Finance Research Letters 65 (2024) 105519

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Lending business models and FinTechs efficiency

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ARTICLE INFO

JEL classification:
C58
G14
G21
G23

Keywords:
Lending business models
FinTech
Efficiency
Stochastic data envelopment analysis

ABSTRACT

The aim of the study is to analyse which managerial issues can be considered the main efficiency drivers for all Italian FinTechs engaged in lending. We measure their efficiency in the period 2020–2022 via Stochastic Data Envelopment Analysis. The main determinants seem to be ROA and cost-to-income ratio; this means that the ability to control both the business risk level and costs is crucial for FinTechs' managers and other players interested in M&A deals in this industry. The results are useful for FinTechs, other financial players, regulators and supervisors in defining homogeneous rules in the lending sector.

1. Introduction

One of the phenomena that continues to have a significant impact on the worldwide financial systems structure, leading to substantial changes in their business, is the growing presence of FinTech firms (Chemmanur et al., 2020; Suryono et al., 2020; Takeda and Ito, 2021; Basdekis et al., 2022; Cornelli et al., 2023). Previous literature studied FinTechs from different perspectives.

As is well known, they have considerably revolutionised the functioning of the different financial sectors (Gai et al., 2018; Gomber et al., 2018) thanks to the possibility to develop new different business models (Laidroo et al., 2021) through the adoption of highly technological solutions. In this way, among other things, they facilitated access to financial services, made possible new financing and investment opportunities, suggested the implementation of sustainable business models based on circular economy criteria (Pizzi et al., 2021), and, generally, increased efficiency in terms of operativeness (Chen, 2020; Wang et al., 2021; Lee et al., 2021).

The FinTech sector is, inevitably, itself progressively evolving due to the continuous search for new technologies and services (Lee and Shin, 2018; Chen et al., 2019; Dong and Yu, 2023) and is, therefore, one of the most dynamic areas within the financial sector (Claessens et al., 2018; Ashta et al., 2018; Giglio, 2022). Indeed, while FinTechs created new business opportunities in various contexts (from payments to investment management, from P2P lending to insurance, and much more), increasing disintermediation has substantially changed the way users access financial services and, as a direct consequence, people are now demanding increasingly cheap, accessible and digital solutions (Campanella et al., 2023; Stefanelli and Manta, 2023).

In addition, despite the disruptive role that some literature attributes to the arrival of FinTechs in the financial system (Cuadros-Solas et al., 2024), there are extensive collaborations between FinTech firms and traditional financial institutions (Navaretti et al., 2018;Stultz, 2019; Borello et al., 2022; Murinde et al., 2022; Banerjee et al., 2024) to maximise the innovation benefits in order to

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https://doi.org/10.1016/j.frl.2024.105519
Received 7 March 2024; Received in revised form 3 May 2024; Accepted 9 May 2024
Available online 10 May 2024

improve the experience of the end user (the customer) (Demir et al., 2020; Kim and Kim, 2020; Torriero et al., 2022). Moreover, some peculiarities of FinTech and InsurTech services were decisive in the critical moments experienced during the Covid Pandemic period (Najaf et al., 2022; Fu and Mishra, 2022).

All these changes brought to the forefront, on the one hand, the need (i) to have new more homogeneous rules for all the players within the financial systems (Financial Stability Board, 2017b; Vučinić, 2020) that are facing the new challenges and opportunities created by the FinTech world (among the others, Buchak et al., 2018; Bromberg et al., 2017; Cuadros-Solas et al., 2024) and, on the other hand, (ii) to measure the efficiency level achieved in their business by FinTech firms, as this will inevitably affect the efficiency of financial systems (Financial Stability Board, 2017a).

As it was pointed out, even though previous literature studied FinTechs from different perspectives and showed that FinTech provides an opportunity to increase financial literacy, financial inclusion, banks' exposure and contribution to systemic risk as well as the efficiency of intermediary institutions with the support of information technology (Pambudianti et al., 2020; Chen, 2020; Le et al., 2021; Wang et al., 2021; Lee et al., 2021; Lin et al., 2022; Muhammad et al., 2022; Xie and Zhu, 2022; Wu et al., 2023), actually, only few researchers are currently taking an interest in the level of efficiency achieved by FinTech firms (Hughes et al., 2022; Chen and Shen, 2024; Onorato et al., 2024).

