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Laurens Cherchye
KULeuven

Bram De Rock
ECARES, Université libre de Bruxelles
Department of Economics, KU Leuven

Bart Dierynck
Department of Economics, KU Leuven
Tilburg School of Economics and Management, Tilburg University

Pieter Jan Kerstens
Department of Economics, KU Leuven

Filip Roodhooft
Department of Economics, KU Leuven
Accounting and Finance, Vlerick Business School.

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ECARES
ULB - CP 114/04
50, F.D. Roosevelt Ave., B-1050 Brussels BELGIUM
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Laurens Cherchye * Bram De Rock† Bart Dierynck‡
Pieter Jan Kerstens§ Filip Roodhooft¶

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Abstract

Firms have become increasingly customer centric, implying that customers, rather than products, are treated as the most important asset of a firm. The switch to customer-centric strategies also implies that firms are collecting an enormous amount of customer-related data. The purpose of this paper is to propose a DEA-based methodology to determine the contribution of customer segments to firm value. We show the practical usefulness of our methodology through an application to Activity Based Costing (ABC) data collected from a large European telecom provider, which offers fixed telephone, mobile telephone, digital television and internet subscriptions. Our analysis reveals that the average cost reduction potential across all customer segments amounts to 1.26% of the total controllable costs, which represents approximately EUR 5 million when expressed in monetary terms. We also document substantial variation in the cost reduction potential across customer segments.

Keywords: data envelopment analysis, customer value, multi-output efficiency, ABC systems

1 Introduction

During the last decade, firms have become increasingly customer centric, implying that customers, rather than products, are treated as the most important asset of a firm, and that acquiring and retaining profitable customers has become the main strategic focus (Fader, 2020; Jain and Singh, 2002; Kumar and Shah, 2009; Palmatier, Moorman, and Lee, 2019). The switch to customer-centric strategies also implies that firms are collecting an enormous amount of customer-related data (Bonacchi and Perego, 2019;

*Department of Economics, University of Leuven (KU Leuven). E-mail: laurens.cherchye@kuleuven.be. Laurens Cherchye gratefully acknowledges the Fund for Scientific Research - Flanders (FWO) and the Research Fund KU Leuven for financial support.

†ECARES, Université Libre de Bruxelles and Department of Economics, University of Leuven (KU Leuven). E-mail: bram.de.rock@ulb.be. Bram De Rock gratefully acknowledges FWO and FNRS for their support.

‡Department of Economics, University of Leuven (KU Leuven). E-mail: Tilburg School of Economics and Management, Tilburg University. Email: b.dierynck@tilburguniversity.edu.

§Department of Economics, University of Leuven (KU Leuven). E-mail: pieter-jan.kerstens@kuleuven.be

¶Department of Accounting, Finance, and Insurance, University of Leuven (KU Leuven) and Accounting and Finance, Vlerick Business School. Email: filip.roodhooft@kuleuven.be

Galbraith, 2005; Latinovic and Chatterjee, 2019). Currently, these customer-related data are analyzed by means of techniques such as customer profitability analysis (CPA; see for instance van Raaij, Vernooij, and van Triest (2003)) and/or customer lifetime value (CLV; see for instance Glady, Baesens, and Croux (2009)). Although these two techniques differ on some important aspects, they both aim to determine the contribution of individual customers or customer groups to firm value based on data about past customer behavior (Holm, Kumar, and Rohde, 2012). The outcomes of both techniques are used to support various managerial decisions, such as the allocation of marketing resources, pricing and customer differentiation decisions.

The purpose of the current paper is to propose an alternative DEA-based methodology to determine the contribution of customer segments to firm value. We illustrate the practical usefulness of our newly developed methodology by using data from a large European telecom provider. To be clear, our purpose is not to develop a substitute for CLV and/or CPA but to develop a methodology that can help to extract additional insights from the customer-related data that firms collect. As such, we believe that our newly developed methodology is complementary with existing approaches to analyze customer-related data.

Our novel methodology has its origins in data envelopment analysis (DEA), which has become popular both as an analytical research instrument and as a practical decision-support tool to evaluate the efficiency of a DMU (i.e. decision-making unit, which is typically a business unit, office unit, or branch of a private or public sector company). DEA determines the efficiency of a DMU by comparing the input-output performance of the DMU to that of other DMUs operating in a similar technological environment (typically business units, offices, or branches of the same company). The outcome of a DEA exercise indicates whether the same output level can be produced with a lower level of inputs or whether a higher output level can be produced with the same level of inputs. Since the seminal work of Charnes, Cooper, and Rhodes (1978), the methodological DEA literature has mainly focused on refinements that account for uncontrollable factors, data variation, economies of scope, and the allocation of inputs to outputs. See, for example, Cooper et al. 2000, Cook and Seiford (2009) for reviews of DEA, and Cherchye, De Rock, and Vermeulen (2008) and Cherchye et al. (2013) for recent developments that are directly relevant to the current study.

We advocate the use of DEA to analyze the massive amounts of data that firms collect on the behavior of their customers. The aim of our methodology is to identify customer segments from which the contribution to firm value can be increased. Our methodology relies on comparing the input-output performance of similar customer segments and indicates for each customer segment the cost reduction that can be achieved without decreasing the output level of the customer segment. In the next section we argue in detail that our DEA-based methodology has several noteworthy strengths. First, it allows for heterogeneity with respect to the way in which the costs that are made to serve customer segments are transformed into outputs such as revenues, upselling, and churn rate. Second, it does not resort to parametric specifications about the way in which inputs are transformed into outputs, which makes that the results of our analysis cannot be driven by an ill-specified transformation function. Third, our DEA-based methodology allows for the inclusion of inputs and/or outputs that are not expressed in monetary terms, which increases the precision of our analysis and opens the possibility to include inputs and/or outputs that are difficult to express in monetary terms.

We show the practical use of our methodology through an empirical application that uses data collected from a large European telecom provider. Our analysis reveals that the average cost reduction potential across all customer segments amounts to 1.26% of the total controllable costs, which represents approximately EUR 5 million when expressed in monetary terms. As expected, there is substantial variation in the cost reduction potential across the customer segments. The average cost reduction potential of the ten segments with the highest cost reduction potential amounts to 28.19% of the total controllable costs. Our analysis also allows us to compute the cost reduction potential of every geographical region, product combination, or socio-demographical segment separately. Such an analysis can be useful as quite some marketing actions, such as advertising through radio, television, and newspapers, cannot yet be targeted on the most detailed customer segmentation level. Next, our analysis gives some guidance to managers on how they can exploit the cost reduction potential of a particular customer segment. Specifically, when our analysis identifies a cost reduction potential, this implies that there is another customer segment that realizes more outputs at lower costs. This dominating customer segment can be identified and the manager can learn from the way in which this customer segment is served in order to exploit the cost reduction potential of the dominated customer segment. Finally, we show how heat maps can be used to visualize the results of our analysis, so facilitating the managerial decision-making process.

The rest of this paper unfolds as follows. Section 2 advocates the use of DEA as a tool for customer value assessment. Section 3 presents our DEA-based methodology to determine the contribution of customer segments to firm value. Section 4 introduces the set-up of our empirical application and Section 5 discusses our results. Section 6 concludes.

