# Demographic Dividend and Manufacturing Employment Absorption in Indonesia: Does Human Capital Quality Moderate Regional Employment Deindustrialization?

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## Abstract

Indonesia is entering the peak of its demographic dividend even as the manufacturing sector keeps losing share, a pattern of premature deindustrialization that threatens its path to high-income status. Deindustrialization is conventionally measured by the manufacturing share of output, yet the demographic dividend is fundamentally about labor supply. This study measures deindustrialization from the labor side, namely the share of manufacturing workers in total employment, and compares it with the output-based measure. Using a panel of 33 provinces from 2010 to 2021 (391 observations), it applies two-way fixed effects, an interaction model with human capital, and separate estimates for the Western and Eastern regions. The results differ by measure. With the output measure the association is not significant, whereas with the employment measure the economic support ratio is positively and significantly associated with the manufacturing employment share, with markedly higher explanatory power and the effect strengthens with years of schooling. The association disappears under a first-difference specification and the moderation weakens without the pandemic years, so it is reported as an association rather than a causal relationship. A subsector decomposition shows that surging manufacturing output in nickel provinces is not always matched by employment: in Central Sulawesi the output share rose 22.5 points but the employment share only 3.3 points. The findings position skill-based, labor-absorbing industrialization as a priority for inclusive development.

***Keywords:*** *demographic dividend, employment absorption, human capital, premature deindustrialization, nickel downstreaming*

## INTRODUCTION

Indonesia's aspiration to become a high-income country by 2045 requires growth of six to seven percent per year, yet growth has appeared to stagnate at around five percent for two decades. The manufacturing sector that could carry industrialization past the income threshold peaked at about 28 to 29 percent of output in 2001 to 2002 and has now fallen to around 18 to 19 percent, while the manufacturing employment share has stalled at around 13 to 15 percent (BPS, various years). This early decline of the industrial sector before a country becomes rich is what Rodrik (2016) calls premature deindustrialization.

Crespo Cuaresma, Lutz, and Sanderson (2014) and Lutz et al. (2019) show that the demographic dividend essentially works as an education dividend: a rising share of the working-age population raises productivity only when the labor force is sufficiently educated. Soldan (2023) distinguishes the demographic window of opportunity, a structural condition, from the actual dividend, an outcome conditional on

policy. For Indonesia, Yusa and Gitaharie (2024) find that interventions on the economic support ratio (ESR) and human capital accelerate inter-provincial convergence. Maryam, Hailuddin, and Endri (2025) document that the demographic-window era arrives unevenly across regions with inelastic sectoral employment absorption, and Nugroho (2024) positions manufacturing as a key labor-absorbing sector toward 2045.

Deindustrialization is conventionally measured by the manufacturing share of gross regional domestic product (GRDP), but for questions about the demographic dividend this measure has a weakness. Tregenna (2009) argues that deindustrialization should be defined through declines in the manufacturing share of both employment and output, because the two can move in different directions. The demographic dividend concerns labor supply, whereas Indonesia's manufacturing output share is also driven by capital-intensive, resource-based metal smelting that absorbs few workers. As a result, the output share can rise without adding jobs. For the Indonesian context, Asyono et al. (2026) finds that nickel down-streaming lowered the labor multiplier from about 6,514 to 3,366 workers per IDR 1 trillion of final demand, with value added rising but employment intensity falling.

Two gaps emerge from prior research. First, studies of the demographic dividend generally assess its effect on aggregate growth or output (Yusa and Gitaharie, 2024; Nguea, 2024), whereas the manufacturing employment dimension, which is closest to the dividend's mechanism, is rarely tested directly at the provincial level. Second, the conditional role of human capital quality and the spatial heterogeneity of the dividend between western and eastern Indonesia have not been examined together within a single provincial deindustrialization model. Maryam et al. (2025) and Siregar et al. (2024) show that the demographic window opens at different times across regions, but its consequences for industrial structure have not been detailed. This study addresses both.

