_t(\bar{a}+1,h,j^-) = 0 \qquad \forall(t, a \leq \bar{a}, h, j^-),$

$P_{j^-\to j,t}(a,h) = \frac{\exp\left(\Upsilon_{j,t}(a,h|j^-)/\xi\right)}{\sum_{m\in\{A,M,L,H\}} \exp\left(\Upsilon_{m,t}(a,h|j^-)/\xi\right)} \qquad \forall(t, a \leq \bar{a}, h, j^-, j),$

$\eta_{j,t+1}(a+1,h) = \sum_m \eta_{m,t}(a,h) P_{m\to j,t}(a,h) \qquad \forall(t, a \leq \bar{a}-1, h, j),$

$\ell_{j,t}(a,h) = \sum_m \eta_{m,t}(a,h) P_{m\to j,t}(a,h) \qquad \forall(t, a \leq \bar{a}, h, j).$

(v) Aggregation and market clearing

$\mathrm{N}_{j,t} = \sum_{a\leq\bar{a}} \pi_t(a) \int_{h_{\min}}^{h_{\max}} \ell_{j,t}(a,h)\, z_j(a,h)\, f_{t-a}(h)\, dh \qquad \forall(j,t),$

$Q_{j,t} = \sum_{a=20}^{A} \pi_t(a)\, c_{j,t}(a) \qquad \forall(j \in \{A,H\}, t),$

$Q_{M,t} = \sum_{a=20}^{A} \pi_t(a)\, c_{M,t}(a) + \sum_{a=20}^{A} \pi_t(a)\, x_t(a) \qquad \forall t,$

$Y_{L,t} = \sum_{a=20}^{A} \pi_t(a)\, c_{L,t}(a) \qquad \forall t.$

Remark. If world prices $p^*_{j,t}$ are already expressed in units of the domestic numeraire, one can set $e_t \equiv 1$ without loss of generality. The open-economy calibration in the paper instead normalizes $p^*_{j,t} \equiv 1$ and lets the real exchange rate $\{e_t\}$ adjust to satisfy balanced trade period by period.

I.2 Numerical solution

1. **Set up grids and primitives.** Fix $t = 1, \dots, T$, ages $a = 20, \dots, A$ (workers $a \le \bar{a}$), sectors $j \in \{A, M, L, H\}$, and tradables $\mathcal{T} = \{A, M, H\}$. Take $\{\pi_t(a)\}$ from the data and compute implied survival rates $\{s_t(a)\}$ using the cohort accounting identity (6), i.e. $s_t(a) = \pi_{t+1}(a{+}1)/\pi_t(a)$ whenever $\pi_t(a) > 0$. Load and extend the exogenous paths for productivity, world prices, and export-demand shifters $\{A_{j,t}\}$, $\{p^*_{j,t}\}_{j\in\mathcal{T}}$, and $\{\Xi_{j,t}\}_{j\in\mathcal{T}}$. Fix parameters $(\beta, \delta_D, \varphi, \sigma, \iota_j, \Omega_j, \eta, \omega_j, \tau_j, \varepsilon, \kappa, \xi, \dots)$.

2. **Guess equilibrium price paths.** Guess sequences of producer prices $\{p^d_{j,t}\}$, the real exchange rate $\{e_t\}$, and the dynasty multiplier $\{\lambda_t\}$. Impose the producer-side numeraire $p^d_{M,t} \equiv 1$ (31). Compute absorption prices $p^Q_{j,t}$ for $j \in \mathcal{T}$ from the Armington price index (33), and set $p^Q_{L,t} = p^d_{L,t}$. Update wages using zero profits: $w_{j,t} = p^d_{j,t} A_{j,t}$ (36).

3. **Outer loop (fixed point in $\{p^d, e, \lambda\}$).** For $it = 1, 2, \dots$ until convergence:

   (a) **Worker sector choice (backward).** Given $\{\lambda_t, w_{j,t}, s_t(a)\}$, solve the worker problem (26) for $a \le \bar{a}$ by backward induction over (t, a). Compute the choice-specific index $\Upsilon_{j,t}(a, h \mid j^-)$ (27) and logit probabilities $P_{j^-\to j,t}(a, h)$ (28), incorporating switching costs $\kappa(j^-, j)$ and continuation values.

   (b) **Simulate labor supply (forward).** Starting from the endogenous entry allocation implied by the sector-choice probabilities, simulate the lagged-sector distribution $\eta_{m,t}(a, h)$ forward using (29). Obtain current choice shares $\ell_{j,t}(a, h)$ from (30). Aggregate effective labor using (43) and output using (19).

   (c) **Non-durable demands (within period).** For each (t, a), solve the dynasty FOC for the non-durable composite from (14). Recover expenditure $E_t(a)$ and demands $\{c_{j,t}(a)\}_j$ from the CLM system (8)–(10).

   (d) **Durables (cohort-specific stock).** Given the full guessed paths $\{p^Q_{M,t}\}_{t=1}^T$ and $\{\lambda_t\}_{t=1}^T$ (and the demographic survival rates $\{s_t(a)\}$ computed in Step 1), compute cohort durable stocks and purchases $\{D_t(a), x_t(a)\}$ using (15)–(18), imposing $x_t(a) \ge 0$. Aggregate durable purchases $x_t = \sum_a \pi_t(a) x_t(a)$.

   (e) **Residuals.** Form composite absorption from household demands: for $j \in \{A, H\}$ use (40), for manufacturing use (41), and for the non-traded sector use (42). For each tradable $j \in \mathcal{T}$, compute $(Y^{abs}_{j,t}, m_{j,t})$ using the Armington demands (34)–(35), and compute exports $X_{j,t}$ from foreign demand (37). Compute:

   - non-traded market residual $R^L_t \equiv Y_{L,t} - \sum_a \pi_t(a) c_{L,t}(a)$ (from (42)),
   - tradable-variety residuals $R^{var}_{j,t} \equiv Y_{j,t} - Y^{abs}_{j,t} - X_{j,t}$ (from (38)),
   - trade-balance residual R^{TB}_t from (39), and
   - dynasty budget residual R^B_t from (13).

   (f) **Update prices and λ.** If the maximum (scaled) residual is below tolerances, stop. Otherwise perform a damped log-tatonnement update:

   - Update $\log p^d_{L,t}$ to reduce R^L_t, and $\log p^d_{j,t}$ for $j \in T \setminus \{M\}$ to reduce $R^{var}_{j,t}$, scaling by the magnitude of corresponding quantities and applying step-size caps and damping.
   - Update $\log e_t$ to reduce R^{TB}_t (depreciate if imports exceed exports), with caps and damping.
   - Update $\log \lambda_t$ to reduce R^B_t (raise λ_t when expenditure exceeds income), with caps and damping.

- Re-impose $p^d_{M,t} \equiv 1$ (31) by a common nominal shift (shift e_t by the same amount and apply the inverse shift to λ_t, i.e. add the shift to $\log \lambda_t$, so that $\lambda_t w_{j,t}$ is unchanged), then recompute absorption prices from (33) and wages from (36).

4. **Counterfactual demographics.** For each counterfactual path $\{\pi^{cf}_t(a)\}$, recompute $\{s^{cf}_t(a)\}$ using (6) and repeat Steps 2–3.