Total factor productivity convergence of Indonesia's provincial economies, 2011–2017

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This study aims to investigate the potential convergence process of total factor productivity (TFP) among 33 provinces in Indonesia in a period between 2011 and 2017. It is the first study that captures the effect of intra-provincial trade and international trade on the TFP convergence. The authors employ stochastic frontier analysis to identify the TFP and generalized methods of moment (GMM) to examine the convergence process. The result of this study confirms that the TFP convergence process in Indonesia occurred in 2011–2017. Concerning intra-provincial and international trades, the study discovered that neither of them promotes TFP growth. Rather, except for the international import, they reduce the gap of TFP growth amongst provinces. The result demonstrates that intra-provincial exports reduce the TFP growth gap by 19.7% more than international exports. This finding indicates that intra-provincial exports are more efficacious in reducing regional inequality. The same is true for the intra-provincial import. This finding delivers essential policy implications such as streamlining the development policies across provinces, albeit the prevailing decentralization program. This should inform the formulation of regional regulations so these will not hinder the provincial growth convergence.

Introduction

The issue of regional disparity became a central point of attention in Indonesia's development master plan, specifically in relation to inequality, resource endowment and population distribution. Attention to this issue has significantly grown after decentralisation was formalised by Indonesian Laws 22/1999 and 25/1999 and was then implemented in 2001 (Vidyattama 2013). Ever since, the central government has been delegating responsibilities in the areas of education, agriculture, industry, investment, infrastructure and trade to regional authorities at province or district levels. As such, there is a possibility of convergence among regions and it is essential to seek the momentum (Rodríguez-Pose–Ezcurra 2010).

Since trade is part of the decentralisation agenda, there is a pressing need for regional authorities to foster economic growth through international and intra-provincial trade activities. Trade activities are pivotal drivers of economic growth as regions can engage and maintain relationships with advanced markets, which can offer sophisticated technology (Blalock–Veloso 2007). Export activities, for instance, are associated with the ability to produce and develop high-standard products to satisfy the demanding advanced markets. Consequently, a region will allocate more budget for human capital improvement, such as training or capacity building, or for the provision of advanced technologies to generate qualified outputs. With this, technology diffusion amongst regions as well as countries is likely to occur.

Analysing economic growth requires an identification of its drivers. Regional factors of production, such as capital and labour, contribute significantly to economic growth, so it is essential to identify the extent to which these factors affect productivity. Total factor productivity (TFP) satisfies this query by providing methods, such as growth accounting and frontier approaches. Growth accounting approach merely acknowledges technological progress or technical change as a unique contributor of TFP. Meanwhile, frontier approach captures more variation of TFP amongst regions because each region has their specific level relative to the optimal level (Farrell 1957). Moreover, measuring TFP with the frontier approach can decompose other elements i.e., economic efficiency change (the change of the distance relatively to the frontier) and the technical change (the shifting frontier condition) (Margonoet al. 2011). Therefore, frontier approach can provide a more holistic perspective.

Studies have examined the significant impact of trade on TFP (e.g., Damijan et al. 2009, Keller 2010, Kotrajaras et al. 2011, Saha 2012) and attempted to identify the possible convergence moments in a decentralised governance (Rodríguez-Pose–Ezcurra 2010). However, to the best of the authors' knowledge, there are no robust studies that have investigated how trade between provinces (intra-provincial trade), and trade with foreign countries (international trade), contribute to promoting TFP inequality reduction and regional catching-up moment in Indonesia.

This study contributes to the literature by identifying, firstly, the TFP growth convergence of 33 provinces in Indonesia in order to capture the contribution of inputs, i.e. gross fixed capital formation and labour force, to the output generation. Secondly, the case of Indonesia is unique as it is an archipelagic country with more than 17,500 islands and 300 ethnic groups (OECD 2018). Hence, the finding can capture the heterogeneity and become a reference for future studies. Thirdly, examining the impact of intra-provincial and international trade on convergence is novel and this will extend the body of knowledge about economic development. The study of the impact of trade activities on productivity convergence is essential in order to find out what channels in trade activities contribute to reduce disparity and accelerate the catch-up among regions. Fourthly, potential technology diffusion across provinces in Indonesia, as well as between Indonesia and other countries, can be captured since trade activities involve the use of technology (Fu et al. 2011). Ultimately this study can be considered as a policy examination intended to evaluate whether the current trade activities at the intra-provincial and international level have promoted equality.

The rest of the paper is organised as follows: discusses the theoretical framework, explains the study's data and methodology, presents the main result. Finally, the conclusion and proposed policy are presented.

Literature review

The impact of trade activities on the economy

A great deal of the literature on convergence issues often refers to the work of Barro–Sala-i-Martin (1992). However, only few studies discuss the impact of trade on the convergence of TFP, apart from Rassekh–Ranjbar (2011). Accordingly, the current study only consults the studies that specifically address the impact of trade activities on economic convergence. Previous studies provide a point of reference to help identify the impact of trade activities on economic convergence on the intra-regional scale within a country (Aritenang, 2016, Jiang 2011, Zhang–Zhang 2003); intra-regional scale of cross-border country (e.g. Velde 2011, Libman–Vinokurov 2012), and the international scale (Berry et al. 2014; Rassekh–Ranjbar 2011).

Jiang (2011) studied the effect of openness on the productivity growth and conditional convergence in Chinese provinces. The study presents historical evidence that China was a closed country until 1978, but then it started its transformation into an open country with a rapid economic growth (over 9%) in 1978–2005. Jiang (2011) highlighted two possible channels through which openness significantly fosters regional economic growth. First, openness may directly affect China's regional productivity, but this seems to have no bearing towards the gap between a Chinese region and the world technology frontier. In this condition, openness would generally impact the regional productivity without driving the underdeveloped regions to catch up. Second, openness may benefit regional performance as there is technology convergence involved. In contrast, Guo (2017) emphasised that as the open economy started, asymmetric trade across regions emerged due to pre-existing income inequality between rural and urban areas. Policy makers seek to reduce the gaps by optimising e.g., factor mobility, the flow of capital, labour, as well as technology.

Another study of intra-regional issue within a country is by Aritenang (2016), which investigated the impact of the devolution and trade liberalisation of Association of Southeast Asian Nations (ASEAN) Free Trade Area (AFTA) on the potential convergence among districts in Indonesia from 1993 to 2005. By examining the unconditional Beta convergence, this study concluded that districts in Indonesia experienced income convergence that boosted poorer districts' growth faster than advanced districts'. The catching-up movement has become more apparent since the government adopted a decentralised system. This result was supported by Aritenang (2016), stating that devolution negatively correlated with economic growth, indicating that the decentralisation reduced the growth gap among districts. In addition to this, the tarrif elimination agreement reflected in AFTA had a positive impact on economic growth, although the effect was statistically insignificant. This confirms the study results by Rodríguez-Pose–Gill (2006) stating that there is a weak influence of trade on disparity and the low intra-trade performance in the AFTA implementation.