The research questions are whether the demographic dividend is related to the manufacturing employment share, whether human capital quality moderates this relationship, and whether the pattern differs between the Western (KBI) and Eastern (KTI) regions of Indonesia. The intended contribution is to place the employment-based measure alongside the output-based measure on the same provincial panel, and then trace the source of their difference through subsector analysis that separates labor-absorbing manufacturing from resource-based smelting.

## RESEARCH METHODOLOGY

The panel of 33 provinces from 2010 to 2021 comprises 396 potential observations. To keep regional boundaries consistent over the period, North Kalimantan, which split from East Kalimantan, is merged back into its parent, and new autonomous regions created after 2021 are also merged into their parent provinces. This merging is straightforward for the output and employment shares because the two areas are simply summed, but the combined ESR for East Kalimantan in 2010 to 2014 cannot be formed because the employment component for North Kalimantan was not yet available in those years. As a result, those five observations drop and estimation uses 391 observations. The period stops in 2021 to avoid the 2022 division of Papua and the shock of down-streaming policy.

The main dependent variable is the manufacturing employment share, namely persons employed in Manufacturing divided by total employed persons, from the National Labor Force Survey (Sakernas), August round. The manufacturing share of GRDP at 2010 constant prices is used as a comparator. The demographic dividend is proxied by the economic support ratio (ESR), the ratio of employed persons to total population,

following Yusa and Gitaharie (2024); this measure is available annually. Human capital quality is measured by the mean years of schooling (RLS). The operational definition of each variable is summarized in Table 1.

**Table 1. Operational Definition of Variables**

| Variable (role) | Symbol | Definition and measurement | Unit | Source |
|---|---|---|---|---|
| Manufacturing employment share (main dependent) | EMP | Persons employed in Manufacturing divided by total employed persons, x100 | Percent | BPS, Sakernas (August) |
| Manufacturing output share (comparator dependent) | - | Manufacturing value added divided by GRDP at 2010 constant prices, x100 | Percent | BPS, GRDP by industry |
| Economic support ratio (independent; demographic-dividend proxy) | ESR | Employed persons divided by total population, x100; mean-centered in estimation | Percent | BPS (Sakernas and population projection) |
| Mean years of schooling (moderator; human-capital proxy) | RLS | Mean years of formal schooling, population aged 25+ (HDI component); mean-centered | Years | BPS |
| Demographic dividend x human capital interaction | ESR x RLS | Product of mean-centered ESR and RLS | - | |
| Regional dummy | KBI | 1 for Western Indonesia region (Sumatra and Java), 0 for Eastern region (Bali-Nusa Tenggara, Kalimantan, Sulawesi, Maluku, Papua), following the 2025-2029 RPJMN classification. | 0/1 | |

Data processing proceeded in several steps. The number of Manufacturing workers per province was compiled from the Labor Force Situation (Keadaan Angkatan Kerja) publications, August rounds 2010 to 2021, and then paired with total employed persons from the same tables. North Kalimantan, which appears separately from 2013, was merged back into East Kalimantan to keep boundaries consistent over the period. Each annual series was checked against the national total published by BPS before being merged into the panel. The manufacturing employment share was then computed, ESR and RLS were mean-centered, and the interaction was formed from their product.

Estimation uses two-way fixed effects, written in Equations (1) to (3). In the notation, i denotes province and t year; EMP is the manufacturing employment share; ESR and RLS are both mean-centered; KBI is a dummy equal to one for the Western region; α is the province fixed effect, λ the year fixed effect, and ε the error term.

$$EMP_{it} = \beta_1 ESR_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (1)$$

$$EMP_{it} = \beta_1 ESR_{it} + \beta_2 RLS_{it} + \beta_3 (ESR_{it} \times RLS_{it}) + \alpha_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$EMP_{it} = \beta_1 ESR_{it} + \beta_2 RLS_{it} + \beta_3 (ESR \times RLS)_{it} + \beta_4 (ESR_{it} \times KBI_i) + \beta_5 (RLS_{it} \times KBI_i) + \beta_6 (ESR \times RLS \times KBI)_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Equation (1) estimates the direct effect of ESR. Equation (2) adds the interaction of ESR with RLS to test moderation by human capital quality. Equation (3) adds interactions

with KBI to test the regional difference, which is examined through the null hypothesis that β4 and β6 equal zero (H0: β4 = β6 = 0). All three equations are run for both dependent measures, the employment share and the output share, so that their difference is visible.