2 DEA as a tool for customer value analysis

Our DEA-based methodology for analyzing customer value determines the efficiency with which different customer segments are served by comparing the input-output performance of serving a particular customer segment to the input-output performance of other customer segments of the same firm. The inputs are typically the controllable and uncontrollable costs that are made to serve the customer segments such as, for instance, operating expenditures, acquisition costs, and development costs. The outputs are the key performance indicators that a firm defines as part of the customer-centric strategy such as, for instance, the realized revenue, the churn rate, and the upselling and cross-selling potential of the customer segment. Importantly, the data about these inputs and outputs are typically available in the firm's information system. The outcome of our analysis determines, for each customer segment, with how much the costs that are made to serve the segment can be reduced while still realizing the same output level. As our model also includes outputs that determine the future and indirect value of a customer segment, this cost reduction potential reflects the unrealized value that the segment can contribute to firm value.

This DEA-based approach to determining the contribution of customer segments to firm value has several benefits that originate from the distinguishing features of DEA as an efficiency measurement methodology. First, as DEA is nonparametric in nature, it does not resort to some (typically unverifiable) parametric specifications of the way in which inputs are transformed in outputs. DEA thus allows for heterogeneity with respect to the way in which inputs are transformed in outputs. Allowing for such heterogeneity is relevant in the context of customer centricity as customer centricity implies that providing service to customers should be adapted to the characteristics of the customer segments (Fader, 2020; Palmatier, Moorman, and Lee, 2019). As a result, the way in which costs to serve customer segments are transformed in outputs likely differs across customer segments. Allowing for heterogeneity with respect to the way in which inputs are transformed into outputs across customer segments is also an important advantage of our DEA-based approach compared to CLV models, which often assume that the way in which inputs are transformed to outputs is homogeneous across customer segments (Holm, Kumar, and Rohde, 2012). Specifically, CLV models usually adopt a parametric approach and determine the contribution of a customer segment to firm value by using stochastic models in which customer behavior is modeled by means of probabilistic functions. Next to the fact that CLV models assume homogeneity across customer segments in transforming inputs to outputs, the parametric approach as adopted by most CLV models also implies that an identified low contribution of a particular customer segment to firm value may well be driven by an ill-specified transformation function (rather than a truly low contribution).

A final important benefit of our methodology is that it allows for heterogeneity with respect to the unit of account of the inputs and outputs. Suppose, for instance, that the outputs of serving a customer segment are the realized revenues, which are expressed in monetary terms, and customer complaints, which are typically expressed as a percentage reflecting the total number of customer complaints relative to the total number of served customers. To analyze the efficiency of the input-output transformation of the different customer segments by means of DEA, it is not required to estimate the monetary consequences of customer complaints by means of deterministic or stochastic models. The heterogeneity that DEA allows with respect to the unit of account of the inputs and/or outputs implies that it is not very restrictive with respect to the inclusion of inputs and/or outputs in the model. Moreover, the detected inefficiencies cannot be caused by errors in expressing inputs and/or outputs in monetary terms.

3 Methodology

We begin this section by introducing some necessary notations and concepts, and we subsequently explain how our methodology can be used in the context of customer analysis. In a following step, we present our cost efficiency measure, and we show its practical implementation through linear programming.

3.1 Preliminaries

The telecom operator wishes to evaluate the cost effectiveness of its customer segments: can resources be decreased without lowering the level of the current objectives? Its objectives are not only monetary but also include customer satisfaction, which was measured indirectly by the churn rate and the number of upsells. Detailed activity-based costing (ABC) data are available to evaluate these objectives. To align with the literature on efficiency analysis, we use the term “inputs” to refer to resources and “outputs” to refer to objectives.

We assume K observed customer segments that produce M different outputs. For each segment k ($k = 1, ..., K$), the output quantities y_k^m ($m = 1, ..., M$) are captured by the M-dimensional vector $\mathbf{y}_k$. The production of each output involves N^{spec} output-specific inputs, $N^{subjoin}$ sub-joint inputs and N^{join} joint inputs. Output-specific inputs $\mathbf{q}_k^m \in \mathbb{R}_+^{N^{spec}}$ are exclusively used by segment k in the production of their output $y_k^m \in \mathbb{R}_+$. Joint inputs are used in the production of all outputs. Sub-joint inputs are situated between output-specific and joint inputs. They cannot be assigned to one output exclusively, but are also not used by all outputs (Cherchye, De Rock, and Walheer, 2015). We use $N = N^{join} + N^{subjoin}$ for the total number of subjoint and joint inputs, and we let $\mathbf{Q}_k \in \mathbb{R}_+^N$ represent the vector of joint and subjoint inputs of segment k. We formally distinguish between sub-joint and joint inputs by defining a binary $N \times M$ matrix $\mathbf{D} = (\mathbf{d}_1, \ldots, \mathbf{d}_M)$ with the j-th ($j = 1, \ldots, N$) entry of every vector $\mathbf{d}_m$ given as:

$$D_{j,m} = \begin{cases} 1 & \text{if } Q_k^j \text{ is used to produce output } m, \\ 0 & \text{otherwise,} \end{cases}$$

using $Q_k^j \in \mathbb{R}_+$ for the j-th (sub)joint input quantity of segment k. Thus, for a joint input $j \in N^{join}$ we have that $D_{j,m} = 1$ for all $m = 1, ..., M$. Summarizing, we assume a dataset:

$$S = \left\{\mathbf{y}_k, \mathbf{q}_k^1, \ldots, \mathbf{q}_k^M, \mathbf{Q}_k, \mathbf{D}\right\}_{k=1,\ldots,K}.$$

3.2 Customer lifetime value

Before presenting our DEA-based methodology, we explain the concept of customer lifetime value (CLV) . The cash flow $CF_{k,t}$ a customer k generates at time t for the firm is equal to the profit the firm makes on the customer:

$$CF_{k,t} = \mathbf{w}'_{k,t}\mathbf{y}_{k,t} - \sum_{m=1}^{M} (\mathbf{p}_{k,t}^m)'\mathbf{q}_{k,t}^m + \mathbf{P}'_{k,t}\mathbf{Q}_{k,t},$$

with output prices $\mathbf{w}_{k,t} \in \mathbb{R}_{++}^M$, output-specific input prices $\mathbf{p}_{k,t}^m \in \mathbb{R}_{++}^{N^{spec}}$ and (sub)joint input prices $\mathbf{P}_{k,t} \in \mathbb{R}_{++}^N$.

Customer lifetime value for a customer k is then defined as the discounted sum of future cash flows $\{CF_{k,t+i}\}_{i=1}^T$ that the customer generates over the horizon T. Hence, the CLV of customer k at time t for the next T periods is defined as:

$$CLV_{k,t} = \sum_{i=1}^{T} \frac{CF_{k,t+i}}{(1+\rho)^i} = \sum_{i=1}^{T} \frac{\mathbf{w}'_{k,t+i}\mathbf{y}_{k,t+i} - \sum_{m=1}^{M} (\mathbf{p}_{k,t+i}^m)'\mathbf{q}_{k,t+i}^m + \mathbf{P}'_{k,t+i}\mathbf{Q}_{k,t+i}}{(1+\rho)^i},$$

with (constant) discount rate ρ. Clearly, $CLV_{k,t}$ can be improved by (i) increasing total revenue, (ii) decreasing total costs or (iii) a combination of (i) and (ii). In this paper we opt for (ii), because cost reductions do not affect customers directly, which makes them a safe way to increase profit and customer value. However, one could easily redo the analysis for (i) or (iii) using the framework of Cherchye, De Rock, and Walheer (2016).

