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MODELING A THREE-STAGE NETWORK DATA ENVELOPMENT ANALYSIS MODEL – A CASE OF EFFICIENCY ANALYSIS FOR EXCHANGE TRADED FUNDS

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Abstract. *In order to explore the efficiency of Taiwan's Exchange Traded Funds, we apply a three-stage network data envelopment analysis model to assessing overall and stage-level performance. These empirical results reveal that good overall performance, generally, may not suggest good allied process performance or good portfolio management performance. In the ETF performance appraisal literature, the focus is predominantly on the fund portfolio with main considerations being risks, returns, and costs. Our performance appraisal approach is beneficial to ETF management because findings are based on models that accommodate multiple measures of performance and in a comprehensive network representation of the overall fund management process. Out of the 87 ETFs considered in our empirical analysis of Taiwan ETFs, we find the top 10 best performers ETFs in terms of overall efficiency, each of these ETFs is either a bond ETF or an ETF that shortens (or bets against) the financials space. The portfolio managers can use the source of ETF's inefficiency revealed by three-stage network DEA to identify which ETFs that they could emulate in order to achieve efficiency in the future.*

Keywords: Network data envelopment analysis, Efficiency decomposition, Exchange traded funds

1. **Introduction.** Exchange Traded Fund (ETF) is a new financial tool with a history of only 30 years. ETF is a type of investment company, typically structured as an open-end fund or UIT, whose shares are traded intraday on stock exchanges at market-determined prices [1]. Like shares of any publicly traded company, investors can buy and sell ETF shares through a broker. Most ETFs are pegged to financial indices and seek to replicate the performance of specific domestic, sector, regional, or international indexes. ETFs do not have any restriction on their contract period and thus can be permanently traded at the current stock exchange price in the same way as shares. Because ETFs with passive management aim to reproduce a benchmark index as accurately as possible, ETFs

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can never outperform the development of the associated index [2]. ETFs combine the advantages of three asset classes: shares, certificates, and funds. Like shares, ETFs can be traded at any time at the current stock exchange value and are thus a very flexible investment instrument. In addition, because they have a cost structure similar to that of certificates, they are of interest to private investors [3]. The composition of ETFs also guarantees broad diversification, as is common for funds, which is why they are regarded as a relatively secure asset class [4,5].

Within recent decades, there has been raising a question about the ability to consistently earn positive risk-adjusted returns of ETFs, which is essential to our knowledge of the efficient capital market [6]. Because there is a considerable debate on whether ETFs managerial skills exist, measuring and comparing the performance of mutual, trust, and superannuation funds have become an important issue for managers and investors alike in the finance industry, and hence there is a pressing need for a credible measure for assessing and ranking the performance of these managed funds [7]. Since the late 1990s, there is a growing body of research applying an operation research technique called Data Envelopment Analysis (DEA) [8] to mutual fund performance evaluation. Murthi et al. [9] developed this technique as a means to measure portfolio performance and capture the multidimensional aspect of mutual fund performance. Compared to other parametric approaches, DEA requires neither a theoretical framework as a benchmark such as the Capital Asset Pricing Model (CAPM) or the Arbitrage Pricing Theory (APT) model nor a priori assumption of the relationship between inputs and outputs [10]. Instead, it measures how well a fund performs relative to the best funds. Furthermore, it can address the problem of endogeneity of transaction costs in the analysis by simultaneously considering expense ratios, turnover, and loads, as well as returns. Galagedera and Silvapulle [7] used DEA to measure the relative efficiency of 257 Australian mutual funds, and logistic regression to examine the dependence of efficiency on fund attributes, management strategy, and the operating environment.

Early DEA studies of Mutual Funds (MF) performance appraisal treat funds' operation as a "black box" in which its internal structures are ignored. Recent studies of MF performance appraisal using DEA look inside the "black box" to capture internal structures of the overall fund management process. Basso and Funari [11] provided a comprehensive list of DEA studies that evaluate MFs and other managed funds such as pension and hedge funds dating up to 2014. Out of the 61 DEA approaches of MF performance listed therein, only one study of Premachandra et al. [12] adopted a network structure. Galagedera et al. [13] assessed MF performance by extending the two-stage network structure of [12] to accommodate independent output at the first stage.

The main focus of this paper is to develop a serial-network DEA model proposed by Galagedera et al. [14] to evaluate ETFs performance. In multi-stage processes, the measures that link consecutive stages are referred to as "intermediate measures". Intermediate measures represent resources deemed generated and consumed within the production process, and thus they may be considered as internal resources. Premachandra et al. [12] and Galagedera et al. [13] in their two-stage MF performance appraisal modeling framework, considered operational management and portfolio management as the two consecutive processes with Net Asset Value (NAV) as an intermediate variable. Further, they consider NAV, fund size, standard deviation of returns and expense ratio as the inputs of the second stage (portfolio management process). Galagedera et al. [14] proposed a three-stage network model in multiplier DEA setting for MF performance appraisal and conceptualized the overall MF management process as a serially linked three-stage process comprising of operational management, resource management, and portfolio management processes.

This paper contributes to the existing literature in several ways. First, we extend the three-stage network DEA model developed in Galagedera et al. [14] by integrating some new variables to measure Internal Resource Imbalance (IRI). Second, the greatest share of investment company assets is held by households. As households have come to rely more on investment funds such as ETFs over the past decade, their demand for directly held equities has fallen. Hence, given this significant reliance by individual investors on the performance of such investment products, it is important to analyze the performance of ETFs in a comprehensive way and provide consumer-friendly performance measures on different aspects of ETF management. We investigate this issue empirically. In our empirical investigation, we use the proposed model to assess the relative performance of a comprehensive sample of 87 Taiwan ETFs. We believe that the findings are useful to investors in selecting ETFs and to managers in identifying the source of inefficiencies. The portfolio managers can use the source of ETF's inefficiency revealed by three-stage network DEA to identify which ETFs that they could emulate in order to achieve efficiency in the future.