**Classical Assumption Tests**

Before interpretation, the model was checked against classical assumptions and panel-data features. The Hausman test does not reject the random-effects model at the five percent level (chi-square = 6.22; p = 0.10), but fixed effects are retained on the theoretical grounds that unobserved provincial characteristics correlate with the regressors, with random effects giving the same qualitative conclusion. Multicollinearity is not a problem: the variance inflation factor of the three regressors is close to one (at most 1.04), because mean-centering reduces the correlation of the interaction term. The Breusch-Pagan test rejects homoskedasticity (p = 0.01) and the Wooldridge test rejects the absence of autocorrelation (p < 0.01); both are common in macro panels and are addressed by standard errors clustered by province. Residuals are non-normal by the Jarque-Bera test (p < 0.01), but with 391 observations inference relies on asymptotic properties and is not materially affected.

Standard errors are clustered by province. Robustness tests include estimation excluding the pandemic years 2020 to 2021 and a first-difference specification to respond to the trending nature of ESR and RLS. Because ESR uses employed persons in the numerator while the dependent variable uses it in the denominator, any mechanical bias works toward a negative coefficient, so the positive results are conservative.

Two features specific to macro panels were also examined. The Pesaran cross-sectional dependence (CD) test on the residuals does not reject independence across provinces (CD = -0.52; p = 0.61), because the year fixed effects absorb common shocks, so the fixed-effects estimator and clustered standard errors are adequate. Panel unit-root tests indicate that the three series are persistent: the Fisher-ADF test (Maddala and Wu, 1999) does not reject the unit-root hypothesis for the manufacturing employment share, ESR, or RLS (p close to one), while the second-generation CIPS test that is robust to cross-sectional dependence (Pesaran, 2007) gives mixed results (the employment share and ESR reject the unit root, RLS is at the critical value). Because the series trend, year fixed effects are included to absorb the common trend and a first-difference specification is used as a robustness test.

## RESULTS AND DISCUSSION

**Descriptive Statistics**

The manufacturing employment share averages 9.4 percent, far below the output share of 16.0 percent, a reminder that manufacturing contributes more to value added than to jobs. The contrast between regions is sharp: the manufacturing employment share averages 12.1 percent in KBI versus 6.9 percent in KTI, while the ESR is almost the same (Table 2).

**Table 2. Descriptive Statistics**

| Variable | Mean | Std. deviation | KBI | KTI |
|---|---|---|---|---|
| Manufacturing employment share (%) | 9.40 | 5.94 | 11.96 | 6.93 |
| Manufacturing output share (%) | 16.03 | 11.38 | 21.71 | 10.80 |
| Economic support ratio (%) | 45.77 | 4.11 | 45.82 | 45.72 |
| Mean years of schooling (years) | 8.10 | 1.03 | 8.42 | 7.82 |
| Human Development Index | 68.73 | 4.56 | 70.75 | 66.93 |

Table 3 places the two measures side by side. The ESR coefficient is 0.27 and significant (p=0.02) for the manufacturing employment share, and the within R-squared rises to 0.19 compared with 0.01 for the output share. A one-percentage-point increase in ESR is associated with about a 0.27-percentage-point increase in the manufacturing employment share, or about 1.1 points for one standard deviation of ESR. For the output measure the same coefficient is not significant. The interaction of ESR with mean years of schooling is positive and significant for the employment measure (0.09; p=0.02) but not for output.