At this point, we remark that one cannot exclude seasonal (temporary) effects on the customer lifetime value. For example, a marketing campaign affecting costs/revenues or customers switching subscriptions. Therefore, in our empirical application we will average the results over time to reduce these seasonal effects and drop the time subscripts on the variables. The result of our analysis should then be interpreted as average potential cost reductions and, accordingly, average potential customer lifetime improvements.

3.3 Multi-output cost efficiency

In light of the above, we analyze customer value by using the multi-output cost efficiency framework of Cherchye et al. (2013) with the minor adaptation that we also allow for sub-joint inputs, which –as explained above– are just a special case of joint inputs (see also Cherchye, De Rock, and Walheer (2015)). For a given specification of the outputs, output-specific inputs and (sub)joint inputs, we can define the production technology in terms of input sets that represent all combinations of inputs that can produce a given quantity y^m of output m:

$$\mathcal{I}^m(y^m) = \{(\mathbf{q}^m, \mathbf{d}_m\mathbf{Q}) \text{ can produce } y^m\}.$$

We assume that these sets $\mathcal{I}^m$ satisfy the following property:

Axiom 1 (nested input sets). $y^{m*} \geq y^m \Rightarrow \mathcal{I}^m(y^{m*}) \subseteq \mathcal{I}^m(y^m)$.

In words, this axiom implies that we can always freely dispose of some output y^{m*} to produce a lower output y^m. Put differently, if we observe a certain input-output combination, then we can always achieve lower (and worse) objectives for the same inputs.

In order to assess cost efficiency for every output separately, we need some way of assigning portions of the (sub)joint input costs over the different outputs. For this purpose, we use "implicit prices":

Definition 1 (Implicit prices). *For customer segment k with (sub)joint input prices $\mathbf{P}_k \in \mathbb{R}^N_{++}$ and binary matrix $\mathbf{D} \in \mathbb{R}^{N\times M}$, implicit prices are any vectors $\mathbf{P}^m_k \in \mathbb{R}^N_{++}$ for $m = 1, \ldots, M$ that satisfy $\sum_{m=1}^M \mathbf{P}^m_k \mathbf{d}_m = \mathbf{P}_k$.*

The vector $\mathbf{d}_m$ in the above definition ensures that the price/cost of a subjoint input is only distributed over the outputs that use it. These implicit prices are essentially an accounting trick to distribute the cost of shared inputs over the different outputs.

We are now in a position to adapt the cost efficiency definition of Cherchye et al. (2013) to our specific set-up:

Definition 2 (Cost efficiency). *Customer segment k is multi-output cost efficient if, for each output m, there exist an input set $\mathcal{I}^m(y^m)$ that satisfies Axiom 1 and implicit prices $\mathbf{P}^m_k \in \mathbb{R}^N_{++}$ such that:*

- $(\mathbf{q}^m_k, \mathbf{d}_m\mathbf{Q}_k) \in \mathcal{I}^m(y^m)$,
- $(\mathbf{p}^m_k)'\mathbf{q}^m_k + (\mathbf{P}^m_k\mathbf{d}_m)'\mathbf{Q}_k = \min_{(\mathbf{q}^m,\mathbf{Q})\in\mathcal{I}^m(y^m)} (\mathbf{p}^m_k)'\mathbf{q}^m + (\mathbf{P}^m_k\mathbf{d}_m)'\mathbf{Q}$.

Intuitively, this definition says that a customer segment is multi-output cost efficient if, for every output m, its chosen input combination is (i) technically feasible and (ii) is the lowest cost combination for the given prices. For given implicit prices and the input sets, Definition 2 can be easily operationalized: it suffices to find $(\mathbf{q}^m, \mathbf{Q})$ that produces y^m at minimal cost.

The first task is to reconstruct the input sets from the dataset S. Cherchye et al. (2013) show that the reconstructed set $\mathcal{I}^m$ is completely characterized by

$$D^m_k = \{s | y^m_k \leq y^m_s\},$$

which contains all observed customer segments s that dominate segment k in terms of the m-th output (i.e. $y^m_s \geq y^m_k$). For a given specification of the implicit prices, Definition 2 in combination with Axiom 1 then gives us the necessary tools to verify cost efficiency. First, let

$$c_k^m \equiv \min_{s \in D_k^m} \{(\mathbf{p}_k^m)'\mathbf{q}_s^m + (\mathbf{P}_k^m \mathbf{d}_m)'\mathbf{Q}_s\}$$

denote the minimal cost to produce y^m. Then, it suffices to check whether

$$CE_k^m \equiv \frac{c_k^m}{(\mathbf{p}_k^m)'\mathbf{q}_k^m + (\mathbf{P}_k^m \mathbf{d}_m)'\mathbf{Q}_k}$$

equals 1. If CE_k^m is smaller than 1, then costs can be reduced for customer segment k, which means that the customer lifetime value can be improved.

In practice, price information is often not available to the empirical analyst, which hinders the above calculation. However, we can evaluate cost efficiency using "most favorable" (shadow) prices $\mathbf{p}_k^m, \mathbf{P}_k$ and implicit prices $\mathbf{P}_k^m$. In that case, we compute:

$$\begin{aligned} CE_k \equiv \max_{c_k^m, \mathbf{p}_k^m, \mathbf{P}_k, \mathbf{P}_k^m} & \frac{\sum_{m=1}^M c_k^m}{\sum_{m=1}^M (\mathbf{p}_k^m)'\mathbf{q}_k^m + (\mathbf{P}_k^m \mathbf{d}_m)'\mathbf{Q}_k} \\ & c_k^m \leq (\mathbf{p}_k^m)'\mathbf{q}_s^m + (\mathbf{P}_k^m \mathbf{d}_m)'\mathbf{Q}_s \qquad \forall s \in D_k^m,\ \forall m = 1, \ldots, M \\ & \sum_{m=1}^M \mathbf{P}_k^m \mathbf{d}_m = \mathbf{P}_k, \end{aligned}$$

which means that we select those prices that maximize the cost efficiency for customer segment k. In its original form, the above programming problem is nonlinear, as free variables enter the denominator of the objective function. However, we can easily linearize it as follows:

$$CE_k \equiv \max_{c_k^m, \mathbf{p}_k^m, \mathbf{P}_k, \mathbf{P}_k^m} \sum_{m=1}^M c_k^m$$

$$\text{s.t. } c_k^m \leq (\mathbf{p}_k^m)'\mathbf{q}_s^m + (\mathbf{P}_k^m \mathbf{d}_m)'\mathbf{Q}_s \qquad \forall s \in D_k^m,\ \forall m = 1, \ldots, M \tag{1a}$$

$$\sum_{m=1}^M (\mathbf{p}_k^m)'\mathbf{q}_k^m + \mathbf{P}_k'\mathbf{Q}_k = 1 \tag{1b}$$

$$\sum_{m=1}^M \mathbf{P}_k^m \mathbf{d}_m = \mathbf{P}_k. \tag{1c}$$

This linear program evaluates customer segment k in the best possible light by choosing (shadow) prices that make the segment appear as efficient as possible when compared to its peers in D_k^m. The program computes a minimal cost c_k^m for every output m. The sum of these output-specific costs gives our measure CE_k of overall cost efficiency of segment k.

