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Decision Support

Double hedonic price-characteristics frontier estimation for IoT service providers in the industry 5.0 era: A nonconvex perspective accommodating ratios

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ABSTRACT

The advent of advanced digital technologies, including the Internet of Things (IoT), image processing, artificial intelligence (AI), blockchain, robotics and cognitive computing that have been embedded in Industry 5.0, is considerably improving the sustainability, resilience, and human-centric performance of industrial organizations. Despite the increasing use of Industry 5.0 technologies in smart product platforming in industrial organizations, a critical issue remains how to assess the providers/suppliers of such technologies in highly competitive markets to fulfil personalized products and services. Following Lancaster's characteristics approach to consumer theory, in this study we contribute to assess digital technologies service providers in the Industry 5.0 era by focusing on both theoretical and empirical evidence inquiring about the convexity of conventional nonparametric frontier estimation methods. To do so, a nonparametric double frontier estimation of the hedonic price characteristics relation is developed from both the buyer's and seller's perspectives. Moreover, a separable directional distance function-based optimization model is developed for the efficiency estimation. Furthermore, a comparable estimation of the convex and nonconvex hedonic price function is proposed. We also explicitly test the impact of convexity in evaluating the efficiency of IoT service providers in the Industry 5.0 context. In this study, we also show that the hypothesis of convexity in assessing the efficiency of IoT service providers is rejected using the Li-test comparing entire densities in the case of the seller's perspective without ratio data. Differences are less pronounced for the buyer's perspective and in the case with ratio data.

1. Introduction

The term Industry 4.0 has been proposed in 2011 by a research team in the German government as an effective strategy for addressing the created challenges in high-tech industries owing to rapid changes in digital technologies (Nguyen et al., 2022). Industry 4.0 has a considerable impact to improve the performance of a wide range of industries by integrating their business environments where machines, equipment, operational processes, etc. are interconnected together autonomously (Ralston & Blackhurst, 2020). The fundamental principle in Industry 4.0 is that organizations can create smart networks across their supply chains (SCs) by autonomously linking machines, equipment, digital processes, internal and external logistics activities, and systems in a well-defined framework (Kunkel et al., 2022; Hoberg & Alicke, 2016; Zhang, 2015). Production platforms throughout SCs can be mechanized and optimized using Industry 4.0 technologies such as artificial intelligence (AI), blockchain, cloud computing (CC), image processing (IP), and the Internet of Things (IoT) (Kamble et al., 2020). These advanced technologies facilitate information flow and real-time data exchange throughout SC from suppliers to end users in a secure environment (Zhang, 2014). The vertical and horizontal integration of information to develop flow information between each component of SCs is created using Industry 4.0 technologies (Núñez-Merino et al., 2020). The digital advanced technologies including IoT, big data analytics (BDA), and AI make SCs platforms to be mechanized, predicted, optimized and controlled (Abdel-Basset et al., 2018). The platforms also provide sustainable and resilient benefits in terms of economic, ecological and social aspects (Gimenez et al., 2012).

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Industry 5.0 represents a new paradigm in the era of advanced digital technologies and is considered a societally driven complement to Industry 4.0′s hallmark features (Valette et al., 2023). Although Industry 4.0 deals with resilience and sustainability aspects in the industry and holds considerable potential for industrial growth, it lacks human-centricity (Khan et al., 2023). In Industry 5.0, this aspect is taken into account while designing advanced digital technologies, aiming to provide resilience, sustainability, and a human-centric approach (Nayeri et al., 2023). In Industry 5.0, AI is used to precisely and efficiently interconnect human intelligence in industrial manufacturing. Furthermore, Industry 4.0 challenges are addressed by meeting social needs and enhancing human-centricity, effectively reducing the mismatch between industrial production and society's needs (Leng et al., 2022). The technologies applied in Industry 5.0 are designed to relieve workers from wearing, monotonous, or hazardous tasks, redirecting their focus toward innovative and value-added activities. These technologies support flexibility in work environments, promoting a work-life balance for workers (Valette et al., 2023). The term ``Industry 5.0′' is not only used in industry, but also in international forums and government policy documents and it aligns with the United Nations' Sustainable Development Goals (Leng et al., 2022).

IoT is considered an advanced digital technology within the Industry 5.0 concept. SC platforms based on IoT are offered by service providers that can facilitate the deployment and applications of required software in industrial systems. IoT can play a key role in presenting potential advantages to SC so that it becomes more productive (Manavalan & Jayakrishna, 2019). Furthermore, the IoT provides SCs managers with deeper and more tangible insights for adopting more effective policies and decisions (Tan & Sidhu, 2022). In SCs, IoT is mostly applied to support information collection and sharing, track material and product tracking, and a connected component of systems in real-time (Kamble et al., 2020). The use of IoT in SCs also increases sustainability by improving coordination, cooperation, and communication between each component of SCs and reducing environmental threats (Prajapati et al., 2022). Increasing resilience is another advantage of using IoT in SCs. In this regard, IoT enhances agility, visibility, and adaptability by addressing various challenges of SCs owing to unexpected disruptions in providing real-time data, detecting potential risks of materials and product delays, identifying the demand-supply gaps, and providing instant solutions (Ben-Daya et al., 2019). Therefore, the use of IoT in SCs platforms can address both sustainable and resilient aspects for improving organizational performance. In many SC platforms, IoT as one of the important advanced digital technologies in Industry 4.0 era has been applied to improve the level of organizational performance.

Although IoT provides many advantages both in production and service sectors for organizations, a key challenge is how to evaluate the efficiency of IoT service providers or suppliers in an intensely competitive market based on quality of service (QoS) requirements. In other words, as IoT provides considerable benefits to organizations, many managers and decision-makers in organizations are interested to build and develop their SCs platforms based on IoT technology. Nevertheless, with the increasing substantial growth of IoT providers/suppliers, it is extremely difficult for organizations to make decisions about which IoT provider or supplier would be able to meet their needs. So many similar services with dissimilar features, different functioning levels and highly competitive prices are provided by IoT providers/suppliers. As a result, a key challenge for IoT consumers is how to assess the performance of the providers to select the most suitable one. In addition, as IoT providers play a key role in transforming traditional SCs platforms into smart platforms, they need to consider the results of the performance evaluation for making better decisions or applying more effective strategies. In this regard, the evaluation of IoT providers becomes more important when an organization is going to build and develop its SC platforms based on IoT technology. This mostly refers to the high expenses of applying IoT throughout the platform. It should be noted that the wrong evaluation of IoT providers/suppliers may result in irreparable costs for organisations. To address this issue, state-of-the-art methods and frameworks are required to be developed by scholars and to be adapted by practitioners. Therefore, the key objective of this contribution is to propose double hedonic price-characteristics frontier estimation for evaluating the efficiency of IoT service providers in the Industry 5.0 era based on a nonconvex perspective with distinguished features. The current study makes substantial contributions to the literature as follows:

- A nonparametric double frontier estimation of the hedonic price characteristics is developed from the buyer's and seller's perspectives.
- A separable directional distance function-based optimization model is suggested for the efficiency estimation.
- For the first time in the literature, a comparable theoretical model and an empirical estimation of the convex and nonconvex double frontier hedonic price function is developed with and without the presence of ratio data.
- An empirical study consisting of 41 IoT service providers is developed in the Industry 5.0 era that contains the presence of ratio data.
- Anticipating our empirical results, we find significant differences between convex and nonconvex double frontiers without ratio data and less pronounced results when ratio data are included.

We organize our study in the following way. In the next section, we develop a literature review on Industry 4.0 and sustainable-resilient SCs, the Industry 5.0 and hedonic price frontiers. The developed models are presented in Section 3 and the two main theoretical results are established. Section 4 presents the empirical study and extends the models to also accommodate ratio data. We conclude and propose future research directions in Section 5.

