Assessment of Interorganizational Technology Transfer Efficiency

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Abstract

In this paper we propose a methodology for assessing the efficiency of technology transfer through merger and acquisition (M&A) and empirically estimate the effect of key factors impacting it. We implement data envelopment analysis (DEA) to calculate an efficiency score of the technology transfer process. The DEA efficiency score integrates a set of outputs (post-merger characteristics of an acquirer) and inputs (pre-merger technological parameters of a target); thus, it provides a multidimensional estimate of efficiency adjusted for the value of the acquired technology base.

In the empirical part of this research, we collect data from 434 M&As to study a channel for transferring a technology base across organizational boundaries. Overall, empirical results suggest the adverse outcomes of accumulation of capability to value external technology: the higher the acquirer's R&D intensity, the lower the efficiency of interorganizational technology transfer. The size of acquirer and relative size of the deal also affect the post-merger outcomes significantly and negatively. At the same time, the estimated effect of such technological characteristics of acquirer as capital expenditure intensity and number of patents is insignificant.

Introduction

Knowledge management and technological development play an important role in firms' successful strategic decisions. In order to stay ahead of industry innovators, many companies are forced to elaborate new business models, adapt quickly to intensifying technological changes, and develop their own technological capabilities. However, firms might face difficulties creating the knowledge required for successful innovation (Tsai, Wang, 2008; Un, Rodríguez 2018) – thus, management often seeks external sources of knowledge and technology to stimulate internal innovation.

In this study we focus on the merger and acquisition (M&A) channel of interorganizational technology transfer (Buono, 1997). Since firms may find it challenging to create successful in-house innovations (Renneboog, Vansteenkiste, 2019; Rong, Xiao, 2017), some use M&As to source externally generated knowledge (Christofi et al., 2019; Rossi et al., 2013). However, as with any technology transfer across organizational boundaries, a M&A creates additional challenges for the firm's management, particularly because of the specific nature of the technological knowledge and high transaction costs (Lichtenthaler, Lichtenthaler, 2010). This paper addresses several issues including the assessment of the efficiency of technology transfers and the identification of the main factors impacting them. Instead of focusing on a single performance measure, efficiency literature often applies a data envelopment analysis (DEA) approach to construct the efficiency score based on several inputs and outputs of the process (Cooper et al., 2011; Lafuente, Berbegal-Mirabent, 2019). We calculated the DEA efficiency score of each deal in our sample using post-merger financial metrics (profitability and market-based indicators) as outputs and the technological parameters of acquired firms as inputs. Such an indicator provides a comprehensive estimate of the efficiency of a technology transfer from the target to the acquirer.

Another issue within the empirical literature is the assessment of determinants of technology transfer efficiency. Various researchers examine pre-merger characteristics of companies and its effect on post-merger outputs (e.g. Maksimovic et al., 2011). Among the key determinants of the efficiency of technology acquisition, we use the number of patents and R&D expenses of acquired firms as proxies for absorptive capacity (ACAP) – an acquirer firm's ability to evaluate and utilize outside knowledge and technology (Cohen, Levinthal 1990; George et al., 2001). To succeed in external technology exploitation, the technology itself is not enough: a firm's learning and innovative capabilities at the organizational level play a crucial role. In the technology transfer literature, the effect ACAP has on the efficiency of the intra- and inter-firm transfer process is a major research question (Apriliyanti, Alon, 2017; Bengoa et al., 2021).

Thereby, our main contribution is twofold. First, we contribute to the innovation management literature by discussing determinants of the efficiency of technology transfers across organizational boundaries. In particular, we document empirical evidence of the negative implications of ACAP metrics (R&D intensity and number of patents) for post-merger efficiency, which exposes a limit for positive performance implications of ACAP and contributes to a discussion of the prerequisites for a successful transfer of technology. Second, we contribute to the empirical vein of technology transfer research by constructing a multidimensional indicator of efficiency weighted by parameters of the absorbed technology.

Conceptual Background and Hypothesis Formulation

Assessment of the Efficiency of Technology Transfers through M&A

Firms often use M&As as a form of corporate development strategy in order to obtain specific knowledge or a technology to increase innovative performance (Hagedoorn, 1993; Cloodt et al., 2006; Ma, Liu, 2016). Acquired technologies and new knowledge could be decisive factors behind technologically motivated M&As (Colombo et al., 2006; Shin et al., 2017). In fact, acquisitions can potentially bring to companies opportunities to stimulate technological capacities through rapid access to knowledge and a shorter development cycle (Warner et al., 2006). Moreover, technology transfer through M&As might further enhance combining knowledge bases, which allows companies to achieve economies of scale and scope with the more efficient utilization of technological resources (Henderson, Cockburn, 1996; Hagedoorn, Duysters, 2002).