This is why, with this paper, we would like to try to say something more on this topic, hoping that this will be useful to start bridging the gap that exists in the literature. Thus, in this particular context, the paper analyses which managerial topics can be considered as the main drivers of the efficiency reached by Italian FinTechs engaged in lending in the 2020–2022 period.

The paper is organised as follows: Section 2 describes the data used and the methodology applied; in Section 3 the obtained results and their discussion and, finally, Section 4 concludes.

2. Data and methodology

As anticipated, in this study we would like to understand which managerial levers can be considered as the main drivers of the efficiency levels achieved by all the Italian FinTech firms engaged in lending in the period 2020–2022 for which the data relevant to carry out the analysis were available.

In more detail, (i) among the different activities developed by FinTechs, the focus is on lending as it has grown rapidly in recent times and, at the same time, represents a well-known traditional business (Berg et al., 2022) for which, to measure efficiency, it is possible to shift to the well-known Intermediation Approach (Berger and Humphrey, 1997; Hughes et al., 1996; Pampurini and Quaranta, 2022) used to identify the banks' output and inputs; (ii) we consider Italian FinTechs engaged in lending because the FinTech phenomenon has affected Italy although its financial system is traditionally considered as bank-based and, finally, (iii) we consider the time-window 2020–2022 since we were able to track down data for that period that related to as many FinTech firms as possible and that were both the most recent and most complete for analysis.

In particular, about the last item, we obtained a set of 27 FinTechs from the PWC FinTech Observatory (PWC, 2020, 2021, 2022) while we extracted their accounting data from AIDA (Bureau Van Djik).[1]

Starting from this information, we will calculate the level of efficiency reached by each FinTech firm in relation to the three years considered.

As for the measurement of a production unit efficiency, as is well known, the literature still suggests the use of two approaches, despite the different limits revealed by each of them (Quaranta et al., 2018; Onorato et al., 2024). The first method, that has an econometric origin, is known as the Stochastic Frontier Approach (SFA – Aigner et al., 1977; Meeusen and van Den Broeck, 1977; Forsund et al., 1985; Battese and Coelli, 1995; Berger and Humphrey, 1997; Berger and Mester, 1997; Beccalli, 2004; Coelli et al., 2005; Pampurini and Quaranta, 2018; Pagano, 2021), while the second, coming from the field of operational research, is known as (deterministic) Data Envelopment Analysis (DEA - Charnes et al., 1978; Thanassoulis et al., 2004; Ray, 2004). In any case, regarding the data at our disposal, we decided to use Stochastic Data Envelopment Analysis (SDEA - Huang, and Li, 2001; Kao and Liu, 2009; Khodabakhshi et al., 2010; Olesen and, Petersen, 2016; Wanke et al., 2018) since it seems to be the best method able to ovecome the well-known problems that characterise the two above mentioned methodologies (Onorato et al., 2024).

In a nutshell, SDEA is an extension of (deterministic) DEA since the latter is augmented with a statistical framework that takes into consideration uncertainty in the input and output variables. Indeed, SDEA adopts a stochastic nature for the input and output variables considering for them a random variability. Consequently, it obtains the efficiency score of each decision-making unit (DMU) by considering both the mean and the standard deviation of the variables distribution. This approach is particularly useful in situations where the input and the output variables are subject to measurement errors or, like the case with balance sheet data, when the efficiency scores are obtained taking into consideration variables values 'photographed' on a particular day.

As for the implementation of the SDEA approach, we will refer to the model described in Appendix 1, which belongs to the family of the Stochastic Input-Oriented Data Envelopment Analysis (SIODEA) models (Demerdash et al., 2013; Balak et al., 2021; Mourad, 2022). We would like to emphasize, to avoid any misunderstanding that might confuse the reader, that the definition *Input-Oriented* refers to everything that is included within the model as the value of numerical vectors (and thus, in our case, both to the values assumed by the variables that, for us, are the inputs of the production process of FinTech firms, and to those that are assumed by the variable that represents the result, and thus the output, of the same process).

[1] For privacy reasons, the name of the FinTech firms analysed will not appear and they will be generically referred to as DMUs each marked with a number.