2. Industry 4.0, industry 5.0, and hedonic price frontiers: literature review

2.1. Industry 4.0 and sustainable-resilient supply chains

The term the Fourth Industrial Revolution or Industry 4.0 has been presented by a group of scholars because of the swift advancements in manufacturing processes and business mechanization (Ricci et al., 2021). Industry 4.0 has been combined horizontally and vertically throughout values networks and manufacturing systems and supports organizations to manage their complicated systems by making them sensitive to real-time data and using intelligent technologies (Tortorella et al., 2021; Luthra et al., 2020). In an Industry 4.0 approach, inter-organizational collaboration is fostered through horizontal integration. Dissimilar hierarchical subsystems are also integrated using vertical integration to produce a dynamic, flexible, and efficient production system (Sun et al., 2020; Dalenogare et al., 2018). Industry 4.0 is supported by internet-based intelligent technologies such as AI, IP, CC, IoT, sensors, and blockchain. By applying these advanced technologies across organizations' SCs, equipment, machines, devices, networks, and individuals are connected in an integrated system (Frank et al., 2019). The sustainability concept in SCs has been crucial for many organizations to meet their customers' and stakeholders' criteria in contemporary highly competitive markets (Mastrocinque et al., 2022). To benefit from Industry 4.0 for enhancing the level of sustainability of SCs, several factors should be taken into consideration, such as applying state-of-the-art information technologies, applying high-quality raw materials, and manufacturing green products (Zekhnini et al., 2022). As a business strategy, Industry 4.0 has considerable potential for influencing all levels of SC networks, production processes, systems, and patterns aimed at enhancing sustainability and resilience in organizations (Belhadi et al., 2022; Ralston & Blackhurst, 2020).

2.2. Industry 5.0: a complementary perspective

In the realm of Industry 4.0, the primary focus has been on digitizing the industry, with comparatively less attention directed towards the role of human beings in the past decade (Kazancoglu et al., 2023). Enter Industry 5.0, a fresh paradigm in the age of advanced digital technologies that doesn't replace Industry 4.0 but builds upon it. While both paradigms underscore the digital transformation of industrial settings, Industry 5.0 places significant emphasis on fostering human collaboration and interaction with machines (Mourtzis et al., 2023). The implementation of Industry 5.0 in industrial settings means that human workers take on a more substantial role in fostering creativity to enhance process efficiency (Nayeri et al., 2023). Recently, various projects in European countries have been proposed to explore the human-centric aspect of Industry 5.0, aiming to improve the efficiencies of industrial organizations (Kazancoglu et al., 2023). Sustainability, resilience, and human-centricity emerge as the three core values of Industry 5.0. While sustainability and resilience have also found a place in Industry 4.0, sustainability involves preserving resources and using digital technologies to balance economic, environmental, social, growth, and developmental needs. Resilience refers to the ability to revert to the initial state after an unexpected interruption caused by crises, such as a pandemic or earthquake (Leng et al., 2022). Designing or redesigning supply chains with resilience indicators can mitigate unexpected disruptions during times of crisis. Human-centricity involves creating safe workplaces, improving the physical and mental conditions of the workforce, and respecting workforce rights. In Industry 5.0, human-centric design means working together with collaborative robots, known as cobots, and the perfect human partner. The aim is to facilitate personalized autonomous manufacturing by utilizing enterprise social networks. Essentially, this involves humans teaming up with cobots and an ideal human companion to create a manufacturing process that is personalized and can operate autonomously with the support of social networks within the enterprise. This collaboration leads to machines and humans working hand in hand (Maddikunta et al., 2022). Cobots, unique technologies in Industry 5.0, are designed to work alongside humans. By using cobots, physical and mental pressures are alleviated, the workplace is shared with humans, and repetitive and hazardous tasks are taken over from humans (Asif et al., 2023). In conclusion, Industry 5.0 enhances process efficiency in organizations, integrating the brainpower and creativity of humans with machines, promoting trusted autonomy, reducing expenses and waste, and providing a safe and healthy work environment.

2.3. Economics of differentiated products: theoretical background and hedonic price frontiers

By defining the utility function of the consumer as a function of the characteristics of these commodities rather than just as a function of a goods vector, Lancaster (1966, 1979, 1990) creates a ``characteristics'' perspective on consumer theory. These characteristics are objective features of the goods (as opposed to the notion of attributes used in marketing and psychology). For modeling the viable combinations of characteristics in the household production process, this characteristics viewpoint employs activity analysis. Key presumptions in this context include (a) whether or not combinations of goods are feasible in any given market, and (b) whether or not such combinations are linear, (c) if the number of characteristics is greater or smaller than the number of goods containing them, etc. Essentially, the hedonic hypothesis states that (a) heterogeneous goods are aggregations of objective characteristics, and (b) economic behavior is essentially motivated by these characteristics.

Within this characteristics perspective to consumer theory, the first economist to create a theoretical framework to investigate market equilibrium for differentiated goods with many distinguishing characteristics is Rosen (1974). In essence, in order to aggregate these characteristics into a measure of consumer value, one tries to determine an implicit price for the characteristics vector (e.g., Greenstone, 2017; Nesheim, 2008 for recent evaluations of this seminal contribution).

The literature on identification demonstrates in general that (a) the implicit pricing functions for characteristics are not linear as commonly assumed by empirical studies, but rather are nonlinear, and (b) in hedonic equilibrium the market does not need to offer a continuum of products. Markets contain clusters of products with similar characteristic combinations, while products with other characteristic combinations are sparsely available (e.g., Ekeland et al., 2004 for the additive case and, e.g., Heckman et al., 2010 for the nonadditive instance). These theoretical considerations complicate the task for the empirical researcher: he or she must now carefully consider whether the hedonic pricing function in characteristics space is smooth or not, among other things, in addition to the variable selection, specification, and estimation concerns.

Following partially Fernandez-Castro and Smith (2002),[1] and especially the works by Lee et al. (2005) and Chumpitaz et al. (2010), one of the main concerns in this contribution is the question of whether the observed connection between prices and characteristics is convex, as traditionally assumed, or nonconvex. This theoretical concern about nonconvexity can be retraced to the seminal Lancaster (1966) contribution that warns about the influence of indivisibilities: he talks about "combinable" and "non-combinable" goods. He repeatedly states that indivisible goods are central in his reconsideration of conventional consumption theory. Shephard (1978) provides the first axiomatic analysis of this home production theory and emphasizes that the frontier that results from the conversion of products into characteristic space is not convex (see Shephard, 1978: p. 454). Thus, instead of adopting the traditional convexity assumption, researchers should appraise it against a nonconvex hedonic price function making minimal assumptions (in essence, monotonicity or strong disposability). Apart from Chumpitaz et al. (2010), none of the studies known to us tests explicitly for the effect of convexity.

Hedonic price functions are frequently used to calculate quality-adjusted price indices and the value of environmental externalities (for example, traffic noise), among other things, in index theory and mainly in agricultural and environmental economics at large (see, e.g., the surveys of Nicholls, 2019; Outreville & Le Fur, 2020, among others). However, we are unaware of any empirical applications of nonconvex hedonic price frontiers in evaluating advanced digital service providers such as IoT, cloud computing, and AI. We are equally unaware of any nonconvex hedonic price frontiers in the broader operations management literature.

Instead of focusing on average practice relations between price and hedonic characteristics, the -to the best of our knowledge- seminal articles of Doyle and Green (1991) and Smith et al. (1991) are the first to estimate the relation between price and hedonic characteristics using deterministic nonparametric frontiers and stochastic parametric frontiers, respectively. This has led to the limited literature on developing a variety of empirical applications. Most, if not all of these articles, adopt a buyer's perspective: they look for the lowest prices and the best amounts of characteristics to select the most attractive product for the buyer.

Related literature develops so-called double frontiers, whereby a buyer's perspective is supplemented with a seller's perspective: the latter look for the highest prices that can be obtained and the lowest amounts of characteristics needed for the seller to get his product sold in the market. To the best of our knowledge, the articles by Polachek and Yoon (1987) and Estellita Lins et al. (2005) are the first to estimate the relation between price and hedonic characteristics in a double frontier

[1] In Fernandez-Castro and Smith (2002) linearity is combined with nonconvexity. But, as argued above, the nonlinear nature of the price characteristics connection is in conflict with linearity. Therefore, it is an excessive assumption for a hedonic price frontier.

framework using stochastic parametric frontiers and deterministic nonparametric frontiers, respectively.