Intuitively, this overall cost efficiency can be decomposed as a weighted sum of output-specific efficiencies, as follows:

$$CE_k = \sum_{m=1}^M w_k^m CE_k^m, \tag{2}$$

where the weights w_k^m represent the share of the output-specific cost in the overall cost:

$$w_k^m = \frac{(\mathbf{p}_k^m)'\mathbf{q}_k^m + (\mathbf{P}_k^m \mathbf{d}_m)'\mathbf{Q}_k}{\sum_{m=1}^{M}(\mathbf{p}_k^m)'\mathbf{q}_k^m + (\mathbf{P}_k^m \mathbf{d}_m)'\mathbf{Q}_k}.$$

As a final note, we remark that our above definition of D_k^m overlooks an important aspect: it does not control for the relative size of the customer segments. Particularly, customer segments with many customers generate a lot of profits (output) and, therefore, will appear in the dominating set D_k^m of many k. Arguably, however, it is unfair to compare these large customer segments against the smaller ones. To account for this, we can adapt an original proposal of Ruggiero (1996) to our setting, and control for differences in the customer environment (such as size of the segment) by using a slightly modified definition of D_k^m:

$$D_k^m = \{s | y_k^m \leq y_s^m\} \cap \{s | \mathbf{z}_s \leq \mathbf{z}_k\},$$

where the vector $\mathbf{z} \in \mathbb{R}_+^{Env}$ captures environmental conditions, with higher values indicating a more favorable environment.

4 Empirical application: set-up

We demonstrate the practical applicability of our methodology by means of a unique data set collected from a large European telecom provider that offers fixed telephone, mobile telephone, digital television and internet subscriptions. The inputs of our model are controllable costs, such as operating expenditures, acquisition costs and development costs, and uncontrollable costs, such as interconnection costs with other operators, roaming costs, IT-costs and billing costs. The outputs of our model are the revenue streams realized in the different product categories of the company, the churn rate of a customer segment, and the number of upsells of a customer segment. In total, our model contains 20 inputs and 7 outputs. To increase the empirical validity of our analysis, we assigned the inputs to particular outputs based on the Activity Based Costing system (ABC) of the telecom provider (Cherchye et al., 2013). In what follows, we first introduce the way in which the telecom provider segments its customer base. Next, we describe in more detail the inputs and the outputs that we use in our application.

4.1 Customer segments

The telecom operator segments its customer base on the basis of the product combination the customer has, the region in which the customer lives, and the socio-demographic category to which the customer belongs. The telecom operator offers fixed telephone, mobile telephone, digital television and internet, and customers can choose any possible combination. The main distinction for the product combination is the number of products, leading to product combinations, which we will label Xplay packs', with 4, 3, 2, or 1 product respectively. The 0play pack is a rest category. Furthermore, the telecom operator distinguishes 11 regions and 6 socio-demographic groups. As our newly developed methodology boils down to comparing the input-output performance of different customer segments, it is important to only compare customer segments that operate in a similar environment. For that reason, we only compare customer segments within a particular Xplay pack. Specifically, we only compare customer segments that have the same number of products (i.e. 1, 2, 3, or 4) in their Xplay pack. Obviously, as the telecom operator offers 4 products, there are 4 different combinations for the 3play pack, 6 different combinations for the 2play pack and 4 different combinations for the 1play pack. Combining the number of combinations within each Xplay pack with the 11 regions and 6 socio-demographic groups leads to 66 customer segments for the 4play pack, 264 customer segments for the 3play pack, 396 customer segments for the 2play pack, and 264 customer segments for the 1play pack.

4.2 Data

The telecom operator provided us with data for the year 2014. For each month, we have detailed data on all costs and all revenues associated with every customer segment. We also have data about the total number of customers in each segment as well as about the migration of customers from one customer segment to another customer segment. The efficiency scores are computed on a monthly basis by comparing each customer segment with all similar customer segments in all periods (i.e. we assume no change in technology over time).[1] While this is a strong assumption, the advantage of this approach is that we have much more observations to compare with. These results were then averaged over all months, because the telecom operator did not see benefits in analyzing the contribution of customer segments on a monthly basis. This averaging also reduces potential seasonal (temporary) effects. The telecom operator has $32,121,558$ customers in total and the average net margin per customer, which we calculate as (total revenues minus total costs)/number of customers, amounts to -0.5850 EUR. Upon looking into more detail, a clear pattern emerges: the net margin per customer is almost always negative for socio segment A. In order to illustrate this and the considerable heterogeneity in net margin per customer, we present heat maps in Figure 1 for all 2play packs.

Our model contains different outputs which together reflect the current contribution of a customer segment and the future potential of a customer segment. The current contribution of a customer segment is reflected by five revenue streams, which are the revenues for each customer segment for fixed telephone, mobile telephone, digital television, internet and other revenues. The future potential of a customer segment is reflected by the churn rate and the number of upsells for each customer segment. The churn rate of an Xplay pack represents the percentage of customers that cancel their subscription entirely. The number of upsells for every customer segment is constructed from the monthly migration data and is defined as the number of existing customers of the telecom operator that change their subscription to that particular customer segment.

The inputs in our model are the costs that the telecom operator makes to realize the outputs. These costs typically consist of controllable and uncontrollable costs. Uncontrollable costs are usage costs, such as the interconnection costs between telecom operators and roaming costs, or fixed costs that are only controllable in the long run, such as billing costs, IT costs and costs for bad debt. After consulting with the management team of the telecom operator, we decided to ignore the uncontrollable costs for our analysis, as these costs can never be used to realize cost reductions in the short run. The controllable costs

[1] We checked whether there is significant intertemporal variation on average (i.e. H_0: $F\left(\left\{\sum_{k=1}^{K} CE_{k,t}\right\}_{t=1,\ldots,T-1}\right) = F\left(\left\{\sum_{k=1}^{K} CE_{k,t}\right\}_{t=2,\ldots,T}\right)$) by using a Kolmogorov-Smirnov test. We cannot reject H_0 based on the p-value of 0.3378. We find the same outcome when we test for the individual Xplay packs.