The rest of the paper is organized as follows. In Section 2, we briefly discuss ETF performance appraisal using network DEA and apply this three-stage network DEA model to the efficiency analysis of ETFs. In Section 3, we describe the data and present the input, intermediate, and output measures used in the empirical investigation and demonstrate the application of the models. The results are also discussed in this section. The paper concludes in Section 4.

2. Three-Stage Networks with Alliance and Intermediate Resource Imbalance.

Within recent decades, many studies use DEA models to evaluate the performance of DMUs in various financial markets, such as banks and MFs. This model has been proven as one of the most effective methods to benchmark the performance of competitive organizations and received many improvements from researchers (for instance, [15]). However, the traditional DEA models consider the financial management process as a single-stage production process with multiple inputs and multiple outputs [7,9,11,16,17]. Indeed, a single-stage production process is a black box. The newly developed Network DEA models (NDEA) incorporate the internal structure of the production process into performance analysis. Because of this versatility, network DEA is becoming increasingly popular in performance appraisal and a variety of network structures are created in some leading researches [18,19]. In the financial markets, performance appraisal of banking industry [20-22] and MFs are also popular. Our research is mainly based on two studies on MF using network DEA approach, that are, Premachandra et al. [12] and Galagedara et al. [14]. The network structure that they applied is a two-stage process. Both studies highlight that stage-level inefficiency may vary across MFs and their contributions towards overall inefficiency provide useful managerial information.

2.1. Proposed network structure.

The proposed network structure for MF performance appraisal conceptualizes the overall ETF management process as a serially linked three-stage process comprising of operational management, resource management, and portfolio management processes. Studies highlight that ETF performance may be associated with many factors including fund size, returns, variability in the returns, cost, fees, redemption, and net asset value. Adverse macroeconomic conditions can make the task of ETF management even more difficult [23,24]. Furthermore, ETF-specific micro-level information is not available freely. Hence, ETF performance appraisal is not a straightforward exercise. Subject to these limitations, we endeavor to apprise ETF performance by considering a large set of measures deemed important in ETF performance appraisal. We draw a parallel between ETF performance appraisal and bank performance appraisal in the variable section. In bank performance appraisal, whether to treat deposits as an input or as an output is a dilemma. One way that this issue is addressed in the literature is to conceptualize the bank's operation as a two-stage production process. A similar dilemma arises in ETF performance appraisal as fund size and net asset value may be considered as inputs or as outputs. Using both fund size and net asset value together as inputs or as outputs, however, is not prudent as both proxy scale of operation in some ways and is generally highly positively correlated. We propose an alternative. We argue that net asset value may be considered as total funds transformed through a management process different from operational management and portfolio management.

2.2. **Three-stage production process with alliance between the first two stages.** A general serially linked three-stage process with alliance between the first two stages is illustrated in Figure 1. The dash-lined rectangle of Figure 1 signifies the alliance between stage A and stage B. In this section, we derive DEA models for performance appraisal in the general three-stage network structure depicted in Figure 1. When adopting the models derived in this section for performance appraisal in our empirical study, we set $Y_j^A = \{\}$ and $Y_j^B = \{\}$. Throughout this section, we assume there are n homogeneous MFs generically referred to as Decision Marking Units (DMUs) in the DEA terminology.

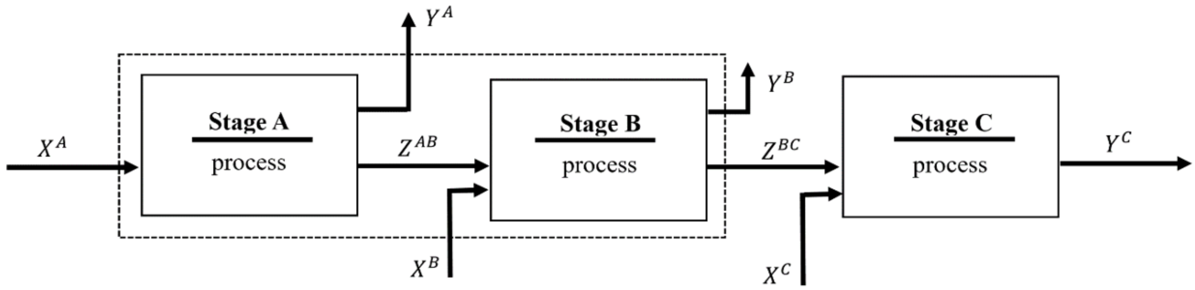

FIGURE 1. Three-stage process with alliance between the first two stages

Let i_A, i_B, i_C indicate the number of inputs at stage A, stage B, and stage C; $X_j^A = \{x_{1j}^A, x_{2j}^A, \ldots, x_{i_Aj}^A\}$, $X_j^B = \{x_{1j}^B, x_{2j}^B, \ldots, x_{i_Bj}^B\}$, $X_j^C = \{x_{1j}^C, x_{2j}^C, \ldots, x_{i_Cj}^C\}$ denote these inputs of DMU_j observed at stage A, stage B, and stage C; d_{AB}, d_{BC} = the number of intermediate products connecting stage A with stage B and stage B with stage C; $Z_j^{AB} = \{z_{1j}^{AB}, z_{2j}^{AB}, \ldots, z_{d_{AB}j}^{AB}\}$, $Z_j^{BC} = \{z_{1j}^{BC}, z_{2j}^{BC}, \ldots, z_{d_{BC}j}^{BC}\}$ denote the observed values of the intermediate measures linking stage A with stage B and stage B with stage C of DMU_j; r_A, r_B, r_C indicate the number of independent outputs at stage A, stage B, and stage C; $Y_j^A = \{y_{1j}^A, y_{2j}^A, \ldots, y_{r_Aj}^A\}$, $Y_j^B = \{y_{1j}^B, y_{2j}^B, \ldots, y_{r_Bj}^B\}$, $Y_j^C = \{y_{1j}^C, y_{2j}^C, \ldots, y_{r_Cj}^C\}$ denote these outputs of DMU_j observed at stage A, stage B, and stage C, respectively.

