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Analyses of topical policy issues

Technical progress, technical efficiency, and environmental change: New insights into Vietnam's productivity growth

Thanh Viet Nguyen [a,*], Michel Simioni [b,c]

[a] Faculty of Natural Resource Sciences, University of Akureyri, Iceland
[b] MOISA, INRAE, University of Montpellier, France
[c] Toulouse School of Economics, France

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ABSTRACT

Vietnam has experienced remarkable economic growth over last three decades, but the country's development fundamentals remain fragile. This growth has been primarily driven by an expanding labor force and capital deepening, with less emphasis on productivity growth. In this article, we aim to provide insights into technical progress, environmental change, and technical efficiency at the provincial level in Vietnam from 2010 to 2019 using stochastic production frontier analysis with endogenous inputs and external factors. We analyze differences in productivity and efficiency during the study period to determine the impact of the production environment, technology, and management at the provincial level in Vietnam. Our findings reveal a notable increase in productivity, averaging 3.6 percent per year across all provinces. Assessing technical efficiency, we identify a positive impact of the provincial competitiveness index and a negative influence of foreign direct investment. The implications underscore the need for Vietnam to strengthen provincial institutions and enhance financial, educational, and technological policies to improve productivity. This article offers valuable insights for policymakers and stakeholders engaged in sustainable economic development in Vietnam and beyond.

1. Introduction

Vietnam's economic growth over last three decades has been remarkable, transforming the country from one of the world's poorest in the 1980s to a lower middle-income country today (Baum, 2020). However, the foundations of this growth remain vulnerable. As emphasized by Le et al. (2014), the implementation of the "Đổi Mới" policy aimed to shift Vietnam towards a market economy.[1] Recently, Coppola et al. (2024) have raised concerns that Vietnam may face difficulties in transitioning from its

* Corresponding author.
E-mail addresses: thanh@unak.is (T.V. Nguyen), michel.simioni@inrae.fr (M. Simioni).

[1] At the 6th Party Congress in December 1986, the Communist Party launched the "Đổi Mới" (Renovation) reforms to address economic inefficiencies and worsening living conditions in the 1980s, opting for gradual economic change without altering the political system (Diez, 2016; Baum, 2020). The "Đổi Mới" policy brought wide-ranging changes across multiple domains. In economic management, it liberalized domestic trade by ending price controls and state monopolies, reduced subsidies to state-owned enterprises, and officially encouraged private enterprise and foreign investment (Barker and Üngör, 2019; Baum, 2020; Nguyen and Hoang, 2024). In governance, the reforms promoted administrative decentralization and enhanced the role of local authorities to improve public sector efficiency (see, e.g., Rab et al., 2015; Jaax, 2020; Bui et al., 2023; World Bank, 2025). In international relations, "Đổi Mới" marked a decisive shift toward pragmatic diplomacy; notably, in 1988, the Politburo adopted Resolution No. 13 (6th Tenure, May 1988), which sets the direction of "more friends and fewer enemies" (see Thayer, 2018, for further discussion). Social life, once tightly controlled and ideologically uniform, also began to diversify and open up, as exposure to foreign media and cultural influences increased (see, e.g., Horat, 2018; Minh and Anh, 2024).

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current status as a lower middle-income country acquired in 2009 to a higher status in terms of income due to rising labor and land costs, coupled with declining competitiveness in low-cost manufacturing. These challenges, already noticed by Pincus (2015) and Herr et al. (2016) about ten years ago, are compounded by slower productivity growth, limited technological innovation, and an over-reliance on foreign-invested enterprises. The main drivers of economic growth in Vietnam have been the expanding labor force and capital deepening, both through foreign direct investment and domestic investment, with less emphasis on productivity growth (World Bank, 2021). However, high-income economies have typically achieved sustained growth by generating positive externalities through technological progress and the development of interdependent networks of corporations in a free market economy (Dau et al., 2020; Backus, 2020). Without significant and sustained improvements in productivity and efficiency, Vietnam may fall into a middle-income trap (Herr et al., 2016).

This paper aims to contribute to the existing literature on growth drivers in Vietnam. Thereby, research has recently been devoted to assessing the impact of factor productivity on growth in Vietnam. According to Nguyen et al. (2019), these assessments have primarily been conducted at the macroeconomic level (see, among others, Park, 2012; Barker and Üngör, 2019). At the microeconomic level, research often focuses on firm-level or sectoral productivity (Ha and Kiyota, 2014; Nguyen, 2017; Le et al., 2018). While research conducted at the microeconomic level using firm-level data offers intricate insights into the production process, it is crucial to acknowledge some of its potential limitations, such as concerns regarding firm sample representativeness and comparability across firms. Therefore, the use of aggregate-level data, such as province-level data, can provide more valuable insights into the productivity and efficiency of the provincial-level economy in Vietnam. These insights have implications for regional-level policies and strategies aimed at enhancing productivity and fostering sustainable economic growth.

Moreover, the use of aggregated provincial-level data in this paper aligns with previous research on regional productivity analysis (Li and Liu, 2011; Gong, 2018; Liu et al., 2021; Nguyen et al., 2019; Hiep et al., 2022). Although Vietnamese provincial governments operate under national directives, they can be viewed as decision-making units because they are exercising control over critical factors such as infrastructure investment, economic incentives, and regulatory frameworks, all of which influencing productivity at the regional level. Employing province-level data provides a comprehensive view of regional disparities and policy impacts, even if it does not fully capture microeconomic dynamics at firm level.

In the context of developing economies, research has highlighted the role of institutional quality (Gong, 2018; Nguyen et al., 2024), infrastructure development (Sahoo and Dash, 2009; Na et al., 2020), and foreign direct investment (Borensztein et al., 1998; Su and Liu, 2016; Alvarado et al., 2017) in shaping productivity growth. While previous studies on Vietnam's economy (Le et al., 2014; Anwar and Nguyen, 2014; Nguyen et al., 2019; Barker and Üngör, 2019) provide insights into productivity trends, they do not incorporate recent structural changes or environmental factors. In this study, we include institutional quality, proxied by the Provincial Competitiveness Index (PCI), and foreign direct investment (FDI) as key external determinants of productivity growth across Vietnamese provinces, alongside capital as a frontier input. These choices reflect both theoretical relevance and empirical applicability in the Vietnamese context. Institutional quality, as captured by the PCI, is crucial in Vietnam's decentralized governance system (World Bank, 2025). Provinces with higher PCI scores tend to exhibit more transparent regulations, reduced entry barriers, and improved administrative efficiency—conditions that support firm-level productivity and innovation (Malesky et al., 2015; Nguyen et al., 2025). FDI plays a central role in Vietnam's economic growth model. It has contributed significantly to industrial upgrading, technology transfer, and productivity spillovers, particularly in export-oriented sectors (Anwar and Nguyen, 2014; Kim, 2024; Phi et al., 2024). Although infrastructure development is widely recognized as a foundation for long-term productivity growth, we do not include it as a separate variable in our empirical analysis. This decision is driven by both data limitations and conceptual overlap with capital investment, which is already accounted for in the production frontier. In our 2010–2019 provincial dataset, reliable and consistent indicators of infrastructure quality or investment at the provincial level are scarce. Moreover, given that much infrastructure investment is captured within broader capital formation measures, disentangling its specific effect poses both methodological and empirical challenges. Additionally, prior studies have noted that the returns to infrastructure investment have often been constrained by inefficiencies and suboptimal allocation, potentially limiting its short-term impact on productivity (Solihin et al., 2024). For these reasons, we focus our analysis on institutional quality and FDI as more immediate and empirically observable external drivers of productivity, while acknowledging that infrastructure remains an important long-term enabler that is not explicitly addressed in this study. Building on existing research, this paper extends the literature by incorporating climate variables and institutional dynamics into a stochastic frontier analysis (SFA) framework, offering a more comprehensive assessment of the determinants of provincial productivity in Vietnam.

This paper's contributions are threefold. First a stochastic production frontier model is used to investigate technical progress, environmental change, and technical efficiency. Following O'Donnell (2018), we define variables physically involved in production processes within the province and controlled by managers as inputs and outputs. Inputs encompass products and services that are used in production processes, while outputs refer to products and services that result from these processes. Variables not under managerial control, such as weather conditions, are referred to as environmental variables or characteristics of the production environment. The characteristics of the production environment should be distinguished from those of market environments, such as the degree of competition in output markets, and institutional environments. O'Donnell (2018) argues that characteristics of market and institutional environments typically do not influence the input–output combinations that are physically possible (i.e., they do not affect the underlying physical processes). However, they often influence output through their effect on inefficiency (see also, Kumbhakar et al., 2020). In O'Donnell (2018), technical progress is defined as the discovery of new techniques, methods, and systems for transforming inputs into outputs. Environmental change refers to changes in environmental variables, while technical efficiency can be viewed as a measure of how well production technologies are selected and utilized.

Second, this paper distinguishes itself from other papers on productivity and efficiency at the provincial level in Vietnam (see, among others, Nguyen et al., 2019; Hiep et al., 2022) by employing an estimation strategy that handles the endogeneity problem in both the production frontier and inefficiency function, and by simultaneously estimating these two functions. By doing so, we can address endogeneity issues such as functional form errors, measurement errors, and omitted variable bias. The chosen strategy is based on recent developments on the estimation of stochastic production frontiers in the presence of endogeneity proposed by Karakaplan and Kutlu (2017a,b). This strategy is based on modeling the joint distribution of the left-hand side variable in the production frontier and the endogenous variables. It is then possible to modify the writing of the production frontier by revealing an estimable function controlling for the endogeneity of both production factors and market and institutional factors explaining technical inefficiency. Estimation is then proceeded in only one step using maximum likelihood. Compared to the usual two-step approach with estimation of inefficiency levels and then regression of potential determinants on these estimated levels (see, for instance, Hiep et al., 2022), the chosen single-step approach is statistically more efficient and does not necessitate any bootstrap procedure to get correct standard errors. Kumbhakar et al. (2020) recommends avoiding two-step approaches as they lack of any strong statistical foundation and are widely agreed upon to yield poor insights into the actual behavior of inefficiency.