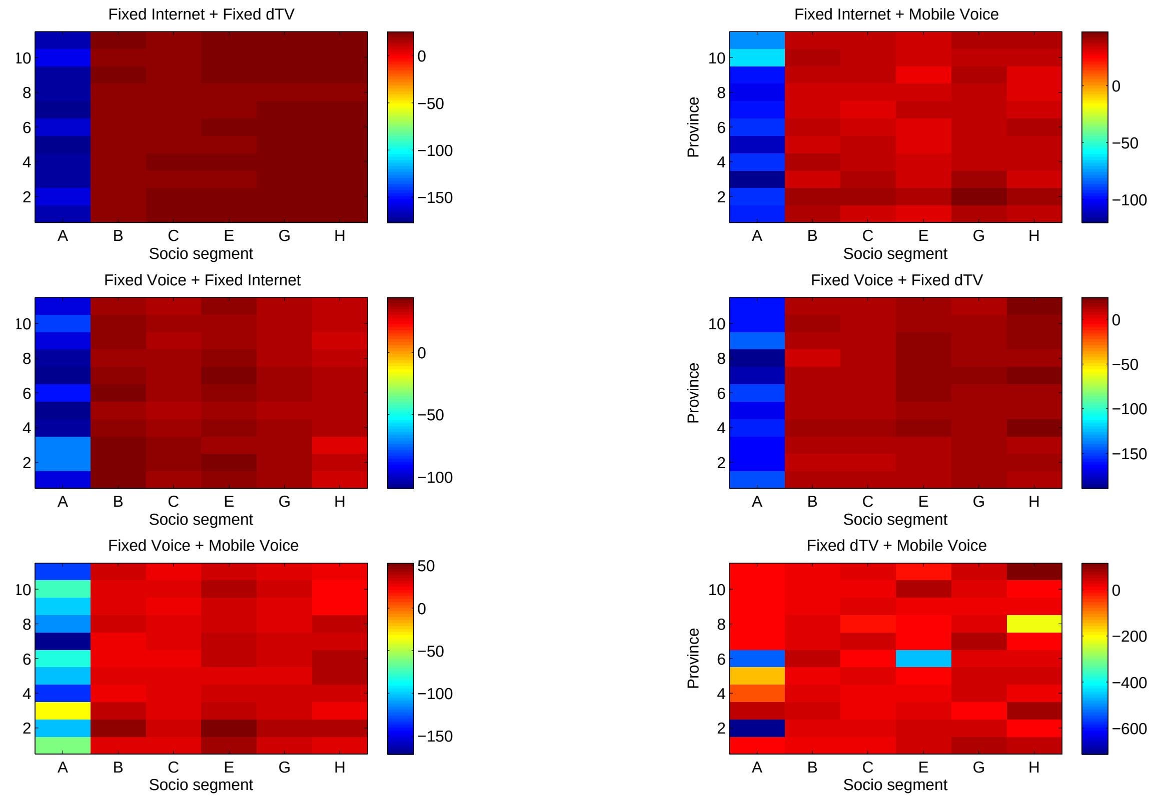

Figure 1: 2P, average net margin per customer

include various operating expenditures, acquisition costs and development costs. The acquisition and development costs for every customer segment are constructed from the monthly migration data by multiplying the acquisition cost, respectively the development cost, for a particular customer segment with the number of customers that migrate to that particular customer segment. In total, we have 14 cost categories that serve as an input in our model. The name of every cost category including a short description of the cost is presented in Table 1. In cooperation with the management team of the telecom operator, we assigned inputs to outputs to ensure that our model is a better reflection of reality. Table 1 present an overview of the descriptive statistics of the different inputs and outputs that we include in our model.Table 2 does the same at Xplay pack level. These descriptive statistics learn that there is a lot of variation in both the inputs and the outputs across the different customer segments.

Input	Mean	Std	Min	Max
ICX_COst	126534,7	558300,1	0	7691876
ROAM_COST	5983,757	21220,79	0	263047,4
COGS_CONTENT	115619,1	334864,7	1,5956	3136804
OPEX_BILLING	17124,49	38740,08	0,456	363408,3
OPEX_BAD_DEBT	16094,74	34516,34	-0,8384	345770,6
OPEX_IT	11929,29	39141,26	-160,649	411506,4
OPEX_REPAIR	114447,1	263642,8	0	2061820
OPEX_CPE	51,11962	222,2961	-172,135	3210,98
OPEX_CCA	77834,9	173275,8	1,2973	1772943
OPEX_OWN_SHOPS	19497,31	45203,92	0,4157	470081,2
OPEX_ECH	6281,529	14644,32	0,1264	152493,6
OPEX_COMMISSIONS	6869,482	18229,62	0,0905	173461,4
SAC_CHANNEL	45381,83	181909,1	0	2315726
SAC_INSTALL	26449,44	114983,7	0	1955994
SAC_TERMINAL	19450,96	96713,02	0	1771770
SAC_CCA_BACK_OFFICE	4152,572	19661,31	0	374602,8
SDC_CHANNEL	24048,75	68878,44	0	983809,9
SDC_INSTALL	18407,64	39758,43	0	445857,9
SDC_TERMINAL	14045,75	34255,48	0	383237,4
SDC_CCA_BACK_OFFICE	2617,542	6804,588	0	80528,87
Output	Mean	Std	Min	Max
Mobile revenues	404850,2	1394090	-77,3397	15637947
Fixed access revenues	396283,5	1167457	-605,956	13472855
Fixed internet revenues	351610,5	867189,8	-68,2616	8210710
Fixed TV revenues	213808,5	617779,2	-187,173	5921540
Other revenues	2831,775	8740,084	-415,099	139795,4
Churn rate	-0,13577	0,13623	-0,48667	0
Upsells	29919,82	71029,37	0	603054
Number of customers	30826,83	72117,02	1	620704

Table 1: Summary statistics of costs and revenues

	4P		3P		2P		1P		0P	
Input	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Repair costs	454499.29	506769.11	162391.00	307091.52	67038.17	121062.10	78552.40	240117.62	1292.63	1286.11
Rental costs devices	143.31	435.27	68.27	281.72	44.28	185.36	30.44	111.65	11.82	119.46
Call center costs	341731.08	392709.48	99664.88	180986.28	32838.94	56822.25	74216.30	145802.74	4032.03	3430.03
Shops costs	90802.42	104468.34	26351.87	48045.70	7950.84	14812.51	16251.70	34125.03	1089.01	930.04
Web costs	29349.02	33748.44	8493.28	15425.38	2534.66	4817.63	5244.59	11334.93	365.49	314.28
Commissions	32187.31	37880.92	6423.97	9096.37	1811.28	3000.56	9934.00	25645.21	844.17	719.37
SAC CHANNEL	84181.39	132197.61	53732.74	215607.91	15206.82	61934.33	83371.60	268187.65	0.00	0.00
SAC INSTALL	48508.31	76176.96	44440.04	181988.87	18849.24	77574.83	20579.95	91401.23	0.00	0.00
SAC TERMINAL	43939.58	69002.28	39712.93	164955.68	15039.30	69769.69	4148.08	24514.12	0.00	0.00
SAC CCA BACK OFFICE	9518.34	14947.51	8175.63	34831.72	2501.36	10691.17	2211.08	7725.90	0.00	0.00
SDC CHANNEL	197355.11	183100.06	32953.60	40251.84	7628.21	11691.40	1496.62	3466.20	0.00	0.00
SDC INSTALL	105024.60	88256.50	28910.82	36839.06	10537.02	18080.53	2113.03	8069.98	0.00	0.00
SDC TERMINAL	90139.03	75916.81	22959.44	32025.80	6450.71	15284.73	520.11	2204.44	0.00	0.00
SDC CCA BACK OFFICE	18854.18	15833.80	4141.30	6092.69	898.36	1493.36	165.50	665.20	0.00	0.00
Output	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Mobile revenues	1609028.16	1932590.72	211823.12	336505.18	49896.88	128735.41	915997.39	2417011.43	35109.44	27414.26
Fixed access revenues	1294707.19	1497576.23	463405.67	1019595.33	205638.11	470249.40	482764.07	1794354.21	3676.24	3428.55
Fixed internet revenues	1485713.15	1703256.65	592675.31	1147821.29	225368.95	491208.91	94561.38	300294.55	4188.88	4301.56
Fixed TV revenues	1119748.99	1282514.40	394958.02	809351.93	111568.24	309895.42	3400.10	5195.58	10101.49	12169.81
Other revenues	21045.20	25447.77	3693.96	6200.80	685.34	1358.57	1133.67	2469.05	412.51	570.50
Churn rate	-0.03	0.00	-0.06	0.04	-0.09	0.09	-0.22	0.10	-0.49	0.00
Upsells	59741.65	68229.48	24126.11	45126.88	12371.78	21999.89	60341.74	120496.68	6058.38	6008.06
Number of customers	60993.89	68906.95	24991.31	46034.43	12821.23	22390.94	61963.66	122203.20	6647.06	6132.40

