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Assessing container operator efficiency with heterogeneous and time-varying production frontiers

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A B S T R A C T

We build an empirical model under the stochastic frontier framework to assess production efficiencies of container operators from the world's major container ports in the years between 1997 and 2004. The empirical model measures efficiencies, efficiency changes, and time-persistence of efficiencies after controlling for the individual heterogeneity in technology and technical change. The model is estimated using a Bayesian approach via the Markov Chain Monte-Carlo simulation. We find that the mean efficiency level of the container operators is in the range of 70–90% of their full efficiencies, and the mean efficiency changed with time slightly. However, the percentage of highly efficient operators has increased since 1997. Common model misspecifications without controlling for the individual heterogeneity and technical change can alter the results dramatically.

1. Introduction

Since the mid-1970s, most general cargos traditionally transported by the break-bulk method have been transported in containers. The container port industry has become a very important link in the international trade network since then. Although the efficiency of container ports has drawn much attention from both academic research and governmental policy agendas, it is still lacking a rigorous modeling framework that can take the intrinsic characteristics of this industry into account in evaluating efficiency. In this paper, we construct an empirical model for such purpose and measure the technical efficiencies and efficiency changes of container operators from the world's major container ports in the years between 1997 and 2004, during which major container ports in the world experienced significant institutional changes.[1]

One common approach in efficiency studies for container port industry is the use of surveys on subjective perception of port users. Typically, these surveys ask port users to rate a particular port efficiency measure as a scale, for example, a scale from 1 to 7 with 1 indicating the least and 7 indicating the highest efficiency level. An overall efficiency score for a port is then constructed with the ratings on multiple efficiency measures. For example, Sánchez et al. (2003) use this kind of data to construct efficiency measures for Latin American ports and find that such measures are important to explain trade flows. Results obtained from surveys of perceptions are useful for port operators to understand customers' port choice behavior, but do not necessarily measure the technical efficiency of port production.

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[1] More details on this can be found in Baird (2002).

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There exist two alternative approaches which have been applied to empirical assessment of technical efficiency of container ports. One is the nonparametric data envelopment analysis (DEA)[2] and the other is the parametric stochastic frontier analysis (SFA)[3] Cullinane et al. (2006) compare the results from both DEA and SFA on port efficiencies and find high correlations between the results from the two approaches. However, two intrinsic characteristics of the port industry – the individual heterogeneity in production technology and the time-varying nature of technical efficiency, have been generally ignored in these studies.

Individual ports face different natural conditions and business environments which are largely uncontrollable for port management. Given the same inputs but under different outside factors, the possible maximal outputs of two ports are likely to differ. Such a difference in outputs should be interpreted as *technology heterogeneity* rather than *efficiency difference* because both the two operators are in fact using their inputs in the best way. DEA model cannot deal with the technology heterogeneity, and the heterogeneity has not been taken into account in aforementioned SFA studies on port efficiency.

Efficiencies of container ports are likely to vary with time because the macroeconomic factors driving the port demand vary with time; market structures and government policies vary also with time in the process of devolution of international port sector (Brooks and Cullinane, 2007). When panel data are available, efficiency changes can in theory be tracked by both SFA and DEA approach. However, among the aforementioned port efficiency studies, only Cullinane et al. (2004) tried to account for efficiency change by applying dynamic DEA approaches.

This paper applies a stochastic production frontier analysis to a recently compiled panel data of container operators from the top 100 container ports in the world. Efficiency of an operator under the stochastic frontier model is measured as the percentage of achieving its best output target (production frontier). The empirical model of this paper measures efficiencies and efficiency changes of these container operators and has the features to deal with individual technology heterogeneity and to separate *technical change*, i.e., change of production technology, from *efficiency change*. The model is estimated by a Markov Chain Monte-Carlo (MCMC) simulation method under the Bayesian framework.

Container operators, not ports or terminals in other port efficiency studies, are treated as individual units in this paper because operators are true decision makers. A container operator is a firm which operates one or several container terminals in a port to optimize its own objective. For example, the nine container terminals in Hong Kong port are operated by five container operators. A recent trend in container port industry is that several large port companies and shipping firms have invested in terminals across countries. As a result, several container operators, even from different countries, can belong to the same company, which is termed as *port group* in this paper.[4] We treat this special feature as panel data structure in modeling such that two operators which are located in two different ports but belong to the same port group are still two individual units; the individual effects at the port group level are controlled by the port group dummy in model specification.

We find that the mean efficiency level of these container operators is in the range of 70–90% of their full efficiency in the years between 1997 and 2004. Although the mean efficiency level increases with time slightly, the percentage of highly efficient operators increases. These results shed light on possible effects of market structure and institutional changes on the efficiency of the container port industry. Finally, we find that common misspecifications without controlling for the individual heterogeneity and technical change can alter the results dramatically.

2. Econometric model

The empirical model in this paper is developed under the stochastic frontier framework first expounded by Meeusen and van den Broeck (1977) and Aigner et al. (1977). Let y_{it} be log of the output of operator i at time t; X_{it} be the vector of log of inputs and possible interactions among them, the empirical stochastic production frontier model in the paper can be stated in the following form:

$$y_{it} = \alpha_{it} + X_{it}B - \Delta_{it} + \varepsilon_{it} \tag{1.1}$$
$$a_{it} = \bar{\alpha} + Z_i\Theta + \tau t + v_i \tag{1.2}$$
$$v_i \sim N(0, \sigma_v^2) \tag{1.3}$$
$$\Delta_{it} = \exp(\gamma_{i1} \cdot d9798 + \gamma_{i2} \cdot d9901 + \gamma_{i3} \cdot d0204) \tag{1.4}$$
$$[\gamma_{i1}, \gamma_{i2}, \gamma_{i3}]' \sim N(\bar{\gamma}, \Sigma) \tag{1.5}$$
$$\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2) \tag{1.6}$$

In Eq. (1.1), $\alpha_{it} + X_{it}B$ is the log of production frontier representing the maximal output that operator i can achieve at time t given the inputs of X_{it}; Δ_{it} is a positive *random* deviation from the frontier; ε_{it} represents the measurement error with a normal distribution (specified in Eq. (1.6)) independent across both operators and years. Eq. (1.1) implies that the actual output from operator i at time t is $\exp(a_{it} + X_{it}B) \cdot \exp(-\Delta_{it})$, where $TE_{it} \equiv \exp(-\Delta_{it}) \in (0,1)$ is a deflator to deflate the actual output

[2] Examples of using DEA to derive port efficiencies can be found in Martínez et al. (1999), Tongzon (2001), Cullinane et al. (2004), Park and Prabir (2004), Cullinane et al. (2005), Wang and Cullinane (2006) and Cullinane and Wang (2007).

[3] Examples of using SFA on port efficiencies can be found in Liu (1995), Coto-Millan et al. (2000), Notteboom et al. (2000), Cullinane et al. (2002), Cullinane and Song (2003) and Tongzon and Wu (2005).

[4] A few operators in our data are invested by several port groups jointly. We classify an operator under joint investment into the port group which owns the largest share of the operator.

from the frontier and is used as the efficiency measure in stochastic frontier analysis. TE_{it} can be basically interpreted as the percentage of achieving the frontier. By modeling the inefficiency term as random, the specified model here is an example of random effects stochastic frontier model in Kumbhakar and Lovell (2000).

In order to control for technical change and technology heterogeneity in measuring efficiency, we allow the intercept of the production frontier to vary with time (with a time trend) and across terminal operators, as shown in Eq. (1.2). Part of the variation across operators can be explained by operators' profiles denoted as Z_i and part of the variation is unobserved and is thus modeled as random denoted as v_i, whose distribution is parameterized as normal shown in Eq. (1.3). It is also possible to randomize the slope coefficients (B) of the log frontier in (1.1) in order to control for technology heterogeneity in a more comprehensive way, but a specification like that introduces too many parameters and thus requires data with large sample size.

