Journal of Business Research 131 (2021) 92–102

Contents lists available at ScienceDirect

Journal of Business Research

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

Worth the risk? The profit impact of outcome-based service offerings for manufacturing firms

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ARTICLE INFO

Keywords:
Outcome-based service offerings
Financial consequences of servitization
Digital servitization
Product-service systems (PSS)
Business Model Innovation (BMI)

ABSTRACT

Because research on outcome-based service offerings (OBS) is very case study oriented, we lack empirical knowledge of OBS provider profitability in general. Drawing upon an unbalanced panel dataset (n = 1566, N = 14,756), we found that an average OBS provider manufacturer has a 4.40-percentage-point higher gross margin than an average non-OBS manufacturer. In addition, we found that large OBS providers generate lower profits. Since OBS offerings are complex and highly customized, scaling them is a challenge that requires investments in digital technologies and solution modularity. Thus, we tested the moderating role of R&D investments on the scale-profitability relationship and found that for OBS firms, R&D investments moderate the negative relationship between scale and profitability. For managers, these results highlight the profit potential of OBS but also that large OBS providers in particular must be prepared to invest in digital servitization to ensure profitability.

1. Introduction

Many original equipment manufacturers (OEMs) have turned to outcome-based service offerings (OBS; Sjödin et al., 2020) in which providers are paid based on the outcome of activities rather than the time and resources used to conduct those activities (Ng et al., 2013). In the contracting type based on time and materials, manufacturers have no contractual incentives to decrease the demand for spare parts and repair activities (Ng et al., 2013). In OBS offerings, however, the logic is reversed because the provider assumes a role that bears close resemblance to that of the customer. For example, the inputs and service activities the provider previously deemed as their profit drivers will now have to be considered costs (Sjödin et al., 2020, p. 159), as higher customer gains will entail higher provider gains (Sumo et al., 2016). The contracts involved in OBS offerings are inherently complex (Hou & Neely, 2018) and include features such as liquidated damages (Korkeamäki & Kohtamäki, 2020), performance targets/bands (Mouzas, 2016; Nowicki et al., 2008), and review period specifications (Tan et al., 2017).

However, the increased accountability also enables the provider to optimize its outcome production processes to yield marginal gains (Visnjic et al., 2017). Additionally, the customer may offer the provider additional incentives to seek improvements in, for example, energy savings (Li et al., 2014) or carbon emission reductions (Selviaridis & Spring, 2018). Subsequently, the underlying profit generation logic of OBS offerings for providers is to sustainably operate and maintain the systems offered (Ng & Nudurupati, 2010, p. 670) and thus extend the useful lifecycle of equipment (Tan & Yavuz, 2015). The OBS literature has therefore focused on ways in which OBS can be delivered successfully and profitably. The given studies have shed light on, for instance, incentive management (Kim et al., 2010; Selviaridis & Van der Valk, 2019; Sjödin et al., 2020), network management (Kleemann & Essig, 2013), system/component reliability considerations (Bakshi et al., 2015; Guajardo et al., 2012) and inventory-related factors (Liang & Atkins, 2013; Tan et al., 2017) in OBS offerings. However, given the case- and scenario-specificity of these inquiries, we still lack broader empirical knowledge on OBS firm profitability in general.

Prior servitization research, from which the OBS literature stems (Batista et al., 2017), suggests that larger manufacturers especially struggle to yield service returns (Neely, 2009). OBS offerings, as a specific case of servitization, may also be difficult to scale up due to their complex and highly customized nature (Kohtamäki et al., 2019). For example, manufacturing firms often limit offering OBS to pilot projects with key account customers. Hence, there is a need to test whether large

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https://doi.org/10.1016/j.jbusres.2021.03.048
Received 30 October 2020; Received in revised form 16 March 2021; Accepted 21 March 2021
Available online 6 April 2021

OBS providers (and not just servitizing manufacturers in general) also face difficulties in generating profits through services. At the same time, studies suggest that OBS offerings are more likely to be successful when providers have a strong investment climate (Randall et al., 2011; Schaefers et al., 2020) and that the long-term nature of OBS offerings both encourages and compels providers to actively invest in digital servitization technologies (Kohtamäki et al., 2019; Visnjic et al., 2017). For instance, to be able to effectively deliver outcomes, providers need not only monitoring technologies (Grubic & Jennions, 2018a) but also resources that enable preventive actions (Öhman et al., 2015). Furthermore, digitalization may also enable new forms of service innovations, such as modular solution designs (Cenamor et al., 2015; Rajala et al., 2019). Arguably, these considerations should theoretically decrease the tradeoff between offering complex/customized solutions and scale advantages (Salonen et al., 2018). Therefore, to advance the understanding of the profit impact of OBS offerings for manufacturing firms, there is a clear need to assess the role of R&D investments.

To address the gaps outline above, we conducted a longitudinal panel data analysis in two stages. First, we compared OBS provider firms to non-OBS provider firms among manufacturers in the machinery and equipment industry segment and found that there is indeed a linear relationship between OBS offerings and firm profitability. The results highlight the linear profit potential of OBS beyond case-specific and scenario-based studies, thus adding to the external validity of those studies. The results are also in contrast to the findings of studies suggesting that the path to profits through services is at least nonlinear (Kohtamäki et al., 2013; Visnjic Kastalli & Van Looy, 2013). In terms of the OBS literature, the results of the first-stage analysis specifically contribute to the OBS consequences stream of literature (Schaefers et al., 2020). More generally, the given contribution is positioned in the literature on the financial consequences of servitization (Eggert et al., 2011; 2014; Kohtamäki et al., 2015; Neely, 2009) and on advanced services (Baines & Lightfoot, 2014; Story et al., 2017; Ziaee Bigdeli et al., 2018).