Table 2: Summary statistics of controllable costs and revenues per play pack

A first approach to distill management recommendations based on the available data is to look at key performance indicators such as the number of customers in the different segments or the number of upsells in different customer segments. A second approach is to construct key performance indicators that combine revenues and costs such as the gross margin of a customer segment, which we define here as the difference between the total revenues of a customer segment and the usage costs (i.e. interconnection costs, roaming costs and costs of content), or the average net margin per customer for each customer segment, which we define as the difference between total revenues and total costs per customer segment divided by the total numbers of customers in the particular customer segment. The main conclusion of such an analysis is that the results very strongly depend on the key performance indicator one is analyzing, which calls for an approach in which the input-output performance of different customer segments is analyzed in a more structural way. This is what we do next.

5 Main results and managerial implications

We begin this section by presenting the main results of our empirical analysis. Subsequently, we discuss alternative managerial applications and we motivate the use of heat maps as a user-friendly visualization of the many results generated through our methodology.

5.1 Main results

The results we present are the outcome of analyses in which we only compare the customer segments offering a play pack with the same number of products to each other, which are 66 customer segments for 4play pack, 264 customers segments for 3 play pack, 396 customer segments for 2play pack, 264 customer segments for 1 play pack, and 64 customer segments for no play. For each of these customer segments, our methodology identifies a potential cost reduction, which reflects the cost reduction that can be realized in that particular customer segment while achieving the same output level. By doing so, our methodology analyzes the potential increase in customer lifetime value for each customer segment.

The results of our analysis reveal that the total potential cost reduction amounts to approximately EUR 5 million, which equals 1.26% of the total controllable costs. For each customer segment based on socio segment, play pack, and geographical region, our methodology calculates a particular potential cost reduction. Table 3 presents the summary statistics of the aggregated potential cost reductions for each play pack. A minority of 244 customer segments is efficient. As it can be argued that it is difficult to target individual customer segments to address the potential cost reductions, analyzing the aggregated potential cost reductions can be useful. Given the variation in the number of customers across play packs, we also present the aggregated potential cost reduction per customer. We observe that the highest aggregated potential cost reduction can be realized by focusing on the 2play pack. Overall, our methodology allows us to calculate the potential cost reduction of each individual customer segment and thus also allows for aggregating the potential cost reduction to a level that fits with the level at which the firm targets its customers. Importantly, our methodology calculates potential cost reductions and it is up to the telecom operator to verify (1) the extent to which these potential cost reductions can be realized in particular customer segments and (2) the impact of realizing the potential cost reductions. To determine whether a potential cost reduction in a particular customer segment can be realized, operational knowledge concerning the particular segment should be combined with the results of our analysis.

Play pack	Mean	Std.	Max	EUR/`nb_cust`
4play	4823.4558	8757.2108	37114.6421	0.3379
3play	4872.5900	10480.9505	64859.3471	1.1683
2play	5793.3951	20800.1563	243108.9998	2.5960
1play	4392.2554	20551.9157	289958.2872	1.2699
0play	248.0972	245.4731	1024.4908	0.0649

Table 3: Summary statistics on potential cost reductions

Table 4 shows summary statistics of the cost efficiency per play pack. This table shows that the 2play packs contain the most variation in efficiency which is in line with our conclusion in Table 3. In contrast, Table 4 shows that 0play has the lowest efficiency on average, although Table 3 shows that the least cost reductions are located in 0play. This highlights that it is important to consider both efficiency levels and the potential cost reductions.

Play pack	Mean	Std.	Min
4play	0.9967	0.0056	0.9707
3play	0.9845	0.0258	0.8521
2play	0.9553	0.0568	0.6324
1play	0.9770	0.0362	0.8016
0play	0.9523	0.0433	0.8379

Table 4: Summary statistics on efficiency scores

5.2 Managerial implications

So far, we have focused on identifying customer segments where potential cost savings could be realized. Of course, only the firm can now analyze if it is indeed doable (and desirable) to realize these cost savings. After all, these are clearly strategic decisions. Below we show how we can guide the management of the firm in this process.

5.2.1 Highest potential cost savings

As the resources to realize the potential cost reductions are limited, managers have to make choices regarding the customer segments on which they will focus. One criterion to determine the customer segments one wants to focus on is the potential cost reduction of the customer segments. Table 5 presents the ten customer segments that have the highest potential cost reduction. These ten customer segments represent a total potential cost reduction of EUR 1 409 309.20, which is 28.19% of the total potential cost reduction identified by our methodology. The results reveal that a lot of cost reductions can be realized in socio segment A among customers that have a 2play pack. This is not surprising given the pattern established earlier where we found negative net margins per customer for socio segment A. Given the high amount of potential cost reductions that can be realized in these customer segments, the telecom operator should have a close look at these customer segments and question whether and how operational improvements can be made and/or whether these customer segments should be kept in the customer portfolio.

Table 6 lists the 5 customer segments with the largest potential cost reduction for every play pack. It also shows the total potential cost saving over all play packs as well

Cost reduction	Xplay pack	Socio-segment	Province
289958.29	1play	A	2
243109.00	2play	A	2
139757.09	2play	A	5
127931.43	2play	A	10
127316.70	2play	A	9
125255.35	2play	A	1
106027.85	2play	A	4
88498.77	2play	A	8
82489.43	2play	A	11
79038.53	1play	A	1

Table 5: Overall top-10 of potential cost reductions accounting for 28.19% of total potential cost reductions.

as the share of these cost savings represented by the top 5 customer segments. Many potential cost savings are located in segment A and E.

The ranking of potential cost reductions of the different customer segments can also be used to verify whether the focus of certain strategic and marketing actions is justified. That is, in some cases, firms decide to focus on particular customer segments because of actions by a competitor or because external events increase the saliency of a particular customer segment. Before investing resources in marketing actions targeted towards these customer segments, it can be useful to examine the amount of potential cost reductions that can be realized in the segments. If the potential cost reduction is high, targeting that particular customer segment seems warranted and one can do a more extensive analysis of the particular customer segment in order to develop a marketing strategy that also enables realizing the potential cost reductions. If the potential cost reduction is rather low, one should question whether resources should be invested in developing marketing actions targeted towards these particular customer segments.