Generally, MF performance metrics are positive with the exception of average return. In our case, average return is an output of the final stage and to ensure that average return is positive we add a positive constant to the returns. Such transformation of output does not affect the optimal solutions of Banker et al. [25] input-oriented variable returns to scale model, known as the BCC model. Therefore, analogous to the studies that used DEA to appraise MF performance with average return as output, we employ input-oriented models under the variable returns to scale assumption. Furthermore, this is consistent with our empirical situation as in practice; MF managers have more control over the inputs (fees, expenses, and risk) than with output (return).

We first develop the efficiency scores for each stage with the assumption that there is no connection between stages. The input-oriented BCC models to compute the efficiency of stage A $\left(\theta_0^A\right)$ in DMU_0 can be written as the following

$$\theta_0^{A^*} = Max \frac{\sum_{d=1}^{d_{AB}} \eta_d^{AAB} z_{d0}^{AB} + \sum_{r=1}^{r_A} u_r^A y_{r0}^A + \tau^A}{\sum_{i=1}^{i_A} v_i^A x_{i0}^A} \tag{1}$$

$$\begin{aligned} s.t. \quad & \sum_{d=1}^{d_{AB}} \eta_d^{AAB} z_{dj}^{AB} + \sum_{r=1}^{r_A} u_r^A y_{rj}^A + \tau^A \le \sum_{i=1}^{i_A} v_i^A x_{ij}^A, \ \forall j \\ & \eta_d^{AAB}, u_r^A, v_i^A \ge \varepsilon; \ \tau^A \ \textit{free} \end{aligned}$$

where n is the number DMUs selected to appraise, thus $j = 1, 2, \ldots, n$. Because the intermediate measures play a dual role in model formulation, to make this distinction clear, we denote the weight assigned to η_d^{AAB} and η_d^{BAB} when z_{d0}^{AB} is viewed as outputs of stage A and as inputs of stage B, respectively. Similarly, we use η_d^{BBC} and η_d^{CBC} as the multipliers for the intermediate products Z_d^{BC} when they are considered as outputs in stage B or inputs in stage C, respectively. The last constraint implies that all decision variables (also referred to as multipliers) should be positive (ε is a small positive constant). In the similar manner, the efficiency of stage B and stage C can be derived as the following

$$\theta_0^{B^*} = Max \frac{\sum_{d=1}^{d_{BC}} \eta_d^{BBC} z_{d0}^{BC} + \sum_{r=1}^{r_B} u_r^B y_{r0}^B + \tau^B}{\sum_{d=1}^{d_{AB}} \eta_d^{BAB} z_{d0}^{AB} + \sum_{i=1}^{i_B} v_i^B x_{i0}^B} \tag{2}$$

$$\begin{aligned} s.t. \quad & \sum_{d=1}^{d_{BC}} \eta_d^{BBC} z_{dj}^{BC} + \sum_{r=1}^{r_B} u_r^B y_{rj}^B + \tau^B \le \sum_{d=1}^{d_{AB}} \eta_d^{BAB} z_{dj}^{AB} + \sum_{i=1}^{i_B} v_i^B x_{ij}^B, \ \forall j \\ & \eta_d^{BBC}, \eta_d^{BAB}, u_r^B, v_i^B \ge \varepsilon; \ \tau^B \ \textit{free} \end{aligned}$$

$$\theta_0^{C^*} = Max \frac{\sum_{r=1}^{r_C} u_r^C y_{r0}^C + \tau^C}{\sum_{d=1}^{d_{BC}} \eta_d^{BCB} z_{d0}^{BC} + \sum_{i=1}^{i_C} v_i^C x_{i0}^C + \sum_{i=1}^{i_s} \gamma_{i0} v_i^S x_{i0}^S} \tag{3}$$

$$\begin{aligned} s.t. \quad & \sum_{r=1}^{r_C} u_r^C y_{rj}^C + \tau^C \le \sum_{d=1}^{d_{BC}} \eta_d^{BCB} z_{dj}^{BC} + \sum_{i=1}^{i_C} v_i^C x_{ij}^C + \sum_{i=1}^{i_s} \gamma_{ij} v_i^S x_{ij}^S, \ \forall j \\ & U_{ij}^{\gamma} \le \gamma_{ij} \le L_{ij}^{\gamma}, \ \forall j \\ & \eta_d^{CBC}, u_r^C, v_i^C, v_i^S \ge \varepsilon; \ \tau^C \ \textit{free} \end{aligned}$$

In our empirical investigation, we conceptualize the first two stages operated as an allied process. We model this alliance by imposing the condition that the corresponding intermediate measures are valued the same regardless of their role, either as output at stage A or as input at stage B. This is a commonly used assumption in DEA studies of two-stage processes [26,27]. Specifically, we assume that the multipliers associated with the intermediate measures linking stage A and stage B are the same so that in Models (1) and (2) $\eta_d^{AAB} = \eta_d^{BAB} = \eta_d^{AB}$. This condition ensures that the implied value of stage A output associated with the intermediate resources z_{d0}^{AB} is equal to the implied value of the stage B input associated with the same set of intermediate resources. We interpret this condition as stage A and stage B operating with no Intermediate Resource Imbalance (IRI). We define the level of IRI between stage A and stage B as

$$I_0^{A\text{-}B} = \frac{\sum_{d=1}^{d_{AB}} \eta_d^{BAB} z_{d0}^{AB}}{\sum_{d=1}^{d_{AB}} \eta_d^{AAB} z_{d0}^{AB}} \tag{4}$$