Second, to fill in the gap related to the relationship between OBS firm size (scale) and profitability, we conducted another panel data analysis on a subset of our data containing only OBS firms. In alignment with earlier servitization research (Neely, 2009), we found that large OBS providers in particular face challenges in achieving profits. To address the gap related to the role of R&D investments for OBS providers, we subsequently tested a moderation effect. The findings revealed that R&D investments of OBS provider firms moderate the negative relationship between scale and profitability. Although the findings of the second-stage analysis also pertain to OBS profitability, its main contributions are related to the OBS requirements stream of literature (Schaefers et al., 2020). We argue that digital servitization technologies and digitally enabled service innovations are paramount for coping with the scale-induced issues of OBS. Therefore, our second-stage analyses also contribute to the digital servitization literature (Coreynen et al., 2017b; Kamalaldin et al., 2020; Kohtamäki et al., 2020b). For managers, we empirically elaborate the profit potential of OBS offerings, emphasize the need for caution on scale-induced issues and highlight the importance of R&D investments in digital technologies and modular solution development.

2. Theoretical background

2.1. Profit potential of outcome-based service offerings

After-sales services such as OBS offerings contain significant profit potential for manufacturers (Kim et al., 2007). In brief, OBS offerings are defined as a service business model (Ng et al., 2013) in which at least a part of provider payment (Selviaridis & Wynstra, 2015) is dictated by functional results (Grubic & Jennions, 2018b). Typically, OBS is positioned in the servitization (Baines et al., 2017; Rabetino et al., 2018; Raddats et al., 2019) and digital servitization literatures (Kohtamäki et al., 2019; Paiola & Gebauer, 2020; Parida et al., 2019). Following Schaefers et al. (2020), we prefer the prefix 'outcome' because 'performance' is a more ambiguous term that varies by use context (e.g., engine performance or performing an act). Examples of OBS offerings include Rolls-Royce's Power by the Hour and Total Care packages, through which the company sells flying hours of jet engines (Grubic & Jennions, 2018b; Ng et al., 2012), and Caterpillar's offering of guaranteed availability and cost per operating hour of their products, such as mining equipment (Visnjic et al., 2017).

In traditional services based on time and materials (Roels et al., 2010), in which the industrial customer pays after the agreed activities are performed, there are no contractual incentives for the provider to keep the systems operating and maintained in a sustainable way since breakdowns actually feed into the profitable spare parts and repair business (Ng et al., 2013, p. 733). In the OBS relationship, the business models of the provider and the customer become closely intertwined (Visnjic et al., 2018). That is, higher customer gains will entail higher provider gains—a premise that will induce the provider to engage in activities that improve efficiency (Sumo et al., 2016, p. 1486). For example, as the majority of the total cost of ownership (TCO) of related PSS constitutes operations, maintenance and disposal-related costs (Kim et al., 2017), it is in the interest of the provider to cut the consumption of resources needed for outcome delivery to yield service returns. Accordingly, a specific branch of the OBS literature has focused on factors to minimize OBS providers' costs (or, alternatively, maximize profits; Patra et al., 2019, p. 370). For instance, since equipment/system reliability will affect the contractually penalized downtimes and/or output shortcomings (Mirzahosseinian & Piplani, 2011; Patra et al., 2019), optimizing reliability is of prime financial importance for OBS providers (Jin & Tian, 2012; Jin & Wang, 2012; Öner et al., 2015). Extant provider profit-centric models provide valuable operational frameworks that have often been validated through case or scenario applications (e.g., Patra et al., 2019; Jin & Tian, 2012; Brown & Burke, 2000; Huang, Liu, Parker, Tan, & Xu, 2019). In addition, beyond the agreed outcome guarantees, the OBS customer often incentivizes the provider to pursue energy savings, the gains of which are then shared (Li et al., 2014; Tan & Yavuz, 2015). Given the aforementioned case-specific evidence and extant knowledge, we propose Hypothesis 1:

H1. OBS offerings have a direct positive impact on manufacturing firm profitability.

2.2. Challenges of outcome-based service offerings

Prior research on servitization has found that large manufacturers in particular struggle to yield service returns (Neely, 2009). Among many plausible reasons for this result, the diseconomies of scale theory may offer one explanation. In the given theory, when the scale in terms of organizational size and/or output increases, management problems such as complexity (Waddock et al., 2015), increased transaction costs (Riordan & Williamson, 1985) and bureaucracy (Child, 1973) emerge. This arguably especially true in the case of OBS, since such advanced services are endemically plagued with complexity (Hou & Neely, 2018; Schroeder et al., 2020). For example, as successful outcome delivery often depends on the activities of external parties such as suppliers (Kleemann & Essig, 2013), the provider must also manage these upstream third-party risks. Furthermore, industrial OBS are often highly customized to suit the idiosyncratic and complicated needs of customers (Kohtamäki et al., 2019). In other words, the same OBS offering may not meet the requirements of all customers and market areas. This is in contrast to equipment sales, where standardized products are marketed and manufacturing larger quantities may result in lower unit costs. Interrelatedly, literature has found that servitizing manufacturers struggle to cope with the paradoxical pressure of maintaining manufacturing efficiency while pursuing growth through the delivery of increasingly customized services (Kohtamäki et al., 2020a).

Accordingly, we hypothesize that larger OBS providers will be less profitable:

H2. Scale has a direct negative impact on OBS provider firms' profitability.

On the other hand, studies propose that OBS offerings are more likely to be effective when providers have a strong investment culture (Randall et al., 2011; Schaefers et al., 2020). In the context of OBS, investment culture has been defined as "*the inclination of the organization to invest in reliability or process improvements*" (Randall et al., 2011, p. 331), which reflects process innovation and improving existing processes. The long-term contract periods (Brax & Visintin, 2017; Öhman et al., 2015) associated with the business model at hand seem to encourage the providers themselves to commit to continuous investments: "*Caterpillar, for instance, uses long-haul security to invest in prognostic and diagnostic technologies because the data it collects through remote monitoring allows it to optimize production in its customer operations and thereby to create value*" (Visnjic et al., 2017, p. 172). For instance, innovations such as reliability signaling (Bakshi et al., 2015) and adaptive preventive maintenance (Öhman et al., 2015) not only collect valuable data to preempt the occurrence of financially penalized downtimes but also enable flexibility in terms of manufacturing systems and supply chain adaptivity (Jin & Tian, 2012). Thus, technologies such as those above may help deal with increased complexity. Moreover, studies have found that service providers may benefit from developing a modular solution design since service modules are more configurable (Cenamor et al., 2015), thus lowering the scaling barrier of customer-specific customization. These digitally enabled examples arguably entail dedicated investments in R&D activities but have the potential to reduce the tradeoff between high customization and scale advantages (Cenamor et al., 2015; Coreynen et al., 2017a; Salonen et al., 2018). Consequently, we propose Hypothesis 3:

H3. OBS provider firms' R&D investments have a moderating effect on the relationship between scale and profitability.