5.2.2 Output-specific efficiencies

Now that we have identified the customer segments with the largest potential cost reductions, we can dig a bit deeper into the results and explore in which outputs these potential improvements are located. The analysis of the overall top-10 revealed that much of the improvements are situated in 2play. It would be even more useful for 2play to identify the specific outputs in which cost improvements are possible. Figure 2 shows histograms of the output-specific cost efficiencies. More specifically it uses our output-specific decomposition (2) to show the frequency of $w_k^m CE_k^m$ on the x-axis and the number of observations on the y-axis. It turns out that a lot of improvement is possible in the "Fixed Access revenues" and "Other revenues" outputs for all 2play customer segments. The most variation in the efficiency scores is in the "churn rate" output. The remaining outputs have heavy left tails but are less extreme than the "Fixed Access revenues" and "Other revenues" outputs.

Although customer segments can have a similar overall cost efficiency CE_k, their inefficiencies can be located in different outputs. Table 7 illustrates this for three customer segments with overall efficiency scores of approximately 0.8 but with different output-specific efficiency scores. This heterogeneity in output-specific efficiencies across customer

4P		
Total cost saving = 318348.08 EUR, top 5 = 46.84%		
Cost reduction	Socio segment	Province
37114.64	E	1
36296.76	A	9
33858.32	E	10
23166.66	E	9
18683.10	E	8
3P		
Total cost saving = 1286363.75 EUR, top 5 = 20.75%		
Cost reduction	Socio segment	Province
64859.35	E	6
51428.07	A	1
51069.36	E	8
50002.94	A	9
49499.06	A	11
2P		
Total cost saving = 2236250.49 EUR, top 5 = 34.14%		
Cost reduction	Socio segment	Province
243109.00	A	2
139757.09	A	5
127931.43	A	10
127316.70	A	9
125255.35	A	1
1P		
Total cost saving = 1141986.41 EUR, top 5 = 48.85%		
Cost reduction	Socio segment	Province
289958.29	A	2
79038.53	A	1
67698.20	A	10
61533.83	A	5
59595.35	A	9
0P		
Total cost saving = 16374.42 EUR, top 5 = 24.70%		
Cost reduction	Socio segment	Province
1024.49	B	1
869.79	C	9
775.94	B	2
699.00	B	8
675.59	A	2

Table 6: Top 5 of largest potential cost savings per play pack

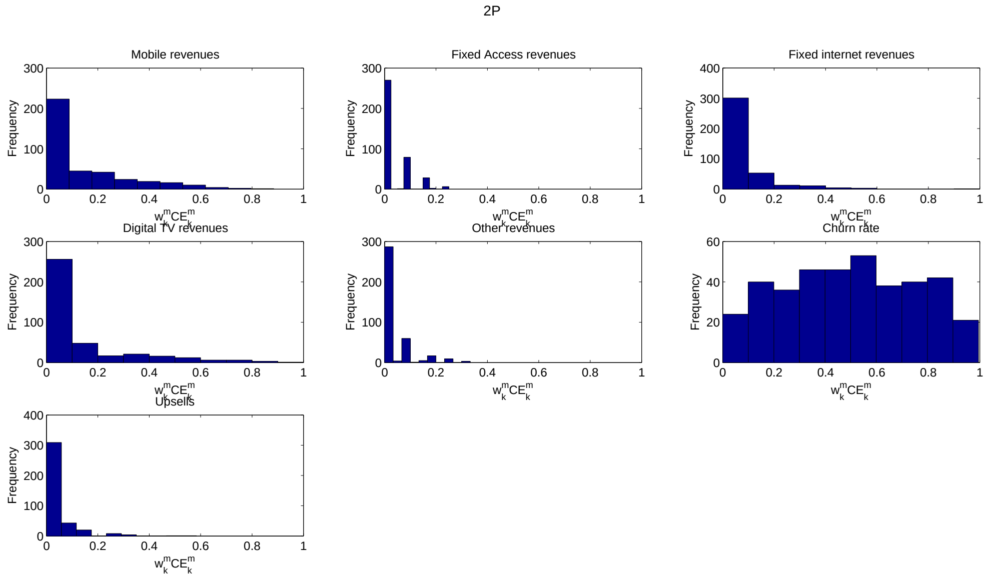

Figure 2: 2P: potential output-specific cost reductions

segments with similar overall efficiencies likely implies different managerial actions for improvement. This highlights the strength of our methodology that allows for starting with a helicopter view and gradually zooming in to a more detailed level in order to establish managerial implications.

Province	Socio segment	Mobile	Access	Internet	Digital TV	Other	Churn rate	Upsells
9	C	0.7899	0.0000	0.9738	0.8178	0.0000	0.7563	0.0000
6	E	0.8299	0.0000	0.0000	0.5910	0.0000	0.7514	0.0000
6	A	0.8802	0.0000	0.0000	0.0000	0.0000	0.7957	0.0000

Table 7: Output-specific efficiency scores CE_k^m for 2play customer segments with $CE_k \approx 0.80$

5.2.3 Dominating peers

A core aspect of our methodology is that the input-output performance of a particular customer segment is compared against the input-output performance of other customer segments in the same play pack. This implies that at least one dominating peer customer segment exists for every customer segment with a non-zero potential cost reduction. Such a dominating peer has a better input-output performance, implying that this customer segment uses less inputs for equal (or greater) amounts of the outputs. Analyzing the dominating peer customer segment(s) can be instrumental to guide managers in realizing the potential cost reductions. That is, by considering how inputs are transformed into outputs at the dominating peer, it can become clear how the potential cost reduction of a particular customer segment can be realized. As a specific illustration, we analyze the dominating peers for a specific customer segment in Table 8. The table shows the dominating peer for every output of this specific customer segment. We learn that the Fixed Voice + Fixed Internet and Fixed Voice + Mobile Voice in segment G are dominating on all but one output.

Output	XPLAY pack	socio segment	province
Mobile revenues	Fixed Voice + Fixed Internet	G	10
Fixed access revenues	Fixed Voice + Mobile Voice	G	4
Fixed internet revenues	Fixed Voice + Fixed Internet	G	3
Fixed TV revenues	Fixed Internet + Fixed dTV	H	11
Other revenues	Fixed Voice + Fixed Internet	G	10
Churn rate	Fixed Voice + Mobile Voice	G	4
Upsells	Fixed Voice + Fixed Internet	G	3

Table 8: Dominating peers characteristics for Fixed Internet + Fixed dTV in socio segment A and province 1

5.2.4 Visualizing the results

Our methodology leads to a large stream of results, making it important to present the results in an appropriate way. We propose to present the results using heat maps. A heat map is a two-dimensional graph that allows for visualizing the differences for a given variable along two dimensions and allows for easier detection of patterns in multidimensional data. In Figures 3 and 4, we present heat maps for the different play packs. Importantly, the heat maps can be made more user-friendly by, for instance, allowing to click in the graph and see the specific results of our methodology (such as potential cost reduction, output-specific efficiency, dominating peers) for the particular customer segment one is clicking on. Thus, by using heat maps, the results of our methodology can be easily distributed among various decision-makers within the firm.