2.4. Knowledge gaps

The existing literature demonstrates there has been considerable attention in the Industry 4.0 era to the use of digital technologies such as AI, blockchain, and IoT. However, the literature shows that despite the significance of IoT service in the Industry 4.0 era, there are no references for assessing the efficiency of IoT service providers. It should be noted that a lack of state-of-the-art approaches and techniques to assess the efficiency of digital technology providers may result in heavy costs in organizations. Hence, organizations need to assess their potential digital technology providers by developing and applying advanced methods and frameworks. Another significant issue with the existing models and methods of service providers of digital technologies is that none of these considers both buyer's and seller's perspectives in the evaluation process. In this regard, double hedonic price-characteristics frontier estimation is a powerful approach that can be used by both buyers and sellers.

It should be noted that all average practice hedonic price functions and most hedonic price frontiers maintain the assumption of convexity. A recent survey on the use of production frontiers in supplier selection only lists convex models and empirical applications. It does not even mention the issue of nonconvexity at all (see Dutta et al., 2022). However, the assumption of convexity is problematic in operations management in general. Operations management and supply chain management focus on a variety of methodologies to streamline and optimize production processes. Some of these production processes are known to involve nonconvexities: examples include cutting stock problems, scheduling problems, and vehicle routing problems, among many others. Some of these problems even turn out to be NP-complete problems. Therefore, it is rather inconceivable that the production process at the level of the firm as a whole can be modeled as being convex when applying deterministic nonparametric or stochastic parametric frontiers (see, e.g., Coelli et al., 2005). Convexity is only justified by the interpretation of perfect time divisibility (Shephard, 1970: p. 15), and such perfect time divisibility does not exist in production processes that are most often characterized by some minimal setup times.

Furthermore, we also argue that this convexity assumption is equally problematic for computing single and double hedonic price frontiers. When computing single and double hedonic price frontiers, convexity leads to imposing some linearity between price and hedonic characteristics, while we know from the theoretical literature (see above) that this relation is potentially nonlinear. Therefore, when one imposes nonconvexity, then one only assumes some monotonous relation between price and hedonic characteristics compatible with eventual nonlinearities.

This, in turn, leads to a question about the eventual embeddedness relation between the nonconvex and the convex double price hedonic characteristics frontier. Moreover, another question is whether the buyer's and seller's perspectives can be solved independently, or whether these problems should be solved jointly. In this study, we address all these practical and theoretical issues by developing a double hedonic price-characteristics frontier estimation approach considering nonconvex and convex assumptions.

3. Hedonic price characteristics frontiers: theoretical framework

3.1. Hedonic price frontiers: the use of the benefit function

Typical econometric techniques that concentrate on average practice relations between characteristics and prices are used to compute the majority of hedonic pricing functions. Implicit prices are the primary outcomes of this traditional econometric technique. More recently, empirical applications based on best practice or frontier specifications characterizing the correspondence between prices and quality characteristics have emerged. With this frontier approach, efficiency measurements are obtained that show any frontier deviations, in particular the eventual presence of price inefficiencies. Most studies use nonparametric frontier models (for example, Mouchart & Vandresse, 2007), but a few articles choose parametric stochastic frontiers (for example, Munn & Palmquist, 1997). In addition, this frontier approach can as well reveal implicit prices in the convex case (for instance, Munn & Palmquist, 1997). When a nonconvex specification is imposed, then these implicit prices are absent.

The majority of frontier studies specifically mention incomplete or unequal information as the cause of any potential inefficiencies. There is only one study that we are aware of that creates an external validation for this specific interpretation. In particular, incomplete information is defined by Polachek and Robst (1998) as the difference between a worker's current compensation and their greatest possible salary using a stochastic parametric frontier. These authors discover a sizable positive association when they compare these estimates to a direct quantification of worker knowledge regarding the operation of labor markets.

In this contribution, we make use of rather common nonparametric frontier models to verify the impact of the traditional axiom of convexity. Because there are no adequate parametric specifications that allow for convexity testing, this seems to be impossible using a parametric method. A flexible piecewise frontier combines the price dimension and the many characteristics. In this context, a mathematical programming problem that seeks a lowest or maximum price for some given minimal assumptions on the feasible combinations of characteristics leads to the objective determination of optimal weights. In particular, comparing efficiency measurements in relation to both nonconvex and convex nonparametric frontier models results in a test of convexity by utilizing the relationship between efficiency measures and goodness-of-fit metrics used for hypothesis testing (e.g., Färe & Grosskopf, 1995). In particular, following Chumpitaz et al. (2010), we employ a Li (1996) test to contrast the entire distributions of convex and nonconvex efficiency measures.

Chumpitaz et al. (2010) test for convexity and reject it. Their nonconvex model leads to less inefficient products and smaller inefficiencies. This seems to support the hypothesis that product designs, despite their clustering, are overwhelmingly efficient. Their nonconvex model, as opposed to the conventional convex example, completely explains any inefficiency in terms of vector dominance by other already-existing products.

Suppose that $u(\mathbf{x})$ is a utility function that is defined over a collection $\mathbf{X}$ of possible combinations of prices $\boldsymbol{p}$ and product characteristics vectors $\mathbf{z}$: $\boldsymbol{x} = (\mathbf{p}, \mathbf{z}) \in \mathbf{X}$, where $\mathbf{p} \in R^m_{++}$ and $\mathbf{z} \in R^n_{+}$. Furthermore, let $\boldsymbol{g}$ be a reference bundle or vector that is used to compare utilities ($\mathbf{g} \in R^m_{++} \times -R^n_{+}$, with $\mathbf{g} \neq \mathbf{0}$). Following Luenberger (1992), the *benefit function* with reference $\boldsymbol{g}$ is then defined for $\boldsymbol{x} \in \boldsymbol{X}$ and reference utility value u as follows:

$$B(g;x) = \begin{cases} \sup_{\beta}\{\beta :\ u(x-\beta g) \geq u,\ x-\beta g \in X\} & \textit{if } x-\beta g \in X \textit{ and} \\ & u(x-\beta g) \geq u \textit{ for some } \beta \\ -\infty \quad \textit{otherwise.} & \end{cases} \tag{1}$$

In consumer theory, this benefit function and the expenditure function are dual to one another. The benefit that can be obtained by moving from a given vector $\boldsymbol{x}$ in the direction of $\boldsymbol{g}$ while retaining the reference utility level u is measured. This benefit is (typically) semi-positive. This benefit function is defined at the individual consumer level and it is derived from the utility function. Furthermore, it has a cardinal interpretation (more properties are available in Luenberger, 1992).

To retain a relationship with conventional economic welfare analysis, it is crucial to define efficiency in the price characteristics space in a very general way. For instance, it is simple to combine these individual benefit functions to create a social welfare metric (Luenberger, 1992).

The majority of price hedonic frontier studies do not study consumer transactions at the individual level, but notional choices under the form of list prices. In our study, transaction data are also unavailable and solely list prices are available. In the case of potential rather than actual transactions, one can interpret frontier efficiency analysis in terms of a representative consumer who compares a basket of available heterogeneous goods with various characteristics.

This benefit function is formally equivalent to the shortage function defined in production theory by Luenberger (1995). This shortage function is renamed as a directional distance function by Chambers et al. (1996), who also examine the relationship between the benefit function and the directional distance function. The reference bundle or the direction vector g is selected as the assessed observation itself in the empirical application below, which results in a simple proportional interpretation. This proportionality satisfies generalized commensurability (see Briec et al., 2022).

Geometrically, the benefit function exposes the maximum distance one can move in the direction of the reference bundle g from a given price-characteristics vector x while still retaining the reference utility u. This benefit function searches for increases in the direction of prices as well as the values of the vector of characteristics in our hedonic price frontier setting.

3.2. Double Hedonic price frontiers: buyer's and seller's perspectives

Adopting a stochastic parametric frontier, the seminal article by Polachek and Yoon (1987) has initiated analyzing price-characteristics frontiers by adopting two perspectives: a buyer's and a seller's perspective. The first nonparametric study adopting such a double perspective known to us is the one by Estellita Lins et al. (2005). These articles have created a literature that has sometimes become known as double frontiers. We develop this double frontier perspective on the one hand by contrasting and testing between convex and nonconvex nonparametric frontiers, and on the other hand by employing the benefit function developed before.