The estimation strategy chosen in the paper also differs from that introduced in the literature on productivity originated from Olley and Pakes (1996). This approach is also an approach with a control function, but now this latter is deduced from assumptions as to the behavior of choice of inputs by a firm. This approach is a natural choice for dealing with the problem of endogeneity of inputs because it is based on economic foundations, but it does not make it possible to directly assess the impact of institutional or market factors on productivity. Here too, this assessment is done in two steps and therefore suffers from the same drawbacks as those mentioned above (see, for instance, Peng et al., 2021).

Third, Following O'Donnell (2016, 2018), this paper uses the results of the stochastic production frontier to decompose each province's total factor productivity (TFP) into technical change and efficiency change components to have a better understanding of productivity growth across provinces in Vietnam over the study period. The results of this decomposition enrich those obtained by Nguyen et al. (2019) who uses the non-parametric index approach proposed by O'Donnell (2012). Indeed, the latter does not allow us to take into account any endogeneity problem, nor to consider possible factors explaining inefficiency, which we do in this paper by resorting to the parametric approach proposed by Karakaplan and Kutlu (2017a,b).

The analysis is carried out using panel data for the 63 Vietnamese provinces over the period 2010–2019. The empirical results show that, over this period, productivity increased by an average of 3.6 percent per annum in real terms across all provinces. Increases in labor and capital have led to an increase in output growth, while increases in utilized land have decreased it. Additionally, the estimated elasticity of scale was 0.885, indicating that the production frontier exhibited decreasing returns to scale. Among the factors of production, labor contributed most substantially to output growth with an elasticity of 0.778, followed by capital stock with an elasticity of 0.343. Increasing precipitation has had a positive effect on productivity growth, although the impact was negligible. The results also suggest that the provincial competitiveness index (PCI) has had a positive impact, whereas foreign direct investment (FDI) has had a negative impact on technical efficiency at the provincial level in Vietnam. Moreover, our robustness checks indicate that improvements in labor quality — as measured by trained labor — further enhance technical efficiency. This implies that Vietnam needs to enhance its provincial institutions and improve its financial, educational, and technological policies to boost productivity.

The article is organized as follows: Section 2 presents the methodology used to characterize the production technology. Section 3 provides a description of the data. Section 4 describes the results. Finally, Section 5 concludes the paper.

2. Methodology

2.1. Total factor productivity measurement and decomposition

Benchmarking Vietnamese provinces involves measuring their productive performance. The chosen measure, or index, should allow us to assess to what extent a province viewed as a decision-making unit (DMU) falls short of achieving the best possible productivity in each production period. This index must satisfy certain regularity properties to allow multilateral and multitemporal comparisons of DMUs' performances. The index is then said to be multiplicatively complete. O'Donnell (2012, 2016, 2018) propose a framework for computing such indices and measuring the total factor productivity (TFP) of DMU in multiple input–output context. These multiplicatively complete TFP indexes can be decomposed into measures of technical change and efficiency change, and, in turn, the efficiency change component can be decomposed into measures of technical, mix and scale efficiency change.

In this framework, TFP of province i in year t is defined as

$$TFP_{it} = \frac{Q(q_{it})}{X(x_{it})} \tag{1}$$

where q_{it} denotes the vector of L outputs and x_{it} the vector of M inputs. $Q(.)$ and $X(.)$ are nonnegative, nondecreasing, linear homogeneous scalar aggregator functions. The choice of these aggregator functions will be discussed in the following. For now, we focus on the decomposition of TFP, as defined by Eq. (1), into its technical change and efficiency change components. This decomposition is illustrated in Fig. 1. Point A represents here the aggregated input and output of a given province A in year t. Its TFP, we denote by TFP_{At}, is thus equal to the slope of ray (0A). The curve (II) represents the production frontier corresponding to the technology used by this province in year t under the assumption of variable returns to scale (VRS), while the ray (OE) which, by construction, is tangent to the curve (II), captures the same production frontier, but now under constant returns to scale (CRS).

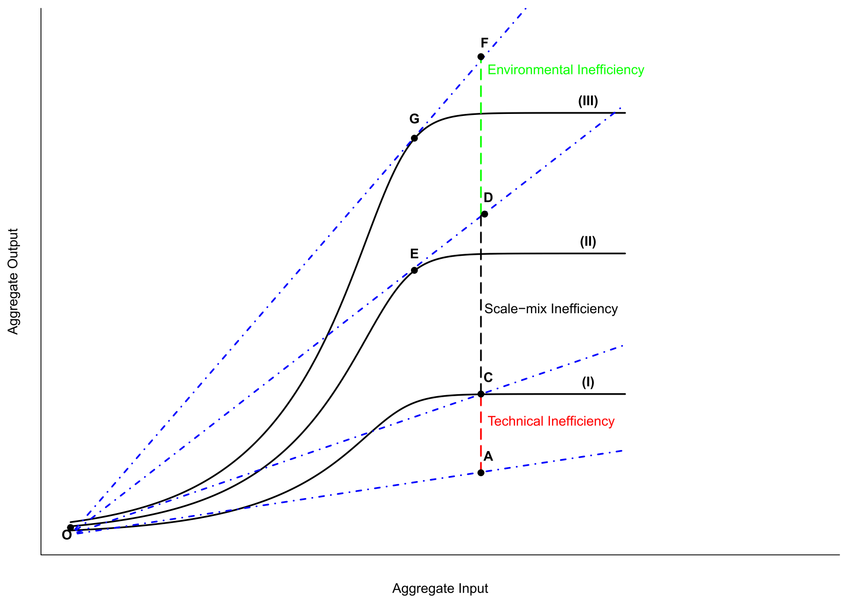

Fig. 1. An output-oriented decomposition of Total Factor Productivity.

The maximum TFP that a province can achieve in year t, or TFP_t^*, is measured by the slope of the ray (OE) or, equivalently the ray (0D). The overall performance of province A in year t, or $TFPE_{At}$, is measured by the ratio $\frac{slope 0A}{slope 0D}$, or, put differently, by $\frac{TFP_{At}}{TFP_t^*}$.

Consider now curve (I) in Fig. 1. It represents the frontier of production corresponding to the technology used by the province A in year t keeping constant the mix of output. Pure output-oriented efficiency of province A in year t, or OTE_{At}, can then be measured by the ratio $\frac{slope\ 0A}{slope\ 0C}$, and its output-oriented scale and mix efficiency, or $OSME_{At}$, by the ratio $\frac{slope\ 0C}{slope\ 0D}$. It can be easily shown that, by construction,

$$TFP_{At} = TFP_t^* \times OTE_{At} \times OSME_{At} \tag{2}$$

The previous framework was extended by O'Donnell (2016) to take into account the environment in which production decisions are made. This extension is based on the concept of metatechnology. On one hand, the technology a DMU can access in a given year t as a technique, method or system for transforming inputs into outputs in a given environment. The metatechnology, on the other hand, encompasses all technologies available this year, or, put differently, is the library of all available technologies that year. These two concepts can be made more concrete by considering their corresponding production sets. Thus, the production set province i faces in year t is $T^t(z_{it}) \equiv \{(x,q) \in \mathbb{R}_+^{L+M} : x$ can produce q in period t in an environment characterized by $z_{it}\}$, or the set of output–input combinations that it is possible to produce in a production environment characterized by a set of environmental factors taking z_{it} as values. These environmental factors are not under the control of the province (weather conditions, for example) but play a role in the technology choice from the set of possible options defined by the metatechnology. For instance, the frontier of $T^t(z_{At})$, z_{At} denoting the values of environmental factors for province A, is represented by curve (II) in Fig. 1. The production set corresponding to year-t metatechnology is defined as $T^t \equiv \{(x,q) \in \mathbb{R}_+^{L+M} : x$ can produce q in period $t\}$, and its frontier as the envelop of all provinces production frontiers (curve (III) in Fig. 1).