3. Methodology

3.1. Sample

Data on the manufacturers of machinery and equipment (NACE Rev. 2: 2800–2899) came from Bureau Van Dijk's Orbis database. The Orbis database contains information on 375 million companies, out which 40 million report detailed financial information (Bureau Van Dijk, 2020). The sampling timeframe was the ten most recent available years (relative, latest available year varied from 2016 to 2019). Two rounds of sampling were conducted: the first to obtain a sample of the firms that state they are offering OBS and the second to obtain a referent group of firms not offering OBS. The search steps for the first round of sampling were as follows. First, the sample was limited to firms that had NACE Rev. 2 classification 28 (manufacture of machinery and equipment) as their primary industry code and had consistent profitability reporting. Last, using the activity text search function provided by the database, the first sample was limited to manufacturing firms using OBS-related terminology in their main activities, primary business lines, products and services, secondary activities, secondary business lines or strategy, organization and planning descriptions. The choice of terms was guided by extant research, as demonstrated in Table 1.

The second round of sampling followed the same procedure (industry code, consistent profitability reporting) except for the OBS keyword search step. To ensure objectivity in reference group sampling, the "Generate a random sample" function was used to generate a non-OBS sample. Subsequently, to ensure that the second export did not contain OBS companies, duplicates with regard to the first export were removed. The firms in the two exports were labeled 1 (OBS firms) and 0 (non-OBS firms), and the lists were combined into one file and converted from a wide format to longitudinal format. In total, the panel data used in the alternative estimations contained 1674 companies, among which 810 were OBS firms (N = 7637) and 864 were non-OBS firms (N = 7858). The autocorrelation specification used for the primary estimation, on the other hand, caused an omission of 108 groups and 739 observations due to existing gaps in the given panels' time series. Out of the remaining 1566 (N = 14,756) groups included in the PA model, 777 were OBS firms (N = 7433) and 789 were non-OBS firms (N = 7323). An approximately even split between the comparison groups of interest can be deemed desirable in comparative research settings such as the current one.

Table 1
OBS-related terminology used in sampling.

Terms	Examples in the literature
"power by the hour"	*"Thus, '**power by the hour**' is not only a product and service contract bundle…"* (Visnjic et al., 2018p. 47)
"pay for performance"	*"The literature **on pay-for-performance** contracting is mainly underpinned by agency theory…"* (Selviaridis & Spring, 2018p. 733) *"In contrast, **pay-for-performance** induces the supplier to behave in the interest of the buyer and to engage in activities that improve performance, as the increased net profits will (partly) accrue to the supplier."* (Sumo et al., 2016p. 1486)
"service-level agreement"	*"In operations management, **service level agreements (SLAs)** are widely used to evaluate and manage supplier performance in long-term business relationships."* (Alamri, Abbasi, Minas, & Zeephongsekul, 2018p. 142) *"**Service level agreements (SLAs)** are widely adopted performance-based contracts in operations management practice…"* (Tan et al., 2017p. 1971)
"as-a-service"	*"…offering energy-saving technologies **as a service** is a win–win–win situation for the service provider, its customer and for the environment."* (Tan & Yavus, 2015p. 7119) *"Besides software companies, manufacturers also move towards "**as-a-Service**" business models. They are able to draw on insights from the **SaaS** transformation. Yet, manufacturing companies generally cope with a more complex environment, which is likely to influence the path towards **XaaS**."* (Classen, Blum, Osterrieder, & Friedli, 2019p. 62)
"operational availability"	*"The outcome in general can be defined by several, individually determined, dimensions, for example, **operational availability**…"* (Glas, Henne, & Essig, 2018p. 2074) *"While there are many potential PBL metrics, **availability** is central to any PBC. The U.K.'s Ministry of Defence (MOD) uses '**operational availability**' as a metric in its PBL procurement contracts…"* (Patra et al., 2019p. 370)
"business interruption insurance"	*"Besides designing better contracting mechanisms, operators have sought other means of mitigating the risk arising from operational failures. In practice, **business interruption (BI) insurance** represents an increasingly important tool to cover tangible income losses…"* (Qin, Shao, & Jiang, 2020p. 177)
"operations and maintenance"	*"To achieve the high demand of smart manufacturing in terms of high productivity with near-zero downtime, many manufacturers introduce the smart **O&M services** to extended their **operations** forward by micro-vertical integration with the help of emerging technologies, to undertake a range of activities such as condition monitoring, maintenance, repair, overhaul and management of their own products on behalf of their customers."* (Huang, Chen, Sun, Zhang, & Yao, 2020 pp. 1271–1272)
"operating services"	*"Managed service solutions* **[operating services]** *are output- or outcome-based solutions in which the customer owns the system. Some studies indicate that the systems can be produced in collaboration with third parties or completely sourced from them. The **provider operates** the system and is responsible for the systems functionality."* (Brax & Visintin, 2017p. 28)

3.2. Measurement

The gross margin is used as the dependent variable because it represents the amount of profit made after subtracting the cost of goods sold (COGS), therefore measuring how efficiently a firm manages the resources that directly contribute to the production of goods and services (Bhimani et al., 2015). Because gross margins should be compared among similar businesses, we not only focused on the NACE Rev. 2 industry code 28 (manufacture of machinery and equipment) firms but also controlled for the differences between the 26 subcodes from 2800 to 2899. Furthermore, to control for the other firm characteristics, scale (turnover), country of origin (51 for the primary estimation, 53 in total, country IDs ranging alphabetically from Arab Emirates to South Africa) and overall profitability (profit margin percent) were introduced as control variables. To account for the time-series structure of the data, a natural logarithmic transformation was applied for the dichotomous variables of scale and R&D investments. Because R&D investments rarely pay off during the same accounting period, the R&D investment variable was lagged by one year. The panel summary is presented in the Table 2.