The buyer and seller sets can be estimated from a sample of observed or notional choices. The seller set $S(\mathbf{p},\mathbf{z})$ can be represented as follows:

$$S(\mathbf{p},\mathbf{z}) = \left\{ (\mathbf{p},\mathbf{z}) : \sum_{k=1}^{K} \lambda^k \mathbf{p}^k \geq \mathbf{p},\ \sum_{k=1}^{K} \lambda^k \mathbf{z}^k \leq \mathbf{z},\ \sum_{k=1}^{K} \lambda^k = 1,\ \lambda \in \Gamma \right\} \tag{2}$$

where the set $\Gamma \in \{\Gamma^C, \Gamma^{NC}\}$ has two subsets: (i) $\Gamma^C = \{\lambda \in R_+^K\}$ and (ii) $\Gamma^{NC} = \{\lambda \in \{0,1\}^K\}$ representing, respectively, the axioms of convexity and nonconvexity. Note that, prices are like outputs and characteristics are like inputs in this formulation: the seller ideally likes to obtain the highest price for the lowest value of the vector of characteristics. However, to the extent that he/she is ill-informed, he/she may be willing to sell at a lower price and/or by providing better characteristics.

Next, the buyer set $B(\mathbf{p},\mathbf{z})$ is represented as follows:

$$B(\mathbf{p},\mathbf{z}) = \left\{ (\mathbf{p},\mathbf{z}) : \sum_{k=1}^{K} \mu^k \mathbf{p}^k \leq \mathbf{p},\ \sum_{k=1}^{K} \mu^k \mathbf{z}^k \geq \mathbf{z},\ \sum_{k=1}^{K} \mu^k = 1,\ \boldsymbol{\mu} \in \Gamma \right\} \tag{3}$$

where the set $\Gamma \in \{\Gamma^C, \Gamma^{NC}\}$ has again two subsets as defined in (2) above. Note that, in this formulation, prices are like inputs and characteristics are like outputs: the buyer ideally likes to obtain the lowest price for the highest value of the vector of characteristics. However, to the extent that he/she is ill-informed, he/she may be willing to buy at a higher price and/or by accepting worse characteristics.

The market for prices and characteristics for heterogeneous goods $M(\mathbf{p},\mathbf{z})$ is defined as the intersection of both the buyer $B(\mathbf{p},\mathbf{z})$ and seller $S(\mathbf{p},\mathbf{z})$ sets:

$$\begin{aligned} M(\mathbf{p},\mathbf{z}) &= B(\mathbf{p},\mathbf{z}) \cap S(\mathbf{p},\mathbf{z}) \\ &= \left\{ (\mathbf{p},\mathbf{z}) | \sum_{k=1}^{K} \lambda^k \mathbf{p}^k \geq \mathbf{p},\ \sum_{k=1}^{K} \lambda^k \mathbf{z}^k \leq \mathbf{z},\ \sum_{k=1}^{K} \lambda^k = 1, \right. \\ &\quad \left. \sum_{k=1}^{K} \mu^k \mathbf{p}^k \leq \mathbf{p},\ \sum_{k=1}^{K} \mu^k \mathbf{z}^k \geq \mathbf{z},\ \sum_{k=1}^{K} \mu^k = 1,\ \{\lambda, \boldsymbol{\mu}\} \in \Gamma \right\}. \end{aligned} \tag{4}$$

Thus, to evaluate the market efficiency in price-characteristics space one should take the intersection of two complementary buyer's and seller's correspondences in price-characteristics space.

We give a two-dimensional Fig. 1 to help the reader understand the basic idea underlying this double frontier technique. One typical characteristic is placed on the horizontal axis, and the vertical axis is used to show the price. Using a buyer's perspective and a set of characteristics and prices denoted by points a to l, Fig. 1 shows a piecewise linear frontier that encircles these data on the southeast side. For this set of data, the points c, d, e, and f define the linear segments of this frontier and display the best possible combinations between quality and price from the perspective of the buyer. The interior of this frontier's points are inefficient.

When convexity is questioned, discrete observations alone can be observed, and vector dominance reasoning can be used. This presumption results in a staircase-type price-characteristics frontier in the same Fig. 1 that identifies a more limited range of price-characteristic combinations. Clearly, the nonconvex buyer's frontier is embedded in the convex one: $B^{NC}(\mathbf{p},\mathbf{z}) \subseteq B^C(\mathbf{p},\mathbf{z})$. Now, the polyline connecting points c, d, h, e, and f defines the outer edge of a price-characteristics frontier $B^{NC}(\mathbf{p},\mathbf{z})$ that resembles a staircase. Obviously, fewer observations are inefficient. For instance, point h is no longer inefficient with regard to the convex frontier $B^C(\mathbf{p},\mathbf{z})$, because it is now a part of the nonconvex frontier$B^{NC}(\mathbf{p},\mathbf{z})$.

For example, we project an observation onto the hedonic price frontier in the direction of its own characteristic vector and in the direction of the negative of its price when using the benefit function to assess efficiency for observation a. This results in projection points a′ and a″ on the nonconvex and convex frontiers, respectively. The distance to the convex frontier is obviously wider, making this product appear more inefficient.

When adopting the seller's perspective, then the frontier is situated on the northwest side. Now again, the nonconvex seller's frontier is embedded in the convex one: $S^{NC}(\mathbf{p},\mathbf{z}) \subseteq S^C(\mathbf{p},\mathbf{z})$. The projections of the benefit function are now oriented towards the frontier in the northwest: observation a yields projection points a‴ and a⁗.

We now turn to the specification of the optimization problems to derive the benefit function about the seller $S(\mathbf{p},\mathbf{z})$ and buyer $B(\mathbf{p},\mathbf{z})$ sets. For each observed product j, one simply needs to find the solution to the following mathematical programming problem. Given a vector of characteristics and a price for $k = 1,\ldots,$ K products, one can evaluate

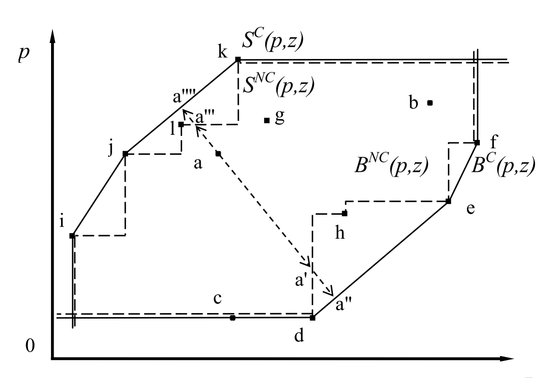

Fig. 1. Double hedonic price frontier under convexity and nonconvexity.

price expansions and characteristic reductions using the benefit function (β^S) relative to this set of observations from a seller's perspective $S(\mathbf{p},\mathbf{z})$:

$$\begin{aligned} & \max_{\beta^S,\lambda^k} && \beta^S \\ s.t. \quad & \sum_{k=1}^{K}\lambda^k\mathbf{p}^k && \geq \mathbf{p}^j+\beta^S\mathbf{p}^j, \\ & \sum_{k=1}^{K}\lambda^k\mathbf{z}^k && \leq \mathbf{z}^j-\beta^S\mathbf{z}^j, \\ & \sum_{k=1}^{K}\lambda^k && = 1, \\ & \beta^S && \geq 0, \qquad \boldsymbol{\lambda}\in\Gamma. \end{aligned} \tag{5}$$

where the set $\Gamma \in \{\Gamma^C, \Gamma^{NC}\}$ has two subsets as defined in (2) above.

For each observed product j, one only needs to find the solution to the following mathematical programming problem in order to assess characteristic enhancements and price reductions using the benefit function (β^B) related to this set of observations from a buyer's perspective $B(\mathbf{p},\mathbf{z})$:

$$\begin{aligned} & \max_{\beta^B,\lambda^k} \quad \beta^B \\ s.t. \quad & \sum_{k=1}^{K}\mu^k\mathbf{p}^k \leq \mathbf{p}^j-\beta^B\mathbf{p}^j, \\ & \sum_{k=1}^{K}\mu^k\mathbf{z}^k \geq \mathbf{z}^j+\beta^B\mathbf{z}^j, \\ & \sum_{k=1}^{K}\mu^k = 1, \\ & \beta^B \geq 0, \quad \boldsymbol{\mu}\in\Gamma. \end{aligned} \tag{6}$$

where the set $\Gamma \in \{\Gamma^C, \Gamma^{NC}\}$ has two subsets as defined in (2) above.