Velde (2011) investigated the effect of regional integration on growth convergence amongst 100 developing countries, which were grouped into certain regional integration agreements, such as ASEAN, Economic and Monetary Community of Central Africa (CEMAC), Common Market of Eastern and Southern Africa (COMESA) and East African Community (EAC). This research found that regional integration is a pivotal solution to foster connections amongst countries, but did not find a considerable effect of intra-regional trade on income disparity reduction. Meanwhile, the role of development financing institution as captured by loan exposure over regional gross domestic product (GDP) has a positive relation with income disparities reduction. As Velde's results (2011) were debatable, subsequent study by Bong–Premaratne (2018) demonstrated the effect of regional integration on economic growth, specifically in Southeast Asian countries. They discovered that the effect of international trade among Southeast Asian countries would be significant if public institutions got involved by reducing the political and macroeconomic instability.

In terms of the effect of trade on regional economic convergence, a study by Rassekh–Ranjbar (2011) covered 77 countries representing various income categories for the period 1960–2003. They found that the effect of trade on the convergence of GDP and TFP only happened during the period of 1960–1979. The following years, 1983–2003, and the whole 1960–2003, were divergent. Regarding this result, Dowrick–Golley (2004) and Cebrián–López (2004) argued that technology transfer, as an impact of trade activities, was indeed transferred from developed countries to developing countries in 1980, which, in turn, narrowed the gap between them. However, since 1980, the presence of information technology

(IT), which benefitted developed countries more than developing countries, widened the gap once again. Therefore, it can be argued that the transfer of knowledge, as a spill-over from trade activities, reduces regional disparities only if developing countries can optimise advanced technology they receive from the more developed countries.

Efficiency and productivity

Efficiency is achieved when an additional output leads to decreasing the least number of other outputs and increasing at least one input. Specifically, technical efficiency is a condition when a producer creates different outputs using minimal input; or optimises input to produce more outputs (Coelli 1996). Technical efficiency measurement was proposed by Debreu (1951) and Farrell (1957) to differentiate between terminology of technical efficiency and economic efficiency. Banker et al. (1984) broke down technical efficiency into two parts: pure technical efficiency and scale efficiency, which measures how close production is to the most efficient scale size.

Technical efficiency is associated in some studies with TFP. For instance, TFP displays the best definition of the productivity notion as it describes how each country transforms physical capital and labour into output. Solow (1956) measured TFP by using the residual approach referred to as the Solow Residual. However, this approach only acknowledges technological progress as a unique contributor to TFP. Farrell (1957) suggested the notion of frontier production function as the best practice, which leads to the variation of the TFP score of observations. Orea (2002) maintains that TFP comprises technical efficiency and scale efficiency, as well as technical change. Technical efficiency contributes to TFP by measuring its growth between periods. Likewise, technical change or technological progress, that is defined as a shifting towards the frontier, contributes to TFP by differentiating the output over time. Another component of TFP is scale efficiency that is calculated from the elasticity of each input to produce outputs.

Data and methodology

Data and variables

This study employs panel data of 33 provinces in Indonesia from 2011 to 2017. The data was collected from the annual reports from the Central Bureau of Statistics (BPS) of Indonesia. Two reasons led to choosing the period of 2011–2017 – because it was the decentralisation period (post 2001) and because of the data availability of both intra-provincial and international export and import. Other periods were not considered in this study because BPS' reports did not separate intra-provincial and international trades.

This study uses three groups of variables: production frontier, inefficiency effect and the determinants of convergence. Variables in the production frontier are: output proxied by nominal gross domestic regional product (GDRP) in Rupiah, inputs that consist of capital proxied by nominal gross fixed capital formation (GFCF) in Rupiah and labour proxied by the number of labour force. Variables in the inefficiency effect only contain the time trend. Meanwhile, variables in the determinants of convergence encompass: intra-provincial export, international export, intra-provincial import, and international import. The determinants of convergence are measured through their ratio to the GDRP (Mitsis 2021).

There might be a biased analysis if the monetary-value variables such as output, capital, intra-provincial export, international export, intra-provincial import, and international import are directly employed. Therefore, this study adjusts monetary variables in accordance with the price index in order to make the data constant. An aggregate price deflator may not be adequate for regional variables, e.g. GDRP and GFCF. Hence, this study uses the deflating methodology and provinces' price indices with 2010 as the base year.

Model for stochastic production frontier

This study is based on the production function defined as a mathematical representation of the technology that converts input into output(s) (Kumbhakar et al. 2015). If inputs and outputs are acknowledged as two categories, the relationship between inputs and outputs can be denoted as $f(x, y)=0$, where x stands for J dimensional non-negative input vector while y is an M dimensional non-negative output vector. Therefore, the general formulation of the production function can be expressed as follows:

$$y = f(x_1, x_2, x_3, \dots x_j) \equiv f(x) \tag{1a}$$

where the function $f(.)$ expresses the technology controlling the input-output relationship and is single valued.

This study employs stochastic production frontier approach that was initially proposed by Aigner et al. (1977). The approach deploys the time varying model of Battese–Coelli (1995) that is estimated with maximum likelihood. The time varying model was selected because this study acknowledges the change of provinces' efficiency over time – be it efficiency improvement or deterioration (Kumbhakar et al. 2015). The model of Battese–Coelli (1995) includes a time variable in the inefficiency effect to capture the dynamic of efficiency scores, whether they converge or diverge towards the frontier. This study hypothesises transcendental logarithmic (Translog) as the most suitable production function to be employed. To test the hypothesis, generalised log-likelihood ratio (LLR) is used by comparing alternative production functions e.g., Hicks-neutral (HN), no technological progress (NTP) and Cobb-Douglas (CD). The production function using Translog specification, which considers a number of N inputs (production factors), can be stated as follows:

$$y_{it} = \beta_0 + \sum_{n=1}^{N} \beta_n xn_{it} + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm}\, xn_{it} xm_{it} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \sum_{m=1}^{N} \beta_{nt}\, xn_{it} t_{it} + \sum_{d=2}^{D} \beta_d Dd_i + v_{it} - u_{it} \qquad (1b)$$

where y is the natural logarithm *ln* of total output and *xn* represents inputs consisting of capital (*k*) and labour (*l*). Subscripts *i* and *t* denote the *i*-th province and *t*-th year. Dd_i is the province specific dummy. v_{it} is the stochastic production frontier model's random variable assumed as $iid.N(0, \sigma_v^2)$, and u_{it} is a non-negative random variable assumed as the half-truncated normal ($N^+(u_i, \sigma_u^2)$) in distribution and is the inefficiency parameter that captures the inefficiency effects, specified as follows:

$$u_{it} = \delta_0 + \delta_1 time + \omega_{it} \qquad (2)$$

where u_{it} is the inefficiency effect needed to calculate technical efficiency (TE) that is explained in (2a)–(2d). δ_1 is the coefficient of time trend that is negative if there is efficiency improvement over time, and vice versa. ω_{it} is error.