Eqs. (1.4) and (1.5) specify the *distribution* of Δ_{it} – the positive random deviation from frontier. In the specification, the 8 years from 1997 to 2004 are grouped into three periods: 1997–1998 as the period of Asia financial crisis, 1999–2001 as the period of between the financial crisis and the 911, and 2002–2004 as the period of post 911; $d9798$, $d9901$, and $d0204$ are the dummies indicating the three periods, respectively. We use $\Delta_{i9798} \equiv \exp(\gamma_{i1})$, $\Delta_{i9901} \equiv \exp(\gamma_{i2})$, and $\Delta_{i0204} \equiv \exp(\gamma_{i3})$ to denote the deviations of operator i in the three periods. Because $[\gamma_{i1}, \gamma_{i2}, \gamma_{i3}]'$ has a joint normal distribution in Eq. (1.5), the deviations follow log-normal distributions and are allowed to be correlated with each other.

The overwhelming standard in stochastic frontier models specifies a time-invariant efficiency such that $\Delta_{it} = \Delta_i$ and employs the computationally convenient half-normal distribution to model the random deviation. The half-normal distribution forces the deviation of most individuals to be close to zero (please see Stevenson (1980), Greene (1990) and Huang (2004) for more details). We therefore employ the log-normal distribution which has a long-tail to allow the existence of very inefficient operators (those with large deviations). The parameter of the log-normal distribution ($\boldsymbol{\gamma}$) is allowed to change with time to capture possible efficiency change; the correlations among the deviations capture possible time-persistence in efficiencies. As argued by Tsionas (2006), efficiency improvement requires adjustment costs; if the adjustment costs are high, individual efficiencies are expected to be time-persistent.

In sum, the model specifications in (1) measure time-varying and time-persistent efficiency after controlling for technical change and technology heterogeneity.

2.1. Connection with related stochastic frontier models

2.1.1. Stochastic frontier models measuring time-varying efficiency

Modeling time-varying efficiency in stochastic frontier analysis is not totally new and it can be traced back to Cornwell et al. (1990) and Kumbhakar (1990). In these two examples, the model is specified as $y_{it} = \alpha_{it} + X_{it}B + \varepsilon_{it}$, and the intercept α_{it} is a quadratic function of time trend to capture time-varying inefficiencies. However, α_{it} here in fact includes both time-varying inefficiency and possible technical change. Our approach to separate time-varying efficiency from technical change is similar to Battese and Coelli (1995) to define a stochastic technical inefficiency effects function that is additional to the time-varying intercept.[5] The stochastic inefficiency effects function in Battese and Coelli (1995) is specified as $\Delta_{it} = W_{it}\boldsymbol{\gamma} + \mu_{it}$, in which W_{it} is the vector of time-varying explanatory variables including time trend or time dummies, and μ_{it} follows a truncated normal distribution which is truncated below $-W_{it}\boldsymbol{\gamma}$ to ensure the positivity of Δ_{it}. Tsionas (2006) extended this specification by specifying $\ln\Delta_{it} = W_{it}\boldsymbol{\gamma} + \rho\ln\Delta_{it-1} + \mu_{it}$ with μ_{it} normally distributed, and the autoregressive component ($\rho\ln\Delta_{it-1}$) is to capture persistence of efficiencies.

Specifications in Battese and Coelli (1995) and Tsionas (2006) force individuals to have the same time pattern in their efficiency change. Our specifications in Eqs. (1.4) and (1.5) relax this restriction because the coefficients associated with the time dummies ($\gamma_{i1}, \gamma_{i2}, \gamma_{i3}$) are individual specific.

2.1.2. Stochastic frontier models controlling for technology heterogeneity

There are three random components in the model of this paper: a symmetric one (v_i) varying across individuals independently to control for the unobserved heterogeneity; a one-sided one (Δ_{it}) varying across individuals independently and varying with time in a correlated way and in a specified temporal pattern (the specification for the time dummies) to measure the stochastic deviation from the frontier, and a symmetric one (ε_{it}) varying with both individuals and time independently to capture the measurement error in data. A conventional random effects stochastic frontier model has only the latter two random components and the specification in this paper is called the "true" random effects stochastic frontier model in Greene (2005). As pointed out by Greene (2005) also confirmed by us in the paper, ignoring the unobserved heterogeneity (v_i) makes the firms in the sample look less efficient. A more comprehensive stochastic frontier model randomizing not only the intercept but also slope coefficients can be found in Tsionas (2002) and Huang (2004). Randomizing slope coefficients is a simple extension in our estimation approach, but that model specification requires data with large sample size. By randomizing only the intercept, the model specification in this paper allows that given the same inputs, two operators can achieve maximal outputs which are different in a scale factor.

[5] Another approach of separating time-varying efficiency from technical change can be found in Karaginnis et al. (2002).

3. Estimation

Because the intercept of the log production frontier is individual-specific in the model, it is worthwhile to discuss briefly how we achieve the identification for the technical efficiency relative to the individual-specific production frontier. First, the identification comes partly from the fact that some observable operators' characteristics (Z_i) provide information to distinguish the individual intercepts of the log production frontier. As we will describe later, we construct many variables in order to control for the *observed* technology heterogeneity. Second, the identification comes partly from the implied assumption of *exchangeability* on the *unobserved* technology heterogeneity (v_i). In other words, Eq. (1.3) assumes that the unobserved technology heterogeneity, which is additive to the observed part explained by Z_i, is a random draw from a population distribution.[6] Moreover, since we have no further information other than the observed output to distinguish this unobserved variation, we need impose the symmetry assumption – normal distribution with zero mean in our model, on the population distribution. The random deviation (Δ_{it}) is then distinguishable from the unobserved heterogeneity (v_i) because from theory that the distribution of Δ_{it} must be one-sided and thus asymmetric.

If some factors affecting production frontier are not included in Z_i, ignoring v_i will cause the observations from the same operator to be correlated. The correlation will be absorbed by the correlation among $(\gamma_{i1}, \gamma_{i2}, \gamma_{i3})$ because the noise term ε_{it} is independent across both time and individual. Therefore, results of technical efficiency from a stochastic frontier model will be affected if technology heterogeneity is not well controlled.

We use the Markov Chain Monte-Carlo (MCMC) simulation under the Bayesian framework to make inference on unknown parameters denoted by $\boldsymbol{\Psi} \equiv \{\bar{\alpha}, \Theta, \tau, \sigma_v^2, B, \bar{\gamma}, \Sigma, \sigma_\varepsilon^2\}$. The adopted Bayesian approach has computational advantages in stochastic frontier analysis as discussed in Van Den Broeck et al. (1994), Koop et al. (1995, 1997), Fernandez et al. (1997), Kleit and Terrell (2001), Tsionas (2002), Huang (2004), O'Donnell and Coelli (2005) and Kumbhakar and Tsionas (2005). Our algorithm is tailored to the specifications in Eqs. (1.1)–(1.6) and the inference is facilitated by the data augmentation proposed by Tanner and Wong (1987). Particularly, rather than working directly on the posterior of $p(\boldsymbol{\Psi}|Data)$, we work on the posterior of $p(\boldsymbol{\Psi},\{v_i,\gamma_i\}_i|Data)$ by taking the unobserved individual level parameters as missing data to be augmented, where $\{v_i,\gamma_i\}_i$ denotes the collection of the individual level parameters for all terminal operators and $\boldsymbol{\gamma}_i = (\gamma_{i1}, \gamma_{i2}, \gamma_{i3})$.[7] The data augmented posterior is expressed as

$$p(\boldsymbol{\Psi}, \{v_i, \gamma_i\}_i|Data) \propto \rho(\Psi) \cdot \prod_{i=1}^{N} \left\{ \phi(\gamma_i; \bar{\gamma}, \Sigma) \cdot \phi(v_i; \sigma_v^2) \cdot \prod_{t=1}^{T_i} \phi(y_{it}; \bar{\alpha}, \Theta, \tau, B, \sigma_\varepsilon^2, \gamma_i, v_i) \right\} \tag{2}$$

where $\rho(\boldsymbol{\Psi})$ denotes the prior density of the unknown parameters; $\phi(\cdot)$ denotes the normal density function; and T_i denotes the size of the time series of individual i (unbalanced panel).