In our case, the alliance assumption on the multipliers $\eta_d^{AAB} = \eta_d^{BAB} = \eta_d^{AB}$ implies $I_0^{A\text{-}B}$. We express the efficiency of the allied processes, θ_0^{AB} as a weighted average of stage A and stage B efficiencies, that is $\theta_0^{AB} = w_A\theta_0^A + w_B\theta_0^B$ and $w_A + w_B = 1$ where w_A and

w_B are user-specified weights. Chen et al. [26] suggested that the relative 'size' of the inputs of a stage may reflect the importance of that stage. They use the ratio of the implied value of the inputs (resources) of a stage to the implied value of the inputs of all stages as the weight for the efficiency of that stage. We do the same because this is a reasonable assumption given that the model we apply is input-oriented. Accordingly, w_A and w_B can be defined as

$$w_A = \frac{\sum_{i=1}^{i_A} v_i^A x_{i0}^A}{\sum_{d=1}^{d_{AB}} \eta_d^{AB} z_{d0}^{AB} + \sum_{i=1}^{i_A} v_i^A x_{i0}^A + \sum_{i=1}^{i_B} v_i^B x_{i0}^B}$$

and

$$w_B = \frac{\sum_{d=1}^{d_{AB}} \eta_d^{AB} z_{d0}^{AB} + \sum_{i=1}^{i_B} v_i^B x_{i0}^B}{\sum_{d=1}^{d_{AB}} \eta_d^{AB} z_{d0}^{AB} + \sum_{i=1}^{i_A} v_i^A x_{i0}^A + \sum_{i=1}^{i_B} v_i^B x_{i0}^B}.$$

The aggregate efficiency of the allied process, θ_0^{AB} can be written as

$$\theta_0^{AB} = \frac{\sum_{r=1}^{r_A} u_r^A y_{r0}^A + \sum_{d=1}^{d_{AB}} \eta_d^{AB} z_{d0}^{AB} + \sum_{r=1}^{r_B} u_r^B y_{r0}^B + \sum_{d=1}^{d_{BC}} \eta_d^{CBC} z_{d0}^{BC}}{\sum_{d=1}^{d_{AB}} \eta_d^{AB} z_{d0}^{AB} + \sum_{d=1}^{d_{BC}} \eta_d^{CBC} z_{d0}^{BC} + \sum_{i=1}^{i_B} v_i^A x_{i0}^A + \sum_{i=1}^{i_B} v_i^B x_{i0}^B} \tag{5}$$

Similarly, we express overall efficiency of the three-stage process of DMU_0, θ_0^{ABC} as a weighted average of the allied process efficiency and stage C efficiency, such that $\theta_0^{ABC} = w_{AB}\theta_0^{AB} + w_C\theta_0^C$ and $w_{AB} + w_C = 1$ where w_{AB} and w_C are user-specified weights. Following the same line of argument, we write w_{AB} and w_C as

$$w_{AB} = \frac{\sum_{d=1}^{d_{AB}} \eta_d^{AB} z_{d0}^{AB} + \sum_{i=1}^{i_A} v_i^A x_{i0}^A + \sum_{i=1}^{i_B} v_i^B x_{i0}^B}{\sum_{d=1}^{d_{AB}} \eta_d^{AB} z_{d0}^{AB} + \sum_{i=1}^{i_A} v_i^A x_{i0}^A + \sum_{i=1}^{i_B} v_i^B x_{i0}^B + \sum_{d=1}^{d_{BC}} \eta_d^{CBC} z_{d0}^{BC} + \sum_{i=1}^{i_C} v_i^C x_{i0}^C}$$

and

$$w_C = \frac{\sum_{d=1}^{d_{BC}} \eta_d^{BC} z_{d0}^{BC} + \sum_{i=1}^{i_C} v_i^C x_{i0}^C}{\sum_{d=1}^{d_{AB}} \eta_d^{AB} z_{d0}^{AB} + \sum_{i=1}^{i_A} v_i^A x_{i0}^A + \sum_{i=1}^{i_B} v_i^B x_{i0}^B + \sum_{d=1}^{d_{BC}} \eta_d^{CBC} z_{d0}^{BC} + \sum_{i=1}^{i_C} v_i^C x_{i0}^C}.$$

The overall system efficiency can be calculated as

$$\theta_0^{ABC^*} = \frac{\sum_{d=1}^{d_{AB}} \eta_d^{AB} z_{d0}^{AB} + \sum_{r=1}^{r_A} u_r^A y_{r0}^A + \tau^A + \sum_{d=1}^{d_{BC}} \eta_d^{BBC} z_{d0}^{BC} + \sum_{r=1}^{r_B} u_r^B y_{r0}^B + \tau^B + \sum_{r=1}^{r_C} u_r^C y_{r0}^C + \tau^C}{\sum_{d=1}^{d_{AB}} \eta_d^{AB} z_{d0}^{AB} + \sum_{d=1}^{d_{BC}} \eta_d^{CBC} z_{d0}^{BC} + \sum_{i=1}^{i_A} v_i^A x_{i0}^A + \sum_{i=1}^{i_B} v_i^B x_{i0}^B + \sum_{i=1}^{i_B} v_i^C x_{i0}^C} \tag{6}$$

In our empirical setup, we assume that the allied and stage C processes operate under different environmental conditions in respect of risk. This situation is somewhat analogous to a two-stage process where each process is undertaken by a different firm. In that case, it is not just to enforce the condition that both firms assign the same value to a resource when that resource plays a dual role – output in one case and input in the other. Such dilemmas arise in the network representation of supply chains involving subcontractors. For example, suppose the firm that operates the second stage is a subcontractor of the firm that operates the first stage. In that case, the subcontractor will be under no obligation to accede to a model-implied conditional valuation scheme unfavorable to it when appraising its performance. Following a similar line of reasoning for processes that operate under different levels of risk exposure, we allow some extent of flexibility in the choice of multipliers associated with the intermediate measures that link the allied and stage C processes. Specifically, we do not impose the restriction that the multipliers of the intermediate measures linking the allied process with stage C process have the same value. The constraints that we impose on the multipliers associated with the intermediate measures Z^{BC} are $\eta_d^{BBC} > \eta_d^{CBC}$. These conditions ensure that the sum of the implied value of the intermediate measures as output of the allied process is greater than or equal to the sum of the implied value of the same set of intermediate measures as input at stage

C. Hence, there is a possibility of imbalance in the implied value of intermediate resources Z^{BC}. In this case, the level of IRI between the allied process and stage C is measured by

$$I_0^{AB\text{-}C} = \frac{\sum_{d=1}^{d_{BC}} \eta_d^{CBC} z_{d0}^{BC}}{\sum_{d=1}^{d_{BC}} \eta_d^{BBC} z_{d0}^{BC}} \tag{7}$$

The assumption on the multipliers guarantees that $0 < I_0^{AB\text{-}C} \leq 1$. The optimal adverse level of IRI of the overall ETF management process of DMU_0, can be expressed as $I_0^* = I_0^{A\text{-}B} * I_0^{AB\text{-}C}$. We refer to I_0^* as IRI index of DMU_0. By assumption we have $I_0^{A\text{-}B^*} = 1$. Therefore, $I_0^* = I_0^{AB\text{-}C^*}$. For a given DMU_0, $I_0^* = 1$ indicates no imbalance in the use of intermediate resources in the overall fund management process which we consider as a desired outcome for DMU_0.