$$TE_{it} = \frac{y_{it}}{\hat{y}_{it}} = \qquad (2a)$$

$$= \frac{f(x_{it}, z_{it}; \beta).\exp\,(v_{it} - u_{it})}{f(x_{it}, z_{it}; \beta).\exp(v_{it})} = \qquad (2b)$$

$$= \exp(-u_{it}) = \qquad (2c)$$

$$= \exp(-\delta_0 - \delta_1 time_{it} - \omega_{it}) \qquad (2d)$$

where y_{it} is the realised output and $\hat{y}_{it}$ is the potential maximum output. Meanwhile, TE is the ratio of y_{it} and $\hat{y}_{it}$, it ranges between 0 and 1. When TEs are closer to 1, the realised outputs are closer to their optimal output value. Under acceptable distributional assumptions for both error components, the parameters of the output frontier and the inefficiency effect are calculated simultaneously using a maximum-likelihood process (Sari et al. 2016). The likelihood function is described by variance $\sigma^2 \equiv \sigma_v^2 + \sigma_u^2$ and $\gamma \equiv \sigma_u^2/\sigma^2$ parameters ranging from 0 to 1. If γ equals or converges to zero or $\sigma_v^2 > \sigma_u^2$, the model is devoted to a traditional production function with the absent of inefficiency function. This means that the ordinary least square (OLS) suits the data better. The frontier model, on the other hand, is appropriate if γ is closer to unity, which means $\sigma_v^2 > \sigma_u^2$ or the presence of inefficiency is essential.

The Translog's coefficients obtained from the estimation of production function cannot be directly interpreted (Sari et al. 2016). Hence, in order to make it interpretable, the elasticities of labour and capital can be observed. Referring to (1b), since the marginal product of input *j* is $MP_x = \frac{\partial y}{\partial x_j} = (\frac{\partial (ln\, y)}{\partial (ln\, x_j)})(\frac{y}{x_j})$, and the ratio of marginal product of capital, as well as marginal product of labour reflect the marginal rate of substitution (Morrison-Paul et al. 2000), the ratio of labour's and capital's elasticities can be interpreted as a normalised indicator of substitutability that is specified as follows:

$$sub_{KL} = \frac{MP_K}{MP_L} \times \frac{K}{L} = \frac{\epsilon_{yK}}{\epsilon_{yL}} \tag{3}$$

where MP_K is the marginal productivity of capital, MP_L is the marginal productivity of labour, K is capital, L is labour, $\in_{yK}$ is the elasticity of capital, $\in_{yL}$ is the elasticity of labour and sub_{KL} is the substitutability between capital and labour. The negative sub_{KL} indicates that capital and labour have a complementary relation by which an increase of one unit of labour is associated, on average, to an increase of capital at a magnitude of sub_{KL}; otherwise, the relation of capital and labour is substitutive (Arazmuradov et al. 2014).

The generalised LLR test is used to select the most suitable production function. There are three alternatives of production functions in this study: CD, NTP, and HN. Referring to (1b), a null hypothesis (H0) that is $\beta_{nm}=\beta_{nt}=\beta_{tt}=0$ or the coefficients of time-squared and interacting input with time is equal to zero, is the hypothesis for CD. A null hypothesis (H0) that is ($\beta_t=\beta_{tt}=\beta_{nt}=0$) or the coefficients of time, interacting input with time, and time-squared are equal to zero, is the hypothesis for NTP. A null hypothesis (H0) that is ($\beta_{nt}=0$) or the coefficients of interacting input with time is equal to zero, is the hypothesis for HN. Test of OLS is also considered to ensure that the utilization of SFA is valid.

The log-likelihood ratio test is conducted by comparing the likelihood ratio statistic obtained from each model. The log-likelihood statistic is obtained from $\lambda=-2[l(H_0)-l(H_1)]$ where $l(H_0)$ is the log-likelihood statistic of CD, NTP, HN, and OLS, while $l(H_1)$ is the log-likelihood value of Translog. The null hypothesis is rejected if the λ statistic is less than the x^2 table with degrees of freedom equal to the number of parameters involved in the restrictions.

Total factor productivity

This study adopts the method of Arazmuradov et al. (2014) to estimate TFP which is a geometric approach that decomposes TFP into two components: technical efficiency change (TEC) and technical change (TC). The formulas to attain those components are shown below:

$$TFP_{it} = TEC_{it} \times TC_{it} \tag{4}$$

$$TEC_{it} = \frac{TE_{it}}{TE_{it-1}} \tag{5}$$

$$TE_{it} = \exp(-u_{it}) \tag{6}$$

$$TC_{it} = \sqrt{\left[\left(1 + f_t(Y_{it}, L_{it}, K_{it}, t, \beta_0, \beta) \times \left(1 + f_{t-1}(Y_{i,t-1}, L_{i,t-1}, K_{i,t-1}, t, \beta_0, \beta)\right)\right)\right]} \tag{7}$$

where TFP_{it} is total factor productivity, TEC_{it} is technical efficiency change, TE_{it} is technical efficiency obtained from (2) and (2a)–(2d). TC_{it} is technical change. As this approach is a geometric mean, TFP>1, TEC>1, TC>1 imply positive magnitudes.

Model of convergence

Convergence theory was proposed by Barro–Sala-i-Martin (1992) who employed the case of growth rate of capital. They postulated that massive developments, e.g., in infrastructures and public facilities, in poor countries lead to the rise of capital allocation growth. Therefore, the capital growth of poor countries is relatively higher than that of the rich countries that have accomplished their infrastructure development some years before poor countries did (Purwono et al., 2020).

Convergence theory is divided into two concepts: Beta convergence and Sigma convergence. The aim of the Beta convergence tests is to regress mean country TFP levels on the initial level; if the TFP is negatively associated with the initial level, the test result is positive, implying that countries with lower initial levels have faster TFP improvements than countries with higher initial levels, which eventually leads to convergence (Wild 2016). Therefore, there is a catching-up moment between countries. Meanwhile, Sigma convergence aims to identify the dispersion or variation evolution between countries (Egri–Tánczos 2018, Weill 2009). Sigma convergence occurs if the dispersion decreases over time, which means that a country converges to the average level of the group of countries.

To capture TFP convergence amongst provinces, this study employs a dynamic generalised method of moment (GMM) approach by Arellano–Bond (1991) with standard model as follows:

$$y_{it} = \alpha_0 y_{it-1} + X_{it}^{'}\alpha_j + \mu_i + \varepsilon_{it} \tag{8}$$

where y_{it} represents the dependent variable of individual i at period t; X'_{it} is vector of other regressors; μ_i and ε_{it} indicate individual-specific effects and idiosyncratic error. It requires difference transformation to purge individual-specific effects so that it yields:

$$\Delta y_{it} = \alpha_0 \Delta y_{it-1} + \Delta X_{it}^{'}\alpha_j + \Delta\varepsilon_{it} \tag{9}$$