Since the functional form of the data augmented posterior in Eq. (2) is complicated, it is impossible to derive analytical properties of it. We will use the Monte-Carlo simulation to take random draws from the posterior and the empirical properties of the draws will be used to approximate the theoretical ones. The MCMC simulation is a special way to implement Monte-Carlo simulation, and it is to take random draws by simulating a Markov process in the space of $(\boldsymbol{\Psi},\{v_i,\gamma_i\}_i)$ which converges to $p(\Psi,\{v_i,\gamma_i\}_i|Data)$. A nice introduction of the MCMC simulation can be found in Gelman et al. (2004). Appendix A of the paper presents the details of the MCMC algorithm to take random draws from the augmented posterior in Eq. (2).

4. Data

The data used in this paper cover operators from the world's top 100 container ports (ranked in 2005) from 1997 to 2004. In order to estimate the stochastic production frontier model, we need define outputs and inputs from a port. Since our study is restricted to container operators, the output can be reasonably measured as the number of handled 20-foot equivalent units (TEU) in a year. This output measure is a standard one used in the industry and has been used by most academic studies in the field. We classify the capital inputs used to handle containers into the following categories: cargo handling equipment, terminal infrastructure, and storage facilities. For cargo handling equipment, we divide them into two types: those at the quay side, such as quay cranes and ship shore cranes, loading and discharging containers to and from ships; and those at the yard, such as forklifts and yard cranes, moving containers at the storage area. We measure the terminal infrastructure on the basis of the number of berths, the length of quay line, and the terminal area. As for the storage facilities, we measure them by using the storage capacity[8] and the number of electric reefer points.[9] The data on the output and capital inputs are compiled from the Containerization International Yearbooks 1997–2004 published by the Lloyd's MIU.

Unfortunately, we are not – nor are others – able to collect credible data on the labor inputs of the terminal operators. The assumption that we can ignore labor inputs is that the ratio between capital and labor inputs varies little across operators.

[6] By this way, the unobserved heterogeneity can be characterized by limited number of hyperparameters of the population distribution. We do not need to estimate v_i for each i but rather estimate the hyperparameters.

[7] We do not actually estimate individual level parameters $\{v_i,\gamma_i\}_i$ but rather estimate the distributions $N(0, \sigma_v^2)$ and $N(\bar{\gamma}, \Sigma)$. The data augmentation technique produces the draws of the individual level parameters from their distributions in the simulation.

[8] Storage capacity here is the stacking capacity.

[9] Reefer points are special facilities connecting the stored containers to the electric network.

Table 1
Summary statistics

Variables	Mean value (std. dev.) or fraction of the sample
A. Output	
Container throughput in TEUs (million)	0.7934 (1.4754)
B. Inputs	
1. Cargo handling equipments	
CHQ: Cargo handling capacity at quay in tonnage (000's)[a]	0.3346 (0.3461)
CHY: Cargo handling capacity at yard in tonnage (000's)[b]	5.0667 (6.8362)
2. Terminal infrastructures	
Berth: Number of berth	4.6516 (4.8174)
Qlength: Length of quay line in meter (000's)	1.2582 (1.0960)
Tarea: Terminal area in squared meters (000's)	571.29 (841.51)
3. Storage facilities	
Storage: Storage capacity in number of TEUs (000's)	22.835 (87.692)
Reefer: Number of electric reefer points	420.21 (444.87)
C. Individual Characteristics	
1. Terminal and port level:	
Depth: Depth of water in meters	12.506 (1.9541)
Call: Number of liners calling the operator[d]	15.060 (13.245)
Operator: Number of operators in port	3.5829 (2.6046)
Terminal: Number of terminals in port	6.9045 (6.3409)
2. Port group dummies (in fraction of total sample):	
HPH: Hutchison Port Holdings	0.04
PSA: Port of Singapore Authority Corporation	0.03
PNO: P& O	0.06
SSA: SSA Marine	0.05
MSK: Maersk	0.02
Other: not belong to any of above groups	0.80
3. Country level:	
GDP:GDP in current US$ (billion)[c]	2382.8 (3413.7)
EXP: Goods exports in current US$ (billion)[c]	265.32 (244.89)
IMP: Goods imports in current US$ (billion)[c]	311.26 (373.39)
4. Continental distribution (in fraction of total sample)	
AS: Asia	0.31
EU: Europe	0.26
NA: North America	0.20
LA: Latin America	0.06
OC: Oceania	0.08
AF: Africa	0.04
ME: Middle East	0.05
Number of countries	39
Number of ports	78
Number of terminal operators	141
Number of observations	597

[a] The aggregated engineering capacity (in tonnage) of: (1) quay cranes and (2) ship shore container cranes.
[b] The aggregated engineering capacity (in tonnage) of: (1) gantry cranes; (2) yard cranes; (3) yard gantries; (4) reachstackers; (5) yard tracktors; (6) yard chasis trailers; (7) forklifts; (8) straddle carriers; (9) container lifters; and (10) mobile cranes.
[c] The country data can be found at the World Bank website: http://devdata.worldbank.org/dataonline/old-default.htm.
[d] Number of shipping liners using the terminals of an operator to offer scheduled shipping service.

The ratio of capital to labor inputs is expected to vary little across operators in the same country, because the inputs' prices are expected to be similar for these operators. However, the ratio can be very different for operators in different countries, and if this is true, the production frontier is expected to be different across operators from different countries. In the analysis, we use GDP, total export value, and total import value[10] at the country level to control for the heterogeneity caused by missing labor inputs, because these variables are highly correlated with inputs' prices.

With the process of port privatization from 1990's, large port groups such as Hutchison Port Holdings have invested in different ports to own and operate the terminals. Through a subscribed database – Containerization Intelligence Online, we find that the major port groups including Hutchinson Port Holdings (HPH), the Port of Singapore Authority Corp (PSA), Maersk, and Stevedoring Services of America (SSA) own multiple terminal operators in the data. Terminal operators owned by the same port group should have similar technologies and management practices even they are located in different countries. We construct the port group dummies in order to control for individual heterogeneity at the group level.

[10] The information can be found at the World Bank Website.

Table 2
Posterior means and standard deviations of coefficients of the Stochastic Production Frontier[a,b]