We will define the lending activity output and inputs according to the widespread Intermediation Approach (Sealey and Lindley, 1977; Hughes et al., 1996; Berger and Humphrey, 1997) and thus we will employ the following variables as proxies: total loans to measure the output (Y), the ratio of staff expenses to total assets to quantify human capital (X_1), the ratio of financial expenses to total liabilities to measure financial capital (X_2), the ratio of other production expenses to fixed assets plus intangible assets to quantity fixed capital (X_3) and, finally, total equity to proxy the netput (X_4).

After obtaining the efficiency levels achieved each year by each FinTech firm, a panel regression analysis will be performed in which these values will be regressed on a set of variables able of adequately represent the main topics under management in a firm, namely, size, profitability, liquidity, capitalisation, leverage, business risk, digitalisation level, seniority and overall efficiency. In this regard, for their quantification, respectively, we will use: total assets, ROE, a liquidity index obtained as liquid assets to total assets, the ratio of total equity to total assets, the ratio of total debts to total equity, ROA, the ratio of intangibles to fixed assets,[2] number of operating years and, finally, cost-to-income ratio.

The values of the beta coefficients provided by the panel regression and linked with each of the aforementioned variables will also give information on which of these possible efficiency drivers have the highest levels of significance, in order to highlight the factors actually able to affect the FinTech efficiency.

3. Results and discussion

In Table 1 we present some general information about the Italian FinTech firms in the considered time period.

The high variability that emerges from this table about all the descriptive variables can be easily explained by the high heterogeneity in terms of FinTechs size.

Before implementing both the SIODEA and the panel regression, the standard analyses (univariate and multivariate) were carried out to search for outliers as well as for multicollinearity among the regressors used, with results that ruled out their presence.[3] As usual, the values reached by all the variables involved in the analyses were then standardised to exclude any distorting effect deriving from the different order of magnitude of each of them during the implementation of both procedures mentioned above.

As underlined in Appendix 1, in a SIODEA model it can be that some inputs are random variables and the remaining inputs are deterministic variables. This was our case because, not to lose the temporal information of how the efficiency level of different DMUs changes over the period analysed, we necessarily had to consider one of the four inputs as deterministic. Having to choose one variable, we decided to assign deterministic value to X_4(total equity) since, among all, it is the one that reasonably does not vary over time with the same frequency and to the same extent as the other input variables considered in this analysis.

Next, about defining the distribution of the values of each variable concerning each DMU necessary for including stochasticity in the model, it was assumed that both the three remaining inputs X_1, X_2 and X_3 as well as the output Y (i.e., all the variables considered as stochastic) are normally distributed.

Thus, for each DMU p−(p = 1, …, 27)- the mean μ_p and the standard deviation σ_p were estimated (see Table 2) considering the variables values in the period 2020–2022.

In implementing the SIODEA model in [Appendix 1], α – the only model parameter to be chosen—was set to 0.3, accordingly to previous literature (Mourad, 2022).

As for the panel regression analysis, we implemented both a fixed and a random effect model. In Table 3 the results.

Since the p-value associated with the Hausman test is not significant ($\text{Prob} > \text{chi}^2 = 0.394$),[4] this leads to the acceptance of the null hypothesis that the specific effects impacting each statistical unit are not correlated with the value of the independent variables, thereby leading to the preference for the results provided by the random effect model.

Thus, the main drivers of the efficiency of FinTech firms engaged in lending would seem to be ROA and Cost to Income ratio. Regarding the negative sign associated with both of them, in the first case, it is explained by the circumstance that this index was used to quantify the business risk and therefore as the riskiness decreases, an increase in overall efficiency is expected. In contrast, in the second case, obviously, the level of overall efficiency increases as the weight of costs to income decreases.

Regardless of what has just been pointed out, a clear insight that comes from the panel regression is the absence of effect on the FinTech firms' efficiency by two variables that, logically speaking, we expected to have a crucial impact on the dependent variable. We refer to the level of digitalisation and seniority.

The explanation as to why we expected a positive and significant relationship of the first of these two variables is almost obvious: indeed, greater investment in technology generally—if nothing else—results in greater efficiency with which lenders perform operations (Irimia-Diéguez et al., 2023) and thus, in this case, it would have been plausible that it may affect their ability to optimise the lending process and thus achieve higher efficiency levels.