3. **Empirical Study of Taiwan Exchange Traded Funds.** The selection of the input, intermediate, and output measures guided by previous DEA studies of MF performance appraisal [14]. The first stage (operational management process – labeled stage A) is where funds are raised and therefore fund size is considered as stage A output. Stage A inputs are marketing and distribution fees and management fees. The second stage (resource management process – labeled stage B) is where the funds raised in stage A are secured for investment in the third stage. We consider Net Asset Value (NAV) as stage B output. Disbursements such as transaction costs and costs incurred for recordkeeping, custodial services, taxes, legal expenses, and accounting and auditing fees are not accounted for in stage A. Therefore, we consider management expense ratio as stage B input in addition to fund size and turnover ratio. The third stage (portfolio management process – labeled stage C) involves management of assets to generate returns with risk taken. Hence, we consider total risk, systematic risk, downside risk, and NAV as inputs and return as output of stage C. We discussed earlier that operational and resource management processes operate under similar environmental conditions. In other words, the operational and resource management processes are subject to similar levels of risk exposure. Because of this commonality, we consider these two processes as an allied process. We show the alliance between stage A and stage B in Figure 1 by enclosing them in a dash-lined rectangle. Taiwan's ETFs samples are obtained from the 2018 fund profile in the Taiwan Economic Journal database. Initially, we collected data on a large number of funds and later reduced to 87 ETFs according to our sample selection criteria. We require that ETFs have inception dates prior to 31 December 2017, have been inactive trading and survived up to 31 December 2018. Hence, our sample is free from survivorship and age-bias. We require all funds to have non-zero values for all measures in all sampled years. Table 1 lists the measures used in the analysis and gives a brief description of their calculation.

There are various types of ETFs in Taiwan available to investors that can be used for income generation, speculation, price increases, and to hedge or partly offset risk in an investor's portfolio. Below are several examples of the types of ETFs. Bond ETFs might include government bonds, corporate bonds, and state and local bonds – called municipal bonds [23]. Industry ETFs track a particular industry such as technology, banking, or the oil and gas sector. Commodity ETFs invest in commodities including crude oil or gold. Currency ETFs invest in foreign currencies such as the Euro or US dollar.

Inverse Equity ETFs invest in various stock assets. Funds in this category often track indices, but can also build portfolios of specific equities without tracking an index. Inverse ETFs allow for downside exposure of certain indexes and sectors. They are used by investors with a bearish market outlook and who want to bet against the market. Inverse ETFs attempt to earn gains from stock declines by shorting stocks. Shorting is selling a stock, expecting a decline in value, and repurchasing it at a lower price. Investors should

Table 1. Performance metrics descriptive statistics

Variables descriptions		Mean
Stage A Input measures	Management fees	Fees paid to investment advisors expressed as a percentage.
	Marketing and distribution fees	Cost of marketing and selling fund shares expressed as a percentage.
Intermediate measure that links stage A and stage B	Fund size	Market value of portfolio in base currency.
Stage B Input measures	Net expense ratio	Annual fee expressed as a percentage to cover expenses such as administrative fees, operating costs and all other asset-based costs incurred by the fund.
	Turnover ratio	Percentage of holdings replaced.
Intermediate measure that links stage B and stage C	Net Asset Value	Total value of portfolio less liabilities in base currency.
Stage C Input measures	Total risk	Standard deviation of weekly return
	Systematic risk	CAPM beta computed using weekly return.
	Downside risk	Downside standard deviation of weekly return.
Stage C Output measures	Annual return	Expressed as a percentage.

be aware that many inverse ETFs are Exchange Traded Notes (ETNs) and not true ETFs. An ETN is a bond but trades like a stock and is backed by an issuer like a bank. When investing in the stock market, some investors may think the only way to profit is from the markets going up. However, that is not the case; there also is a way for investors to profit when the markets decline. For individual stocks and ETFs, an investor can take a short position – in which a stock is borrowed and sold, and the investor hopes to buy back the stock at a lower price. As it pertains to ETFs, there is a convenient way to make money when the market falls without having to take a short position. This is through inverse ETFs, which gain in value when the market or underlying sector in question falls in value. Several inverse ETFs take positions against the entire market or a specific sector of the market. Many investment firms offer investors a wide range of inverse ETFs. For example, in the U.S., the ProShares UltraPro Short S&P 500 ETF (SPXU A-) seeks to return daily investment results that correspond to three times the inverse of the S&P 500's daily performance. And in Taiwan, Yuanta Daily Taiwan 50 Bear -1X ETF seeks daily investment results of 100% of the inverse of the Taiwan 50 Index's performance. As a result, inverse ETFs can be a great opportunity for investors to profit from market declines. However, they are risky because they employ leverage to produce returns. If the market continues to increase, leveraged inverse ETFs can lose a significant amount of value. Investors should consider the risks and opportunities involved before buying an inverse ETF.