Variable	Base model	Model ignoring technical change	Model ignoring unobserved heterogeneity
1. Log inputs			
CHQ (β_1)	0.1013 (0.0487)	0.1314 (0.0475)	0.1219 (0.0587)
CHY (β_2)	−0.0316 (0.0314)	−0.0273 (0.0325)	0.0135 (0.0337)
Berth (β_3)	0.1370 (0.0566)	0.1274 (0.0563)	0.0614 (0.0519)
Qlength (β_4)	0.1515 (0.0590)	0.1741 (0.0586)	0.1908 (0.0552)
Tarea (β_5)	0.0049 (0.0481)	−0.0047 (0.0472)	0.0366 (0.0401)
Storage (β_6)	−0.0066 (0.0270)	−0.0049 (0.0274)	−0.0352 (0.0268)
Reefer (β_7)	0.1914 (0.0448)	0.1943 (0.0452)	0.1808 (0.0388)
2. Individual intercept			
Constant ($\bar{\alpha}$)	−0.9171 (0.3236)	−0.7912 (0.3271)	−0.2896 (0.3108)
Constant × Depth (θ_1)	0.0694 (0.0223)	0.0755 (0.0226)	0.0962 (0.0212)
Constant × Call (θ_2)	0.0101 (0.0027)	0.0090 (0.0028)	0.0962 (0.0212)
Constant × Operator (θ_3)	0.0311 (0.0271)	0.0264 (0.0259)	-0.0268 (0.0221)
Constant × Terminal (θ_4)	−0.0366 (0.0131)	−0.0380 (0.0128)	−0.0284 (0.0120)
Constant × HPH (η_1)	0.7247 (0.2891)	0.6752 (0.2814)	0.4242 (0.1932)
Constant × PSA (η_2)	0.5818 (0.3169)	0.5454 (0.3129)	0.7854 (0.2354)
Constant × PNO (η_3)	0.3354 (0.2587)	0.2916 (0.2573)	0.2780 (0.1613)
Constant × SSA (η_4)	0.2353 (0.3176)	0.2582 (0.3230)	−0.0778 (0.2056)
Constant × MSK (η_5)	0.5529 (0.5066)	0.7109 (0.5088)	2.8632 (0.6105)
Constant × GDP (δ_1)	−0.1222 (0.0493)	−0.1383 (0.0490)	−0.1849 (0.0423)
Constant × EXP (δ_2)	0.5505 (0.2219)	0.5057 (0.2185)	0.4292 (0.1630)
Constant × IMP (δ_3)	0.0881 (0.0402)	0.1176 (0.0427)	0.1346 (0.0416)
Constant × EU (π_1)	−0.8467 (0.1648)	−0.8734 (0.1607)	−0.6957 (0.1060)
Constant × NA (π_2)	−0.9341 (0.2575)	−1.0094 (0.2537)	−0.7109 (0.2184)
Constant × LA (π_3)	−0.2041 (0.2361)	−0.2372 (0.2310)	−0.1232 (0.1856)
Constant × OC (π_4)	−1.0060 (0.2730)	−0.9010 (0.2622)	−0.8733 (0.1775)
Constant × AF (π_5)	0.0914 (0.3876)	0.1562 (0.3815)	−0.1506 (0.2622)
Constant × ME (π_6)	−0.0647 (0.2800)	−0.1416 (0.2739)	−0.1097 (0.1842)
Constant × Time Trend (τ)	0.0438 (0.0116)		0.0362 (0.0132)
Variance of the constant (σ_v^2)	0.3578 (0.0708)	0.3313 (0.0644)	
3. Inefficiency parameters			
Coeff. of time dummy 1997–1998			
Mean($\bar{\gamma}_1$)	−2.1081 (0.5935)	−1.2908 (0.2582)	−0.1489 (0.1444)
Variance (Σ_{11})	1.7539 (0.9915)	0.8234 (0.3600)	0.5812 (0.1615)
Coeff. of time dummy 1999–2001			
Mean($\bar{\gamma}_2$)	−2.4270 (0.6411)	−1.8718 (0.368)	−0.1820 (0.1376)
Variance (Σ_{22})	2.0124 (1.0127)	1.3346 (0.5752)	0.6070 (0.1585)
Coeff. of time dummy 2002–2004			
Mean($\bar{\gamma}_3$)	−2.7762 (0.7778)	−3.2516 (0.8808)	−0.2159 (0.1491)
Variance (Σ_{33})	3.3044 (1.6367)	4.4328 (2.1387)	0.6698 (0.1801)
Covariances			
Σ_{12}	1.3848 (0.8901)	0.7816 (0.4002)	0.5397 (0.1459)
Σ_{13}	1.0747 (1.0702)	1.0821 (0.7902)	0.5270 (0.1438)
Σ_{23}	2.0556 (1.1172)	1.9826 (1.0387)	0.5766 (0.1521)
4. Other parameters			
Variance of noise (σ_ε^2)	0.0504 (0.0039)	0.0518 (0.0040)	0.0522 (0.0042)

[a] Numbers in parentheses are the posterior standard deviations. The production frontier is specified as the Cobb–Doulas expressed as $\ln q_{it} = \alpha_{it} + \sum_{j=1}^{M} \beta_j \ln k_{ijt}$.
[b] All the input and out variables are normalized with respect to their sample means before taking log.

Finally, we construct measures of port/terminal characteristics including water depth, number of calling liners,[11] and number of operators and terminal in a port as proxies of possible missing inputs causing technology heterogeneity at port/terminal level. These variables are also compiled from the Containerization International Yearbooks 1997–2004.

Table 1 presents the summary statistics of the data used in analysis. Due to missing values, we have to drop some operators from analysis. In the end, we have 141 operators from 78 container ports, which were ranked among the top 100 container ports in 2005. The panel data is unbalanced: the 141 operators contribute totally 597 observations.

5. Results

Considering the size of our data, we start to estimate a Cobb–Douglas production frontier. In sensitivity analysis, we test whether the efficiency results change significantly in a more flexible specification like translog. Table 2 summarizes estimation results of the stochastic Cobb–Douglas production frontier model.

[11] This variable measures the number of shipping liners using the terminals of an operator to offer scheduled shipping service.

The first column of Table 2 presents estimation results from the base model specified in Eqs. (1.1)–(1.6). As we argued that conventional stochastic frontier analyses used in previous port efficiency studies failed to control for technical change and individual heterogeneity, we test how the results from the base model would be altered without controlling for these two effects. The second column of Table 2 presents estimation results from the model without controlling for technical change. The intercept of the log production frontier in this model is specified as $a_i = \bar{\alpha} + Z_i\Theta + v_i$, which is not an explicit function of time anymore. The third column of Table 2 presents estimation results from the model without controlling for unobserved heterogeneity, that is, $v_i = 0$ in Eq. (1.2).

The first section of Table 2 presents posterior means and posterior standard deviations of the inputs' coefficients and these results are quite consistent across the three models. The posterior means of two coefficients have the unexpected negative sign, but their magnitudes are very close to zero and the posterior standard deviations of the two coefficients are also relatively large. The inputs on cargo handling equipment, on terminal infrastructure, and on storage facilities are all important to affect the output of container operators. Due to the Cobb–Douglas specification, the sum of the inputs' coefficients, $RS \equiv \sum_{j=1}^{7}\beta_j$, measures the average returns to scale[12] of the container port industry. The median, 5 percentile, and 95 percentile of the posterior distribution of RS are 0.5487, 0.4200, and 0.6742, respectively, indicating that on average the production technology of the container operators has the property of decreasing returns to scale. We offer two possible explanations to this finding. The first one is that the investment on container terminals is mainly driven by the needs to accommodate container ships. In order to enjoy the economy of scale, shipping liners have been employing container ships with large size in past decades. The container terminal operators need large scale of capital inputs to serve the large ships. The second possible explanation is that there is an unmeasured fixed asset, such as the physical size of the harbor, so that adding more equipment runs into diminishing returns. Certainly, returns to scale may vary across operators under the influence of different investment levels on intangible assets; and this heterogeneity in returns to scale can be captured by randomizing the slope coefficients of the log production frontier like the specifications in Tsionas (2002) and Huang (2004). Doing so is straightforward in our estimation algorithm but the size of our data is not large enough to identify such a model with many parameters.

The second section of Table 2 presents estimation results on parameters governing the time-varying and individual specific intercept of the log production frontier. As expected, operators with deeper water terminals and larger numbers of calling liners face higher production frontiers. The number of terminals in a port affects negatively the operators' production frontiers and this negative relationship supports the explanation that fixed harbor size causes the diminishing returns of capital investment. Compared with operators not belonging to any of the considered port groups, those owned by Hutchison Port Holdings have higher production frontiers. The production frontiers of container operators are positively affected by the country's international trade volume. For the same reason, operators in east and south Asia face higher production frontiers. The results from the base model indicate that on average, the production frontiers of container operators increase with time and there exists quite a large heterogeneity in frontiers coming from unobserved sources, as indicated by the posterior mean of 0.3587 and very tight posterior support around the mean for σ_v^2. Ignoring the time trend in production frontier has little effect on individual-specific frontier parameters, because most observable characteristics are not time-varying. However, ignoring the unobserved heterogeneity has certain effects on the parameters associated with the interactions between the intercept and port characteristics. The reason is that the error term, which includes the unobserved individual effects in this case, is correlated with the observable individual characteristics.

5.1. Efficiency results

Section 2.1 of Table 2 presents posterior means and posterior standard deviations of the inefficiency parameters $(\bar{\gamma}, \Sigma)$, and the results vary substantially across the three models. Compared to the results of base model, the differences among the means of $\gamma_i(\bar{\gamma}_1, \bar{\gamma}_2$, and $\bar{\gamma}_3)$ are greater in the model without controlling for technical change. When the unobserved heterogeneity is not controlled for, estimation results of the means of $\gamma_i(\bar{\gamma}_1, \bar{\gamma}_2$, and $\bar{\gamma}_3)$ are less negative and the variances of $\gamma_i(\Sigma_{11}, \Sigma_{22}$, and $\Sigma_{33})$ are smaller. The ignored unobserved heterogeneity has little effect on σ_ε^2 and this suggests that the ignored heterogeneity is mainly absorbed by the inefficiency term (Δ_{it}).