From the knowledge of the production frontier with CRS corresponding to year-t metatechnology (ray (OG), or, equivalently, ray (OF), in Fig. 1), it is possible to measure the maximum TFP that a province could reach that year, or $TFP_t^{*,M}$. The latter is measured by the slope of ray (OF) in Fig. 1. The decomposition reported in Eq. (2) can then be enriched with an additional element called environmental efficiency, or EE_{it}, and measured by $\frac{TFP_t^*}{TFP_t^{*,M}}$ (or the ratio $\frac{\text{slope } 0D}{\text{slope } 0F}$ in Fig. 1), i.e.

$$TFP_{At} = TFP_t^{*,M} \times EE_{At} \times OTE_{At} \times OSME_{At}. \tag{3}$$

Comparison between the performances of two provinces, say k and i; over two different years, say s and t can be performed by comparing their respective TFPs, TFP_{ks} and TFP_{it}, and computing

$$TFPI_{ksit} = \frac{TFP_{it}}{TFP_{ks}} \tag{4}$$

The previous approach can only be implemented if we have aggregators for the quantities of outputs and inputs. O'Donnell (2012) proposes period-and environment-specific output distance function defined as $D_O^t\,(x,q,z) \equiv \inf\{\rho > 0 : (x, q/\rho) \in T^t(z)\}$ and period-and environment-specific input distance function defined as $D_I^t(x,q,z) \equiv \sup\{\theta > 0 : (x/\theta, q) \in T^t(z)\})$ as aggregator functions. More precisely, O'Donnell (2012) shows that a suitable output (resp. input) aggregator function is $Q(q) = D_O^{\bar{t}}(\bar{t}, q, \bar{z})$

(resp. $X(x) = D_I^{\bar{t}}(x, \bar{q}, \bar{z})$) where $\bar{t}$ is a representative time period, and $\bar{x}$, $\bar{q}$, and $\bar{z}$ are vectors of representative inputs, outputs, and environmental variables. Then, for instance, Eq. (4) becomes

$$TFPI_{ksit} = \frac{D_O^{\bar{t}}(\bar{x}, q_{it}, \bar{z})}{D_O^{\bar{t}}(\bar{x}, q_{ks}, \bar{z})} . \frac{D_I^{\bar{t}}(x_{ks}, \bar{q}, \bar{z})}{D_I^{\bar{t}}(x_{it}, \bar{q}, \bar{z})}. \tag{5}$$

Different choices are possible regarding the distance function (O'Donnell, 2012, 2014).[2] Therefore, the log-distance function can be specified as a Cobb–Douglas function, or

$$LnD_O^t(x_{it}, q_{it}, z_{it}) = \sum_{l=1}^{L} \gamma_l lnq_{it} - \lambda_0 - \lambda t - \sum_{j=1}^{J} \delta_j lnz_{jit} - \sum_{m=1}^{M} \beta_m lnx_{mit}, \tag{6}$$

where $\sum_{l=1}^{L} \gamma_l = 1$, and $\sum_{m=1}^{M} \beta_m = r$. It can then be shown that, using this specification of the distance function, the TFPI defined by Eq. (5) takes the following form (O'Donnell, 2016):

$$TFPI_{ksit} = \prod_{l=1}^{L} (\frac{q_{lit}}{q_{lks}})^{\gamma_l} \prod_{m=1}^{M} (\frac{x_{mks}}{x_{mit}})^{\frac{\beta_m}{r}}, \tag{7}$$

and simplifies to

$$TFPI_{ksit} = \frac{q_{it}}{q_{ks}} \prod_{m=1}^{M} (\frac{x_{mks}}{x_{mit}})^{\frac{\beta_m}{r}}, \tag{8}$$

when production can be summarized using only one output, say Gross Regional Domestic Product, as in our application (see below). It is noteworthy that TFPI index computation does not longer require specifying a representative time period, and vectors of representative inputs, outputs, and environmental variables.

As shown by O'Donnell (2016), the estimation parameters can be used to decompose TFP change into technical progress, environmental, scale efficiency and technical efficiency changes, i.e.

$$TFPI_{ksit} = \underbrace{[\frac{exp(\lambda t)}{exp(\lambda s)}]}_{\text{OTI}} \underbrace{[\prod_{j=1}^{J^*} (\frac{z_{jit}}{z_{jks}})^{\delta_j}]}_{\text{OEI}} \underbrace{[\prod_{m=1}^{M} (\frac{x_{mit}}{x_{mks}})^{\beta_m(\frac{r-1}{r})}]}_{\text{OSEI}} \underbrace{\frac{exp(-u_{it})}{exp(-u_{ks})}}_{\text{OTEI}} \underbrace{\frac{exp(v_{it})}{exp(v_{ks})}}_{\text{SNI}}, \tag{9}$$

where OTI is the output-oriented technological progress index, OEI is the output-oriented environmental index, OSEI is the output-oriented scale efficiency index, OTEI is the output-oriented technical efficiency index, and SNI is the statistical noise index.

Nowhere in the aggregation procedure for computing total factor productivity (TFP) is any particular direction regarding input or output explicitly invoked. Eq. (5) involves both output-oriented and input-oriented distance functions. The emphasis on estimating the output-oriented distance function (see Eq. (6)) arises because it is easier to estimate in the case of a single-output, multiple-input technology. In this study, we therefore adopt an output-oriented approach to measuring TFP. While Vietnamese provincial governments often have more direct control over input allocation — such as labor mobilization, capital investment, and infrastructure planning — they operate within broader institutional and economic constraints that limit their ability to dictate output targets. Our objective is to evaluate how effectively provinces utilize their available inputs to expand output, particularly in a context shaped by market demand, policy reforms, and environmental variability. The output-oriented framework is thus appropriate, as it captures the extent to which provinces can increase production given existing input levels. Moreover, once the output-oriented distance function has been estimated, it allows us not only to analyze provincial efficiency from an output-oriented perspective (see Section 4.2), but also to compute TFP change and its decomposition as shown in Eq. (9) (see Njuki et al. (2018) and O'Donnell (2018)). This approach aligns with our focus on identifying the drivers of productivity growth and the potential for output expansion across provinces over time, which are central to assessing regional economic performance in a developing country context.

2.2. Distance function estimation in the presence of endogeneity

Computing the different elements in the decomposition of TFP change presented in Eq. (9) involves estimating the λ_0, λ_1, δ_1, $\ldots$, δ_{J^*}, β_1,$\ldots$, and β_M parameters. This can be achieved using stochastic frontier analysis (SFA) methods. Indeed, let us consider a sample of N Vietnamese provinces followed during T years for which we observe the output, the inputs and only J^* environmental factors. The distance function defined by Eq. (6) can be written as

$$lnq_{it} = \lambda_0 + \lambda\, t + \sum_{j=1}^{J^*} \delta_j\, lnz_{jit} + \sum_{m=1}^{M} \beta_m\, lnx_{mit} - u_{it} + v_{it}, \tag{10}$$

where $u_{it} = -lnD_O^t(x_{it}, q_{it}, z_{it})$. u_{it} can be viewed as non-negative technical efficiency effect. The error term v_{it} accounts for specification error (the possibility that the distance function is not a Cobb Douglas function), omitted variables (notably, the

[2] See, for instance, use of Färe and Primont index in Nguyen and Simioni (2015) or Nguyen et al. (2019).

possibility that we do not observe all the relevant environmental factors, i.e. $J^* < J$), and other sources of statistical noise such as measurement errors.

Estimation of Eq. (10) using classical estimators of stochastic production frontiers will give inconsistent parameter estimates in the presence of endogeneity, potentially due here to omitted factors (Amsler et al., 2016; Karakaplan and Kutlu, 2017a; Kumbhakar et al., 2020; Kutlu et al., 2020). In order to control for the potential endogeneity of some explanatory variables, whether in the production frontier or in the inefficiency specifications, we follow the approach recently proposed by Karakaplan and Kutlu (2017a).[3] The distance function defined in Eq. (10) can then be viewed as a special case of

$$y_{it} = \mathbf{x}'_{yit}\boldsymbol{\beta} + v_{it} - u_{it}, \tag{11}$$

where y_{it} is the logarithm of output, $\mathbf{x}_{yit}$ is the vector including time factor, environmental variables and production factors (in logarithm). v_{it} is the classical two-sided error term, i.e., v_{it} is normally distributed with mean zero and variance σ_v^2, while $u_{it} > 0$ is a one-sided error term capturing the inefficiency. Following Wang and Ho (2010), we assume that the inefficiency term can be expressed as the product of an individual time varying scale factor and a time invariant one-sided error term u_i^*, or

$$u_{it} = h\left(\mathbf{x}'_{uit}\phi\right) u_i^*, \tag{12}$$

The scaling factor $h_{it} = h\left(\mathbf{x}'_{uit}\phi\right)$ is, by definition, positive.[4] This scale can be stretched or shrunk by observation specific factors, or $\mathbf{x}_{uit}$, that can be either exogenous and endogenous. The vector $\mathbf{x}_{uit}$ does not include a constant term for identification purpose. The time invariant one sided error term u_i^* is distributed as a normal distribution with mean μ and variance σ_u^2 which is truncated from below at zero. If μ is set equal to 0, then u_i^* follows a half-normal distribution.

Karakaplan and Kutlu (2017a) propose to take into account the potential endogeneity of some explanatory variables, whether in the production function or even in the inefficiency scale factor, by considering the following auxiliary regression model

$$\mathbf{x}_{\text{end},it} = \mathbf{K}_{it}\delta + \varepsilon_{it}, \tag{13}$$

where $\mathbf{x}_{\text{end},it}$ is the $p \times 1$ vector of endogenous explanatory variables, and $\mathbf{K}_{it} = I_p \otimes \mathbf{k}_{it}$ with $\mathbf{k}_{it}$ the $r \times 1$ vector of all exogenous variables including all the exogenous explanatory variables and some instrumental variables, with $r > p$. u_i^* is assumed to be independent from v_{it} and ε_{it}. Endogeneity is then captured by specifying the joint distribution of the error vectors ε_{it} and v_{it}, or

$$\begin{bmatrix} \tilde{\varepsilon}_{it} \\ v_{it} \end{bmatrix} \equiv \begin{bmatrix} \Omega^{-1/2}\varepsilon_{it} \\ v_{it} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} I_p & \sigma_v\rho \\ \sigma_v\rho' & \sigma_v^2 \end{bmatrix} \right), \tag{14}$$

where Ω is the variance–covariance matrix of ε_{it}, and ρ is the vector representing correlations between elements of $\tilde{\varepsilon}_{it}$ and v_{it}. Hence, u_{it} and v_{it} can be correlated with x_{it}; yet u_{it} and v_{it} are conditionally independent given x_{it} and z_{it}. Moreover, u_{it} and ε_{it} are conditionally independent given x_{it} and z_{it}.