The existence of the dynamic component (y_{it-1}) makes OLS estimation to produce inconsistent parameter estimates due to its correlation with the error $\Delta\varepsilon_{it}$, which is known as Nickell bias (Nickell 1981). To produce consistent estimators, Anderson–Hsiao (1982) and Holtz-Eakin et al. (1988) proposed instrumental variable (IV) estimation of the parameters in the first-difference model using lags of the dependent variable as an instrument. The estimator is called the Arellano-Bond estimator or a difference-GMM (diff-GMM) after the work of Arellano–Bond (1991), which suggested tests of crucial assumption that the idiosyncratic errors are serially uncorrelated. The estimator is based on the following moment condition:

$$E(y_{is}\Delta\varepsilon_{it}) = 0 \text{ for s} \leq \text{t} - 2 \tag{10}$$

The estimation technique has crucial assumptions, which are testable (Gnangnon 2019). First, the error must be serially uncorrelated. If errors are serially uncorrelated, there will be a correlation in the first-order differentiated error (AR(1)) but not in the second-order autocorrelation (AR(2)). In other words, the tests have to reject the null hypothesis stating no autocorrelation in the error term in AR(1), and have to not reject it in AR(2). Second, a test of overidentifying restrictions (OIR test) that decides the validity of the population moment conditions. The Sargan test is employed to test the null hypothesis that population moment conditions are valid. The Sargan test considers the Chi-Square. If Chi-Square value's probability is less than its significance rate at 10%, then the model is not valid (Purwono–Yasin 2020). This study implements one-step difference-GMM (diff-GMM) and uses two-step estimation procedure for checking the robustness of the model. All explanatory variables are treated as exogenous, while the treatment of predetermined and endogenous are considered for robustness tests. To avoid the instrument proliferation as in (10), the study follows Roodman (2009) to collapse the instrument sets.

This study employs two concepts of convergence: Beta convergence and Sigma convergence. We set four different models to robustly capture intra-provincial trade and international trade impact on convergence of TFP growth and TFP growth dispersion. Beta convergence is specified in Model 1 and Model 2, which refer to 11a–11b respectively to capture the impact of intra-provincial export and international export (11a) and intra-provincial import and international import (11b), on the TFP growth. Sigma convergence is specified in Model 3 and Model 4, which refer to 12a–12b respectively to capture the impact of intra-provincial export and international export (12a) and intra-provincial import and international import (12b), on the dispersion of TFP growth. These equations are specified as follows:

$$ln\,TFP_{it} - ln\,TFP_{it-1} = \tau_0 + \tau_1\, ln\,TFP_{it-1} + \tau_2 Intra\ Export_{it} + \tau_3 Inter\ Export_{it} + \epsilon_{it} \quad (11a)$$

$$ln\,TFP_{it} - ln\,TFP_{it-1} = \alpha_0 + \alpha_1\, ln\,TFP_{it-1} + \alpha_2 Intra\ Import_{it} + \alpha_3 Inter\ Import_{it} + \phi_{it} \quad (11b)$$

$$\Delta W_{it} = \zeta_0 + \zeta_1 W_{it-1} + \zeta_2 Intra\ Export_{it} + \zeta_3 Inter\ Export_{it} + e_{it} \quad (12a)$$

$$\Delta W_{it} = \xi_0 + \xi_1 W_{it-1} + \xi_2 Intra\ Import_{it} + \xi_3 Inter\ Import_{it} + \varepsilon_{it} \quad (12b)$$

where TFP_{it} is the total factor productivity in ratio. $lnTFP_{it} - lnTFP_{it-1}$ is total factor productivity growth. τ_1, α_1 are scalars that are negative if Beta convergence occurs. W_{it} is the natural logarithmic of TFP of province i in year t ($lnTFP_{it}$) subtracted from the average natural logarithmic TFP in year t ($MTFP_{it}$). ΔW_{it} is the W_{it} subtracted from W_{it-1}. ζ_1, ξ_1 are scalars that are negative if Sigma convergence exists. $\epsilon_{it}, \phi_{it}, e_{it}, \varepsilon_{it}$ are the error terms. τ_2 and τ_3 are the coefficients of intra-provincial export and international export respectively, which are expected to be positive for Beta convergence (Model 1). ζ_2 and ζ_3 are the coefficients of intra-provincial export and international export, which are expected to be negative for Sigma convergence (Model 3). α_2 and α_3 are the coefficients of intra-provincial import and international import, which are expected to be positive for Beta convergence (Model 2). ξ_2 and ξ_3 are the coefficients of intra-provincial import and international import that are expected to be negative for Sigma convergence (Model 4). The positive signs of $\tau_2, \tau_3, \alpha_2, \alpha_3$ of Beta convergence mean that trades promote the catching up moment of TFP growth's provinces. Meanwhile, the negative signs of $\zeta_2, \zeta_3, \xi_2, \xi_3$ of Sigma convergence mean that trades encourage the TFP inequality reduction among provinces.

Result and discussion

The analysis starts with looking at the result of the generalised log-likelihood ratio test. This test can reveal which production functions are suitable for our observation. The result of the test is reported in the Table 1.

Table 1

Test of log-likelihood ratio (LLR)

Model	Cobb Douglas (df=7) $H0: \beta_{tt} = \beta_{nm} = \beta_{nt} = 0$	No Technological Progress (df=4) $H0: \beta_{tt} = \beta_{nt} = 0$	Hick-Neutral (df=2) $H0: \beta_{nt} = 0$	No Inefficiency (OLS) (df=11) $H0: \gamma = 0$	Decision
Translog (H1)	62.1	42.5	23.0	488.1	Translog
Critical value of x^2 at a=1%	18.5	13.3	9.2	24.7	

By referring to α=1% in x^2 table (see Sari 2019, Sari et al. 2016), the result shows that λ> x^2 table decides the Translog specification as a proper model to measure the impact of determinants on efficiency.

Table 2 reports the estimation of the stochastic production frontier. The first parameter that needs to be considered is γ that shows 0.999. Margono et al. (2011) concluded that this magnitude indicates a majority of error's variations σ^2, which consists of σ_v^2 and σ_u^2 in (1b). They stem from inefficiency component (u_{it}) and is not obtained from the measurement error v_{it}. Therefore, the utilisation of the stochastic production frontier model in this study is appropriate and robust.

According to Table 2, it is observed that five variables in the production frontier are significant at alpha 10%. The coefficient of the Translog function cannot be directly interpreted (Sari et al. 2016). To make the coefficients interpretable, we estimate output elasticity between capital and labour based on (3). This study estimates that the value of substitutability=3.67, which means that one more unit of labour is averagely related to a decrease of a 3.67 unit of capital. This magnitude indicates that there is a substitutive relation between capital and labour in the Indonesian provinces.