Note that in these formulations (5) and (6), the direction vector is each time the price and the characteristics vector of the product under evaluation itself, albeit that the sign of the direction vector differs between both formulations. This means that in evaluating observation j from a seller's perspective $S(\mathbf{p},\mathbf{z})$, the standard direction vector $\mathbf{g} = (\mathbf{p}^j, -\mathbf{z}^j)$ is applied in the formulation (5), while in the buyer's perspective $B(\mathbf{p},\mathbf{z})$, the direction vector $\mathbf{g} = (-\mathbf{p}^j, \mathbf{z}^j)$ is used in the formulation (6). As stated earlier, this yields a simple proportional interpretation.

Furthermore, note that one can conceive two alternative formulations to (5) and (6) by defining a direction vector solely in the price component (i.e., by putting the characteristics component equal to zero): i.e., the direction vectors $\mathbf{g} = (\mathbf{p}^j, \mathbf{0})$ and $\mathbf{g} = (-\mathbf{p}^j, \mathbf{0})$ are used in the formulations (5) and (6), respectively.

We now prove two propositions related to the above developments. First, we prove that the market for prices and characteristics of heterogeneous goods $M(p,z)$ under nonconvexity is contained in the convex case. Next, we show that the solution of formulations (5) and (6) can be done separately as specified and that the optimization does not need to consider explicitly the intersection of the sets $S(\mathbf{p},\mathbf{z})$ and $B(\mathbf{p},\mathbf{z})$ known as $M(\mathbf{p},\mathbf{z})$.

Proposition 1. $M^{NC}(\mathbf{p},\mathbf{z}) \subseteq M^C(\mathbf{p},\mathbf{z})$.

Proof of Proposition 1. See Appendix A.

Proposition 2. *Optimizing the benefit functions β^S and β^B about $M(\mathbf{p},\mathbf{z})$ is equivalent to (i) optimizing the benefit function β^S with regard to the seller set $S(\mathbf{p},\mathbf{z})$ in formulation (5) and (ii) optimizing the benefit function β^B with regard to the buyer set $B(\mathbf{p},\mathbf{z})$ in formulation (6).*

Proof of Proposition 2. See Appendix A.

We are not the first to develop double frontiers in an operations management context. We are at least aware of Badiezadeh et al. (2018) and also Shabanpour et al. (2017), among likely others. However, both these contributions maintain the convexity axiom and do not test for nonconvexity. We are also not the first to adopt nonconvex double frontiers in a price characteristics context. We are aware of Ben Lakhdar et al. (2013) and Wolff (2016). But, none of these contributions explicitly test for the suitability of the nonconvexity axiom. To the best of our knowledge, we are the first to explicitly test for convexity versus nonconvexity in a double frontier price characteristics framework.

Note that in the convex case shadow prices (SP) are readiliy available subject to non-uniqueness for efficient observations. For inefficient observations SP depend on the direction of projection. For the nonconvex case, currently, no shadow price (SP) information can be retrieved. Future work is required to establish certain regularity conditions.

4. Case study: sample, computations, and interpretations

4.1. Basic description of case study and sample data

We apply our developed models (5) and (6) for a prominent chemical and consumer goods company based in Iran to assess the performance of potential IoT service providers.[2] The company has been founded in the early 1970s and is considered one of the biggest chemical and consumer goods companies in Iran. It is active in producing a variety of laundry detergents that are not only consumed in Iran, but also exported to more than 20 countries. The company also produces detergent powder, soaps, shampoos, dishwashing liquids, hand-washing liquids, and toothpastes. Recently, the company has emphasized applying Industry 5.0 digital technologies in all its manufacturing and distribution processes. To enhance the aspects of sustainability, resilience, and human-centricity within the company's supply chains, managers and decision-makers have engaged some of the authors as consultants. This collaboration, along with input from the purchasing department, aims to evaluate and select IoT providers for the procurement of Automotive Multi-service IoT Edge Gateways from a pool of potential suppliers in a fiercely competitive market. These gateways are utilized to provide connectivity to automotive and lightly rugged applications, boasting advanced security features that safeguard system integrity and authenticity against unauthorized manipulations. The company intends to incorporate Automotive Multi-service IoT Edge Gateways into its product manufacturing process. This IoT device, representing an advanced digital technology, has been designed based on Industry 5.0 criteria, prioritizing sustainability, resilience, and human-centricity simultaneously. It is important to note that in this study, the aspect of sustainability encompasses economic, environmental, and social indicators. Moreover, the resilience indicators in this case study demonstrate the IoT device's ability—specifically, the Automotive Multi-service IoT Edge Gateways—to protect the production system in unforeseen circumstances such as power outages or high humidity. Furthermore, the human-centricity aspect in this case study revolves around safety measures and training programs for the company's workers, aspects that have received significant emphasis in the literature. Table 1 presents the list of variables utilized in this study, while associating them with sustainability, resilience, and human-centricity aspects. In 2022, the company's purchasing department gathered data from various IoT service providers based on the established criteria for Industry 5.0′s advanced digital technologies. This data collection involved reaching out to the sales departments of IoT providers, as well as reviewing their websites and catalogs.

Table B.1 (Appendix B) provides the dataset of 41 IoT service providers. In this study, from a buyer's the perspective, there are three inputs: price, power consumption, and cost of training of workers. While the price of the IoT device is economic indicator, power consumption

[2] Note that the company asked the authors not to reveal its name. Thus, we have removed the company's name.

Table 1
Variables related to industry 5.0.

Variables	Nature of variable	Descriptions	References
Price	Economic	Amount of money a buyer pays.	Doyle and Green (1994) Lee et al. (2008)
Power consumption	Environmental	Amount of energy consumed.	Muhoza et al. (2023)
Cost of training of workers	Human-centric	Expenditures for training workers.	Nayeri et al. (2023)
RAM	Economic	Component determining the speed and overall performance.	Doyle and Green (1994) Lee et al. (2008)
After-sales services	Economic	Any service such as training, warranty service repair and upgrades after the purchase.	Ekasari et al. (2023)
Reverse power protection	Resilience	Protects parallel-operated generators against reverse current flows and tripping upon fault conditions.	Machidon et al. (2018)
Reliability (%)	Resilience	Ability to protect electronic devices against unexpected interruptions.	Xing (2020)
Number of security certifications	Social	Number of security certifications acquired to protect data privacy.	Azadi et al. (2023)
Storage	Economic	Amount of data the device can store.	Doyle and Green (1994) Lee et al. (2008)
Humidity resistance (%)	Resilience	Resistance against vulnerability to low and high temperatures and relative humidity levels to preserve its performance.	Banotra et al. (2023)
Number of safety certifications	Human-centric	Number of security certifications in manufacturing based on technologies meeting safety indicators for welfare and health protection of workers.	Nayeri et al. (2023)

and cost of training of workers are environmental and human-centric indicators, respectively. From a buyer's perspective, the outputs are RAM (Random Access Memory), after-sales services, reverse power protection, reliability (%), the number of security certifications, storage, humidity resistance (%), and the number of security certifications. As for outputs, price, RAM, and after-sales services are economic indicators. The environmental indicator is also power consumption. Reliability and humidity resistance are resilient indicators in this case study. Finally, the number of security certifications and the number of safety certifications are social and human-centric indicators, respectively. From a seller's perspective, the role of inputs and outputs is exactly reversed, as indicated in the header of Table B.1. The justification for this selection is based on a combination of traditional hedonic price-characteristics frontiers of computers (see Doyle & Green, 1994; Lee et al., 2008) and specific studies on IoT in an Industry 5.0 context. Thus, price, RAM, and storage are part of hedonic price-characteristics frontier models of computers. The other characteristics are found in specific IoT studies in an Industry 5.0 context. The last column in Table 1 provides one or at most two references justifying our selection.

Note that the buyer's perspective is the most natural one from the point of view of the firm: it wants to select an IoT provider among the 41 candidates and it hopes to obtain a competitive bid. The seller's perspective is a bit of an artifact in that we as researchers are curious to see how these IoT providers could potentially extract economic rents from this firm. While the firm knows the offers provided by all IoT providers, these competitors do not know the price and contract specifications offered by each of them to this firm.