In this context, Karakaplan and Kutlu (2017a) then show that Eq. (11) can be rewritten as

$$y_{it} = \mathbf{x}'_{yit}\boldsymbol{\beta} + (x_{\text{end},it} - \mathbf{K}_{it}\delta)'\eta + e_{it}, \tag{15}$$

where $e_{it} = w_{it} - u_{it}$, $w_{it} = \sigma_v\sqrt{1-\rho'\rho}\ \tilde{w}_{it} = \sigma_w\tilde{w}_{it}$,; and $\eta = \sigma_w\Omega^{-1/2}\rho/\sqrt{1-\rho'\rho}$, with $\tilde{w}_{it} \sim \mathcal{N}(0,1)$. It is then possible to show that the error term e_{it} is conditionally independent from the regressors given x_{it} and z_{it}. Just as in the control function approach initiated by Heckman and Robb (1985), the term $(x_{it} - \mathbf{K}_{it}\delta)'\eta$ thus serves as an endogeneity bias correction term.

Parameter estimates can be recovered by maximum likelihood (see Karakaplan and Kutlu, 2017a, for the derivation of the likelihood). Estimations are usually done in two stages when implementing standard control function (see, for instance Wooldridge, 2015). Here, estimation only proceeds in one step. Consequently, estimators are statistically more efficient than two-stage ones, and no bootstrap procedure is needed to correct standard errors.

Special attention can be devoted to the estimated values of the parameters η. Indeed, they are linked to the vector of correlation between $\tilde{\varepsilon}_{it}$ and v_{it}, the idiosyncratic error terms in the structural model (10) and the auxiliary model (13). Testing the joint significance of parameters η is equivalent to testing the joint significance of correlations in ρ vector. If the elements of vector η are jointly significantly different from zero, this will indicate that there is endogeneity in the model. If not, then bias correction is not necessary and efficiency can be estimated using classical stochastic production frontier estimation techniques.

As an estimation by-product, provincial inefficiency levels can be computed using an estimator in the lines of Jondrow et al. (1982) (see Kutlu et al., 2020, for details).

3. Data

3.1. Description of variables

The main sources of data used are collected from the statistical yearbook. The Vietnam Statistical Yearbook is published every year by the National Statistics Office (NSO),[5] which contains basic statistics that reflect the general dynamics and socio-economic situation of the whole population, regions and localities, as well as weather data (NSO, 2025). Input and output data

[3] This approach has been coded in Stata as the function *xtsfkk* (Karakaplan, 2022).

[4] Thereafter, we will take $h_{it}^2 = \exp(\mathbf{x}'_{uit}\phi)$.

[5] Website: https://www.nso.gov.vn/en/homepage/.

Table 1
Descriptive statistics of data (2010–2019).

Variable	Unit	Mean	Std.Dev	Min	Max
Output					
GRDP	Trillion VND	60.25	109.90	4.12	977.85
Inputs					
Land	Thousand hectares	312.48	180.10	68.10	930.66
Labor force	Thousand persons	836.11	674.49	187.65	4,826.00
Capital stock	Billion VND	197,485.38	313,220.05	25,545.50	2,520,268.13
Influential factors					
Trained Labor	Percentage	16.79	7.08	5.20	48.10
PCI	Standardized value	59.89	4.47	45.12	73.53
FDI	Billion VND	4,787.24	10,337.36	0.00	95,005.97
Temperature	10 °C	2.53	0.21	1.84	3.03
Rainfall	100 mm	18.77	5.21	5.13	44.81

are used within 63 provinces/cities between 2010 and 2019. This study uses Gross Regional Domestic Product (GRDP) as the output and capital, labor, and land (excluding forest area) as inputs. Land is included in the production function because it plays a critical role in key sectors such as agriculture and construction, which are essential to Vietnam's economy. In 2024, agriculture and construction together contributed approximately 18% to GDP and employed about 10% of the workforce. In comparison, manufacturing accounted for more than 24% of GDP and 5% of total employment in 2022 (NSO, 2025).

To assess the labor factor, the study used the official number of workers over 15 years of age. This variable has some limitations. First, it does not include half-time workers that are present in agriculture, and self-employed workers. Second, some activities use labor under 15 years of age, which is not recorded in this study. Despite these limitations, however, the official number of laborers over 15 years of age are considered to be the best figure capturing the current labor force in Vietnam. Therefore, we have employed the aggregated number of workers by province from the annually published Statistical Yearbook of NSO for this study.

As for capital, the World Bank's World Development Indicators (WDI) provide capital formation data for Vietnam starting from 1995, but only at the national aggregated level; data at the provincial level is unavailable. Official statistics in Vietnam do not measure capital stock, but instead, only offer information on total investment. This is a significant limitation since total investment only represents a small fraction of the capital stock that can be analyzed. However, by using a typical conversion formula, as demonstrated in the OECD (2009), total investment in each province can be converted into capital. Capital at time t is thus defined as:

$$K_t = (1 - \delta) \times K_{t-1} + I_t, \tag{16}$$

where K_t denotes capital stock in year t, I_t, total investment in year t, and δ, depreciation rate. In Eq. (16), the total investment series is known, but not the capital series. This latter can be initialized using $K_0 = \frac{I_0}{\delta+\theta}$ where K_0 denotes the capital in the initial year (2010). θ is the growth rate of gross output over the period, computed as $\theta = (\frac{GRDP_T}{GRDP_0})^{\frac{1}{T}}$ where we take $T = 2019$. Depreciation rate is computed as the average of depreciation rates over the 2010–2019 period (Feenstra et al., 2021). All data has been converted to 2010 values.

Two meteorological variables are included as environmental factors: average rainfall and temperature in each province during the study period (sources: annual statistical yearbooks).

For the inefficiency model (u_{it}), we use two explanatory variables, PCI—corresponding to institutional factors and foreign direct investment (FDI), that are considered to have a significant influence on technical efficiency (OTE), or technical efficiency change (TEC) (Andrea and Antonio, 2015). Hayat (2019) argued that in low and middle-income countries, both FDI inflows and institutional quality lead to stronger economic growth. However, in high-income countries, FDI was found to slow down economic growth. Görg and Greenaway (2004) found that among seven studied transition countries using panel data, there was evidence of a negative effect of FDI on the productivity of domestic firms in four of these countries. In Vietnam, Le and Pomfret (2011) identified a negative horizontal linkage, while Anwar and Nguyen (2014) revealed a strong positive impact of FDI on TFP through backward linkages in some regions but a negative impact in others. Le and Pomfret (2011) suggested that while there is potential for technology transfer between foreign firms and their local competitors in Vietnam, this effect is more than offset by the competition induced by the entry of foreign firms. The Provincial Competitiveness Index (PCI) is selected as an explanatory variable to capture the role of subnational institutional quality in shaping productivity outcomes across Vietnamese provinces. Developed collaboratively by the Vietnam Chamber of Commerce and Industry (VCCI) and international development partners, the PCI reflects key dimensions of economic governance at the provincial level, including entry costs, transparency, informal charges, land access, policy bias, and proactivity of local leadership (Malesky et al., 2021). These dimensions are particularly relevant in Vietnam's decentralized administrative system, where provincial authorities exercise significant autonomy over regulatory implementation and business environment conditions. The inclusion of PCI allows us to account for institutional heterogeneity, which can influence firm behavior, resource allocation, and ultimately, technical efficiency and productivity growth. Empirical studies have consistently shown a positive association between higher PCI scores and improved economic performance at the provincial level (Tran et al., 2009; Nguyen et al., 2025), validating its use as a meaningful proxy for institutional quality in the Vietnamese context .

For this study, we utilize implemented FDI at the provincial level and PCI derived from the annual statistical yearbook. The overall PCI index score includes ten components and a province that is considered as performing well on the PCI if it has low entry costs, easy access to resources, a transparent business environment, high-quality business support services for firms (Malesky et al., 2021). Data details are presented in Table 1 and Appendix B. The data show significant variability in the output, inputs, and influential factors except average temperature.

3.2. Endogeneity issues

This empirical study applies the described models to the data collected from 63 provinces over the period 2010–2019. Before estimation the production frontier as discussed in Section 2, this paper discusses the endogeneity problem inherent in the production, as input decisions might be made when some information is available from decision-making unit but unobserved by econometricians (Gong, 2018; Nguyen et al., 2021). Endogeneity refers to a situation where one or more of the explanatory variables in a statistical model are correlated with unobserved factors captured by the error term. In the context of labor and capital, there are several reasons why these variables may be endogenous. Labor and capital are often determined by market forces, which can be influenced by a wide range of factors, including government policies, technological advancements, and changes in demand and supply. These unobserved factors can create correlations between labor and capital and the error term in the production frontier. Estimates of parameters associated to labor and capital may then be biased due to omitted variable bias. Researchers have used legal origin, historical and exogenous characteristics of geographical conditions and the population as instruments (Hoxby, 2000; McCaig and Stengos, 2005; Duflo and Pande, 2007; Beck, 2009). We use fertility rate (FR), number of administration units (TAU), and urbanization index (urbanization index—I measures number of wards and town districts)[6] as instrumental variables to control for the endogeneity of labor force, capital, and FDI variables in our production frontier model and inefficiency function. A higher fertility rate in a province could reduce labor supply (de la Croix and Delavallade, 2018; Ngo, 2020), while a lower total fertility rate — implying smaller family size — may lead to increased investment in human capital quality and a temporary increase in the labor force relative to the total population (Marques, 2025). Therefore, the fertility rate satisfies the condition for instrument relevance. But if fertility rate is unrelated to any of the other factors affecting output, then it will be exogenous because it is uncorrelated with the error term. A higher number of administrations in a province could increase capital,[7] while a larger urbanization index could attract higher FDI[8] in a province. Therefore, those variables also satisfy the condition for instrument relevance. But those variables should not have a direct influence on output, so they satisfy the condition for instrument exogeneity.