We can summarize several efficiency parameters of interest from the estimation results of Table 2. The first efficiency parameter of interest is the mean efficiency level of container operators in a time period (1997–1998, 1999–2001, or 2002–2004). This parameter characterizes the overall picture of the efficiency of container port industry in the studying period. The second efficiency parameter of interest is the probability that the mean efficiency of operators in a time period is greater than the one in another time period. This parameter tests whether the mean efficiency of the world's container port industry changed during the studying period. The third efficiency parameter of interest is the time persistence of efficiencies, and this parameter measures the correlations in individual efficiencies among different time periods. The MCMC approach provides us with easy ways to infer the efficiency parameters of interest (please see Appendix B for the details).

The base model indicates a slight efficiency improvement in the world's container port industry from 1997 to 2004. The posterior median of the mean efficiency of container operators increased from about 80% of the frontier between 1997 and 1998 to about 84% of the frontier between 2002 and 2004. Ignoring technical change causes overestimation of the efficiency improvement; the posterior median of mean efficiency of operators increased from 70% to 86% in the model. Ignoring the

[12] Because we have only capital inputs, the returns to scale should be interpreted as the long-run returns to scale.

unobserved technology heterogeneity causes underestimation of the mean efficiency; the posterior median of the mean efficiency of operators in the model is only about half of the one in the base model. The one-sided random inefficiency term absorbs the uncontrolled heterogeneity in technology, and thus the efficiency level is underestimated.

The efficiency improvement is not clear-cut in the base model. There are only about 89% chances that the mean efficiency level in the years between 1999 and 2001 is greater than the one in the years between 1997 and 1998; the probabilities that mean efficiency was improved between other periods are even less. However, results from the model without controlling for technical change tell us for sure that the mean efficiency of operators had been improved from 1997 to 2004.

The container operators' efficiencies are time-persistent, but the time-persistence is only in the short run. The results in the last panel of Table 3 show that the posterior median of the correlation in the operators' efficiencies between 1997–1998 and 1999–2001 is about 0.66 and the 90% highest posterior density region (5 percentile, 95 percentile) of this parameter does not include zero; the posterior median of the correlation in efficiencies between 1999–2001 and 2002–2004 is about 0.55 and again zero is not included in the 90% highest posterior density region; however, the posterior median of the correlation in efficiencies between 1997–1998 and 2002–2004 is only about 0.25 and zero is included in the 90% highest posterior density region. The model without controlling for individual heterogeneity predicts a strong time-persistence of efficiencies even in the long run. The operators' efficiencies in 2002–2004 are still positively correlated with the ones in 1997–1998. That is as expected, because the missing individual effects cause the correlation among observations and the caused correlation is captured by inefficiencies.

Previous efficiency parameters are not enough to capture the whole picture of efficiency change of the container port industry. Although the mean efficiency of this industry did not change very much in the considered period, the efficiencies of individual operators may change a lot. Such information is helpful to identify successful management practices and public policies. The Bayesian estimator for individual i's efficiency level at time t is represented by the posterior $p(TE_{it}|Data)$, whose mean h_{it} is used as the measure for individual level efficiency. Appendix B of the paper describes the way to calculate h_{it} in the MCMC approach.

As an illustration, Fig. 1 plots efficiency levels of several operators across time periods. Indeed, although the mean efficiency of container port industry did not change much in the years between 1997 and 2004, efficiency changes of individual operators can be quite different. Fig. 2 plots the kernel densities of individual level efficiency for the three time periods (h_{it}). From this figure we can see that although the means of the three distributions do not change very much, the quantiles of the distributions change substantially. In general, compared with the distribution in the years between 1997 and 1998, the two distributions in the years between 1999 and 2001 and between 2002 and 2004 assign much higher densities in the high efficiency range of 0.85–0.90 and lower densities in the middle efficiency range of 0.70–0.85. This observation suggests that many middle efficient operators between 1997 and 1998 improved their production efficiencies to the high efficient range in later years. The existence of a few inefficient "outliers" in both the years of 1999–2001 and the years of 2002–2004 explains the small change of the mean efficiency of container port industry.

5.2. Sensitivity analysis

The production frontier in the base model is specified as the Cobb–Douglas form. In order to test the robustness of the results with respect to the frontier specification, we modify the Cobb–Douglas specification to the more flexible translog form expressed as

Table 3
Estimation results of efficiency parameters

Mean efficiency ($\overline{TE}_t$)	Base model	Model ignoring technical change	Model ignoring unobserved heterogeneity
	Posterior median [5 percentile, 95 percentile]	Posterior median [5 percentile, 95 percentile]	Posterior median [5 percentile, 95 percentile]
1997–1998	0.8072 [0.7009, 0.8293]	0.7015 [0.6221, 0.7832]	0.4138 [0.3376, 0.4880]
1999–2001	0.8393 [0.7406, 0.9153]	0.7816 [0.7202, 0.8675]	0.4267 [0.3652, 0.4825]
2002–2004	0.8423 [0.7415, 0.8986]	0.8602 [0.7867, 0.9267]	0.4344 [0.3676, 0.4925]
$\Pr(\overline{TE}_t > \overline{TE}_{t'})$			
Mean efficiency in 1999–2001 is greater than the one in 1997–1998	0.8911	1.0000	0.6634
Mean efficiency in 2002–2004 is greater than the one in 1997–1998	0.8218	1.0000	0.7327
Mean efficiency in 2002–2004 is greater than the one in 1999–2001	0.5446	1.0000	0.6931
Time persistence of efficiencies ($\mathrm{Corr}(TE_{it}, TE_{it'})$)	Posterior median [5 percentile, 95 percentile]	Posterior median [5 percentile, 95 percentile]	Posterior median [5 percentile, 95 percentile]
(1997–1998, 1999–2001)	0.6624 [0.2481, 0.8063]	0.7116 [0.5094, 0.8180]	0.8451 [0.7917, 0.8922]
(1997–1998, 2002–2004)	0.2527 [−0.0756, 0.5197]	0.2295 [−0.0878, 0.4995]	0.7264 [0.5941, 0.8020]
(1999–2001, 2002–2004)	0.5511 [0.1947, 0.7566]	0.4452 [0.0995, 0.7017]	0.8459 [0.7877, 0.8874]