3.1. **Performance at the individual fund level.** Table 2 shows summary statistics of relative efficiency scores of all ETFs. Table 2 reveals that the average overall management

TABLE 2. Summary of relative efficiency scores of all ETFs

	Stage A	**Stage B**	**Stage C**	**Allied process**	**System**
Mean	0.215	0.303	0.657	0.304	0.676
Std. deviation	0.240	0.253	0.213	0.230	0.207
Min	0.000	0.051	0.289	0.077	0.332
Median	0.140	0.183	0.620	0.195	0.674
Max	1.000	1.000	1.000	1.000	1.000

TABLE 3. Overall management: Top 10 performers

ETF's name	**Stage A**	**Stage B**	**Stage C**	**Allied process**	**System**	**IRI**
Fubon 1-3 Years US Treasury Bond ETF	1	1	1	1	1	1.0000
Fubon 20+ Years US Treasury Bond ETF	0.835	1	0.461	1	1	1.0000
Fuh Hwa 1-5 Yr High Yield ETF	0.361	0.375	1	0.375	0.987	1.0000
CAPITAL TAIEX DAILY INVERSED -1X ETF	0.248	0.314	1	0.314	0.983	1.0000
Cathay TAIEX Daily Inversed ETF	0.030	0.235	1	0.235	0.979	1.0000
Fubon TAIEX Daily -1X Inverse ETF	0.025	0.260	0.995	0.260	0.974	1.0000
Yuanta Daily Taiwan 50 Bear -1X ETF	0.368	0.295	0.994	0.273	0.971	1.0000
Mega Taiwan Blue Chip 30 Daily Inverse ETF	0.114	0.177	1	0.177	0.969	1.0000
Yuanta Daily S&P 500 Bear 1X ETF	0.008	0.156	1	0.156	0.964	1.0000
Fubon TOPIX Inversed -1X Index ETF	0.136	0.153	1	0.153	0.964	1.0000
Average	0.312	0.396	0.945	0.394	0.979	1.0000

efficiency score of all ETFs is 0.676. Here we limit the discussion to the 10 best performing ETFs in each management process.

The 10 best performers ETFs in terms of overall efficiency are listed in Table 3. Out of the 87 ETFs considered in the analysis, only two ETFs are efficient overall. This may be due to the augmented structure of the network representation (Figure 1). Previous studies that adopt network representation of production processes reveal that increased structure may add discriminatory power [13,14]. Fubon 1-3 Years US Treasury Bond ETF is also efficient in all other aspects of management modeled in the analysis. Fubon 20+ Years US Treasury Bond ETF is ranked very poorly in portfolio management but is efficient in allied process management. This is reversed in the case of the other eight ETFs listed in Table 3. In fact, out of the eight ETFs listed in the bottom rows of Table 3, all of them are ranked within the top-ranked part in portfolio management (see Table 5) whereas many of them are ranked poorly in allied process management. These results reveal that generally, good overall performance may not suggest good allied process performance or good portfolio management performance. This brings us to the question: which of the three stage-level management processes may influence the overall performance the most.

Table 4 reports the efficiency scores of the top 10 performers in allied process management. In this case, only one ETF is efficient and as expected it is efficient in operational management and resource management as well. Further, only two of the ten ETFs listed in Table 3 are also listed in Table 4 suggesting positive association in the allied and overall management process performance, but the others are ranked poorly in allied process management. We find that portfolio management performance of the ETFs listed

Table 4. Allied process management: Top 10 performers

ETF's name	**Stage A**	**Stage B**	**Stage C**	**Allied process**	**System**	**IRI**
Fubon 1-3 Years US Treasury Bond ETF	1	1	1	1	1	1.0000
Fubon 20+ Years US Treasury Bond ETF	0.835	1	0.461	1	1	1.0000
Yuanta/P-shares Taiwan Top 50 ETF	1	0.905	0.344	0.904	0.904	0.0009
Cathay US Treasury 20+ YR ETF	0.918	0.870	0.461	0.869	0.869	1.0000
Yuanta U.S. Treasury 20+ Year Bond ETF	1	0.216	0.481	0.866	0.866	1.0000
Fubon TWSE Corporate Governance 100 ETF	0.080	0.869	0.754	0.866	0.866	1.0000
Fubon Taiwan Technology Tracker Fund	0.499	0.823	0.411	0.823	0.822	0.0007
Fubon FTSE TWSE Taiwan 50 ETF	0.506	0.757	0.485	0.757	0.757	0.0007
Fubon Taiwan Eight Industries ETF	0.496	0.709	0.446	0.709	0.709	0.0009
Capital Bofa Merrill Lynch 10+ Year US Banking Index Exchange Traded Fund	0.672	0.623	0.775	0.623	0.770	1.0000
Average	0.701	0.885	0.562	0.842	0.856	0.6003

in Table 4 is generally poor. This is not surprising because we give priority to the allied process over the portfolio management process in overall efficiency decomposition. When we do the opposite, we find a similar result: there is no positive association between portfolio management performance and allied process performance. We advance the lack of positive association between allied process performance and portfolio management performance uncovered here as empirical justification (value-added) for conceptualizing the overall ETF management process as a production process comprising multiple stages.

We find that three ETFs are operational management efficient. Moreover, 7 out of the 10 operational management performers are also among the top 10 allied process performers. This observation and the rank correlation between operational management and allied process management efficiency scores suggest that the association between them is positive and strong. This is important information to ETF managers. Given the earlier finding that there is a strong positive association between allied process performance and overall performance, especially at the high end, a positive step towards achieving excellence in overall performance is to manage the operational management process efficiently. Because there is no active management, the management fee for ETFs is generally considerably lower than for other investment funds. We also observe that the management fee for inverse ETFs is much higher and their operational management performance is generally poor.

Only two funds are resource management efficient. We observe that there is no evidence to suggest that resource management performance may be associated with operational management and portfolio management performance. Because resource management performance is positively associated with overall performance, ETF managers should not take the resource management process lightly in their pursuit of excellence in overall management.