In this study, labor, capital, and FDI are treated as potentially endogenous inputs and are instrumented accordingly to ensure the consistency of the stochastic frontier model. Land is also included in the production function but is not instrumented. This choice is justified by the institutional context in Vietnam, where land use rights are allocated and strictly regulated by the state, and land markets remain underdeveloped, with limited variation across provinces during the study period (Nguyen et al., 2021). As a result, land is treated as a quasi-fixed input that is unlikely to exhibit the same simultaneity bias as other decision-based inputs such as labor and capital. We also acknowledge that PCI, as an external factor, may be influenced by unobserved provincial characteristics correlated with productivity. However, the lack of valid and strong instruments at the provincial level constrains our ability to address their endogeneity fully. In light of this, we interpret the estimated coefficients for PCI with caution and mitigate potential bias by including time-varying controls and accounting for environmental factors such as temperature and rainfall. While the exclusion of instruments for land and PCI represents a limitation, we believe that it does not materially compromise the consistency of our primary estimates due to the model specification, robustness checks, and the theoretical justification for treating land as exogenous.

4. Results

4.1. Production frontier

Endogeneity issues. Table 2 shows the main estimation results for two models. Model EX is the model that ignores endogeneity, while Model EN is the model that handles endogeneity. In Model EN specification, we use the three instrumental variables, namely fertility rate, number of administration units, and urbanization index, to solve the possible endogeneity problem of labor force, capital, and FDI variables. Results from the direct estimation of the auxiliary model (13) where the three instrumental variables are regressed on the two production factors and FDI (first-stage regression in classical two-stage methods), indicate that the correlation between the endogenous variables and the instrumental variables is strong.[9] There does not seem to be any weak IV problem either. Indeed, the effective first-stage F-statistic values are greater than 10 based on the rule of thumb for not being a weak instrument proposed by Stock and Yogo (2005).[10] Moreover, Table 2 reports the endogeneity test result. This test clearly concludes in the rejection of the

6 The TAU and the UI at provincial level in Vietnam have been established based on certain criteria such as characteristics of geographical conditions and the population indicated in Resolution No. 1211/2016/UBTVQH13 dated May 25, 2016 on administration unit and urban classification of the National Assembly Standing Committee.

7 The provincial capital is often determined and allocated by the central government based on administration units (Nguyen et al., 2021).

8 Urbanization could improve productivity for foreign-owned firms (Gokan et al., 2019).

9 These estimation results are available upon requests to authors.

10 Effective first-stage F-statistic was proposed by Montiel Olea and Pflueger (2013) for detecting weak instruments in over-identified and non-homoskedastic linear settings (see also, Andrews et al., 2019, which recommend its use in these settings.). Although this statistic is clearly inappropriate in the highly non-linear setting used here and in the absence of any appropriate statistic, it nevertheless gives us an indication of the weakness of the instruments used. Its value is 255.55, 170.24, and 58.38 for labor force, capital, and FDI, respectively.

Table 2
Estimation results (Model 1).

	Model EX	Model EN
Dep.var: log(GRDP)		
Constant	−3.254*** (0.600)	−3.374*** (0.859)
t	0.034*** (0.002)	0.036*** (0.005)
log(Labor)	0.417*** (0.069)	0.778*** (0.158)
log(Land)	−0.109* (0.055)	−0.236*** (0.061)
log(Capital)	0.498*** (0.026)	0.343*** (0.104)
Temperature	−0.017 (0.037)	0.022 (0.075)
Rainfall	0.001 (0.001)	0.003**** (0.001)
Inefficiency: log(σ_u^2)		
Constant	0.719*** (0.211)	0.810** (0.300)
PCI	−0.001 (0.001)	−0.014** (0.004)
log(FDI)	0.005 (0.004)	0.079*** (0.020)
Idiosyncratic error: log(σ_v^2)		
Constant	−5.385*** (0.060)	–
Idiosyncratic error: log(σ_w^2)		
Constant	–	−5.392*** (0.060)
Control function:		
η_1 (log(Labor))	–	−0.252**** (0.135)
η_2 (log(Capital))	–	0.165 (0.107)
η_3 (log(FDI))	–	0.047*** (0.011)
Endogeneity test	–	χ^2-stat = 21.68
$\mathrm{H}_0 : \eta_1 = \eta_2 = \eta_3 = 0$		with $p < 0.001$
Observations	630	630
Mean Tech. efficiency	0.2820	0.3181
Median Tech. efficiency	0.2548	0.2938

Notes: Standard errors are in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
**** $p < 0.1$.

null hypothesis that all the elements of the vector η are jointly equal to zero, at usual significance levels. Thus, there is a necessity to correct for the endogeneity of labor force, capital, and FDI, as done when using the control function approach.

Cobb–Douglas approximation parameters. The coefficients on time t, log(Labor), log(Land), and log(Capital) in both models are statistically significant. The coefficients on Rainfall, PCI and log(FDI) are also statistically significant in Model EN. Rainfall appears to impact gross regional domestic product only when estimating model EN, while no clear impact has been identified for temperature whatever the estimated model.

The estimated coefficient on t in Model EN implies that productivity, i.e., GRDP for a given level of capital and labor, has increased in real terms by 3.6 percent per year, on average, across all provinces over the period 2010–2019. The estimated coefficients of the log-inputs indicate that increases in labor and capital might have led to increase in the GRDP growth, however, increases in utilized land might have decreased the output growth. Among factors of production, labor might have contributed most substantially to the output growth with the elasticity of 0.778, followed by capital stock (0.343). This finding is consistent with previous studies of economic growth theory (Barseghyan and DiCecio, 2011; Klarl, 2016; Navaretti et al., 2010).

The negative sign for land is not expected but might reflect the land quality (Latruffe et al., 2017; Amsler et al., 2016). In addition, it might also reflect efficient use of land differences among provinces in the context of Vietnam, where the use of land, is determined by the government (Nguyen et al., 2021). Similar results have been reported in the literature. For instance, Feng et al. (2019) found that urbanization centered on land has not only greatly accelerated China's economic and social development but also had negative effects on social development and the environment. They specifically discovered that population growth, economic development, and land urbanization all have significant negative impacts on per capita arable land area, per capita grain output, and rural ecological indicators. Similarly, Li et al. (2018) reported that the dual land system hinders the sustainable development of rural China, which is experiencing rapid depopulation and abandonment of inefficiently used land. The estimated elasticity of scale, i.e., 0.885, indicates that the production frontier might have exhibited decreasing returns to scale. The role of human capital in driving productivity growth cannot be overstated. While physical capital accumulation remains an important factor, human capital — measured through education, skill development, and workforce experience — plays a crucial role in long-term economic performance. Empirical studies have demonstrated that economies with higher levels of human capital tend to experience greater efficiency gains and sustained productivity improvements (Li and Liu, 2011; Chatzimichael and Tzouvelekas, 2014; Vollrath, 2014).

Estimation results indicate that temperature and rainfall may not have had a significant impact on output growth during the study period. Note, first, that the considered ten-year period may be too short to fully capture the climate risks facing Vietnam's economy. Furthermore, the weather indicators used, i.e., annual average rainfall and temperature, also only imperfectly capture climate changes. Nevertheless, we incorporated them into the modeling in order to control for unobserved factors that may be linked to them, and avoid any endogeneity due to the omission of these factors.

4.2. Technical change and efficiency

Table 2 also reports the estimated values of the potential determinants of inefficiency, i.e., PCI and FDI (in logarithms). Due to the fact we are considering a production frontier, it is worth noting that a negative sign of an estimated coefficient on a variable in the efficiency model means that efficiency will be improved when the variable increases and vice versa.

In this regard, PCI has had a positive impact on technical efficiency (the estimation was statistically significant at the 1% level), while FDI has had a negative impact on technical efficiency (the estimation was statistically significant at 0.1%). The estimation indicates that technical efficiency increases with the overall PCI index score; in other words, low entry costs, easy access to resources, a transparent business environment, and high-quality business support services for firms will support well production technologies chosen and used. The results also indicate that technical efficiency decreases with FDI; in other words, there might have been the crowding out and negative spillovers from FDI (Liu, 2008; Suyanto, 2010; Jude, 2019; Navaretti et al., 2010; Khachoo et al., 2018). Foreign-invested enterprises (FIEs) may force domestic firms to cut down production, in this case, the productivity of domestic firms would decline as they have to spread the fixed cost over a smaller quantity of products (Aitken et al., 1997; Aitken and Harrison, 1999). FIEs may also attract the best workers away from domestic firms, leaving them with lower-skilled employees (Girma et al., 2001). In addition, domestic firms may have limited absorptive capacity (Jude, 2019). In this case, FDI in Vietnam may generate a negative effect on the productivity of domestic firms by drawing away demand in the export market and attracting away skilled workers in the domestic labor market (Tian, 2007). Our results are consistent with the findings of Le and Pomfret (2011) and Anwar and Nguyen (2014). Furthermore, our results provide additional insights into the findings of Hiep et al. (2022), which revealed that FDI has a positive impact on productivity growth but a negative impact on technical efficiency. Gönel and Aksoy (2016) found that FDI inflows to ICT-using and producing manufacturing and service sectors (ICT-based sectors) foster growth only if host countries have a threshold level of human capital, financial resources, and technological development. Because industries in that group are more human capital-intensive and financially dependent on external resources, realizing the benefits of FDI depends crucially on absorptive capacities (Gönel and Aksoy, 2016). It implies that in order to gain technical benefits from FDI flows, provinces should plan to promote education in specific areas related to technology-intensive production and encourage foreign firms to participate in highly skilled human capital planning. Provinces should also have strong and established financial and technology policies, including liberalizing, reforming, and deepening financial markets, well-established and regulated intellectual property rights (IPRs), and independent auditors to enhance their absorptive capacity for FDI flows.