4.2. Extending double frontier models for ratios

Two of the above variables are ratio-based performance metrics (in particular, reliability and humidity resistance are percentages). A traditional convex technology is not suitable for these ratio factors. Therefore, we extend our double frontier models incorporating insights from Olesen et al. (2015, 2017), Podinovski et al. (2024) and Papaioannou and Podinovski (2023). This extension aims to refine our methodology in the convex case for the specificities of ratio data. We utilize the ratio measures in its original form, without resorting to any transformation or reliance on underlying volume measures, as suggested by Olesen et al. (2015).

For the convex versions of the seller and buyer sets (5) and (6), we incorporate the axiom of selective convexity (see Podinovski, 2005). This axiom enables the convex combination of feasible price-characteristics combinations, given that the ratio factors share equal values. We designate subsets V and R for volume and ratio factors in both seller and buyer sets, respectively. Importantly, within each factor we assume that the associated volume and ratio index sets are mutually disjoint. Thus, we represent any price-characteristics element in the market as $(\mathbf{p},\mathbf{z}) = (\mathbf{p}^V,\mathbf{p}^R,\mathbf{z}^V,\mathbf{z}^R)$, and each observed market point as $(\mathbf{p}_k,\mathbf{z}_k) = (\mathbf{p}_k^V,\mathbf{p}_k^R,\mathbf{z}_k^V,\mathbf{z}_k^R)$ for $k = 1,\dots,K$.

Following Olesen et al. (2015: Theorem 1), for ratio factor p_r^R in the seller sets (2), we impose the condition $\lambda_k p_{rk}{}^R \geq \lambda_k p_r^R$ on the constraints of the seller set. This condition ensures that observed price combinations within convex combinations of market factors do not surpass the observed price p_{rk}^R in all price ratio items. The integration of this condition aligns seamlessly with the principle of selective convexity, offering a nuanced representation of efficiency within the context of ratio factors. Similarly, for the ratio-type characteristic factor z_i^R in the seller sets (2), the associated constraints take the form $\lambda_k z_{ik}^R \leq \lambda_k z_i^R$. Transposed constraints of a similar nature are required for modeling ratio factors in the buyer sets (3).

This extension augments the flexibility of our double frontier models by accommodating for ratio factors in price-characteristics space while maintaining the integrity of the evaluation process for IoT service providers. We now present the specific mathematical formulations and adjustments for the market space to effectively integrate ratio factors into the efficiency evaluation framework for the convex case solely. In particular, the market encompassing prices and characteristics taking into account both volume and ratio factors can be expressed as the following set:

$$
\begin{aligned}
M(\mathbf{p},\mathbf{z}) = \{(\mathbf{p},\mathbf{z})| &\sum_{k=1}^{K}\lambda_k\mathbf{p}_k^V \geq \mathbf{p}^V, \sum_{k=1}^{K}\lambda_k\mathbf{z}_k^V \leq \mathbf{z}^V,\\
&\lambda_k\mathbf{p}_k^R \geq \lambda_k\mathbf{p}^R, \lambda_k\mathbf{z}_k^R \leq \lambda_k\mathbf{z}^R, \sum_{k=1}^{K}\lambda_k = 1,\\
&\sum_{k=1}^{K}\mu_k\mathbf{p}_k^V \leq \mathbf{p}^V, \sum_{k=1}^{K}\mu_k\mathbf{z}_k^V \geq \mathbf{z}^V,\\
&\mu_k\mathbf{p}_k^R \leq \mu_k\mathbf{p}^R, \mu_k\mathbf{z}_k^R \geq \mu_k\mathbf{z}^R, \sum_{k=1}^{K}\mu_k = 1,\ \{\boldsymbol{\lambda},\boldsymbol{\mu}\} \in \Gamma^C\Bigg\}.
\end{aligned}
\tag{7}
$$

Note that the basic nonconvex model can handle ratio data perfectly well (as admitted in Olesen et al., 2015: p. 448): thus, there is no need for additional constraints in this nonconvex case. This explains why the market set (7) is explicitly conditioned on the convex case.

When assessing the observed product o, we can optimize the benefit functions β^S and β^Brelative to the newly introduced market set (7) via the following multi-objective programming problem, which is again easily solved due to its separable structure (see above Proposition 2):

$$
\begin{aligned}
&\max_{\beta^S,\lambda}\ \beta^S\\
&\max_{\beta^B,\mu}\ \beta^B\\
s.t.\quad &\sum_{k=1}^{K}\lambda_k\mathbf{p}_k^V \geq \mathbf{p}_j^V+\beta^S\mathbf{p}_j^V,\\
&\sum_{k=1}^{K}\lambda_k\mathbf{z}_k^V \leq \mathbf{z}_j^V-\beta^S\mathbf{z}_j^V,\\
&\lambda_k\mathbf{p}_k^R \geq \lambda_k\left(\mathbf{p}_j^R+\beta^S\mathbf{p}_j^R\right),\\
&\lambda_k\mathbf{z}_k^R \leq \lambda_k\left(\mathbf{z}_j^R-\beta^S\mathbf{z}_j^R\right),\\
&\sum_{k=1}^{K}\mu_k\mathbf{p}_k^V \leq \mathbf{p}_j^V-\beta^B\mathbf{p}_j^V,\\
&\sum_{k=1}^{K}\mu_k\mathbf{z}_k^V \geq \mathbf{z}_j^V+\beta^B\mathbf{z}_j^V,\\
&\mu_k\mathbf{p}_k^R \leq \mu_k\left(\mathbf{p}_j^R-\beta^B\mathbf{p}_j^R\right),\\
&\mu_k\mathbf{z}_k^R \geq \mu_k\left(\mathbf{z}_j^R+\beta^B\mathbf{z}_j^R\right),\\
&\sum_{k=1}^{K}\lambda_k=1,\\
&\sum_{k=1}^{K}\mu_k=1,\\
&\{\boldsymbol{\lambda},\boldsymbol{\mu}\}\in\Gamma^C.
\end{aligned}
\tag{8}
$$

Note that the constraints related to the ratio factors are nonlinear. We can employ a linearization procedure suggested in Olesen et al. (2017) or directly use nonlinear optimization packages to compute the optimal values of the benefit functions: we opt for the latter.[3]

Note that in the convex case with ratio data SP are not readiliy available due to the nonlinear nature of the problem: obviously, local Lagrangian multiplier information is available. This requires more work in future research.

4.3. Computations, interpretation of empirical results, and discussion

We present a thorough analysis of benefit functions related to both the seller's and the buyer's sets, providing insights into general and price directions for both convex and nonconvex technologies. The efficiency indicators for the entire sample are summarized in Table 2 under two distinct scenarios: one without and another with consideration of ratio data type. To the best of our knowledge, this is the first empirical comparision for ratio data between convex and nonconvex models.[4] Detailed efficiency indicators for individual observations are in Appendix C: Tables C.1 and C.2 for the case without and with ratio data, respectively. Table 2 provides sample level descriptive statistics, including the number of efficient observations, the mean, standard deviation, as well as minimum and maximum values.

Initially, we computed the benefit function values using the models (5) and (6) for the entire sample excluding the ratio type of data (i.e., reliability and humidity resistance factors). From a buyer's standpoint, the general direction vector yields the following conclusions: Nearly all IoT service providers (40 out of 41) demonstrate efficiency under both convexity and nonconvexity. Secondly, only one provider exhibits slight inefficiency, accounting for approximately 2 %.Note that the similarity in the results of the benefit function indicators between convex and nonconvex technologies in the buyer's perspective may be because the number of observed products in comparison with the dimensions of price and characteristics is relatively small. Another economic interpretation is that the market for IoT services is simply very competitive and that providers do their best to offer a contract that is undominated with respect to other providers: they try to create a niche position such that almost no other provider can beat them. In this way, average inefficiency is extremely low (see also Chumpitaz et al., 2010).

An examination from the seller's standpoint uncovers novel insights through the general direction vector. Firstly, there are now 17 IoT providers exhibiting inefficiency under convexity, whereas only 1 demonstrates inefficiency under nonconvexity. Secondly, the convex inefficient providers are substantially more inefficient compared to the nonconvex counterpart. This suggests a less competitive landscape in the IoT services market, with significant potential to extract economic rents from the consumer. Nevertheless, the average inefficiency remains relatively low—approximately 0.3 % under convexity and even lower under nonconvexity.