Instead, about seniority, most FinTech firms are start-ups and therefore, as new entities operating within the financial sector, it is natural to expect that they have not yet gained a strong experience and expertise like the oldest firms.

[2] As an alternative proxy for digitalisation level, we would also have liked to use the Total Quality Index provided by Orbis Intellectual Properties, but data on this variable were missing for most of the FinTechs considered.

[3] Data available upon request.

[4] Data available upon request.

Table 1
A description of Italian FinTech firms engaged in the lending business (thousands of Euro).

	Total assets	Number of employees	Total loans	Total liabilities	Total equity
2020					
mean	14,095	12	1,782	11,470	2,174
st.deviation	59,952	28	5,152	54,032	6,291
max	319,047	146	23,579	286,854	31,361
min	5	0	1	0	−2,495
cv	4.25	2.27	2.89	4.71	2.89
2021					
mean	18,203	14	2,393	14,905	2,739
st.deviation	77,254	29	7,234	69,713	7,858
max	410,978	153	31,547	370,056	39,869
min	4	0	1	0	−997
cv	4.24	2.03	3.02	4.68	2.87
2022					
mean	26,008	16	4,078	22,242	3,078
st.deviation	113,450	32	12,996	105,310	8,281
max	603,321	166	62,348	558,845	42,215
min	5	0	2	2	−1,159
cv	4.36	2.02	3.19	4.73	2.69

Table 2
Mean (μ) and standard deviation (σ) estimated for each DMU in relation to each considered variable.

	Y		X1		X2		X3	
	μ_p	σ_p	μ_p	σ_p	μ_p	σ_p	μ_p	σ_p
DMU 1	23969,04	8908,81	27,89	6,53	0,66	0,64	1713,90	424,03
DMU 2	1138,88	277,35	29,98	2,36	1,36	0,79	125,55	11,04
DMU 3	2297,02	463,77	6,85	0,71	0,00	0,00	46,67	15,23
DMU 4	39158,00	20474,48	0,91	0,25	0,42	0,22	2,69	0,43
DMU 5	596,73	216,07	100,40	74,18	0,70	0,26	2731,56	1062,96
DMU 6	1032,64	721,84	15,63	2,60	1,02	0,13	45,99	14,61
DMU 7	106,97	34,36	2,85	0,38	0,00	0,00	69,82	25,24
DMU 8	481,40	150,49	40,57	4,28	0,40	0,12	269,69	53,70
DMU 9	105,15	79,72	36,38	5,61	1,38	0,90	140,49	29,32
DMU 10	53,70	52,57	10,59	12,03	0,08	0,12	100,54	119,06
DMU 11	408,67	104,06	10,42	3,69	0,40	0,17	96,41	15,63
DMU 12	81,62	58,42	23,92	17,41	0,05	0,09	604,77	238,65
DMU 13	55,06	20,22	13,94	7,58	0,97	1,10	121,40	64,62
DMU 14	200,98	184,88	14,25	12,21	0,04	0,05	213,63	66,94
DMU 15	481,13	182,78	29,91	8,73	0,00	0,00	248,04	29,68
DMU 16	522,65	246,77	6,98	2,42	1,00	0,26	62,01	14,73
DMU 17	66,28	44,29	18,95	5,93	0,43	0,15	469,38	221,97
DMU 18	39,78	42,42	0,00	0,00	0,15	0,18	301,26	142,57
DMU 19	126,38	47,31	8,49	8,70	0,03	0,02	12,58	11,55
DMU 20	84,23	5,49	16,69	2,92	1,47	0,70	222,73	38,60
DMU 21	27,53	3,18	8,65	7,54	0,04	0,01	148,04	58,34
DMU 22	156,05	81,38	0,00	0,00	0,00	0,00	88,74	34,74
DMU 23	2997,40	968,27	9,21	1,00	0,07	0,07	6022,96	10340,70
DMU 24	78,60	35,62	21,50	10,57	0,02	0,03	197,06	61,30
DMU 25	11,25	5,24	3,90	1,30	0,13	0,12	6,52	9,69
DMU 26	1,21	0,28	0,00	0,00	0,73	1,05	54,51	14,88
DMU 27	1,59	0,70	0,00	0,00	0,00	0,00	1,74	0,67

4. Conclusions

The financial system has been undergoing profound changes for several years due to a number of factors. Among them, there is the growing presence of FinTech firms operating in different sectors, including the lending business.