Pioneering innovation management research emphasizes the importance of companies' ability to commercialize outside knowledge during the innovation process (Cohen, Levinthal, 1990). Since the goal of obtaining a technology assumes its application for commercial ends, firm performance indicators are essential metrics of the technology transfer process (Flatten et al., 2011). However, there are several important exceptions. For example, in the case of M&A deals, the acquirer's strategic motive could be the elimination of a competitor, not the technology transfer (Cunningham et al., 2021). Therefore, M&A researchers usually implement objective estimates of post-merger financial efficiency, including accounting- and market-based variables. The list of accounting-based parameters capturing changes in profitability includes return on assets (ROA), return on sales (ROS), and return on equity (ROE) (Liu et al., 2021). Market-based indicators measuring post-merger efficiency include a cumulative abnormal return (CAR) (Wales et al., 2013) and a market-to-book (M/B) ratio (Maditinos et al., 2011). However, these parameters face two limitations in the case of technology transfer research. First, some scholars emphasized that accounting- and market-based parameters captured different dimensions of efficiency and encouraged integrating several metrics to provide

a comprehensive measurement of financial performance (King et al., 2021). Second, financial metrics alone do not capture the value of the absorbed technology, which is essential when assessing the efficiency of technology transfer. Thus, to assess the efficiency of technology transfer, it is necessary to integrate multiple post-merger financial efficiency metrics weighted by the technological characteristics of the target. Within the efficiency literature, scholars often use a data envelopment analysis (DEA) methodology to construct the multidimensional efficiency score (e.g. Cooper et al., 2011; Lafuente, Berbegal-Mirabent, 2019). In the case of technology transfer through M&A, the DEA allows for estimating relative efficiency of deals by using two sets of input and output variables (Wanke et al., 2017).

Absorptive Capacity as a Determinant of Technology Transfer Efficiency

Technologically motivated M&As tend to be comparatively riskier due to uncertainties such as technological barriers and insufficient development resources (Warner et al., 2006). The integration process between companies is time consuming and in some cases technologies might be quickly substituted or become irrelevant which makes technology acquisition obsolete (Hitt et al., 1991). Thus, the post-merger outcomes are not limited by the acquired knowledge base. The efficiency of technology transfer also depends on the firm's ability to exploit external knowledge, which is known as absorptive capacity (ACAP).

Seminal works primarily suggest that higher levels of ACAP usually positively affect efficiency (Cohen, Levinthal, 1990). ACAP as a dynamic capability enables firms to adapt to the changing market environment and thus constitutes a competitive advantage and improves firm performance (Tsai, 2017; Zahra, George, 2002). However, rather than focusing on the positive consequences of a high ability to exploit external knowledge, several studies raise concerns about effects of ACAP growth. The impact of ACAP on post-merger efficiency can be susceptible to the channel of intraorganizational transfers of technology and the characteristics of this process. In the case of technology transfer across organizational boundaries, three arguments might support the non-linear or negative link between the level of ACAP and transfer efficiency.

First, the literature on the U-shaped ACAP-performance relationship associates higher levels of ACAP with poor technological efficiency (Lichtenthaler, 2016; Wales et al., 2013). Initially, as the firm's knowledge base increases, the firm faces positive outcomes: the costs of finding and exploiting a new technology decrease. However, the positive effect remains at a certain level of ACAP. An increasing lack of commonality results in distortion and loss of information, while limitations of the prior knowledge base restrict the efficient exploitation of the new technology (Wales et al., 2013). Thus, further accumulation of ACAP may result in the declining effectiveness of external technology absorp-

tion (Brettel et al., 2011). Since our research is focused on large-scale businesses, as opposed to SME research (Chaudhari, Batra 2018) we expect the negative impact of ACAP on post-merger efficiency. In the case of technology transfer through M&A, the greater the ACAP of the acquirer, the more carefully it looks for acquisition targets, but the outcomes of exploiting external technologies after the deal are lower. The strong ability of the acquirer to absorb technology from the outside has adverse effects on post-merger technological efficiency because of: i) higher costs of searching for appropriate and novel knowledge, ii) higher organizational costs for incorporating acquired R&D into already established R&D processes, and iii) higher costs of the transformation of R&D processes to adjust them to the inbound technology (Berchicci, 2013). These additional costs are especially high when the organization, product, and technologies differ between the target and the acquirer (Desyllas, Hughes 2010).