Table 2

Stochastic production frontier estimation

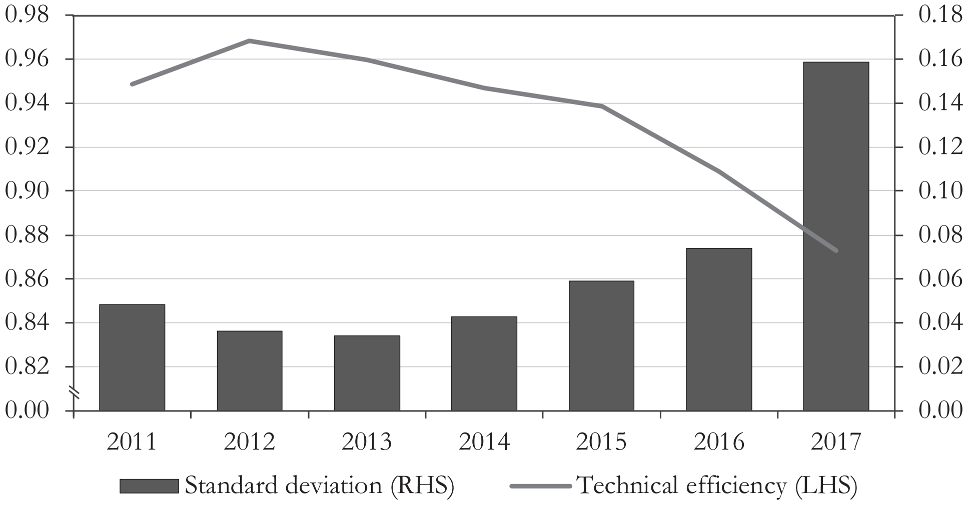
Variable	Parameter	Coefficient
	Production frontier	
lnK	β_k	0.894*** (0.02)
lnL	β_l	0.263** (0.12)
lnK x *lnL*	β_{kl}	–0.080*** (0.03)
lnK x *lnK*	β_{kk}	0.016 (0.01)
lnL x *lnL*	β_{ll}	–0.026 (0.06)
time	β_t	–0.028*** (0.006
time^2	β_{tt}	0.004*** (0.00)
time x *lnK*	β_{kt}	0.005 (0.00)
time x *lnL*	β_{lt}	0.002 (0.00)
	Inefficiency effect	
time	δ_1	0.239*** (0.03)
σ^2	0.087*** (0.00)	
γ	0.999*** (0.00)	

Note: ***, **, *=significance at alpha 1%, 5% and 10%. Dummy variables are not reported. Standard errors are in parentheses.

According to Table 2, the coefficient of time trend variable in the inefficiency effect is found to be positively significant. This suggests that the technical efficiency of provinces in Indonesia worsens over time. This finding is validated in Figure 1, which illustrates the trend of efficiency score and deviation over time.

Figure 1

Average efficiency and deviation of 33 provinces in Indonesia



Note: RHS= right-hand side, LHS=left-hand side.

Figure 1 illustrates that there is a downward trend of technical efficiency among provinces in Indonesia in 2011–2017. This condition is exacerbated by the deviation's upward trend since 2013. This suggests that inequalities of efficiency scores between provinces increase along with their worsened technical efficiency on average. The distribution of technical efficiency (TE) score, total factor productivity growth (TFP), technical change (TC), technical efficiency change (TEC) see Figures A1–A4 in the Appendix.

Table 3 reports the estimation result of TFP and its decomposition that consists of technical efficiency change (TEC) and technical change (TC).

According to Table 3, on average, Indonesian provinces experienced negative TFP growth (–0.1%) during the 2011–2017 period. Concerning sub-periods, 2011–2013 shows a positive TFP growth at 0.3%, in contrast with 2015–2017 that shows a negative TFP growth at –1.7%. The three largest TFP growths are those in North Sulawesi (3%), Bali (2.7%), and Jakarta (2.2%). Meanwhile, the three lowest negative TFP growths are found in East Nusa Tenggara (–4.4%), Riau (–4.8%), and Bengkulu (–15%). Meanwhile, TC averagely shows a positive magnitude at 0.3% in 2011–2017. This suggests that Indonesian provinces have demonstrated a technological progress in terms of the contribution of capital and labour towards obtaining GDRP. This study stresses that three regions which demonstrated the largest technological progress are all on Java Island i.e. Jakarta (1.2%), East Java (1.2%) and West Java (1.1%). This finding indicates that the shifting frontier of capital and labour generating output remains relatively centralised in the area of

Java. With regards to technical efficiency change, the result demonstrates a negative growth of technical efficiency in 2011–2017, by –1.3%. This result confirms the previous conclusion that, on average, efficiency scores relatively worsened.

Table 3

Total factor productivity (TFP), technical change (TC), and technical efficiency change (TEC) of 33 provinces in Indonesia

Province	TFP			TC			TEC		
	2012–2013	2015–2017	2011–2017	2012–2013	2015–2017	2011–2017	2012–2013	2015–2017	2011–2017
Aceh	1.002	0.984	0.984	0.995	1.009	1.003	1.007	0.975	0.981
North Sumatera	0.986	1.005	1.003	1.000	1.014	1.008	0.987	0.991	0.996
West Sumatera	1.029	1.002	1.008	0.996	1.010	1.004	1.034	0.993	1.005
Riau	1.008	0.906	0.952	0.999	1.013	1.007	1.009	0.894	0.945
Jambi	0.955	1.031	1.005	0.994	1.008	1.002	0.960	1.023	1.003
South Sumatera	1.005	1.023	1.012	0.999	1.012	1.006	1.006	1.010	1.006
Bengkulu	1.006	0.701	0.850	0.992	1.006	1.000	1.014	0.698	0.852
Lampung	1.003	0.996	1.005	0.997	1.011	1.005	1.006	0.985	1.000
Bangka Belitung	0.990	0.943	0.965	0.991	1.005	0.999	0.999	0.939	0.966
Riau Islands	1.004	0.979	0.986	0.996	1.010	1.004	1.008	0.969	0.982
Jakarta	1.013	1.018	1.022	1.004	1.018	1.012	1.009	1.000	1.011
West Java	1.033	1.014	1.011	1.003	1.017	1.011	1.030	0.997	1.000
Central Java	1.011	0.991	1.000	1.002	1.016	1.010	1.009	0.975	0.990
Yogyakarta	0.995	0.988	0.986	0.994	1.008	1.002	1.001	0.980	0.984
East Java	1.023	0.997	1.010	1.003	1.018	1.012	1.020	0.980	0.999
Banten	1.045	0.986	1.008	0.999	1.013	1.007	1.047	0.973	1.001
Bali	1.017	1.015	1.027	0.996	1.010	1.004	1.022	1.005	1.023
West Nusa Tenggara	0.925	1.036	0.994	0.994	1.008	1.002	0.930	1.028	0.992
East Nusa Tenggara	1.013	0.941	0.956	0.993	1.008	1.002	1.020	0.933	0.955
West Kalimantan	0.997	1.005	1.003	0.995	1.009	1.003	1.001	0.995	1.000
Central Kalimantan	0.995	1.012	1.001	0.994	1.009	1.002	1.000	1.003	0.999
South Kalimantan	0.994	0.995	0.996	0.994	1.008	1.002	1.000	0.988	0.994
East Kalimantan	0.981	1.008	0.988	0.998	1.012	1.006	0.983	0.997	0.982
North Sulawesi	1.099	0.973	1.030	0.993	1.008	1.001	1.107	0.965	1.029
Central Sulawesi	0.997	1.022	0.993	0.994	1.009	1.002	1.003	1.013	0.990
South Sulawesi	0.986	1.002	0.993	0.998	1.012	1.006	0.988	0.990	0.987
Southeast Sulawesi	1.071	0.991	1.003	0.993	1.008	1.002	1.079	0.984	1.002
Gorontalo	1.022	1.006	1.008	0.989	1.003	0.997	1.033	1.003	1.011
West Sulawesi	0.993	0.988	0.985	0.990	1.004	0.998	1.003	0.984	0.987
Maluku	0.975	0.970	0.981	0.990	1.004	0.998	0.985	0.966	0.984
North Maluku	1.003	0.937	0.972	0.989	1.003	0.997	1.015	0.934	0.975
West Papua	0.953	0.960	0.962	0.990	1.004	0.998	0.963	0.957	0.964
Papua	0.955	1.012	0.983	0.995	1.009	1.003	0.961	1.003	0.980
Average	1.003	0.983	0.990	0.995	1.010	1.003	1.007	0.974	0.987

Note: The magnitudes of which TFP, TC, and TEC are less then 1 show negative TFP.