Fig. 2 shows the frequency distribution of technical efficiency for the 2010–2019 period (excluding Vung Tau). The technical efficiency seems to exhibit a right-skewed (positive skewness) distribution. The mean and median technical efficiency was around 0.32, and 0.29 respectively. The estimated technical efficiency is low and varies significantly across provinces. However, these low values can be attributed to Vung Tau's remarkably high technical efficiency in comparison to other provinces during the study period. It is crucial to note that this pertains specifically to pure technical efficiency, isolated from other efficiency indices such as scale, mixed, and environmental efficiencies. This distinction distinguishes it from the conventional technical efficiency term, which might encompass those indices, as illustrated in Farrell (1957). This finding may help explain why there are large differences in economic size and growth rates across Vietnam's provinces, with primarily rural and agricultural provinces having smaller economic output and slower growth, while urban and more industrialized provinces and cities are experiencing more rapid growth. The findings are consistent with the results of Nguyen et al. (2019), which used a non-parametric approach and indicated the presence of two contrasting groups of provinces in terms of technical efficiency. This divergence in efficiency levels resulted in an overall decline in average technical efficiency during the period from 2010 to 2017 (Nguyen et al., 2019).

The minimum and the maximum technical efficiency were about 0.14 (Cao Bang), and 0.98 (Vung Tau) respectively. There was a huge gap between the maximum and the minimum technical efficiency. Most of the provinces had a low level of technical efficiency, ranging from 0.2 to 0.4. Vung Tau and Ho Chi Minh were only two provinces with a mean of technical efficiency a higher than 0.6 for the period. Those provinces with higher level of technical efficiency seem to have comparative advantages in terms of natural resources (e.g Vung Tau, Gia Lai), investments (e.g.Ho Chi Minh, Hanoi, Bac Ninh, Dong Nai, Vinh Phuc, and Binh Duong), or strategic locations (e.g Vung Tau, Hai Phong). In contrast, those with lower level of technical efficiency seem to be landlocked, lacked natural resources (e.g Cao Bang, Ha Giang), or suffered from high frequency climatic hazards (e.g Ha Tinh, Bac Kan, Ha Giang).

Fig. 3 show technical efficiency of regions for the period 2010–2019. The Southeast region has had the highest mean of technical efficiency, followed by the Mekong delta and Red River regions. The Northeast has had the lowest mean of technical efficiency, followed by the North Central and the Northwest regions. Again, those regions with good location, an abundance of natural resources, and higher investments seem to have higher level of technical efficiency.

4.3. Total Factor Productivity (TFP) and its components

TFPI growth rates and its components for the period 2010–2019 are shown in Table 3. The TFP growth rate (cf. 2010) decompose as $\%\triangle TFPI = \%\triangle OTI + \%\triangle OEI + \%\triangle OSEI + \%\triangle OTEI + \%\triangle SNI$, where the right-hand-side components are percentage rates of growth in the indexes in Eq. (9). These components are derived from the theoretical framework outlined in Eq. (3), which serves as an intermediate step toward the empirical decomposition presented in Eq. (9). By incorporating annual results from this empirical

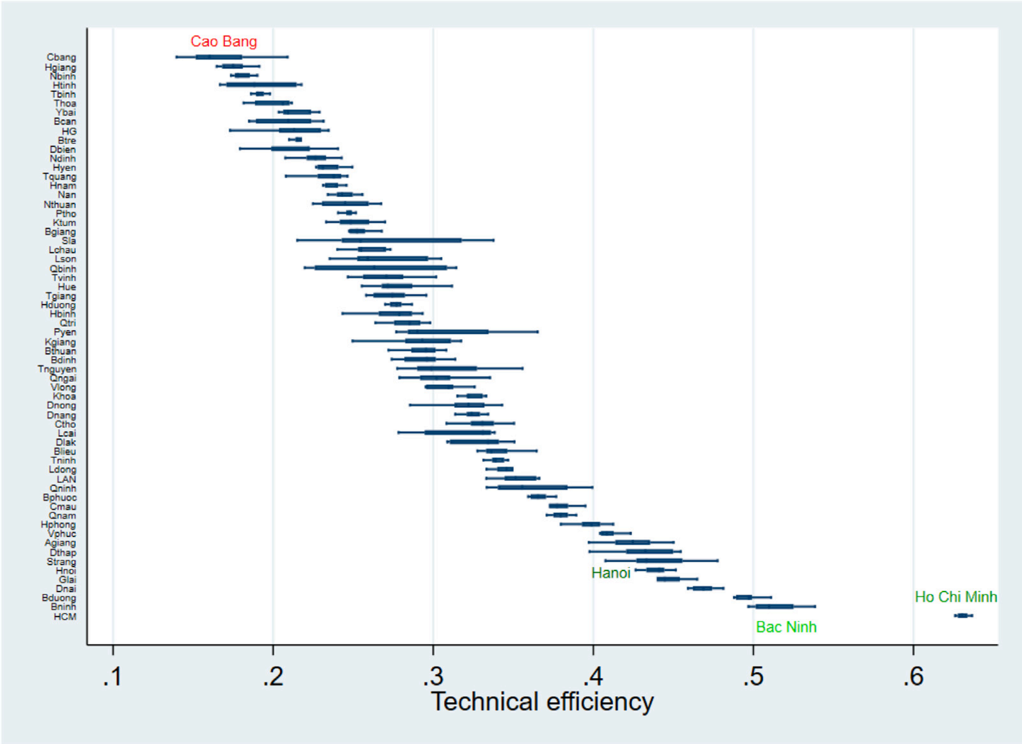

Fig. 2. Technical efficiency by provinces (excluding Vung Tau).

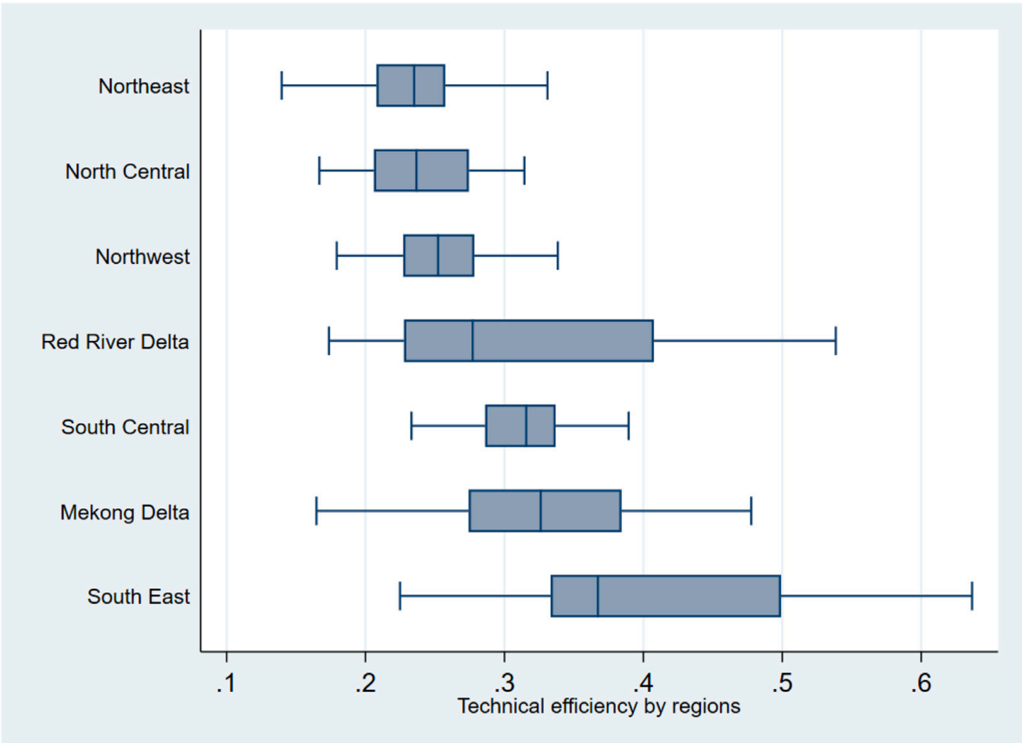

Fig. 3. Technical efficiency by regions.

Table 3
TFPI growth rates and its components for the period 2010–2019.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
TFPI	1.0000	1.0273	1.0581	1.0993	1.1376	1.1948	1.2396	1.2895	1.3453	1.3329
OTI	1.0000	1.0367	1.0747	1.1140	1.1549	1.1972	1.2411	1.2866	1.3338	1.3826
OEI	1.0000	0.9991	0.9979	0.9990	0.9964	0.9968	1.0045	1.0099	1.0054	1.0043
OSEI	1.0000	0.9939	0.9887	0.9837	0.9796	0.9753	0.9713	0.9672	0.9629	0.9599
OTEI	1.0000	1.0147	0.9880	0.9881	0.9843	0.9902	0.9840	0.9990	1.0298	1.0470
SNI	1.0000	0.9834	1.0100	1.0162	1.0252	1.0367	1.0403	1.0272	1.0117	0.9551

Table 4
Regional TFPI growth rates and its components during 2010–2019.

	%TFPI	%OTI	%OEI	%OSEI	%OTEI	%SNI
Northeast	1.3368	1.3826	1.0067	0.9555	1.0893	0.9226
Northwest	1.3826	1.3826	1.0148	0.9554	1.1186	0.9221
Red River Delta	1.4793	1.3826	1.0131	0.9595	1.0253	1.0735
North Central	1.3338	1.3826	1.0052	0.9494	1.0569	0.9564
South Central	1.2463	1.3826	0.9946	0.9582	1.0660	0.8873
South East	1.2133	1.3826	0.9986	0.9542	1.0054	0.9160
Mekong Delta	1.3494	1.3826	1.0016	0.9747	1.0162	0.9837
Vietnam	1.3329	1.3826	1.0043	0.9599	1.0470	0.9551

specification, we capture temporal variations in productivity performance across provinces. This dynamic perspective enables us to trace annual changes relative to the base year (2010), which may reflect the influence of evolving policy environments, economic restructuring, or external shocks.