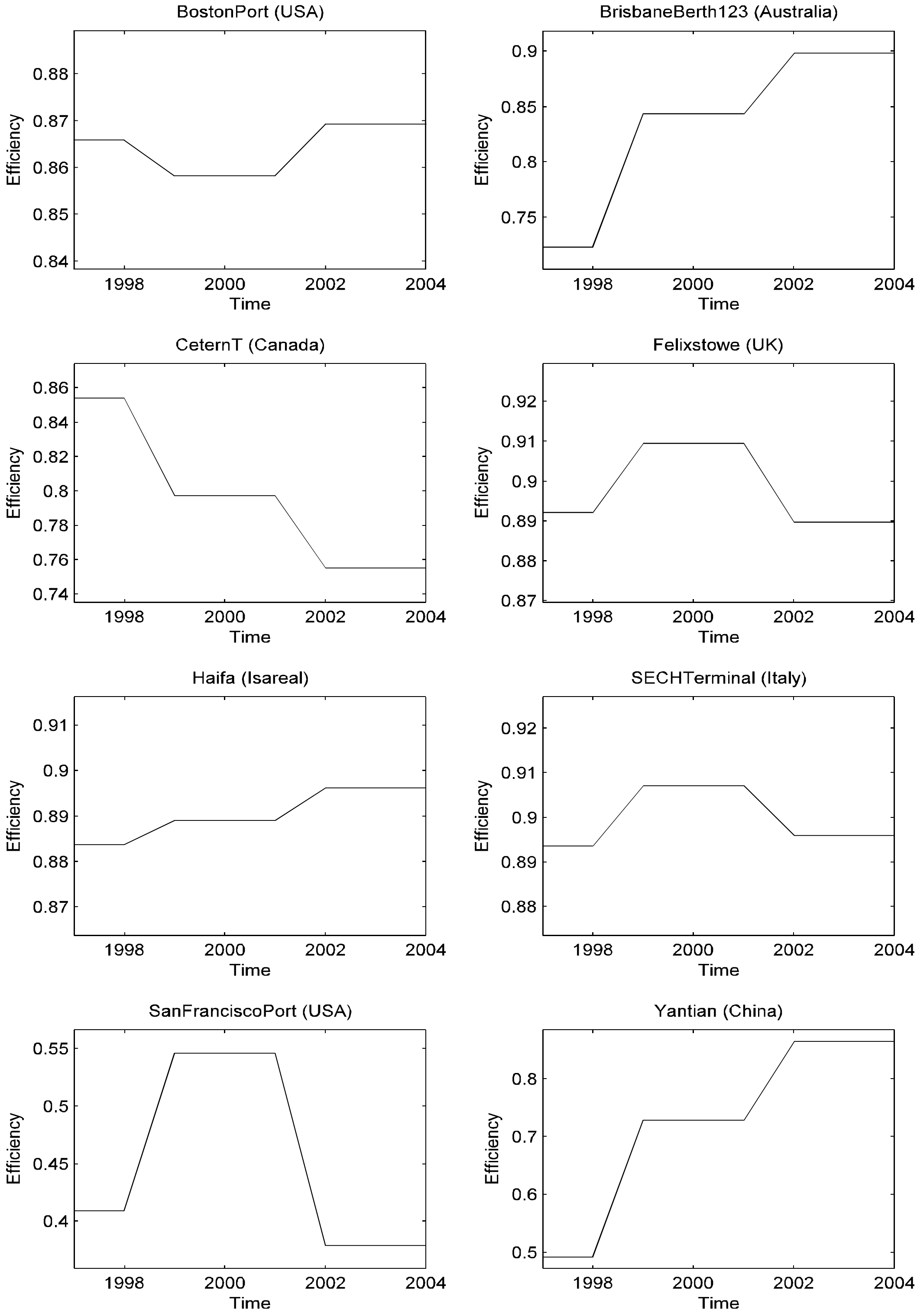

Fig. 1. Examples of individual efficiency change. The plots are the posterior means of individual efficiency.

$$lnq_{it} = \alpha_{it} + \sum_{j=1}^{M} \beta_j lnk_{ijt} + \frac{1}{2} \sum_{j=1}^{M} \sum_{j'=1}^{M} \beta_{jj'} lnk_{ijt} lnk_{ij't} \tag{3}$$

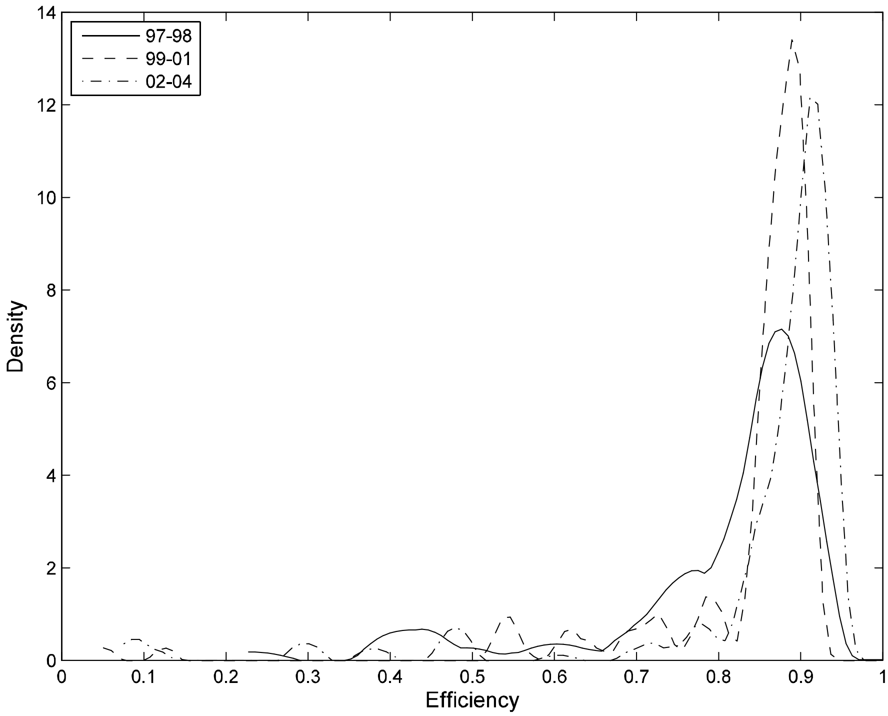

Fig. 2. Distributions of individual efficiencies. This figure plots the distributions of h_{it}, which is the mean of the posterior $p(TE_{it}|Data)$, for each t. The plotted density functions are estimated by kernel densities using Epanechnikov kernel and Silverman's (1985) bandwidth selector.

Table 4
Sensitivity analysis on model specifications

Mean efficiency	Base model	Model with translog frontier[a]	Model with multivariate half-normal distributed inefficiency[b]
	Posterior median [5 percentile, 95 percentile]	Posterior median [5 percentile, 95 percentile]	Posterior median [5 percentile, 95 percentile]
1997–1998	0.8072 [0.7009, 0.8293]	0.7748 [0.6751, 0.8628]	0.7134 [0.6416, 0.7748]
1999–2001	0.8393 [0.7406, 0.9153]	0.7923 [0.7056, 0.8824]	0.7335 [0.6680, 0.7823]
2002–2004	0.8423 [0.7415, 0.8986]	0.8164 [0.7233, 0.8953]	0.7032 [0.6362, 0.7541]

[a] This model is the variation from the base model by replacing the Cobb–Douglas production frontier with the translog production frontier.
[b] This model is the variation from the base model by changing the inefficiency specification as $\Delta_i t = |\gamma_{i1} \cdot d9798 + \gamma_{i2} \cdot d9901 + \gamma_{i3} \cdot d0204|, (\gamma_{i1}, \gamma_{i2}, \gamma_{i3})' \sim N(0, \Sigma)$.

where q_{it} denotes the output; k_{ijt} denotes the jth input of operator i at time t; a_{it} is specified the same as in Eq. (1.1), and $\beta_{jj'} = \beta_{j'j}$ if $j \neq j'$. Column 2 of Table 4 presents the results of the efficiency parameters from the translog frontier specification and the results are very similar to the ones of the base model.

As mentioned before, an overwhelming standard in stochastic frontier analysis is to employ the half-normal distribution to parameterize the distribution of the inefficiency term (Δ_{it}). In the base model, we use the multivariate log-normal distribution in order to allow the existence of very inefficient operators. We also test the robustness of the results with respect to the distribution assumption by specifying

$$\Delta_{it} = |\gamma_{i1} \cdot d9798 + \gamma_{i2} \cdot d9901 + \gamma_{i3} \cdot d0204|, \quad (\gamma_{i1}, \gamma_{i2}, \gamma_{i3})' \sim N(0, \Sigma) \tag{4}$$

that is, the distribution of the inefficiency term is modified to follow a multivariate half-normal distribution. As described in Appendix A, this distributional change requires little modification for our MCMC simulation. The results of the efficiency parameters from this model are presented in the third column of Table 4. Changing the distribution assumption has certain but not substantial effects on results of the efficiency parameters.

We specify the time dummies by grouping the eight years into three periods, and such a specification assumes that all the individuals have the same temporal pattern in their efficiency changes. In order to test the robustness of the results with respect to this assumption, we alter the specification of inefficiency term to

$$\Lambda_{it} = \exp(\gamma_{i1} + \gamma_{i2}t + \gamma_{i3}t^2), \quad (\gamma_{i1}, \gamma_{i2}, \gamma_{i3})' \sim N(\bar{\gamma}, \Sigma) \tag{5}$$

and results of the efficiency parameters form this specification are very similar to the ones from the base model so we do not present the results in order to save space.