Table 5 lists the top 10 portfolio management performers. Here we find that nine ETFs are portfolio management efficient. Moreover, 8 out of the top 10 portfolio management ETFs listed in Table 5 are also listed in Table 3 suggesting that portfolio management performance and overall management performance may have a strong positive association in the case of high-end portfolio management performers. In Table 3, we find that high overall performance may imply high portfolio management performance. Hence, the empirical evidence suggests that while good portfolio management performance may suggest good overall performance, good overall performance may also suggest good portfolio

Table 5. Portfolio management: Top 10 performers

ETF's name	Stage A	Stage B	Stage C	Allied process	System	IRI
Yuanta Daily S&P 500 Bear 1X ETF	0.008	0.156	1	0.156	0.964	1
Cathay TAIEX Daily Inversed ETF	0.030	0.235	1	0.235	0.979	1
Fubon 1-3 Years US Treasury Bond ETF	1	1	1	1	1	1
Fuh Hwa 1-5 Yr High Yield ETF	0.361	0.375	1	0.375	0.987	1
Mega Taiwan Blue Chip 30 Daily Inverse ETF	0.114	0.177	1	0.177	0.969	1
Fubon TOPIX Inversed -1X Index ETF	0.136	0.153	1	0.153	0.964	1
Cathay Bloomberg Barclays U.S. Treasury 20+ Year Daily Inverse 1X ETF	0.138	0.137	1	0.138	0.962	1
Yuanta Daily CSI 300 Bear -1X ETF	0.001	0.096	1	0.096	0.943	1
CAPITAL TAIEX DAILY INVERSED -1X ETF	0.248	0.314	1	0.314	0.983	1
Fubon TAIEX Daily -1X Inverse ETF	0.025	0.260	0.995	0.260	0.974	1
Average	0.206	0.290	1	0.290	0.973	1

management performance. We find further that the top-performing portfolio management ETFs are ranked poorly in other aspects of management namely operational management and resource management. This is important information to ETF managers because without overall efficiency decomposition they would be blinded as to what management processes or which aspects of ETF management may influence their overall performance. It is often debated whether good ETF performance is due to management skill or luck. ETF performance in that context is assessed in terms of abnormal returns after controlling for costs such as fees and expenses and focusing primarily on the management of the portfolio. Our coverage of ETF performance appraisal is much broader and therefore we contribute to this debate from a wider perspective.

3.2. **The intermediate resource imbalance.** Our measure of intermediate resource imbalance I_0^* varies between 0 and 1 (inclusive) with $I_0^* = 1$ revealing no IRI. We interpret $I_0^* = 1$ as efficient use of internal resources. The results reveal that I_0^* based fund rankings are not associated with the rankings based on the performance in any of the three aspects of fund management considered in the analysis. Therefore, I_0^* may be considered as an index that provides additional information on managerial performance.

Table 6 lists the ETFs with $I_0^* \neq 1$. There are four such ETFs. None of these ETFs are efficient in any of the management aspects investigated in this study except Yuanta/P-shares Taiwan Top 50 ETF with operational management efficient. Yuanta/P-shares Taiwan Top 50 ETF is an ETF established in Taiwan. The Fund's objective is to track the performance of the TSEC Taiwan 50 Index. The Fund invests in stocks that are listed on the TSEC and the OTC exchange and this provides investors with an exposure to a

Table 6. ETFs with intermediate resource imbalance

ETF's name	Stage A	Stage B	Stage C	Allied process	System	IRI
Fubon Taiwan Technology Tracker Fund	0.499	0.823	0.411	0.823	0.822	0.0007
Fubon FTSE TWSE Taiwan 50 ETF	0.506	0.757	0.485	0.757	0.757	0.0007
Yuanta/P-shares Taiwan Top 50 ETF	1	0.905	0.344	0.904	0.904	0.0009
Fubon Taiwan Eight Industries ETF	0.496	0.709	0.446	0.709	0.709	0.0009
Average	0.625	0.799	0.421	0.798	0.798	0.0008

group of Taiwan's leading blue chip stocks. The practical value of I_0^* is that we may use I_0^* to discriminate ETFs ranked equal at any level of performance. For example, Table 4 reveals that ETFs are top 10 allied process management performers; however, their I_0^* are different. We rank the efficient ETF with the highest I_0^* because the higher the I_0^*, the better the efficiency in utilization of internal resources.

4. **Summary and Concluding Remarks.** The main focus of this paper is to extend a three-stage network DEA model of Galagedera et al. [14] to evaluate ETFs' performance and to capture internal structures of the overall fund management process. In the first quarter of 2020, on-exchange ETF trading volumes increased by 47% as markets reacted to the implication of the global spread of coronavirus. As the Asia-Pacific index funds market is forecasted to grow from $1.5trn to $5trn over the next five years, the ETF market is expected to grow in tandem and Taiwan is ideally placed to benefit from this growth. As the ETF industry has evolved, it has the way index providers weight equities within benchmarks. Now investors can get their hands on hundreds of ETFs that employ weighting methodologies such as equal weight, weighting by factors such as growth or value, and dividend yield. Some indices go even further, scoring stocks based on profitability, cash flow, or management-related criteria. "Companies with smaller relative market caps, particularly firms that are of higher quality, have historically been associated with returns that beat a broad market index", according to Morningstar.

In the ETF performance appraisal literature, the focus is predominantly on the fund portfolio with main considerations being risk, returns and cost. Our performance appraisal approach is beneficial to ETF management because findings are based on models that accommodate multiple measures of performance and in a comprehensive network representation of the overall fund management process. Last but not the least, the existence of the internal resources imbalance proposed in our framework was shown as an index to improve the discriminatory power of performance assessed in the network DEA model.

Out of the 87 ETFs considered in our empirical analysis of Taiwan ETFs, we find the top 10 best performers ETFs in terms of overall efficiency, each of these ETFs is either a bond ETF or an ETF that shortens (or bets against) the financials space. At the beginning of 2018, optimism for the financial sector was reasonably high. Unfortunately, throughout 2018 the banks, real estate funds, and other companies which make up the financial sector were slammed by a series of strong headwinds. During this volatile time, the entire market fell precipitously heading into 2019, ending 2018 with the worst overall performance since the 2008 financial crisis. Investors focused on ETFs which target the financial sector generally did not find much to celebrate at the end of 2018 either. This is unsurprising, as these ETFs, which track indexes of financial stocks based on various strategies and criteria, tend to perform poorly when their underlying stocks do so as well. Nonetheless, there were a handful of financial ETFs that managed to not only stave off declines for 2018 but in fact, earned significant returns for the year.