The paper aimed to analyse a still under-investigated topic, namely that of measuring the efficiency level achieved by FinTech firms engaged in lending.

The analysis refers to the period 2020–2022; Stochastic Input Oriented Data Envelopment Analysis (SIODEA) was adopted to quantify efficiency and then, via a panel regression, we tried to test which managerial aspects of a FinTech firm had the greatest impact on its efficiency level.

As a result, the main drivers of efficiency seem to be ROA and cost to income ratio, while, surprisingly, digitalisation level and seniority—i.e. variables that logically should have consistently impacted efficiency levels—do not seem to exert any effect. Concerning

Table 3
Panel regression analysis results.

	Fixed effect	Random effect
VARIABLES	SDEA	SDEA
TOTALASSETS	3.809**	0.0246
	(1.645)	(0.0373)
ROE	0.0108	0.0117
	(0.0351)	(0.0304)
LIQUIDASSTOTASS	−0.0115	−0.0339
	(0.0433)	(0.0238)
CAPITALISATION	0.0471	−0.0100
	(0.0577)	(0.0322)
TOTDEBTOTEQ	0.00461	0.00509
	(0.0320)	(0.0264)
ROA	−0.111**	−0.0620*
	(0.0548)	(0.0376)
DIGITALISATION	−0.000256	0.00800
	(0.112)	(0.0440)
SENIORITY	−0.0100	−0.00458
	(0.00962)	(0.00905)
COSTINCOME	−0.0507*	−0.0383*
	(0.0306)	(0.0232)
Constant	0.952***	0.936***
	(0.0338)	(0.0355)
Observations	81	81
R-squared		
	0.222	0.101
- Within	0.018	0.255
- Between	0.009	0.165
- Overall		
Number of FinTech firms	27	27

Standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

the digitalisation lack of impact, maybe, it should depend on the use of a proxy that was not fully able to capture this phenomenon.

In any case, these results must necessarily be considered as preliminary. In fact, the surprising lack of significance of many of the variables used to describe the main topics under management in a firm may have been strongly influenced by the actual data availability and quality.

Undoubtedly, however, this is a fundamentally important issue that deserves further study, and this for several reasons. In fact, knowledge of the results of an analysis of this kind can be useful at a strategic level, both for FinTechs themselves and for other players in the financial system, with particular reference to the assessments that precede and accompany merger and acquisition processes and, trivially, to the self-assessment that each firm performs periodically as part of its management control. Moreover, one cannot fail to consider also the circumstance that the results that may derive from an analysis such as the one proposed in the paper may have some relevance for the regulatory and supervisory authorities constantly engaged in monitoring the operations of all those who play a fundamental role within the financial system and therefore, now and increasingly, also FinTechs.

Furthermore, measuring efficiency of FinTechs engaged in lending is absolutely crucial to assess their impact in the financial sector and the economy as a whole. FinTechs, through their ability to innovate and adopt cutting-edge technologies, have the potential to improve the efficiency and transparency of financial services. This aspect cannot therefore be ignored by policymakers who, consequently, are called upon to take it into account when defining homogeneous rules for all intermediaries engaged in lending and aimed at containing information asymmetries, reducing risks and potential vulnerabilities that may impact on the overall stability of the financial system.

Therefore, we aim to rerun the analysis as soon as possible, hoping to be able to rely on information inherent in a significantly larger number of FinTech firms engaged in lending business as well as data (accounting and non-accounting) that also allow the use of additional proxies referring to the different managerial areas investigated.

CRediT authorship contribution statement

Francesca Pampurini: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Annagiulia Pezzola:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Anna Grazia Quaranta:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

The data that has been used is confidential.