From a buyer's perspective, the following conclusions emerge for the price-oriented direction vector. First, since we are only seeking improvements in a lower dimension space rather than in a multitude of dimensions, we now find 15 IoT providers inefficient under convexity while only 9 are inefficient under nonconvexity. This amount of inefficiency is much higher than for the general direction vector. Second, in general, the convex inefficiencies are more substantial than the nonconvex ones. In terms of strict price competition, one finds that about one-third to one-fifth of IoT providers are not competing on prices depending on the convexity assumption. Average inefficiency increases now to about 3.92 % under convexity and only 1.57 % under nonconvexity.

Examining the seller's standpoint through a price-oriented direction vector reveals distinct patterns within the current dataset. Specifically, 18 IoT providers demonstrate inefficiency under convexity, contrasting with only 5 exhibiting inefficiency under nonconvexity. The average inefficiency now stands at approximately 1.42 % under convexity and merely 0.46 % under nonconvexity. These nuances highlight subtle variations in inefficiency levels between convex and nonconvex technologies within the realm of the price-oriented dimension.

To formally test the difference in densities between convex and nonconvex efficiency estimates, we use the Li (1996) nonparametric test. This nonparametric Li-test, improved by Fan and Ullah (1999) and by Li et al. (2009), compares entire densities instead of looking at, e.g., first moments (as, for example, done by the signed-rank test of Wilcoxon). To be precise, it evaluates whether differences between two kernel-based estimations of the density functions f and g of a random variable x are statistically significant. Both of the density functions are equal under the null hypothesis (H_0: $f(x) = g(x)$ for all x). The alternative hypothesis only contests the equality of the two densities (H_1: $f(x) \neq g(x)$ for some x). For both scenarios of dependent and independent variables, this Li-test is valid. Keep in mind that dependency, in which inefficiency levels depend on the sample size among other factors, is characteristic for frontier estimators.

In our investigation, the null hypothesis is that the benefit functions for both convex and nonconvex technologies have the same distribution. The alternative hypothesis in our situation is that these distributions are different.We give the exact p-value using 2000 bootstrap replications for

[3] For computations we use the Lingo 20.0 software running on an Intel(R) Core(TM) i5 CPU @ 2.90GHz and 8.00 GB RAM system. CPU time remains negligible, even in the case of nonlinear programming models.

[4] Olesen, Petersen and Podinovski (2017: Section 10) offer a small numerical example comparing convex and nonconvex models for ratio data.

Table 2
Benefit function values in both perspectives and both technologies without and with considering ratio data type: descriptive statistics.

Observations	Results in general direction without ratio data				Results in price direction without ratio data			
	Buyer's perspective		Seller's perspective		Buyer's perspective		Seller's perspective	
	Model 6_C	Model 6_NC	Model 5_C	Model 5_NC	Model 6_C	Model 6_NC	Model 5_C	Model 5_NC
#Effic. Obs.	40	40	24	40	26	32	23	36
Mean	0.0007	0.0005	0.0036	0.0005	0.0392	0.0157	0.0142	0.0046
St. Dev.	0.0044	0.0032	0.0062	0.0032	0.0612	0.0366	0.0271	0.0205
Min.	0	0	0	0	0	0	0	0
Max.	0.0281	0.0206	0.0288	0.0202	0.1627	0.1133	0.1402	0.1278
Li-test	H0 Not Rejected		H0 Rejected		H0 Not Rejected		H0 Rejected	
p-value	0.6970		0.0000		0.1640		0.0030	
Test-statistic	−0.0176		2.7260		0.2196		1.7867	
	Results in general direction with ratio data				Results in price direction with ratio data			
#Effic. Obs.	40	40	40	40	26	32	32	36
Mean	0.0005	0.0005	0.0005	0.0005	0.0391	0.0157	0.0067	0.0046
St. Dev.	0.0032	0.0032	0.0032	0.0032	0.0612	0.0367	0.0232	0.0205
Min.	0	0	0	0	0	0	0	0
Max.	0.0206	0.0206	0.0202	0.0202	0.1627	0.1133	0.1402	0.1278
Li-test	H0 Not Rejected		H0 Not Rejected		H0 Not Rejected		H0 Not Rejected	
p-value	1		1		0.1560		0.3945	
Test-statistic	4.8330e−15		4.8330e−15		0.2233		−0.0172	

a traditional 5 % significance level (i.e., $\alpha = 0.05$). These Li-test statistics are computed in each case: test statistics and *p*-values are reported in Table 2.

In the initial scenario excluding the ratio data, the Li-test is used to assess distribution equality between convex and nonconvex technologies from the buyer's perspective in both general and price directions. The Li-test results reveal insufficient evidence to reject the null hypothesis, implying that the distributions of convex and nonconvex technologies are statistically indistinguishable. This is substantiated by the calculated *p*-values, registering at 0.6970 and 0.1640 for general and price directions, respectively. Conversely, when examining the seller's standpoint in the same scenario and directions, the null hypothesis asserting equal distributions between convex and nonconvex technologies is rejected. The calculated *p*-values, reaching 0.0000 and 0.0030 for general and price directions, respectively, underscore a significant difference in the distributions. The Li-test outcomes indicate marked distinctiveness in these cases from the seller's perspective.

Turning to our second scenario of the empirical analysis, we assess the impact of including the two ratio factors reliability and humidity resistance. Examining both general and price-oriented directions under both convex and nonconvex technologies, we aim to uncover variations in inefficiency levels. This analysis sheds light on how these ratio data eventually influence the competitive landscape and strategic positioning of IoT service providers, offering valuable insights into potential economic opportunities within this market.

When examining ratio data, our analysis reveals a consistent level of efficiency (40 out of 41) among IoT service providers from the buyer's perspective. The same providers consistently demonstrate efficiency under both convexity and nonconvexity, indicating a uniformly competitive market for IoT services. Importantly, the impact of ratio data on the market is negligible. Shifting our focus to the seller's standpoint under the general direction vector and considering ratio data, a similar pattern emerges. Almost all IoT providers (40 out of 41) exhibit efficiency under both convexity and nonconvexity. It is noteworthy that considering ratio factors has no influence on the nonconvex case, as expected, but has a significant impact on the convex case. This observation provides valuable insights into the dynamics of efficiency in the IoT services market from the seller's perspective.

Transitioning to the price-oriented direction vector with ratio data, our findings reveal no discernible difference in the benefit function values across both perspectives and technologies. This suggests that the inclusion of ratio data has negligible effects on market evaluations for this data. The consistency in benefit function values underscores the robustness of our analysis and reinforces the notion that considerations of ratio data do not significantly alter the outcomes in this market.

Examining the seller's perspective through the price-oriented direction vector with ratio data unveils distinct patterns within the dataset. Nine IoT providers exhibit inefficiency under convexity, in contrast to only five under nonconvexity. Subtle similarities in average inefficiency become apparent, with the average now standing at approximately 0.67 % under convexity and merely 0.46 % under nonconvexity. These minor differences in inefficiency levels between convex and nonconvex technologies in the price dimension imply limited opportunities for economic rents in the market.

In the second scenario with ratio data, the outcomes of the Li-test differ significantly. From both the buyer's and seller's perspectives and across both directions, the Li-test results fail to provide evidence to reject the null hypothesis of equal distributions between convex and nonconvex technologies. In modeling ratio variables, the models retain only those observations that perform as well as or better than the unit under evaluation in the reference sets. IoT providers not meeting these criteria are excluded from the evaluations by setting their intensity variables (λ_k) to zero. Consequently, the observations that remain in the evaluation process dominate the units in the ratio factors, operating in a manner somewhat akin to nonconvex models. This approach sheds light on the observed equal distribution outcomes in both perspectives, underscoring the impact of the selective convexity concept in the modeling process. The computed *p*-values, amounting to 1 and 0.1560 for the buyer's standpoint and 1 and 0.3945 for the seller's perspective, affirm the absence of significant differences in the distributions between convex and nonconvex technologies.

In both scenarios, Figs. 2 and 3 depict the differences between the calculated maximum (obtained from model (5)) and minimum (obtained from model (6)) prices for all observations, specifically in the price direction. These visual representations aim to highlight a fundamental observation aligned with Proposition 1: the gap between maximum and minimum prices, and thus the potential for rent extraction, is consistently narrower under nonconvexity. Moreover, the figures serve to visually reinforce a noteworthy empirical finding discussed earlier: within our sample, the potential for rent extraction in terms of average inefficiencies is more pronounced from a buyer's perspective than from a seller's perspective. Additionally, this potential is attenuated when taking into account ratio-type factors.