6. Conclusion

This paper builds an empirical model under the stochastic frontier analysis framework to study technical efficiencies of container operators from the world's major container ports. The model is built upon recently collected panel data covering the years between 1997 and 2004, and the data set is the largest and the most comprehensive one ever used in port efficiency studies. The empirical model in this paper measures efficiencies and efficiency changes of the container operators after controlling for technology heterogeneity and technical change. The main findings of the paper can be summarized as:

- There is no clear evidence that the mean efficiency level of container operators changed from 1997 to 2004, but there is a large diversity among individual operators' efficiency changes.
- The percentage of high efficient operators increased after 1997–1998.
- The common "misspecifications" in stochastic frontier analysis – measuring efficiency without controlling for technical changes and the individual heterogeneity can alter the conclusions dramatically. Also, the time-invariant efficiency specification in conventional stochastic frontier analysis would lose the genuine picture of technical efficiency change in worldwide container port industry.

There are still several questions for future research on container port efficiency. First, the production process of container ports may be better characterized as the one with multiple outputs. For example, a large part of handled containers in many international hubs like Singapore and Hong Kong is for transshipment. The production process for transshipment containers is different from the one for imported/exported containers because the transshipment containers do not require the customs services. Another example is that container ports may serve both deep sea ships and barges. Handling containers transported by different types of ships may require different production practices. In the model of this paper, the diversity among operators caused by different percentages of transshipment and barge containers is treated as individual heterogeneity in the single-output production process. This individual heterogeneity can be partly captured by the random intercept. An interesting extension for current model can be a stochastic production frontier model treating different types of containers as multiple outputs.

A second extension can be a stochastic frontier model incorporating congestion. Some ports, especially those owned and operated by public agencies, may have excess capacity for the purpose to reduce port congestion. The efficiency of those ports from the current analysis can be low because the model of this paper focuses only on operators' production efficiency. However, from government's viewpoint, efficiency measures including both operators' production efficiency and port users' time efficiency are more relevant to public policy purposes.

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Appendix A. MCMC algorithm

We assume prior independence across parameters such that

$$\rho(\mathbf{\Psi}) = \rho(\bar{a}, \Theta, \tau, B) \cdot \rho(\bar{\gamma}) \cdot \rho(\Sigma) \cdot \rho(\sigma_v^2) \cdot \rho(\sigma_\varepsilon^2)$$

Specifically, we have $\Lambda \equiv (\bar{\alpha}, \Theta, \tau, B) \sim N(\Lambda_0, V_\Lambda)$, $\bar{\gamma} \sim N(\bar{\gamma}_0, V_{\bar{\gamma}})$, $\Sigma \sim \text{IW}(r, rS)$, $\sigma_v^2 \sim \text{IG}\left(\frac{d_v}{2}, \frac{d_v c_v^2}{2}\right)$, and $\sigma_\varepsilon^2 \sim \text{IG}\left(\frac{d_\varepsilon}{2}, \frac{d_\varepsilon c_\varepsilon^2}{2}\right)$, where IW($r$,$rS$) denotes the inverted Wishart distribution with the degree of freedom of r and the scale matrix of S;IG$(\frac{d_v}{2}, \frac{d_v c_v^2}{2})$ denotes the scaled inverted chi square distribution with the degree of freedom of d_v and the scale parameter of c_v^2. The properties of the two distributions can be found in Gelman et al. (2004).

The MCMC simulation is implemented by a Metropolis sampling within Gibbs algorithm, in which the parameters, including the augmented individual level parameters, are grouped into the following blocks: Λ ,σ_ε^2, $\{\gamma_i\}_i$, $\{v_i\}_i$, $\bar{\gamma}$, Σ, and σ_v^2. The Gibbs sampler iterates through sampling from the following complete conditional posteriors derived from $p(\Psi,\{v_i,\gamma_i\}_i|Data)$ in Eq. (2) of the text. In all the steps, we use $p(x|\bullet,Data)$ to denote the conditional posterior density of parameter x conditional on all other parameters except for itself, denoted by $\bullet$, and the data.

Step 1. Sampling v_i for each i from $p(v_i|\bullet, Data)$. Let $\hat{y}_{it} = y_{it} - \alpha_{it} - X_{it}B + \Delta_{it}$, this step is to draw from $N\left(\frac{\sum_{t=1}^{T_i}\hat{y}_{it}/\sigma_\varepsilon^2}{T_i/\sigma_\varepsilon^2+1/\sigma_v^2}, \frac{1}{T_i/\sigma_\varepsilon^2+1/\sigma_v^2}\right)$.

Step 2. Sampling γ_i for each i from $p(\gamma_i|\bullet, Data)$. Let $Y_i = \{y_{it} - \alpha_{it} - v_i - X_{it}B\}_t$, and from $p(\boldsymbol{\Psi}, \{v_i, \gamma_i\}_i \,|Data)$ in Eq. (2) of the text, we have

$$p(\gamma_i|\bullet, Data) \propto \exp\left\{-\frac{1}{2}\left[(\gamma_i - \bar{\gamma})'\Sigma^{-1}(\gamma_i - \bar{\gamma}) + \frac{1}{\sigma_\varepsilon^2}(Y_i + \exp(M_i\gamma_i))'(Y_i + \exp(M_i\gamma_i))\right]\right\} \tag{A.1}$$

where $M_i = [d9798, d9901, d0204]$. We use Metropolis sampling to draw from (A.1), in which the candidate draw of γ_i, $\hat{\gamma}_i$, is drawn from a normal jumping density as $N(\gamma_i^c, \kappa_i\Sigma)$, where γ_i^c represents the current draw of γ_i, and κ_i is a parameter to adjust the step length of the jumping from the current draw. Following Gelman et al. (2004), we calibrate the value of κ_i such that the rate of acceptance is between 0.20 and 0.30 for each operator i. The candidate draw from this Markov density is accepted with the probability of $\min\left\{1, \frac{p(\hat{\gamma}_i|\bullet, Data)}{p(\gamma_i^c|\bullet, Data)}\right\}$. In the sensitivity analysis of the text, we modify the specification of the inefficiency term as

$$\Delta_{it} = |\gamma_{i1}\cdot d_{9798} + \gamma_{i2}\cdot d_{9901} + \gamma_{i3}\cdot d_{0204}|, \quad [\gamma_{i1}, \gamma_{i2}, \gamma_{i3}]' \sim N(\bar{\gamma}, \Sigma)$$

With this modification, step 2 is to draw from

$$p(\gamma_i|\bullet, Data) \propto \exp\left\{-\frac{1}{2}\left[(\gamma_i - \bar{\gamma})'\Sigma^{-1}(\gamma_i - \bar{\gamma}) + \frac{1}{\sigma_\varepsilon^2}(Y_i + |M_i\gamma_i|)'(Y_i + |M_i\gamma_i|)\right]\right\} \tag{A.2}$$

and the above Metropolis sampling is still applied to draw from (A.2).

Step 3. Sampling $\Lambda \equiv (\bar{\alpha}, \Theta, \tau, B)$ from $p(\Lambda\bullet, Data)$. This step is to draw from $N(Dd, D)$, with $D = \left(\frac{1}{\sigma_\varepsilon^2}\tilde{X}'\tilde{X} + V_\Lambda^{-1}\right)^{-1}$, and $d = \frac{1}{\sigma_\varepsilon^2}\tilde{X}'\tilde{Y} + V_\Lambda^{-1}\Lambda_0$, where $\tilde{Y} = \{y_{it} - v_i + \exp(M_i\gamma_i)\}_{i,t}$, and $\tilde{X} = \{1, Z_i, t, X_{it}\}_{i,t}$.