Although we use a PA model, which accommodates correlated data by using a working correlation specification (Liang & Zeger, 1986), we will discuss correlation next. As the pairwise correlation matrix does not account for the panel structure of the data, it disregards the fact that repeated observations within firms are likely to be correlated. Furthermore, it does not correspond to the working correlation specified by the PA model. Thus, we do not present correlation matrices. In the first-stage analysis, most of the independent variables used were uncorrelated with each other. Only the OBS dummy and scale were moderately correlated (0.4709), and country and scale were weakly correlated (−0.3557). Because the Woolridge test for autocorrelation (Drukker, 2003; Wooldridge, 2002) indicated the presence of autocorrelation, the working correlation used in the first-stage analysis was autoregressive. In the second-stage analysis, none of the control variables were correlated with each other or with the independent variables. Instead, expectedly, the main effects (scale-R&D investments: 0.8381) and their interaction (scale-interaction: 0.9395, R&D investments-interaction: 0.9690) were highly correlated. This is logical for two main reasons discussed below.

First, as both main effects were discrete variables and measured on the same scale (log transformed), one can reasonably expect companies with lower turnover (scale) to not realistically invest as much in R&D (in actual currency) as their larger peers. This is in line with prior studies referencing the Schumpeterian argument of a positive correlation/relationship between firm size and R&D investments (e.g., Fisher & Temin, 1973; Morbey, 1988; Shefer & Frenkel, 2005). Third, it is natural for constitutive terms to be highly correlated with their product, that is, the interaction term (Friedrich, 1982). As long as the confidence intervals remain small enough to generate significant p-values, multicollinearity (or micronumerosity; Goldberger (1991)) has no adverse effects, as it practically violates none of the assumptions of the multiple linear regression (Wooldridge, 2012).

Because research on interaction methods states that to avoid omitted variable bias, one should include not only the interaction but also the terms that constitute the interaction (Brambor, Clark, & Golder, 2005; Greene, 2003), we further specified the model used in the second-stage analysis to account for the correlation structure rather than omitting the variables. Subsequently, we specified in the model that observations are clustered within firms and constrained the PA model with an exchangeable correlation structure (Wang & Carey, 2003). The resulting working correlation (Liang & Zeger, 1986) estimated by the model was 0.8289. Given the statistically significant results and reasonable standard errors presented in Section 4.2, our model successfully isolates the studied effect with the specifications used. Conclusively and in accordance with the above arguments, we do not report the correlation matrices, as they would mislead interpretations by disregarding the panel data structure and because they do not accurately correspond to the model specifications.

3.3. Research approach

Due to the panel structure of the data, three panel data models were used to estimate the gross margin impact of OBS offerings. The statistical

Table 2
Panel summary.

Variable		Mean	Std. Dev.	Min	Max	Observations	
ID	overall	2101.468	1512.082	1	4244	N =	14,756
	between		1506.387	1	4244	n =	1566
	within		0	2101.468	2101.468	T-bar =	9.42273
Year	overall	5.485904	2.873995	1	10	N =	14,756
	between		0.9165155	1.5	9.5	n =	1566
	within		2.824843	0.985904	9.985904	T-bar =	9.42273
Gross Margin	overall	28.54112	17.76427	−85.714	100	N =	14,756
	between		17.7674	−26.47333	100	n =	1566
	within		8.7447	−84.07628	106.163	T-bar =	9.42273
Profit Margin	overall	4.929819	13.18156	−99.201	100	N =	14,756
	between		8.612338	−61.025	41.9285	n =	1566
	within		10.18433	−93.02408	111.2202	T-bar =	9.42273
Scale	overall	16.83568	2.600811	7.113107	25.73101	N =	14,756
	between		2.570632	9.107584	25.48803	n =	1566
	within		0.4559938	12.62773	20.54561	T-bar =	9.42273
OBS Firm	overall	0.5037273	0.500003	0	1	N =	14,756
	between		0.500145	0	1	n =	1566
	within		0	0.5037273	0.5037273	T-bar =	9.42273
NACE Rev2	overall	2856.567	36.95788	2800	2899	N =	14,756
	between		36.95054	2800	2899	n =	1566
	within		0	2856.567	2856.567	T-bar =	9.42273
Country	overall	35.63811	16.57763	1	60	N =	14,756
	between		16.42452	1	60	n =	1566
	within		0	35.63811	35.63811	T-bar =	9.42273
OBS providers only							
R&D	overall	15.22281	2.402924	5.83703	22.88819	N =	2250
	between		2.586982	5.83703	22.52599	n =	336
	within		0.5522211	11.37089	17.96032	T-bar =	6.69643

software used was Stata (16) by Stata Corporation. The current research constitutes two stages of analysis: the first-stage analysis compares OBS provider firms to non-OBS firms, while the second-stage analysis tests the effects of scale on profitability for only OBS provider firms and the hypothesized moderation effect of R&D investments on the aforementioned relationship. The first model fitted in the first-stage analysis was a pooled ordinary least squares (POLS; Wooldridge, 2002, p. 150) model that does not take the panel structure into account and treats all 15,495 observations as unique. The panel data models accounting for the within- and between-firm variation and the time variation were the random effects model (RE; Wooldridge, 2002, p. 257) and the semi-parametric population-averaged model (PA; Liang & Zeger, 1986; Zeger et al., 1988). The PA model was also used for the second-stage analysis considering a subset of data consisting of only OBS provider firms that reported investments in R&D. In addition, multiplicative interaction including all constitutive terms (i.e., each of the elements that constitute the interaction term; Brambor et al., 2005, p. 66) was used to further specify the second-stage model. Next, the statistical methods and choices applied in the first-stage analysis are presented in detail, followed by the subsequent presentation of the statistical methods and choices applied in the second-stage analysis.