The following analysis is meant to investigate the potential convergence process that may occur across provinces. Table 4 reports this identification from the perspective of Beta convergence and Sigma convergence.

Table 4

Beta and Sigma convergence

Variable	Beta convergence		Sigma convergence	
	Model 1	Model 2	Model 3	Model 4
TFP_{it-1}	–0.731*** (0.16)	–0.836*** (0.12)		
W_{it-1}			–0.702*** (0.18)	–0.810*** (0.14)
Intra – Export	–0.744*** (0.03)		–0.723*** (0.03)	
Inter – Export	–0.513*** (0.08)		–0.526*** (0.08)	
Intra – Import		–0.409*** (0.01)		–0.399*** (0.01)
Inter – Import		–0.006 (0.12)		–0.124 (0.14)
AR(1) *– p value*	0.000	0.000	0.000	0.000
AR(2) *– p value*	0.167	0.355	0.321	0.550
Sargan – p value	0.247	0.604	0.550	0.895
Number of instruments	6	6	6	6
Number of provinces	33	33	33	33
Number of observations	132	132	132	132

Note: ***, **, * represent significance at alpha 1%, 5%, and 10%. Standard errors are in parentheses. AR(1) and AR(2) are Arellano–Bond (1991) tests for auto correlation in differences. Sargan is a test for over identification restrictions.

According to Table 4, our model specifications for both Beta and Sigma convergences are valid since they satisfied the specification tests at a 10% significance level. According to the result, the serially uncorrelated error assumption is satisfied since the null hypothesis stating no autocorrelation is rejected at order 1 (AR (1)) but not at higher orders (AR (2)). Sargan overidentifying restriction test meant to justify the validity of the instrument sets provides no evidence to reject the null hypothesis that population moment conditions are correct. See Table A1 in the Appendix for a statistical description of the variables. Our model is also robust according to robustness checks, whose results are provided in the Table A2 and

Table A3 of the Appendix. Even when the two-step estimation procedure is employed, the estimated coefficients do not differ significantly. Finally, our result also does not change dramatically after an attempt to treat all explanatory variables into a dynamic component as predetermined and endogenous variables.

According to Table 4 for all employed models, the convergence process occurred amongst provinces in Indonesia in 2011–2017, both Beta and Sigma. This implies that in addition to the disparity reduction, provinces with lower TFP growth were catching up with the provinces with higher TFP growth. Additionally, the coefficient of Beta convergence that is lower than Sigma convergence implies that the process of TFP growth gap reduction is faster than the catching-up process. In spite of the different observation in the convergence test, this finding supports previous studies by Aritenang (2016), Purwono et al. (2018) and Ibrahim et al. (2019) that discovered the presence of Beta and Sigma convergence among 33 provinces in Indonesia. In contrast, a longitudinal observation by Kurniawan et al. (2019) that covered the period 1969–2012 found no convergence process for per capita gross regional product (GRP) among 33 provinces in Indonesia.

A more intriguing analysis is related to the determinant of the convergence process. This study found that there are negative impacts of trade, both export and import, on TFP growth convergence. The impact of intra-provincial and international exports on the Beta convergence are observed as being significantly negative with the coefficient –0.744 and –0.513. Likewise, the impact of intra-provincial and international imports on the TFP growth is negative. However, the result shows that only intra-provincial import is significant. The negative coefficient in these findings implies that the trade activities do not contribute to the TFP growth of Indonesian provinces. Although theoretical studies, such as Amiti–Konings (2007), De Loecker (2013), Liu–Nishijima (2013), argue that export-import activities are likely to promote countries' productivity, in practice, export-import do not always contribute to TFP growth. Mok et al. (2010) suggested that exporters benefit from export activities if they export in large quantity, otherwise exporters should bear the high cost of transaction as well as the demanding technical barriers of the trade, which may reduce their profits, as well as their efficiency and TFP growth.

Another finding in this study is the impact of trade activities on the gap reduction of TFP growth estimated by Sigma convergence. The results show that intra-provincial export and international export significantly reduce TFP gaps between provinces. Accordingly, the result identifies that intra-provincial exports reduce 19.7% more TFP growth gap than international exports. This finding indicates that intra-provincial exports are more efficient to reduce regional inequality. This is strengthened by the import side showing that intra-provincial imports significantly reduce TFP growth inequality, while international imports have no significant impact. This result is plausible as the international imports may subtract GDRP of a province. This effect may be different from the effect of intra-provincial imports where trade flows more easily from one province to another. In this case, ultimately, increasing intra provincial exports and imports will contribute positively to the GDRP, which may subsequently lead to the disparity reduction.

The different impact of trade on the TFP growth and TFP disparity may also indicate the rising provincial autonomy. The decreasing TFP growth inequality might imply that transfer of knowledge occurs amongst provinces via trading, supporting the hypothesis of Fu et al. (2011). Nonetheless, the negative impact of trade on the TFP growth means that trade does not improve economic condition in general. This reason might stem from the inefficient operation on the trade activities amongst provinces. In a report about regional economic governance (TKED) by Murwito et al. (2013), the regional autonomy implementation monitoring committee (KPPOD) identified negative economic performance that could be attributed to regional regulations about commodity trading.

Moreover, Murwito et al. (2013) argued that the fact that 48% of business operators have to pay official fees for the distribution of goods amongst regions is not beneficial for business performance. That is to say, technology transfer may indeed occur amongst provinces, but the large cost tips the balance and leads to inefficient operational trade that discourages TFP growth. This evidence indicates that collaboration to arrange policy programs across provinces is yet to be seen.

Conclusion

The aim of this study is to investigate the potential convergence process of total factor productivity (TFP) growth among provinces in Indonesia in 2011–2017. Trade activity, composed in this study from intra-provincial trades and international trades (i.e., export and import), may contribute to this convergence process. The result of this study confirms that the convergence process in Indonesia occurred in 2011–2017. Concerning intra-provincial and international trades, the study discovered that both of these do not promote TFP growth, but (except for international import) reduce TFP gaps amongst provinces. This finding may indicate the regional autonomy in each province.

This study conveys essential messages for the Indonesian policymakers. First, as there is a contrast finding between promoting catching-up process and reducing inequality of trade-related TFP, it is vital to decide the development priority. It is worth noting that this study does not imply that international trade activities (export and import) should be reduced because it leads to technological transfer somehow, i.e., foreign countries-to-provinces, if consumer goods are involved e.g. machinery and equipment commodities. However, this study recommends establishing international trade priority policies that could be more effective in controlling non-productive international trade intensity in order to increase economic growth.