Step 4. Sampling σ_ε^2 from $p(\sigma_\varepsilon^2|\bullet, Data)$. This step is to draw from $\mathrm{IG}\left(\frac{d_\varepsilon+\sum_{i=1}^N T_i}{2}, \frac{d_\varepsilon c_\varepsilon^2+\sum_{i=1}^N\sum_{t=1}^{T_i}e_{it}^2}{2}\right)$, with $e_{it} = y_{it} - \alpha_{it} - X_{it}B - v_i + \exp(M_i\gamma_i)$.

Step 5. Sampling σ_v^2 from $p(\sigma_v^2|\bullet, Data)$. This step is to draw from $\mathrm{IG}\left(\frac{d_v+N}{2}, \frac{d_v c_v^2+\sum_{i=1}^N v_i^2}{2}\right)$.

Step 6. Sampling$\bar{\gamma}$ from $p(\bar{\gamma}|\bullet, Data)$. This step is to draw from $N(Dd, D)$, with $D = \left(N\Sigma^{-1} + V_{\bar{\gamma}}^{-1}\right)^{-1}$, $d = \sum_{i=1}^N \Sigma^{-1}\gamma_i + V_{\bar{\gamma}}^{-1}\bar{\gamma}_0$.

Step 7. Sampling Σ from $p(\Sigma|\bullet, Data)$. This step is to draw from $\mathrm{IW}(r + N, rS + (\gamma_i - \bar{\gamma})(\gamma_i - \bar{\gamma})')$.

Under certain regularity conditions, the posterior draws from the successive sampling of the complete conditional posterior distributions (from step 1 to step 7) converge to the drawing from the joint posterior distribution $p(\Psi, \{v_i, \gamma_i\}_i|Data)$ (Gelman et al., 2004).

The chosen priors in estimation are diffuse as: $\Lambda \equiv (\bar{\alpha}, \Theta, \tau, B) \sim N(\mathbf{0}, 1000 * \mathbf{I})$, $\bar{\gamma} \sim N(\mathbf{0}, 1000 * \mathbf{I})$, $\Sigma \sim \mathrm{IW}(4, 4^{*}\mathbf{I})$, $\sigma_v^2 \sim \mathrm{IG}(1, 1)$, and $\sigma_\varepsilon^2 \sim \mathrm{IG}(1, 1)$. The diffuse priors on $\bar{\gamma}$ and Σ imply noninformative prior on the efficiency under the log-normally distributed inefficiency term. To overcome the high autocorrelation, we generate long chains from the Gibbs sampler. The reported results are based on 300,000 Gibbs draws, after dropping the first 100,000 draws in the "burn-in" period. In order to check the robustness of the results, we also try much more diffuse priors, and only the prior changes on $\bar{\gamma}$ and Σ have certain but not substantial effects on the results.

Appendix B. Calculating the efficiency parameters of interest

The MCMC approach provides us with easy ways to calculate the efficiency parameters of interest.

B.1. Mean efficiencies of operators in the three periods

In our specification, the efficiencies of operator i in the three periods are

$$TE_{i9798} = \exp(-\Delta_{i9798}) = \exp(-\exp(\gamma_{i1})) \tag{A.3a}$$
$$TE_{i9901} = \exp(-\Delta_{i9901}) = \exp(-\exp(\gamma_{i2})) \tag{A.3b}$$
$$TE_{i0204} = \exp(-\Delta_{i0204}) = \exp(-\exp(\gamma_{i3})) \tag{A.3c}$$

where $\gamma_i \equiv [\gamma_{i1}, \gamma_{i2}, \gamma_{i3}]' \sim N(\bar{\gamma}, \Sigma)$. The average efficiency over operators in a time period can be calculated as a Monte-Carlo way. For example, the mean efficiency in the period between 1997 and 1998 can be calculated as

$$\overline{TE}_{9798} \approx R^{-1}\sum_{r=1}^{R}\exp(-\exp(\gamma_{i1}^r))$$

where γ_{i1}^r is the rth random draw of γ_{i1} from the joint distribution of $N(\bar{\gamma}, \Sigma)$; R is the total number of draws.

We can account for parameter uncertainty by building the calculation in the Gibbs sampling. For the gth Gibbs draw of $\bar{\gamma}$ and Σ, denoted as $\bar{\gamma}^g$ and Σ^g, respectively, we draw γ_i from $N(\bar{\gamma}^g, \Sigma^g)$ for R times and use the draws to calculate the mean efficiencies of operators in the three periods. Let G denote the total number of post-convergent Gibbs draws, from the process we can finally get the G draws of $\overline{TE}_{9798}$, $\overline{TE}_{9901}$, and $\overline{TE}_{0204}$. We report the 5th, 50th, and 95th quantiles of them in the first panel of Table 3. From this process, we can also calculate the second efficiency parameter of interest.

B.2. Probability of mean efficiency of operators in a period is greater than the one in another period

We use the example of $\Pr(\overline{TE}_{9901} > \overline{TE}_{9798})$ to illustrate the calculation. This probability can be easily approximated by $num(\overline{TE}_{9901} > \overline{TE}_{9798})/G$, where $num(\overline{TE}_{9901} > \overline{TE}_{9798})$ denotes the total number of $\overline{TE}_{9901} > \overline{TE}_{9798}$ in the G trials. We report the results of these probabilities in the second panel of Table 3.

B.3. Time persistence of efficiencies

This parameter is defined as $\mathrm{Corr}(TE_{it}, TE_{it'})$, that is, the correlation in individual efficiencies between time t and t'. The posterior distribution of the parameter is characterized as the following way. Given the gth Gibbs draw of $\bar{\gamma}^g$and Σ^g, we take R random draws of γ_i from $N(\bar{\gamma}^g, \Sigma^g)$; from the draws we get the sample of individual efficiencies with the size of R for each of the three periods. The correlations among TE_{i9798}, TE_{i9901}, and TE_{i0204} given $\bar{\gamma}^g$ and Σ^g are calculated on the samples. Repeating this calculation for the G post-convergent Gibbs draws, we obtain G draws of correlations, and we report the 5th, 50th, and 95th quantiles of the draws in the last panel of Table 3.

B.4. Efficiency of individual operator

Eq. (2) in the text specifies the joint posterior distribution of *population* parameters $\mathbf{\Psi}$ and *individual* parameters $\{v_i, \gamma_i\}_i$. Form the joint posterior distribution, the marginal distribution of $\boldsymbol{\gamma}_i$ is

$$p(\gamma_i|Data) = \int p(\mathbf{\Psi}, \{v_i, \gamma_i\}_i|Data)d(\mathbf{\Psi}, \{v_i\}_i, \{\gamma_j\}_{j\neq i}) \tag{A.4}$$

where $\{\boldsymbol{\gamma}_j\}_{j\neq i}$ denotes the collection of $\boldsymbol{\gamma}$ across individual operators excluding $\boldsymbol{\gamma}_i$. The marginal distribution of γ_{it} (t = 1997–1998, 1999–2001, or 2002–2004) is then

$$p(\gamma_{it}|Data) = \int p(\gamma_i|Data)d(\gamma_{it'}, \gamma_{it''}) \tag{A.5}$$

where $t' \neq t$ and $t'' \neq t$. Efficiency of operator i at time t is specified by equations Eq. (A.3). The Bayesian estimator for the individual efficiency is represented by the posterior $p(TE_{it}|Data)$, which can be derived from (A.5) by applying the technique of transformation of variables. The adopted MCMC approach can characterize the individual efficiency easily. At step 2 of each Gibbs iteration, we get the draw of γ_i for each i; given the draw we can calculate TE_{it} for each i and each t; the distribution of $p(TE_{it}|Data)$ can then be approximated by the empirical distribution of the draws of TE_{it}. We report the mean of $p(TE_{it}|Data)$, which is denoted by $h_{it}$and calculated as$h_{it} \approx \frac{1}{G}\sum_{g=1}^{G} TE_{it}^{g}$, where TE_{it}^{g} is TE_{it} evaluated at the gth draw of γ_i.

Above procedure is the standard Bayesian approach to infer individual-level parameters from a random parameter model. More details of the approach can be found in Allenby and Rossi (1999). The precision of the inference on individual efficiency depends on the number of repeated observations from the individual.

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