3.3.1. First-stage analysis

To assist in deciding between the POLS and RE, a Breusch-Pagan Lagrangian multiplier test (Breusch & Pagan, 1980) was performed. Based on the significant (p-value = 0.0000) results, the null hypothesis (i.e., no variance across entities) was rejected, and the conclusion follows that RE should be preferred over the POLS. The RE was fitted using three different estimators: the between estimator (BE; Wooldridge, 2002, p. 269), the maximum likelihood estimator (MLE; Wooldridge, 2002, p. 385) and the generalized least squares (GLS; Wooldridge, 2002, p. 257) estimator. The BE uses the cross-sectional data and time averages to produce estimates (Cameron & Trivedi, 2009, p. 251). Bootstrap standard errors (Freedman, 1981) were used for the BE. The MLE, on the other hand, aims not to minimize the least squares but rather to maximize likelihood (Myung, 2003). Observed information matrix (OIM) standard errors were used for MLE, as they are the standard for likelihood-based estimators (Gould et al., 2010). For the GLS estimator, which is the generalization of the ordinary least squares estimator (Kmenta, 1986), clustered standard errors (Liang & Zeger, 1986) were used to adjust for the observations' correlation within firms. To test for the RE assumption of no correlation between the regressor and the unobserved heterogeneity and individual errors, a Hausman specification test (Hausman, 1978) was conducted. In addition, the presence of autocorrelation was tested using a Woolridge test for autocorrelation (Drukker, 2003; Wooldridge, 2002).

In contrast to cluster-specific methods, the PA model is a marginal method and therefore models marginal expectations (Diggle et al., 2002; Ghisletta & Spini, 2004; Zeger et al., 1988). In the first-stage analysis of the current longitudinal study, PA is best understood as a comparison between an average OBS firm and an average non-OBS firm. In contrast, RE, which fully specifies the population distribution (Wooldridge, 2002), compares changes in the dependent variable for a firm offering OBS to the same company if it did not offer them. The PA model was also fitted using clustered standard errors (Liang & Zeger, 1986) and autoregressive specifications (Ballinger, 2004; Diggle et al., 2002) to account for clustering on IDs and the unbalanced panel. Generalized estimating equations (such as the PA) are highly popular in disciplines such as medicine (see, e.g., Gülcan et al., 2016; Hu et al., 1998; Young et al., 2007) and have gained interest in the social sciences (see, e.g., Muth et al., 2016; Park & Pugh, 2018; Yan et al., 2013). This is especially due to PA's ability to accommodate correlated panel data (Ghisletta & Spini, 2004). RE models, in contrast, assume that the independent variables are uncorrelated with unobserved heterogeneity and idiosyncratic errors (Joshi & Wooldridge, 2019). To test whether this assumption holds, a Hausman specification test was conducted for the RE. Because the results were significant (p = 0.0000), it was concluded that the regressors are indeed endogenous, making the RE model inconsistent. Thus, the PA model is used as the primary estimation method.

3.3.2. Second-stage analysis

Because extant research has found that larger manufacturers in particular struggle to yield higher service returns (Neely, 2009), the second-stage analysis focused on testing negative effects of scale for a subset of OBS providers (n = 336, N = 2250). Furthermore, prior studies claim that OBS are more likely to be successful when providers have a strong investment climate (Randall et al., 2011; Schaefers et al., 2020). Indeed, digital technologies are not only a critical prerequisite for offering OBS (Grubic, 2018; Öhman et al., 2015, p. 457), but the associated long-termism in OBS has been shown to encourage providers to invest in prognostic and diagnostic technology (Visnjic et al., 2017, p. 172). Thus, the second-stage analysis of this study uses the PA model with clustered standard errors (Liang & Zeger, 1986) and an exchangeable correlation structure to marginally test the moderating effect of R&D investments of OBS providers on the relationship between scale and gross margins. The moderator variable was R&D investments, lagged one year and log transformed (natural logarithm). Not only was the interaction term (R&D investments * scale) included in the model but also both the independent variable (scale) and the moderator variable (R&D investments) were included to avoid omitted variable bias (Brambor et al., 2005; Greene, 2003). To visualize the results, a spotlight analysis (Aiken & West, 1991) was conducted to estimate the slope of scale using three values of R&D investments. The three values used for R&D investments were at one standard deviation above the mean, at the mean level and one standard deviation below the mean (Aiken & West, 1991). First, the average marginal effects of the three levels of R&D investments on the scale-profitability relationship were computed and plotted. Furthermore, we plotted the interaction between the variables at approximately min and max value of scale using the same above-mentioned values of R&D investments.

4. Findings

4.1. OBS offerings' impact on provider gross margins

Regardless of the models and estimators used, they all have the power to reject H0, which states that there is no direct relationship between OBS offerings and manufacturing firms' gross margins. Indeed, significant evidence was found from all the fitted models to confirm H1, which predicted a direct positive relationship between manufacturing firms' OBS offerings and their gross margin. The primary estimation method, that is, the population averaged model (PA) with the autoregressive specification, estimated that an average manufacturing firm offering OBS has a gross margin that is approximately 4.400481 (p = 0.000) percentage points higher than that of an average manufacturing firm not offering OBS. The alternative panel-specific (RE GLS and MLE), semiparametric (BE) and pooled (POLS) estimators also found significant (p = 0.000) concurring evidence supporting H1, with coefficients ranging from 2.328788 to 4.448881 for the gross margin percentage points, as displayed in Table 3.

In terms of the control variables, profit margin and scale were very significant (p = 0.000) across all the models and estimators. As expected, the general profitability (profit margin) regressor produced a positive coefficient (PA: 0.398792 and the rest between 0.4254773 and 0.457434). The results for scale (log turnover), on the other hand, showed a negative relationship with regard to the dependent variable (PA: −2.404381 and the rest between −1.144911 and −2.728127). Among the country-specific factor variables, only five were statistically insignificant (p = > 0.05) throughout all the estimators. The 26 industry codes (NACE Rev 2. 2800–2899) were all statistically significant (p = < 0.05) in the POLS model, whereas eight codes were insignificant in all of the remaining estimators (2820, 2821, 2822, 2830, 2840, 2849, 2892,

Table 3
First-stage regression results.