**Table 3. Two-way Fixed Effects, Employment Share (EMP) vs Output Share**

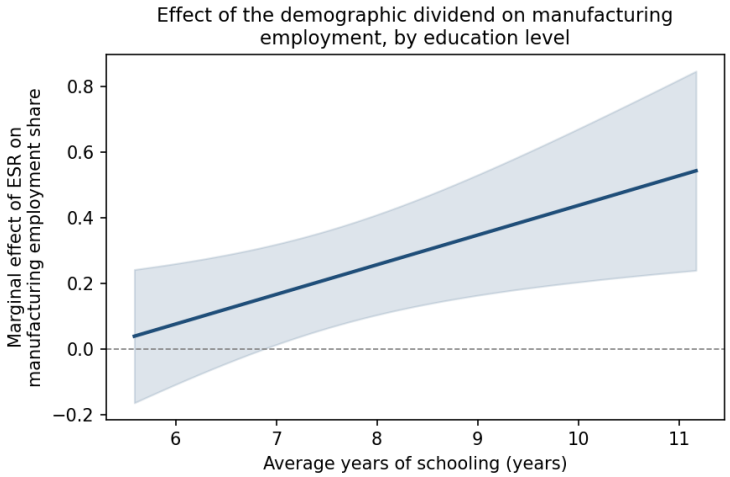
| Variable | Emp: M1 | Emp: M2 | Output: M1 | Output: M2 |
|---|---|---|---|---|
| Economic support ratio | 0.266* | 0.266*** | 0.157 | 0.148 |
| | (0.116) | (0.079) | (0.117) | (0.100) |
| Mean years of schooling | | 3.254* | | 3.954 |
| | | (1.360) | | (3.690) |
| ESR x schooling | | 0.090* | | 0.033 |
| | | (0.037) | | (0.062) |
| Within R-squared | 0.19 | 0.14 | 0.01 | - |
| Observations | 391 | 391 | 391 | 391 |

Province-clustered standard errors in parentheses. * p<0.05; *** p<0.01. Year fixed effects included.

The schooling coefficient should be read with care. The figure of 3.25 is the effect of a full additional year, yet schooling changes slowly within a province, with a within standard deviation of only 0.38 year, so the effect for a realistic within-province movement is about 1.2 percentage points, comparable to the within variation of the employment share (1.6 points). The coefficient is identified from small within variation, so it is large but imprecise. A leave-one-province-out jackknife confirms that no single province drives it: the coefficient remains positive in the range 2.0 to 3.6, lowest when the Riau Islands is dropped.

The effect of ESR on manufacturing employment strengthens with education, from near zero in the least-educated provinces to about 0.54 in the most educated (Figure 1). This is an empirical form of the demographic-dividend-as-education-dividend argument: the demographic window turns into manufacturing jobs when the labor force is sufficiently educated. For the output measure this moderation is not visible at all.

**Figure 1. Marginal Effect of ESR on the Manufacturing Employment Share by Years of Schooling**




The relationship is concentrated in KBI, where the direct effect (0.25; p=0.02) and the moderation (0.19; p=0.03) are both significant, while in KTI neither is significant (p=0.58; p=0.70). The formal test shows that the difference in the direct effect across regions is not significant (ESR × KBI = −0.010; p=0.92), but the difference in moderation is significant (ESR × RLS × KBI = 0.205; p=0.014; Table 4).The channel from the dividend to jobs through education appears stronger in the West, and the regional gap lies specifically in how education converts the dividend into manufacturing jobs.

**Table 4. Regional heterogeneity of the demographic dividend (RPJMN classification)**

| | Dependent variable: manufacturing employment share | |
|---|---|---|
| | West — KBI | East — KTI |
| ***Panel A. Subsample estimates*** | | |
| Economic support ratio (ESR) | 0.247* | 0.050 |
| | (0.099) | (0.087) |
| Mean years of schooling (RLS) | 3.589 | 1.370 |
| | (3.195) | (0.959) |
| ESR × RLS (moderation) | 0.186* | −0.021 |
| | (0.082) | (0.054) |
| Observations | 192 | 199 |
| Provinces | 16 | 17 |
| ***Panel B. Cross-region difference (pooled Eq. 3)*** | | |
| ESR × KBI (Δ direct effect) | −0.010 (0.107) | p = 0.924 |
| RLS × KBI | −1.455* (0.647) | p = 0.025 |
| ESR × RLS × KBI (Δ moderation) | 0.205* (0.083) | p = 0.014 |
| Joint test (H0: Δ direct = Δ moderation = 0) | — | p = 0.046 |
| Within $R^2$ / Observations (pooled) | 0.366 | 391 |