Second, it is true that Indonesia has a policy known as *Tingkat Komponen Dalam Negeri* (TKDN) that obliges companies to keep the local components of goods and services at a certain level and limit import intensity. Yet, we have observed little commitment to this policy as some sectors largely depend on internationally imported material in their production process. To prevent this, again, the role of intra-provincial trade is vital in balancing out the import in some sectors. Third, the role of central government is essential in order to streamline the development policies in each province, albeit the currently practiced decentralised system. This is to ensure that regional regulations will not hinder the growth convergence across provinces.

Appendix

Table A1

Statistics descriptive

Variable	Units		2011	2012	2013	2014	2015	2016	2017
GDRP	Thousand billion rupiah	Mean	182,032.4	268,791.7	214,855.0	238,698.3	271,771.8	294,789.3	317,774.9
		Std Dev	254,381.2	370,244.3	303,277.1	337,918.6	392,150.7	426,387.7	458,983.6
		Min	12,888.2	19,935.9	15,330.9	17,346.0	20,102.5	22,562.4	4,911.1
		Max	957,917.4	1,397,959.0	1,169,446.0	1,314,348.0	1,566,510.0	1,715,868.0	1,855,248.0
GFCF	Thousand billion rupiah	Mean	56,536.0	86,651.5	67,712.4	75,628.2	86,848.8	94,076.8	102,051.9
		Std Dev	86,826.7	131,919.6	104,046.9	113,264.5	131,046.9	138,329.2	150,454.3
		Min	3,314.6	5,292.3	3,985.4	4,480.0	5,467.8	6,467.2	7,704.0
		Max	425,635.4	653,723.9	516,874.5	550,811.9	640,241.5	661,300.1	721,240.1
Labor	Thousand people	Mean	3,518.1	3,631.8	3,641.6	3,693.1	3,699.9	3,792.6	3,870.7
		Std Dev	5,063.4	5,280.6	5,322.7	5,320.1	5,264.0	5,266.5	5,561.1
		Min	355.0	367.5	376.1	398.4	413.6	434.8	430.5
		Max	19,500.0	20,500.0	20,600.0	21,000.0	20,600.0	21,100.0	22,400.0
Intra Export	Thousand billion rupiah	Mean	45,044.0	68,945.9	53,490.6	61,501.5	68,058.9	77,457.8	87,647.9
		Std Dev	66,231.4	92,988.7	73,029.6	84,597.5	95,977.5	110,562.2	131,597.1
		Min	1,121.3	1,596.2	1,146.0	1,205.3	1,281.0	1,846.9	1,376.0
		Max	299,904.2	360,203.6	280,869.3	321,262.4	354,253.9	422,260.8	531,865.9
Intra Import	Thousand billion Rupiah	Mean	43,447.2	67,506.7	49,812.3	55,756.3	65,330.6	74,833.2	84,072.3
		Std Dev	43,040.5	72,542.2	49,476.7	57,537.7	70,999.0	86,822.2	101,315.8
		Min	5,312.4	8,739.2	6,851.2	8,041.2	5,828.6	4,052.3	5,791.0
		Max	184,753.5	322,667.3	202,241.8	236,552.3	295,005.3	347,525.6	422,660.9
Inter Export	Thousand billion rupiah	Mean	48,001.2	66,826.1	51,089.1	54,888.0	56,213.8	54,945.7	62,893.9
		Std Dev	67,358.4	98,086.0	71,429.0	77,170.7	78,333.7	77,807.0	83,401.5
		Min	19.7	19.9	15.4	166.1	153.4	89.5	57.4
		Max	282,466.8	393,158.8	262,953.3	254,048.2	274,431.7	274,724.8	308,408.2
Inter Import	Thousand billion rupiah	Mean	44,089.7	66,938.6	53,308.3	58,595.5	58,268.7	56,082.4	62,961.8
		Std Dev	108,494.9	164,700.5	131,441.9	141,686.1	145,480.8	142,772.7	160,146.1
		Min	9.6	15.3	13.8	9.9	11.8	170.3	102.0
		Max	584,935.8	887,633.7	709,311.9	754,420.2	787,059.4	775,715.6	869,469.8
Observation			33	33	33	33	33	33	33

Note: Mean is arithmetic average, Std Dev is standard deviation, Min is minimum amount value in observation, Max is maximum amount in observation.

Table A2

Robustness check for Model 1 and Model 2

	Model 1				Model 2			
	Exogeneous (One-Step)	Exogeneous (Two-Step)	Predetermined (One-Step)	Endogenous (One-Step)	Exogeneous (One-Step)	Exogeneous (Two-Step)	Predetermined (One-Step)	Endogenous (One-Step)
TFP_{it-1}	–0.731***	–0.842***	–0.776***	–0.728***	–0.836***	–0.878***	–0.793***	–0.774***
	(0.16)	(0.13)	(0.19)	(0.19)	(0.12)	(0.08)	(0.16)	(0.17)
Intra – Export	–0.744***	–0.753***	–0.551***	–0.554**				
	(0.03)	(0.10)	(0.17)	(0.22)				
Inter – Export	–0.513***	–0.520**	–0.295**	–0.327**				
	(0.08)	(0.22)	(0.14)	(0.14)				
Intra – Import					–0.409***	–0.410***	–0.321***	–0.311***
					(0.01)	(0.01)	(0.05)	(0.05)
Inter – Import					–0.006	0.006	-0.001	0.006
					(0.12)	(0.11)	(0.19)	(0.20)
AR(1) – p value	0.000	0.010	0.001	0.000	0.000	0.003	0.000	0.000
AR(2) – p value	0.167	0.291	0.476	0.427	0.355	0.498	0.607	0.622
Sargan – p value	0.247	0.247	0.823	0.867	0.604	0.604	0.925	0.906
Hansen – p value		0.126				0.780		
Number of instruments	6	6	16	14	6	6	16	14
Number of provinces	33	33	33	33	33	33	33	33
Number of observations	132	132	132	132	132	132	132	132

Note: ***, **, * represent significance at alpha 1%, 5%, and 10%. Standard errors are in paratheses. AR(1) and AR(2) are Arellano–Bond (1991) tests for auto correlation in differences. Sargan and Hansen are tests for over identification restrictions.