We find that TFPI, on average, across all provinces increased about 33.29% over 2010–2019. We also find that technological progress has been the main driver of TFP growth (OTI increased 38.26% over 2010–2019), whereas output-oriented environmental effects and output-oriented technical efficiency only contributed to an increase of 0.43% and 4.7% in TFP growth over 2010–2019, respectively. In contrast, managerial efficiency (OSEI) contributed to a decline of 4.01% in TFP growth over 2010–2019. It implies that new techniques, methods and systems for transforming inputs into outputs might have been rapidly developed in Vietnam. However, those production technologies might have not been well attracted and used at the provincial level for the period. Perhaps incentives might have not been created enough for technological spillovers. In addition, environmental change or providing different types of public infrastructure might also have had little or no effect on TFP growth . Changing some of the key variables that drive managerial behavior might have worsened TFP growth for the period.

Table 4 reveal that TFP has been expanding in all regions, and the growth in TFP has largely been driven by technological progress for the period. The Red River Delta region has had the highest TFPI growth rate (47.93%) for the period, followed by the Northwest (38.26%) and Mekong delta (34.94%) regions. The Southeast region has had the lowest TFPI growth rate (21.33%), followed by the North Central (33.38%) and the Northeast (33.68%) regions for the period. Regarding the output-oriented technical efficiency index, the Northwest region had the highest growth rate (11.86%), while the Southeast region had the lowest growth rate (0.54%) over 2010–2019. The output-oriented environmental index (OEI) and the output-oriented scale efficiency index (OSEI) was relatively stable for all regions over 2010–2019.

Fig. 4 shows TFPI of some selected provinces (cities): Hanoi, Ho Chi Minh, Quang Nam, Gia Lai, Bac Ninh, Thai Nguyen, Dong Nai and Vung Tau, between 2010–2019. All indexes compare the relevant variable in a particular year with the value of that variable in 2010. In these figures, the components of the TFPI are the output-oriented technological index (OTI), the output-oriented environmental index (OEI), the managerial efficiency index (OSEI), and the output-oriented technical efficiency index (OTEI). These provinces had the output-oriented technical efficiency higher than 0.5 over the 2010–2019.

Figs. 5–8 show detailed variations of the general TFP index (TFPI), the output-oriented technological index (OTI), the output-oriented environmental index (OEI), the managerial efficiency index (OSEI), and the output-oriented technical efficiency index (OTEI) at the provincial level in Vietnam over 2010–2019. The figures reveal that TFP has been expanding at all provinces except for Bac Can and Hoa Binh, those provinces that had the most significant effect of environmental change on TFP growth. The managerial efficiency has had a significant effect on TFP growth in Thai Nguyen, Ha Tinh, Bac Ninh, and Binh Duong provinces. Quang nam, Ca mau, Son La, and Lang Son have had significant improvement in technical efficiency for the period.

4.4. Robustness checks

In order to assess the robustness of our main results, we estimate three alternative model specifications. Our main model includes PCI and log(FDI) in the inefficiency equation (Model 1, as described in Table 2). In the first robustness check (Model 2, as described in Table A1 in Appendix A), we extend Model 1 by incorporating Trained Labor alongside PCI and log(FDI). Finally, in Model 3 (as described in Table A2 in Appendix A), we exclude PCI and instead rely solely on Trained Labor and log(FDI) in the inefficiency equation. Across all three models, the production function results remain stable. The key determinants of economic output — log(Labor), log(Land), and log(Capital) — consistently exhibit significant coefficients, with the estimated coefficient for log(Labor)

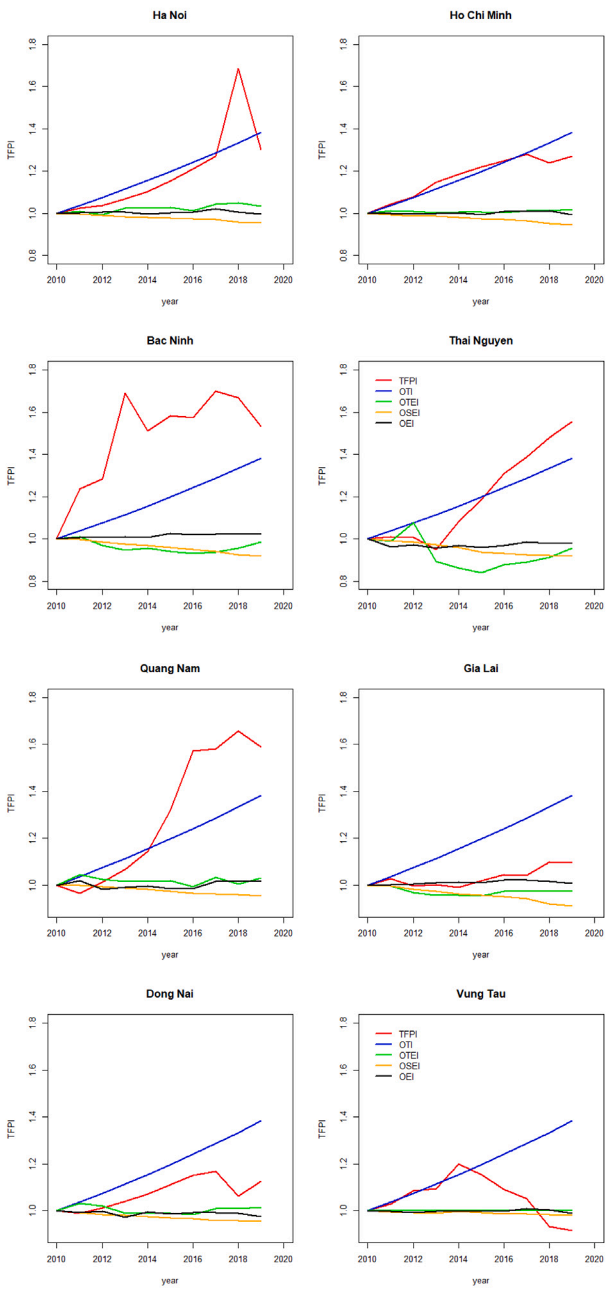

Fig. 4. TFPI change and its components of selected provinces.

ranging from 0.407 to 0.728 and log(Capital) remaining robustly positive. These consistent findings underscore the stability of the production technology estimates regardless of the model specification. Even when land use is dropped due to an unexpected negative sign, the estimations still consistently exhibit significant coefficients. The key determinants of economic output remain robust, reinforcing the reliability of the model estimates.

Differences emerge, however, in the inefficiency equation. In Model 1, PCI is statistically significant (with a negative coefficient in the endogeneity-corrected specification), indicating that higher PCI is associated with lower inefficiency (i.e., improved technical efficiency). In Model 2, when both PCI and Trained Labor are included, the PCI coefficient becomes statistically insignificant while Trained Labor maintains a significant negative effect on inefficiency (−0.005 in Model EX and −0.009 in Model EN). Model 3 confirms this pattern; even when PCI is omitted, the negative and statistically significant impact of Trained Labor persists (−0.005 in Model EX and −0.010 in Model EN). This evidence suggests that Trained Labor is a more robust and direct measure of labor quality, which is key to enhancing technical efficiency, while the potential multicollinearity between PCI and Trained Labor in Model 2 may

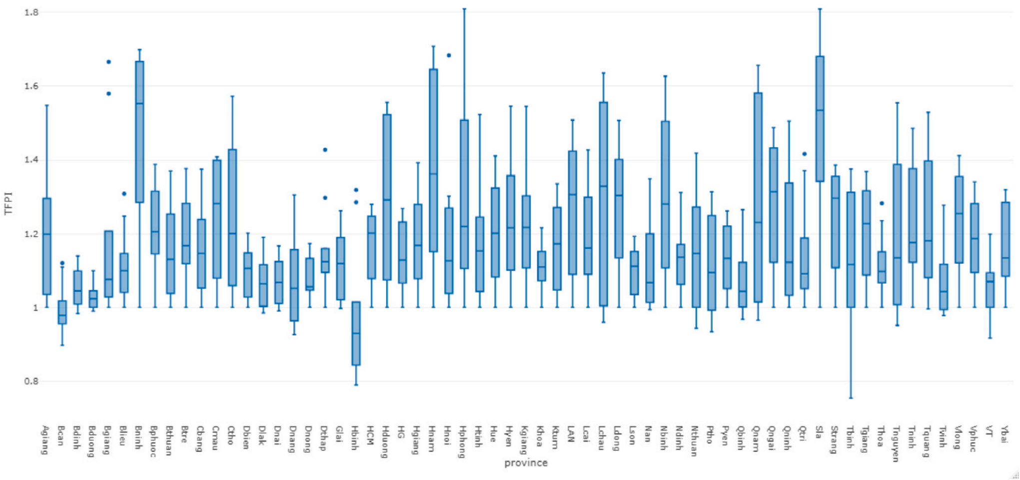

Fig. 5. The general TFP index (TFPI) for provinces.