*Notes: Two-way fixed effects (province and year); province-clustered standard errors in parentheses. ESR and RLS are mean-centered. * p < 0.05; *** p < 0.01.*

This study recognizes the potential endogeneity of ESR. An attempt to control for it using dynamic panel specifications (difference and system GMM) was made. However, diagnostic testing shows that the internal instruments do not meet the validity criterion (Hansen test) and the model fails the AR(2) autocorrelation test. The GMM estimates are therefore not retained. Instead, the study relies on the two-way fixed-effects specification with clustered standard errors and presents first-difference estimates as a robustness test. Consequently, the results are interpreted cautiously as a strong conditional association rather than an absolute causal claim.

**Robustness Test**

Excluding the pandemic years 2020 to 2021, the direct effect holds (0.26; p=0.02) but the moderation weakens and loses significance (p=0.24). Under the first-difference specification, which responds to the trending nature of ESR and RLS, the direct association disappears (p=0.20). The findings are presented as a level association with fixed effects, not a causal relationship. ESR is potentially endogenous and identification has not ruled out other channels. What can be claimed is that the employment-based measure captures a demography-industry link that the output measure misses, it cannot prove that the demographic dividend slows deindustrialization.

The difference between the two measures is rooted in the composition of manufacturing. Table 5 compares the change in the output share and the employment share from 2010 to 2021. In Central Sulawesi the manufacturing output share rose 22.5 percentage points after nickel smelters began operating, but its employment share rose only 3.3 points, showing that capital-intensive smelting absorbs little labor. North Maluku, by contrast, shows a large increase in the employment share, so there the nickel boom appears to have added manufacturing jobs as well. In densely populated provinces such as Banten and West Java, both output and manufacturing employment shrank.

**Table 5. Change in manufacturing output share vs employment share, 2010 to 2021**

| Province | Change in output share (pp) | Change in employment share (pp) |
|---|---|---|
| Central Sulawesi | +22.5 | +3.3 |
| North Maluku | +12.2 | +14.3 |
| Banten | -6.1 | -2.2 |
| West Java | -2.2 | -0.6 |

Source: BPS

## CONCLUSION

When deindustrialization is measured from the labor side, the demographic dividend is positively associated with the manufacturing employment share and its effect strengthens significantly with mean years of schooling, a structural link that is not detected using the output measure alone. The explanatory power of the employment model exceeds that of the output model. However, this association is sensitive to specification, since its significance disappears under first-difference and weakens without the pandemic observations. The relationship is interpreted as a level association rather than an absolute causal claim. The data decomposition explains the root of the difference between the two measures: the surge in the output share in some eastern provinces rests on capital-intensive nickel smelting that is inelastic in absorbing labor. This shows that a higher

output share does not necessarily mark inclusive industrialization.

## RECOMMENDATION

### Policy recommendations

First, skills investment should be directed to regions with a surplus of young labor, through vocational training aligned with industry needs (Nugroho, 2024; Kumar and Shukla, 2026; Singh, 2025), because the demographic dividend turns into manufacturing jobs only when the labor force is sufficiently skilled. Second, incentives can be given to labor-absorbing manufacturing rather than adding capital-intensive smelting capacity that absorbs few workers, resource down-streaming should be tied to local-linkage obligations and the development of more labor-intensive downstream industries so that rising output also opens jobs. Third, policy should be targeted spatially, in the western region strengthen the education-to-industry pathway that is already more responsive, while in the eastern region prioritize the prerequisites, namely the quality of basic and secondary education and a supporting industrial ecosystem, before the demographic dividend can be absorbed.

### Future research

The limits to causal identification in this study open opportunities for further research. Future work can move to the district and city level to enlarge the variation in observations (N). The greater availability of district-level data would allow the application of spatial econometrics to test agglomeration spillovers across regions, and the use of dynamic panel estimators with longer instrument lags to resolve the endogeneity that remains unsettled at the provincial level. In addition, future research could include other variables that shape the demographic dividend's interactions, such as the agricultural sector, gender, investment, and other factors. Measuring human capital quality can also use expected years of schooling and competency levels, in addition to the currently used mean years of schooling.

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