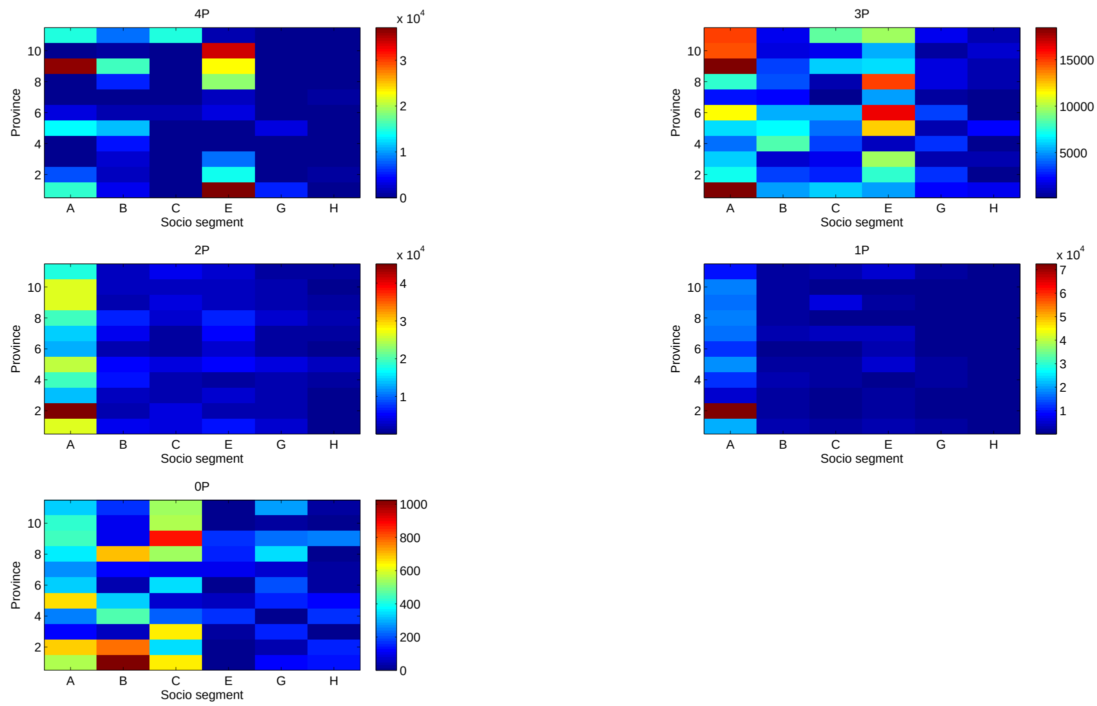

Figure 3: Average cost reductions

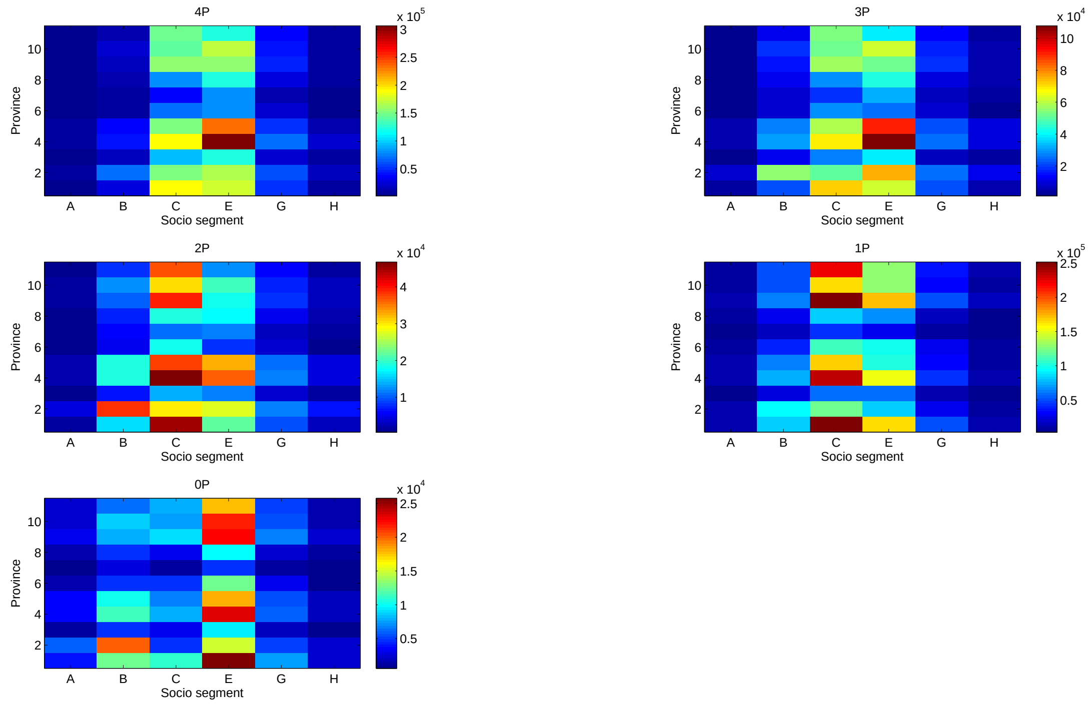

Figure 4: Average number of customers

6 Conclusion

We have presented a DEA-based methodology to analyze customer value. We argue that this method provides a useful complement to existing methods such as CLV and CPA, stemming from the distinguishing features of DEA as a nonparametric efficiency evaluation tool. We have demonstrated our newly proposed methodology through an empirical application to customer segments of a large European telecom provider. In this application, we illustrated our method in identifying potential cost reductions as well as alternative managerial applications. Finally, we made a case for using heat maps to visualize the large amount of empirical results generated through our newly proposed methodology.

The practical relevance of our DEA-based methodology stems from the fit between our methodology and the importance of customer centricity in today's business environment. A first important aspect of customer centricity is that the way in which customer segments are served needs to be tailored to the characteristics of the customer segment. Our DEA-based methodology allows to incorporate heterogeneity in the way customer segments are served. Using our DEA-based methodology will thus provide managers with more realistic insights into the improvement potential of customer segments allowing managers to take better decisions regarding for instance the allocation of marketing resources and pricing. A second important aspect of today's customer-centric business environment is that an enormous amount of data about customers is available. For instance, firms collect data about the revenues that customers generate, customer complaints, website visits, as well as behavior on social media such as whether customers speak positively about the firm. However, these data are not always expressed in monetary terms, making them difficult to use for existing methodologies such as CLV and CPA. Our DEA-based methodology can deal with data that vary with respect to the unit of account and does not require that data are expressed in, or are transformed into, monetary terms. By including more diverse data, we believe that our DEA-based methodology can generate insights regarding the improvement potential of customer segments that are difficult to generate from existing methodologies such as CLV and CPA.

We see multiple avenues for future research. At the methodological level, one can integrate into our framework the many existing theoretical and statistical insights from the DEA literature in order to better grasp specific features of the business environment and/or the data generating process. At the application level, we look forward to applications of our DEA-based methodology in other environments that adapt the way customers are served based on characteristics of the customer segment. Given that customer centricity seems to be an imperative in both the for-profit and not-for-profit environment, we believe that our DEA-based methodology has potential to be applied in, for instance, online retailing, banking, health care, and education. Applications in other environments should be encouraged not only because they will help to discover the usefulness and boundaries of our DEA-based methodology but also because such applications can help to develop methodological refinements which may inspire the DEA literature.

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