For the convex case SP is provided in Appendix D for some efficient and inefficient observations. We leave the case with ratio data as well as the nonconvex case for future work.

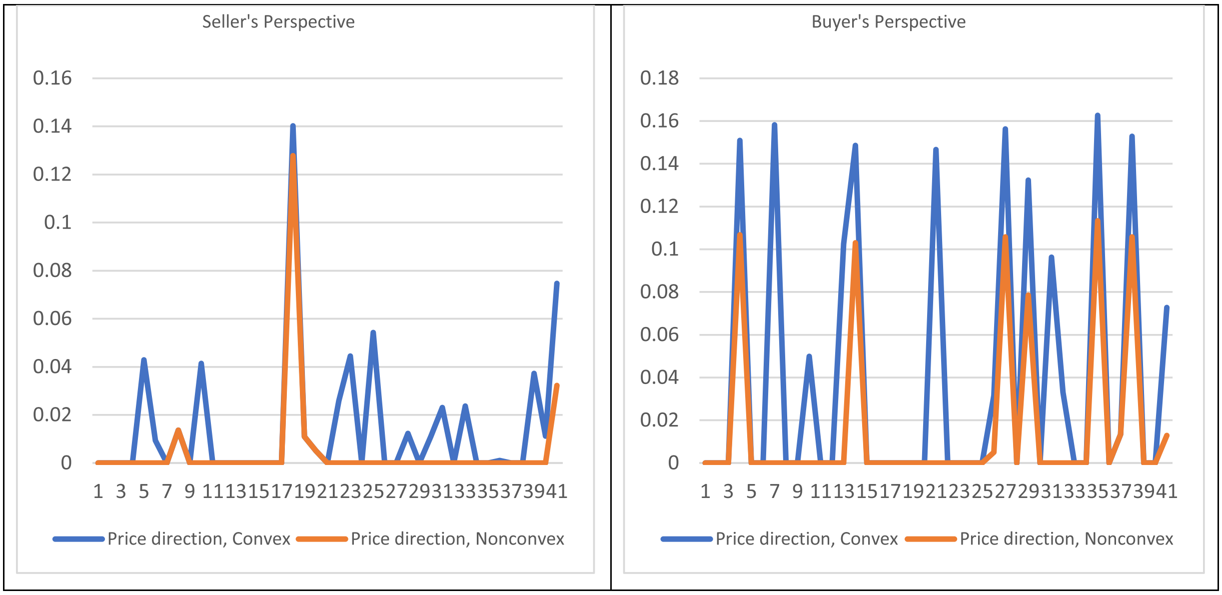

Fig. 2. Evaluation in Price direction without ratio data: Seller's and buyer's perspective.

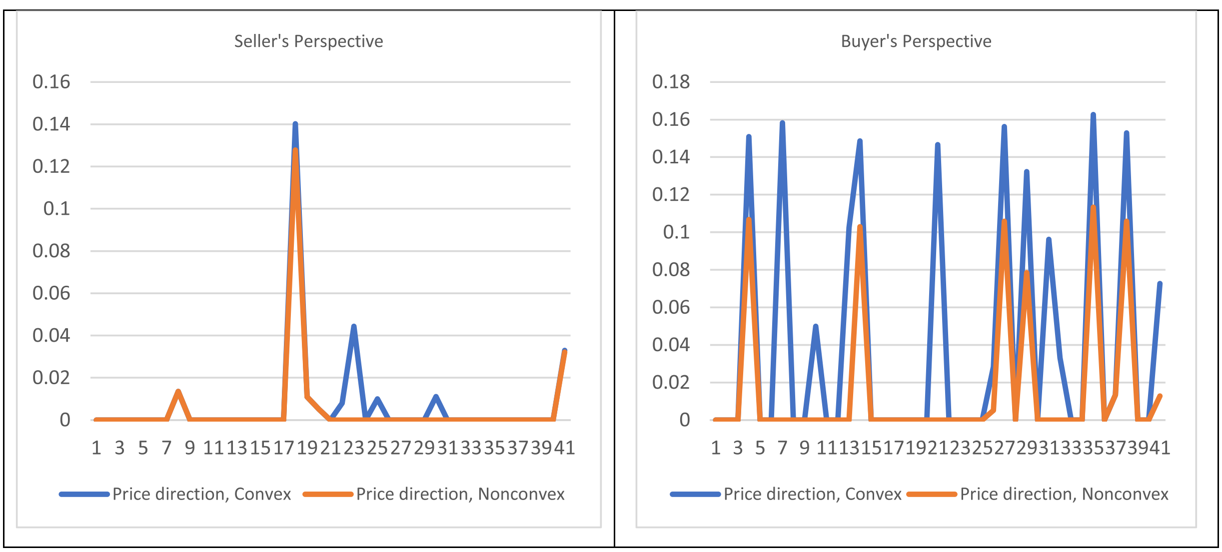

Fig. 3. Evaluation in Price direction with ratio data: Seller's and buyer's perspective.

4.4. Insights for practice

In the realm of advanced digital technologies, managers and decision-makers can gain valuable insights from our study. The competitive landscape among providers necessitates the application of advanced tools for performance evaluation and the strengthening of competitive advantages. These tools are equally valuable for buyers seeking to identify the most efficient providers. In the competitive market, only a single IoT contract shows slight inefficiency from a buyer's perspective, making choices challenging. Sellers, however, may find opportunities to extract rents from the Iranian firm selecting its IoT provider.

The impact of price on the evaluation and ranking of IoT service providers is evident from both buyer's and seller's viewpoints. Analyzing the market using price direction reveals a less competitive buyer's market, with a significant proportion of contracts being efficient. Sellers, accordingly, have increased opportunities to extract potential rents. Nonconvex technologies prove more effective in identifying inefficient IoT service providers compared to convex technologies, as illustrated by the empirical results. Opting for nonconvexity in decision-making allows buyers and sellers to more reliably identify efficient contracts and enhance their competitive advantages, though the effect is somewhat influenced when ratio data are considered in the analysis.

5. Conclusions and future research

Over the last few years, a substantial focus has been on building smart platforms in organizations through applying Industry 5.0, including IoT, cloud computing, and AI. These technologies can enhance transparency, visibility, sustainability, resilience, connectivity, and financial productivity throughout supply chains. In this regard, evaluating the efficiency of service providers of these technologies is of considerable significance. In this contribution, we propose a nonparametric double frontier estimation of the hedonic price characteristics based on the buyer's and seller's perspectives to evaluate IoT service providers in the Industry 5.0 era. We developed a separable directional distance function-based optimization model and proposed a comparable estimation of the convex and nonconvex hedonic price function to estimate the efficiency of IoT service providers. In addition, the hypothesis of convexity in measuring the efficiency of IoT service providers was tested to endorse the obtained results of the proposed models.

Here, we provide some research directions based on the proposed model in this contribution. Another topic in the frontier literature in which an intersection of technologies is taken is the so-called by-production model proposed by Murty et al. (2012). In this case, a conventional, as well as an emission-generating technology, are combined into a by-production technology to model the joint production of good and bad outputs along with the abatement process to mitigate the bad outputs. Ang et al. (2023) provide a recent empirical example of computing the by-production technology under both convexity and nonconvexity and citing similar articles. For the by-production technology as an intersection of conventional and emission-generating technologies, the same questions arise as posed in our Propositions 1 and 2. While Proposition 1 may be readily transposed, we are unaware of such a result in the literature. The eventual transposition of Proposition 2 depends on the exact nature of the efficiency measures defined with respect to the by-production technology. Murty and Russell (2022) develop some heuristic arguments, but a formal proof seems so far missing. Another avenue for future research is checking the remarkably similarity between the convex models with ratio data and the basic nonconvex models for alternative data sets. Finally, the issue of shadow pricing for the convex case with ratio data and for the nonconvex case requires more work.

CRediT authorship contribution statement

Kristiaan Kerstens: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Majid Azadi:** Data curation, Writing – original draft, Writing – review & editing. **Reza Kazemi Matin:** Data curation, Formal analysis, Software, Validation, Writing – original draft, Writing – review & editing, Methodology. **Reza Farzipoor Saen:** Data curation, Writing – original draft, Writing – review & editing.

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Supplementary materials

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