Gross Margin	Primary estimation	Alternative estimation methods			
	Model 1	Model 2			Model 3
	PA	RE GLS	RE MLE	BE	POLS
Profit Margin	0.398792***	0.425579***	0.4254773***	0.457434***	0.4458642***
	(0.0233084)	(0.0201843)	(0.0066615)	(0.0444622)	(0.016946)
Scale	−2.404381***	−2.728127***	−2.716501***	−1.144911***	−1.298483***
	(0.2520561)	(0.2622871)	(0.1204628)	(0.3257708)	(0.0838269)
OBS Provider	**4.400481*** **	**4.448881*** **	**4.434844*** **	**2.328788*** **	**2.697451*** **
		(0.7780315)			
Yes	(0.7646302)		(0.7722238)	(0.1692739)	(0.2717953)
Constant	66.47135***	73.59333***	73.40207***	44.78469***	53.5101***
	(10.01568)	(11.23483)	(16.17227)	(1.954988)	(3.770813)
Country dummies included?	Yes	Yes	Yes	Yes	Yes
Industry dummies included?	Yes	Yes	Yes	Yes	Yes
10 Year dummies included?	No	No	No	No	Yes
n	1566	1674	1674	1674	15,495
N	14,756	15,495	15,495	15,495	15,495
n for OBS/non-OBS	777/789	810/864	810/864	810/864	7637/7858
N for OBS/non-OBS	7433/7323	7637/7858	7637/7858	7637/7858	7637/7858
SE Robustness	Clustered	Clustered	OIM	Bootstrap	Robust
Rho	N/A	0.69740473	0.6931902	N/A	N/A
R-squared					
within	N/A	0.2276	N/A	0.2120	N/A
between	N/A	0.4830	N/A	0.5038	N/A
overall	N/A	0.3209	N/A	0.3372	0.3404

Standard errors are reported in parentheses.
*, **, and *** indicate significance at 95%, 99%, and 99.9%, respectively.
Results for the 53(51) country dummies and the 26 NACE Rev 2. industry dummies can be provided upon request.

2895). The constant term was very significant (p = 0.000) in all of the models.

With regard to the goodness-of-fit of the models, both Rho and the within, between and overall R^2 can be used. It is worth mentioning that the PA is missing Rho and R^2 because no generally accepted, absolute goodness-of-fit tests exist for marginal models as of yet (for alternatives for binary responses, see, e.g., Barnhart & Williamson, 1998; Horton et al., 1999). The coefficients of the MLE estimator of the RE model, on the other hand, aim to maximize likelihood rather than minimize variance (Myung, 2003). Ergo, the normal take on goodness-of-fit will not apply. For the RE GLS, BE and POLS, however, the value can be inspected. Not surprisingly, the between estimator's R^2 between is higher than that of the RE GLS (0.5038 VS 0.4830), whereas RE GLS outperforms BE in terms of the R^2 within (0.2276 VS 0.2120). Out of the two, BE has a slightly higher overall R^2 (0.3372 VS 0.3209). Should one wish to estimate only the between effects, the between estimator could be used. Interestingly, the POLS model has the highest overall R^2 (0.3404). As already discussed above, in terms of explaining the random effects, the GLS performs slightly better than the MLE (Rho = 0.69740473 VS 0.6931902) and should thus be preferred if one wishes to explain random effects. Should one wish to do so, however, they would have to consider ways to specify the autoregressive structure to account for the detected autocorrelation. Furthermore, because the RE model's assumption that the independent variables are uncorrelated with the unobserved heterogeneity and the idiosyncratic errors (Joshi & Wooldridge, 2019) was violated, the results of the PA model that relaxes this assumption and accommodates correlated data should be preferred as the primary estimation.

4.2. *The moderating effect of R&D investments on the scale-profitability relationship*

The second-stage analysis provided significant supporting evidence for H2, which posited that there is a direct negative relationship between scale and OBS provider profitability. The subset of data used in the second-stage analysis consisted of 336 OBS providers (N = 2250). As hypothesized, Model 1 (PA), with only the main effects and the controls, produced a positive coefficient for R&D investments (p = 0.032) and a negative coefficient for scale (p = 0.000). The profit margin control was very significant (p = 0.000) and positive. Among the country factors, 18 out of 30 were significant (p = < 0.05), while out of the 22 industry codes, only 6 were significant (p = < 0.05). The constant term was very significant (p = 0.000). H3 predicted that OBS providers' R&D

Table 4
Second-stage regression results.

Dependent Variable Gross Margin	Model 1 PA	Model 2 PA with interaction
Main effects		
R&D Investments	0.5876318*	−5.15264**
	(0.2685678)	(1.934328)
Scale	−2.521434***	−7.575396***
	(0.5527884)	(1.846112)
Moderation effect		
R&D Investments * Scale		**0.3099916*** *
		(0.104654)
Controls		
Profit Margin	0.3033425***	0.3037369***
	(0.0404368)	(0.0401513)
Country	Provided upon request	Provided upon request
Industry	Provided upon request	Provided upon request
Constant	77.7913***	181.7021***
	(9.556101)	(33.93073)
SE Robustness	Clustered	Clustered
n =	336	336
N =	2,250	2,250

Standard errors are reported in parentheses.
*, **, and *** indicate significance at 95%, 99%, and 99.9%, respectively.