As households have come to rely more on investment funds such as ETFs over the past decade, their demand for directly held equities has fallen. Hence, given this significant reliance by individual investors on the performance of such investment products, it is important to analyze the performance of ETFs in a comprehensive way and provide consumer-friendly performance measures on different aspects of ETF management. We investigate this issue empirically. In our empirical investigation, we use the proposed model to assess the relative performance of a comprehensive sample of 87 Taiwan ETFs. We believe that the findings are useful to investors in selecting ETFs and to managers in identifying the source of inefficiencies. The portfolio managers can use the source of

ETF's inefficiency revealed by three-stage network DEA to identify which ETFs that they could emulate in order to achieve efficiency in the future.

REFERENCES

[1] S. Anderson, Closed-end funds versus market efficiency, *Journal of Portfolio Management*, vol.13, pp.63-65, 1986.

[2] G. Gastineau, Exchange traded funds: An introduction, *Journal of Portfolio Management*, vol.27, pp.88-96, 2001.

[3] C. Alexander and A. Barbosa, Hedging index exchange traded funds, *Journal of Banking & Finance*, vol.32, pp.326-337, 2008.

[4] W. Aber, D. Li and L. Can, Price volatility and tracking ability of ETFs, *Journal of Asset Management*, vol.10, pp.210-221, 2009.

[5] F. Adjei, Diversification, performance, and performance persistence in exchange-traded funds, *International Review of Applied Financial Issues and Economics*, vol.1, pp.4-19, 2009.

[6] D. U. Galagedera, H. Fukuyama, J. Watson and E. K. Tan, Do mutual fund managers earn their fees? New measures for performance appraisal, *European Journal of Operational Research*, vol.287, no.2, pp.653-667, 2020.

[7] D. Galagedera and P. Silvapulle, Australian mutual fund performance appraisal using data envelopment analysis, *Managerial Finance*, vol.28, no.9, pp.60-73, 2002.

[8] A. W. Charnes, W. W. Cooper and E. L. Rhodes, Measuring the efficiency of decision making units, *European Journal of Operational Research*, vol.2, no.6, pp.429-444, 1978.

[9] B. Murthi, Y. Choi and P. Desai, Efficiency of mutual funds and portfolio performance measurement: A non-parametric approach, *European Journal of Operational Research*, vol.98, no.2, pp.408-418, 1997.

[10] L. M. Seiford and J. Zhu, Modeling undesirable factors in efficiency evaluation, *European Journal of Operational Research*, vol.142, no.1, pp.16-20, 2002.

[11] A. Basso and S. Funari, DEA performance assessment of mutual funds, in *Data Envelopment Analysis. International Series in Operations Research & Management Science*, J. Zhu (ed.), Boston, MA, Springer, 2016.

[12] I. Premachandra, J. Zhu, J. Watson and D. U. Galagedera, Best-performing US mutual fund families from 1993 to 2008: Evidence from a novel two-stage DEA model for efficiency decomposition, *Journal of Banking & Finance*, vol.36, pp.3302-3317, 2012.

[13] D. U. A. Galagedera, J. Watson, I. M. Premachandra and Y. Chen, Modeling leakage in two-stage DEA models: An application to US mutual fund families, *Omega*, vol.61, pp.62-77, 2017.

[14] D. U. A. Galagedera, I. Roshdi, H. Fukuyama and J. Zhu, A new network DEA model for mutual fund performance appraisal: An application to U.S. equity mutual funds, *Omega*, vol.77, pp.168-179, 2018.

[15] M. Zeng, Y. Yang and B. Yan, Evaluation system for the investment efficiency of distribution network: Improved data envelopment analysis model approach, *International Journal of Innovative Computing, Information and Control*, vol.10, no.2, pp.797-809, 2014.

[16] B. S. Ko and M. S. Cho, Evaluating the relative efficiency of defense R&D projects in a multi-project environment using EVM and CAIV measures, *ICIC Express Letters, Part B: Applications*, vol.11, no.7, pp.675-682, 2020.

[17] L. Abdullah, W. Ong and N. A. Sanusi, Efficiency measures of islamic banks using data envelopment analysis frontier: Evidence from malaysia, *ICIC Express Letters, Part B: Applications*, vol.10, no.8, pp.689-695, 2019.

[18] C. Kao, Efficiency decomposition and aggregation in network data envelopment analysis, *European Journal of Operational Research*, vol.255, no.3, pp.778-786, 2016.

[19] L. Liang, W. D. Cook and J. Zhu, DEA models for two-stage processes: Game approach and efficiency decomposition, *Naval Research Logistics*, vol.229, no.1, pp.643-653, 2008.

[20] M.-T. Phung, C.-P. Cheng, C. Guo and C.-Y. Kao, Mixed network DEA with shared resources: A case of measuring performance for banking industry, *Operations Research Perspectives*, vol.7, 2020.

[21] L. M. Seiford and J. Zhu, Profitability and marketability of the top 55 U.S. commercial banks, *Management Science*, vol.45, no.9, pp.1270-1288, 1999.

[22] X. Zhou, Z. Xu, J. Chai, L. Yao and S. Wang, Efficiency evaluation for banking systems under uncertainty: A multi-period three-stage DEA model, *Omega*, vol.85, pp.68-82, 2018.

[23] C. Dannhauser, The impact of innovation: Evidence from corporate bond exchange-traded funds (ETFs), *Journal of International Economics*, vol.125, pp.537-560, 2017.
[24] S. Nazlioglu, R. Gupta, A. Gormus and U. Soytas, Price and volatility linkages between international REITs and oil markets, *Energy Economics*, vol.88, pp.1-13, 2020.
[25] R. D. Banker, A. Charnes and W. W. Copper, Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science*, vol.30, no.9, pp.1078-1092, 1984.
[26] Y. Chen, W. D. Cook, N. Li and J. Zhu, Additive efficiency decomposition in two-stage DE, *European Journal of Operational Research*, vol.196, no.3, pp.1170-1176, 2009.
[27] C. Kao and S.-N. Huang, Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan, *European Journal of Operational Research*, vol.185, no.1, pp.418-429, 2008.