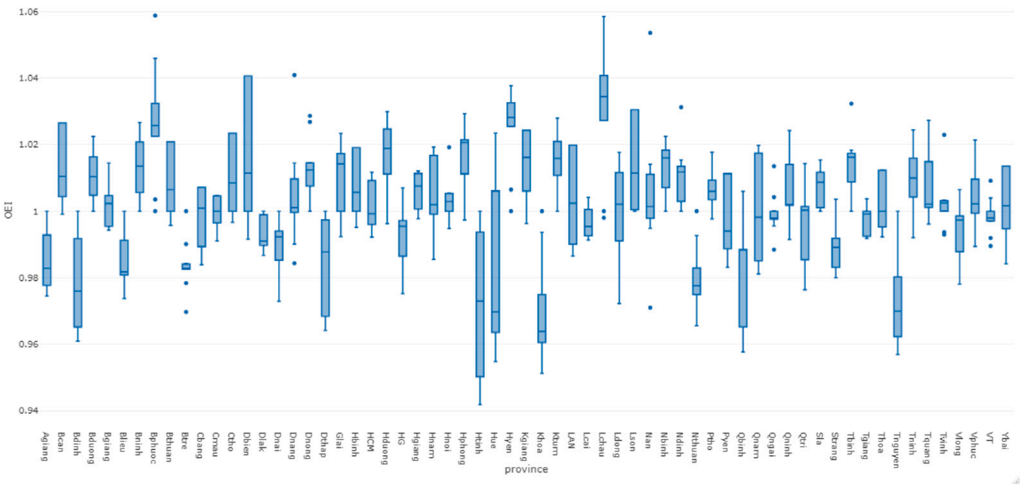

Fig. 6. The output-oriented environmental index (OEI) for provinces.

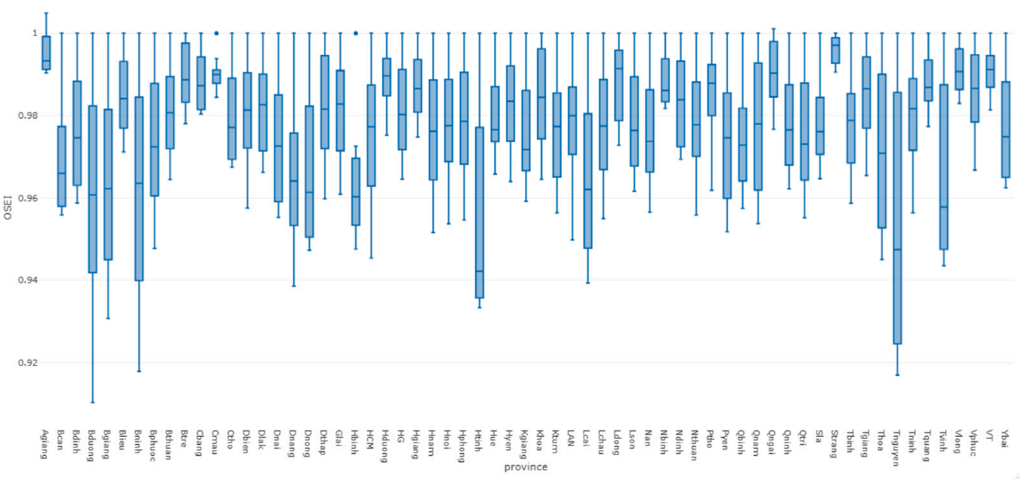

Fig. 7. The managerial efficiency index (OSEI) for provinces.

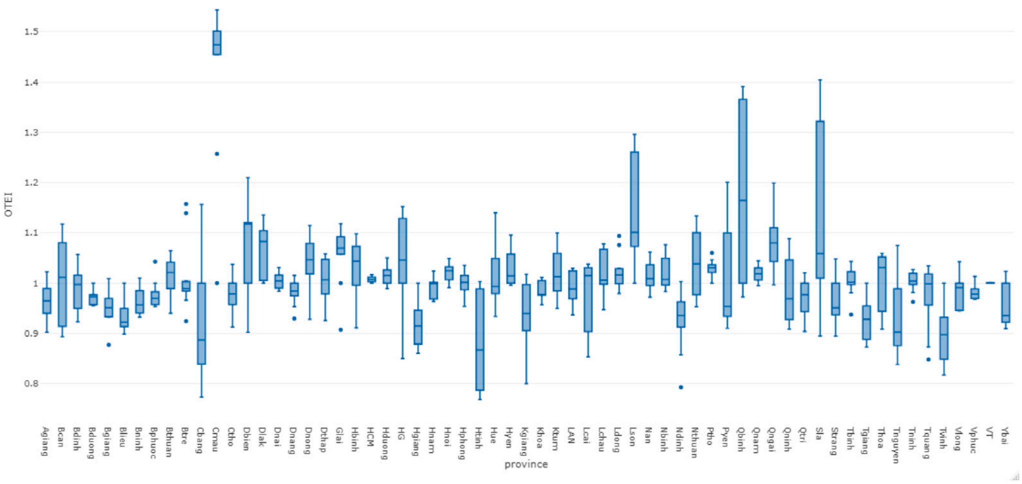

Fig. 8. The output-oriented technical efficiency index (OTEI) for provinces.

obscure PCI's individual contribution. Endogeneity tests further support these findings. With χ^2 statistics of 21.68, 11.41, and 7.92 for Models 1, 2, and 3 respectively, the endogeneity-corrected specifications (Model EN) yield more reliable estimates, reinforcing the importance of addressing potential biases.

Overall, while the significance of PCI varies across the specifications, the core conclusions of our analysis remain robust. The production function estimates are stable, and the consistent negative effect of Trained Labor on inefficiency highlights the critical role of labor quality in enhancing economic efficiency. These findings suggest that policies focused on improving human capital through enhanced training and education are likely to be instrumental in sustaining Vietnam's economic growth.

5. Conclusion

Vietnam's economic growth has been remarkable over the last three decades, however, the fundamentals of the growth are still fragile. The growth drivers in Vietnam have been largely dominated by the expanding labor force, capital deepening, and less on productivity growth. This article aims to provide further insight into technical progress, environmental change, and technical efficiency at the provincial level in Vietnam during 2010–2019 using stochastic production frontier analysis. We further analyze the change in productivity and efficiency in the study period to determine the impacts of production environment, technology, and management. The empirical results show that the productivity has increased in real terms by 3.6 percent annually, on average, across all provinces. We also find that increases in labor and capital might have led to an increase in the output growth, however, increases in utilized land might have decreased the output growth. Moreover, the estimated elasticity of scale was 0.885, indicating that the production frontier might have exhibited decreasing returns to scale. Among factors of production, labor might have contributed most substantially to the output growth with the elasticity of 0.778, followed by capital stock with the elasticity of 0.343, and increasing precipitation might have had a positive effect on productivity growth, although the impact is negligible.

We also find that the provincial competitiveness index (PCI) has had a positive impact, while foreign direct investment (FDI) has had a negative impact on technical efficiency for the study period. It indicates that there might have been the crowding out and negative spillovers from FDI as the findings from Liu (2008), Suyanto (2010), Jude (2019), Navaretti et al. (2010) and Khachoo et al. (2018). The findings of our study emphasize the critical role of institutional quality and government policies in shaping productivity dynamics at the provincial level. Policies aimed at improving governance efficiency, transparency, and investment climate can significantly enhance total factor productivity (TFP). In particular, fostering stronger public–private partnerships and enhancing regulatory frameworks can encourage innovation and capital utilization efficiency. Additionally, targeted investments in education and workforce training programs can enhance human capital development, which is a key driver of long-term productivity growth. Given the limited impact of climate variables on productivity in the short term, policymakers should consider long-term strategies for climate adaptation, including infrastructure resilience and sustainable agricultural practices.

This study underscores the significance of institutional quality and the complex role of foreign direct investment (FDI) in shaping productivity across Vietnamese provinces. Based on these findings, several concrete policy directions can be proposed. First, to strengthen provincial governance, targeted reforms should focus on improving transparency, regulatory quality, and administrative efficiency—dimensions reflected in the Provincial Competitiveness Index (PCI). Practical measures may include capacity-building for local officials, the digitalization of administrative procedures, and the implementation of performance-based incentives to reduce bureaucratic inertia and foster a more enabling business environment.

Second, the negative association between FDI and technical efficiency in some provinces suggests that Vietnam must enhance the absorptive capacity of domestic firms. This could involve promoting linkages between foreign and domestic enterprises through supplier development programs, encouraging technology transfer, and expanding vocational and technical training tailored to sectors with high FDI concentration.

Third, the considerable heterogeneity in productivity performance across provinces calls for region-specific development strategies. National policy frameworks should incorporate localized productivity diagnostics to tailor interventions — such as infrastructure investments, innovation support, or skills upgrading — to address the distinct needs and constraints of each province. By translating empirical findings into differentiated, evidence-based policy responses, Vietnam can better support inclusive and sustained productivity growth.

While this study provides valuable insights into the technical progress, environmental changes, and efficiency of productivity at the provincial level in Vietnam, it has certain limitations. First, our TFP measurement does not incorporate undesirable outputs such as pollution indicators, which are essential for a comprehensive assessment of environmental productivity. Future research could integrate these factors to provide a more holistic view. Second, while we employ SFA to address inefficiency explicitly and account for endogeneity, alternative methods such as multi-stage DEA could provide complementary perspectives. Exploring and comparing different methodologies would enhance robustness and validation of findings. Additionally, our analysis covers a ten-year period, which may be insufficient to fully capture long-term climate and policy effects on productivity. Future studies should consider longer time frames and explore extreme climate events, as well as the impact of rising sea levels, which is a critical threat to Vietnam's economy. Finally, further investigation into the role of institutional quality and sector-specific dynamics in influencing productivity efficiency would provide valuable policy insights.

CRediT authorship contribution statement

Thanh Viet Nguyen: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Michel Simioni:** Writing – review & editing, Validation, Software, Methodology, Conceptualization.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

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