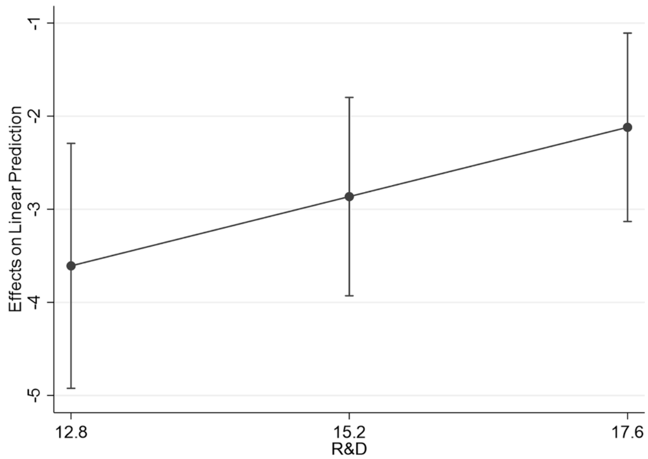

Fig. 1. Average marginal effects of scale * R&D investments (95% confidence intervals).

investments moderate the relationship between scale and OBS provider profitability. Model 2, that is, PA with the continuous interaction term, produced statistically significant ($\beta = 0.3099916$, $p = 0.003$) evidence of the moderation effect, as shown in Table 4. Thus, H3 was also confirmed in the second-stage analysis. Accordingly, there is a direct negative relationship between OBS provider profitability and scale, but R&D investments of the provider mitigate this negative relationship. Again, due to the PA model used, the goodness-of-fit measures are not reported.

Fig. 1 illustrates the moderating effect of R&D investments on the negative relationship between scale and gross margin, using average marginal effects. The mean for R&D investments was 15.22281, and the standard deviation was 2.402924. All of the margins were statistically significant ($p = 0.000$). As demonstrated in Fig. 1, the negative effect of scale on profitability is strongest for the lowest level of R&D investments (mean – standard deviation = ~12.8) and weakest for the highest level of R&D investments (mean + standard deviation = ~17.6). Thus, there is statistically significant evidence that R&D investments linearly moderate the negative relationship between gross margin and scale.

Fig. 2 illustrates R&D investments' moderation effect by showing the estimated slope of scale using the same three values for R&D investments. For the sake of presentation, the range used for the scale is from 15 to 25, incremented by 1 (min scale = 14.61567, max scale = 25.69392). The margins were statistically significant ($p = < 0.05$) throughout. As seen in the interaction plot, the higher the investments in R&D are, the lower the negative effect of scale on gross

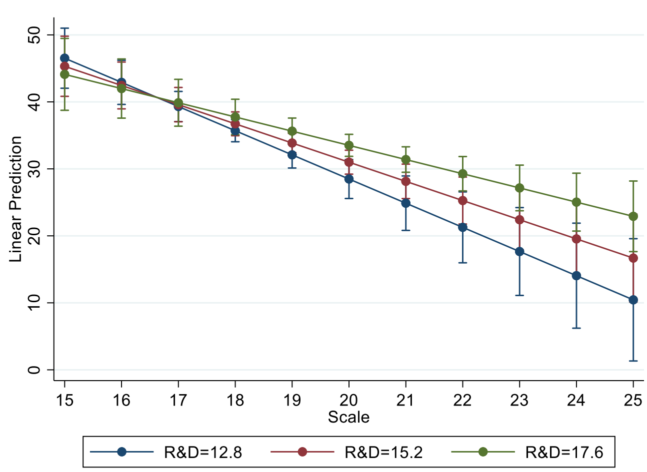

Fig. 2. Linear moderation effect of R&D investments on the relationship between OBS provider profitability and scale (95% confidence intervals).

margins for OBS providers. However, for the smaller OBS providers, the moderation effect is weaker. On the other hand, for average-sized (mean scale = 19.31409) OBS providers, higher investments in R&D seem to pay off. An aspect worth noting is that the slope for low-level R&D investments (blue) is considerably steeper than the flatter slope of high-level R&D investments (green), amplifying the importance of R&D investments for larger OBS providers.

5. Discussion

Prior studies concerning the financial implications of servitization have found that the path to profits through services is nonlinear (Kohtamäki et al., 2020; Visnjic Kastalli & Van Looy, 2013). For instance, the number of service offerings alone is not directly efficient in decreasing the likelihood of bankruptcy for servitizing manufacturing firms (Benedettini et al., 2017). Thus, the difference seems to lie in the service qualities and different service strategies (Gebauer et al., 2010; Sjödin et al., 2019) rather than extensiveness. Additionally, studies have identified that separate financial consequences of services that support products and services that support customer processes depend on the context (Eggert et al., 2011) but have a complementary nature (Eggert et al., 2014). Subsequently, OBS offerings have emerged as an appealing business model for manufacturers (Ng et al., 2013; Visnjic et al., 2017) because they allow the mentioned complementarity to be leveraged by selling outcomes instead of the products and activities leading to them. The inherent long-termism of OBS offerings provides multiple opportunities for both providers and customers. For example, providers are often incentivized to perform better (Nowicki et al., 2008) and thus benefit from, for example, energy savings (Li et al., 2014; Tan & Yavuz, 2015) and cutting carbon emissions (Selviaridis & Spring, 2018). Furthermore, since the crux of OBS offerings is to extend the operational lifetime of assets, equipment and systems, the need for new production decreases (Ng & Nudurupati, 2010). Given these benefits, both customers and manufacturing firms have explored the potential to achieve sustainability through OBS. The same resource efficiency-driven logic works in favor of provider profits as well: since the provider's revenues depend on outcomes achieved instead of resources used, the less resources are used (or the more resources are recycled) to produce the outcome, the higher the provider gain.

5.1. *Theoretical contribution*

Given the mutually appealing premises of OBS offerings, a significant number of case studies have explored ways in which OBS offerings can be delivered efficiently in different industries. For instance, OBS providers must consider inventory costs (Settanni et al., 2017; Tan et al., 2017), equipment and system reliability (Ge et al., 2018; Guajardo et al., 2012; Kim et al., 2017) and contract design (Liang & Atkins, 2013; Liinamaa et al., 2016; Selviaridis & Van der Valk, 2019). However, no general investigations on OBS providers' profitability existed before the current study. To fill this gap, we drew upon an unbalanced panel dataset and conducted a two-stage longitudinal analysis. In the first-stage analysis of this study, we globalized the results of earlier case-focused OBS studies by showing that an average OBS provider has gross margins 4.40 percentage points higher than those of an average manufacturer that does not offer them. Thus, our first-stage analysis specifically contributes to OBS consequences stream of literature (Schaefers et al., 2020) by providing external validity of extant studies advocating the financial potential of OBS. More generally, we contribute to the financial consequences of servitization literature (Neely, 2009; Eggert et al., 2011, 2014) and the movement towards advanced services (Baines & Lightfoot, 2014; Story et al., 2017; Ziaee Bigdeli et al., 2018), given the positive findings in terms of profitability.