Table A3

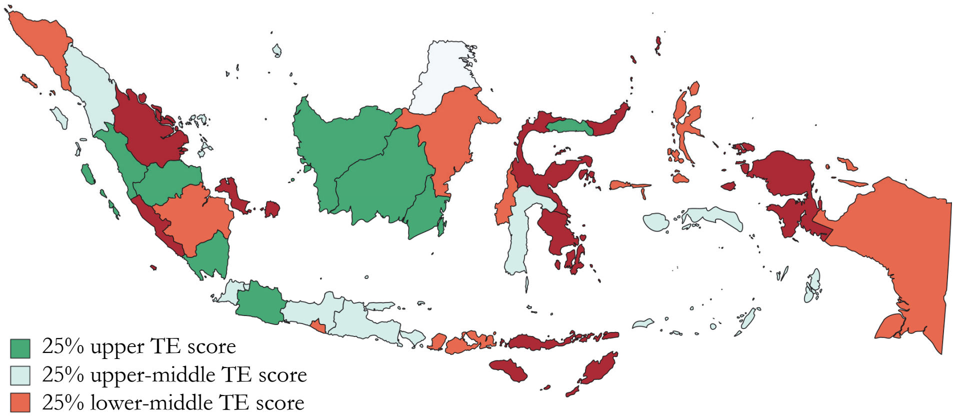
Robustness check for Model 3 and Model 4

	Model 3				Model 4			
	Exogeneous (One-Step)	Exogeneous (Two-Step)	Predetermined (One-Step)	Endogenous (One-Step)	Exogeneous (One-Step)	Exogeneous (Two-Step)	Predetermined (One-Step)	Endogenous (One-Step)
W_{it-1}	–0.702***	–0.825***	–0.725**	–0.657*	–0.810***	–0.875***	–0.655**	–0.627**
	(0.18)	(0.13)	(0.31)	(0.39)	(0.14)	(0.11)	(0.27)	(0.30)
Intra – Export	–0.723***	–0.728***	–0.241	–0.075				
	(0.03)	(0.08)	(0.27)	(0.42)				
Inter – Export	–0.526***	–0.536***	–0.261	–0.281				
	(0.08)	(0.18)	(0.22)	(0.27)				
Intra – Import					–0.399***	–0.400***	–0.195***	–0.170**
					(0.01)	(0.01)	(0.07)	(0.08)
Inter – Import					–0.124	–0.110	–0.187	–0.141
					(0.14)	(0.13)	(0.33)	(0.36)
AR(1) – p value	0.000	0.013	0.059	0.153	0.000	0.006	0.011	0.020
AR(2) – p value	0.321	0.552	0.950	0.987	0.550	0.723	0.756	0.768
Sargan – p value	0.550	0.550	0.971	0.997	0.895	0.895	0.995	0.998
Hansen – p value		0.417				0.871		
Number of instruments	6	6	16	14	6	6	16	14
Number of provinces	33	33	33	33	33	33	33	33
Number of observations	132	132	132	132	132	132	132	132

Note: ***, **, * represent significance at alpha 1%, 5%, and 10%. Standard errors are in paratheses. AR(1) and AR(2) are Arellano–Bond (1991) tests for auto correlation in differences. Sargan and Hansen are tests for over identification restrictions.

Figure A1

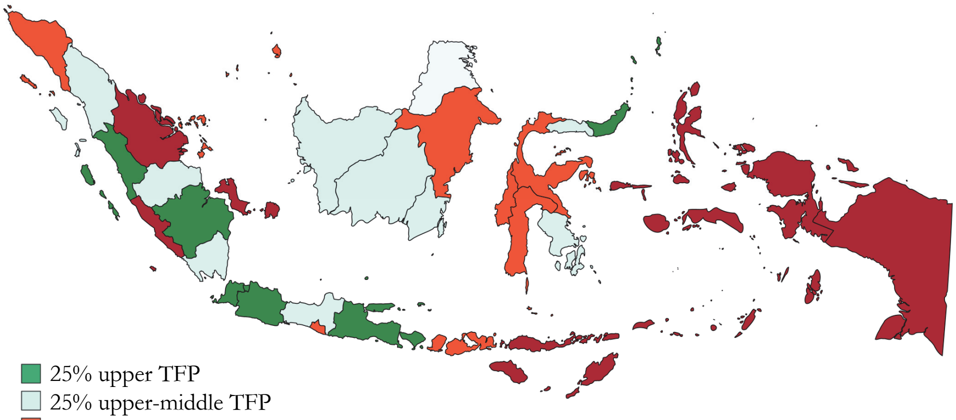
Distribution of technical efficiency (TE) score of 33 provinces in Indonesia



Source: Authors (created with www.mapchart.net).

Figure A2

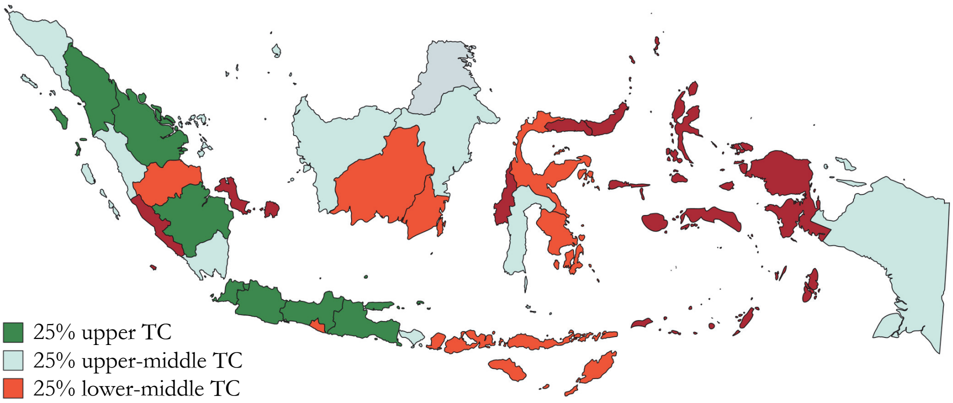
Distribution of total factor productivity growth (TFP) of 33 provinces in Indonesia



Source: Authors (created with www.mapchart.net).

Figure A3

Distribution of technical change (TC) of 33 provinces in Indonesia

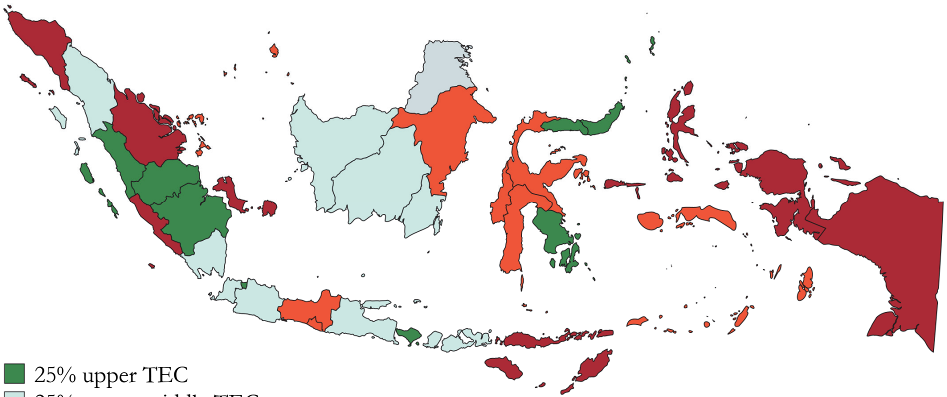


25% upper TC
25% upper-middle TC
25% lower-middle TC
25% lower TC
Not included in the analysis

Source: Authors (created with www.mapchart.net).

Figure A4

Distribution of technical efficiency change (TEC) of 33 provinces in Indonesia



25% upper TEC
25% upper-middle TEC
25% lower-middle TEC
25% lower TEC
Not included in the analysis

Source: Authors (created with www.mapchart.net).

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