Appendix 1

A bridging between SFA and deterministic DEA is achieved via the definition of hybrid models able to overcome the limits of the original methods. This is how we arrive at the models that fall under the so-called Stochastic Data Envelopment Analysis (SDEA). They can actually be obtained by following two different strategies. The first starts from specific statistical assumptions and obtains a kind of modified deterministic DEA that, by leveraging a sampling process and a statistical model, allows the efficiency frontier to be obtained. The second uses instead distributions of values, both of inputs and outputs, referring to each DMU (in our case the specific FinTech firm) to substitute the values used in a standard deterministic DEA approach (Olesen and Petersen, 2016).

The model referred to in this paper belongs to the second approach. In particular, reference will be made to the Stochastic Input-Oriented Data Envelopment Analysis (SIODEA) model (Demerdash et al., 2013).

We consider N DMUs ($1 \leq n,p \leq N$), where p is the unit for which efficiency is measured. Let I_S (resp. O_S) be the set of indices i (resp. r) for which $(x_{in})_{1 \leq n \leq N}$ (resp. $(y_{rn})_{1 \leq n \leq N}$) is a stochastic input variable (resp. stochastic output variable), where S is the set of random variables. Let I_D (resp. O_D) be the set of indices l (resp. j) for which$(x_{ln})_{1 \leq n \leq N}$ (resp. $(y_{jn})_{1 \leq n \leq N}$) is a vector of deterministic inputs (resp. outputs). Then, $I_D \cup I_S = \{1, \cdots, m_I\}$ is the set of the union of all input indices and $O_D \cup O_S = \{1, \cdots, m_O\}$ is the all output indices. The stochastic variables are assumed to be normally distributed, thus for each of these variables we estimate the parameters mean and variance. The SIODEA with variable returns to scale (VRS) is an optimization problem of the following form:

$$e_p = \min(\theta_p)$$

$$P\left\{\sum_{n=1}^{N} \lambda_n x_{in} \leq \theta_p x_{ip}\right\} \geq 1 - \alpha, \; i \in I_S$$

$$\sum_{n=1}^{N} \lambda_n x_{ln} \leq \theta_p x_{lp}, \; l \in I_D$$

$$P\left\{\sum_{n=1}^{N} \lambda_n y_{rn} \leq y_{rp}\right\} \geq 1 - \alpha, \; r \in O_S$$

$$\sum_{n=1}^{N} \lambda_n y_{jn} \geq y_{jp}, \; j \in O_D$$

$$\sum_{n=1}^{N} \lambda_i = 1 \; (\text{VRS constraint})$$

$$\lambda_n \geq 0, \; 1 \leq n \leq N \tag{1}$$

where θ_p is the ratio of outputs to inputs, $e_p \in [0,1]$is the relative efficiency score for the *p*th DMU, λ_n measures the rate of input/output utilisation and $\alpha \in [0, 1)$ is a small prescribed real number. It is a so-called chance-constrained programming (CCP), i.e. the required constraint of the deterministic DEA is preserved by enforcing the probability value of this constraint to be almost one.

In particular, in a SDEA model—and then in a SIODEA model too - it can be that:

- some variables are random and the remaining are deterministic variables or that all variables have a stochastic nature;
- each input $x_i, i \in I_S$ and each output $y_r, r \in O_S$ are normally distributed with mean μ_p and variance σ_p^2 in relation to the p-th DMU;
- the relation between the same stochastic input and output variable through different DMUs is dependent, i.e. $cov(x_{in};x_{ip}) \neq 0$ as well as $cov(y_{rn},y_{rp}) \neq 0$.

Assuming these hypotheses and after some mathematical manipulations, for each p-th DMU the model becomes:

$$\min(\theta_p)$$

$$\sum_{n=1}^{N} \lambda_n \mu_{in} - \theta_p \mu_{ip} \leq \sum_{n=1}^{N} \lambda_n x_{ln} \leq \theta_p x_{lp}$$

$$\sum_{n=1}^{N} \lambda_n \mu_{rn} - \mu_{rp} \geq \sum_{n=1}^{N} \lambda_n y_{jn} \geq y_{jp}$$

$$\sum_{n=1}^{N} \lambda_n = 1$$

$$\lambda_n \geq 0, \; (1 \leq n, p \leq N) \tag{2}$$

Therefore, we obtain an optimization problem, which is a second-order conic optimization problem. In this way, we are able to manage stochastic variables that can allow for the proper handling of any possible error in data collection as well as of the possible variability of the values extracted from the financial statements.

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