On the other hand, the second-stage analysis in the current study contributes especially to the OBS requirements stream of literature (Schaefers et al., 2020). Prior servitization research has argued that larger manufacturers often struggle to convert servitization activities into profits (e.g., Neely, 2009), and we found that the same applies to OBS provider firms. Given the complexity (Hou & Neely, 2018; Schroeder et al., 2020) and the high customer-specific customization (Kohtamäki et al., 2019; Ng & Nudurupati, 2010) endemic to OBS offerings, we argue that in order to cope with such scale-induced issues, OBS providers must continually invest in digital technologies and modular service development. Providentially, the long-term nature of OBS offerings has been found to provide security for providers to invest in digital technologies (Visnjic et al., 2017), such as adaptive preventive maintenance (Öhman et al., 2015), sensor technology (Sjödin et al., 2020) and remote diagnostics (Brax & Jonsson, 2009). Indeed, our second-stage analysis of OBS provider firms only revealed that R&D investments of OBS providers moderate the negative relationship between scale and profitability, in contrast to the findings of some earlier studies on the effect of R&D investments on technology firm performance (Ribeiro-Soriano, 2010). Therefore, although our second-stage analysis deals with OBS consequences (i.e., profitability implications), it also offers a valuable contribution to the OBS requirements stream of literature (Schaefers et al., 2020). In terms of the servitization literature more generally, the second stage of the current study contributes to the digital servitization literature (Coreynen et al., 2017a; Kohtamäki et al., 2019; Kohtamäki et al., 2020b; Vendrell-Herrero et al., 2017).

5.2. Managerial contribution

The current study provides managers with clear and tangible contributions. First, it demonstrates that OBS offerings have been a profitable servitization strategy for manufacturers of equipment and machinery. The underlying business logic of OBS offerings is to reduce excessive inputs and harmful outputs—in other words, to operate machinery and systems sustainably. In effect, many traditional machinery manufacturers have turned sustainability trends to their advantage. For example, one of the main drivers of Wärtsilä's engine power plants in markets such as the US is actually increasing renewable energy production (Yang, 2020). This is due to the intermittent nature of renewable energy: when solar energy is unavailable, flexible energy generation units with quick ramp up and guaranteed availability are needed. Second, we show that OBS offerings do not pay off only for the few advanced market leaders but also offer viable ways to capitalize on servitization for organizations of various sizes. However, we caution that larger OBS providers tend to struggle to generate returns. Third, for large providers struggling with scaling problems, we show that investments in R&D may offer a helping hand. We also pinpoint some digital technologies and modular service development as potential targets for investments. However, these results should be interpreted with caution in the wake of the global COVID-19 pandemic. For instance, as the revenues of the iconic Power-by-the-Hour and Total Care jet engine offerings of Rolls-Royce greatly depend on flying hours, the company reported record-breaking losses for the first half of the year 2020 (Partridge, 2020).

5.3. Limitations and future research

Despite its high attention to detail, the current study has limitations. Because the aim of the study was to draw more general inferences to contrast the numerous existing case studies, some of this generality meant sacrificing granularity. For instance, due to the technical limitations of the database, we could not account for whether the OBS firms had just recently started offering OBS or whether they had offered them for a while. The given limitation is an attractive avenue for future research to investigate the profitability effects before and after OBS using the fixed effects (i.e., within-firm estimator) model, for instance. Furthermore, due to the database-sampled data, we could not account for the more relational aspects adding value to the OBS relationship. Thus, taking note of the paper by Randall et al. (2011), future research could further investigate how relational assets (Ng et al., 2013), such as regular exchange and trust (Hypko et al., 2010; Korkeamäki & Kohtamäki, 2020), affect OBS financial success. Additionally, in the second stage of this study, we only focused on one of the required factors for successfully delivering advanced services (i.e., R&D investment), and we recognize that the relationship is more complex (Sjödin et al., 2016). Hence, more research on the topic is required. Last, although provider success stories are important to garner both academic and practitioner interest, failure cases and customer perspectives merit further attention.

6. Conclusions

This study considered the profit impact of OBS offerings on manufacturers of machinery and equipment. The research approach was two-staged and utilized a PA model to accommodate correlated data in both stages of the panel data analysis. The first-stage analysis aimed to fill the gap in the empirical knowledge on OBS firm profitability since extant studies have investigated OBS profit potential through case studies, analytical frameworks or survey-based data. The results of the first-stage analysis showed that there is a direct positive relationship between OBS offerings and manufacturer firm profitability. Thus, the first-stage analysis of the current study globalizes the results of extant studies by building on time series financial data ($n = 1566$ ($N = 14{,}756$, consisting of 49.62% OBS providers and 50.38% non-OBS firms)). The alternative estimation methods generated concurring evidence as well. At best, in terms of the alternative estimation methods that aim to minimize the sum of squares (POLS, BE, and RE GLS), the models capture half of the between-firm variation and slightly over one-third of the overall variation in the manufacturer gross margin percentage.

The second-stage analysis drew upon a subset of data ($n = 336$, $N = 2250$) consisting of only OBS provider firms and tested the relationship between scale and profitability as well as the moderating effect of R&D investments on the given scale-profitability relationship. In alignment with extant servitization studies that have found negative relationships between servitizing firm size and profitability, the results showed that there is also a direct negative relationship between scale and OBS firm profitability. On the other hand, statistically significant evidence showed that OBS firm R&D investments mitigate the aforementioned diseconomies of scale effect. To draw more general inferences than earlier studies, some granularity in the data sampling needed to be sacrificed when compared to survey-based sampling, for instance. Therefore, future studies could pay attention to before-and-after profitability effects of OBS offerings for providers using a fixed effects (or within estimator) model. For managers, the current study offers empirical evidence of OBS profit potential, warns about scale-related issues, and emphasizes the role of R&D investments in digital technologies and modular solution development in OBS offerings.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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