Second, technology acquisition may be the subject of substitutional effects (Desyllas, Hughes, 2010; Szücs, 2014). Particularly in horizontal mergers, patent and R&D activities tend to decline in post-merger periods, indicating the presence of a push-out effect (Haucap et al., 2019). Such difficulties as the incompatibility of knowledge (Wang et al., 2017) and differences in corporate culture (Zhu et al., 2019) may lead to unsuccessful integration between firms and failure to gain value from acquired technologies.

Third, the high level of acquirers' ACAP indicates that the firm has extensive resources to pursue strategic M&As. However, strategic planning may also consider an M&A deal a tool to increase a market share, not a source of outside technology. Here, the argument focuses on large technology-based companies that use M&As to eliminate competitors and shut competitors' technology down protecting their technological advantages (Motta, Peitz 2021). The "killer acquisitions" tend to be pursued by larger companies (Cunningham et al., 2021) that have invested in appropriability to protect their market power (see Capobianco (2020) for examples and further discussion).

Hence, we posit the central hypothesis: the higher the acquirer's ACAP, the lower the efficiency of technology transfers through M&A deals. Considering the complexity of the technology transfer process in terms of antecedents and outcomes, a number of studies suggested measuring the ACAP construct using several variables to capture the richness of the knowledge structure (Jiménez-Barrionuevo et al., 2011). Based on the previous literature, we proxy two subsets of ACAP. Cohen and Levinthal (1990) suggest that a prior related knowledge base enhances the ability to recognize and exploit new knowledge. At the firm level, a pre-existing knowledge base can be proxied by investments in R&D, which remains the most popular proxy of ACAP (Lee et al., 2010; Zahra, Hayton, 2008). Thus, we use the R&D intensity to measure the capacity to value external technology (George et al., 2001), and the first hypothesis proceeds as follows:

H1. The higher the acquirer's R&D intensity, the lower the post-merger firm's performance.

At the same time, we use the number of patents as a second proxy to estimate the ability to apply and exploit external technology (George et al. 2001). The patent count reflects such an aspect of innovation activity as an appropriability mechanism to protect one's innovative competitive advantages (Sun, Zhai, 2018) and the level of appropriability positively correlates with the external technology absorption capabilities (Hurmelinna-Laukkanen, Yang, 2022; Ng, Sanchez-Aragon, 2022). Thus, the second hypothesis proceeds as follows:

H2. The higher the acquirer's patent count, the lower the post-merger firm's performance.

Capital Expenditure, Relative Size of the Deal, and Firm's Size as Determinants of Technology Transfer Efficiency

In addition to the ACAP metrics, we estimate the effect of the acquirer and deal parameters. If we assume that absorptive capacity may decrease the post-merger outcomes, it might also be expected that the relative size poses limits to the positive implications of technology transfer through M&A. Therefore we test the effect of the relative size of the deal on the adjusted financial performance (the ratio of the deal value and total assets) (Asquith et al., 1983). Moeller et al. (2004) found that relative size significantly affects performance, implying that a sizeable acquiring company may overpay for the target and thus be prone to hubris, which is not the case for smaller acquiring companies. Thus, it might be expected that the increase of the relative size of the deal affects M&A efficiency negatively:

H3. The greater the relative size of deal value, the lower the post-merger firm's performance.

M&A scholars often include the size of acquirer as a factor determining the post-merger outcomes (e.g. Moeller et al., 2004; Du, Boateng, 2015). The large size of the acquiring company may indicate managerial hubris or an intention to "empire build". In our study, the model is controlled for acquirer's revenue since total sales is one of the most popular proxies for the size of the firm (Dang et al., 2018). It is expected that large firms achieve fewer gains from technological acquisitions:

H4. The higher the revenue of the acquirer, the lower the post-merger firm's performance.

CAPEX intensity can capture economic shocks to an industry's operating environment (Harford, Li, 2007). Some studies suggest that the intensity of capital investments reflects the company's internal innovation activity (Balsmeier et al., 2017; Stoneman, Kwon, 1996). CAPEX provides resources for a firm's organic growth (Bushman et al., 2011). On the other hand, some researchers consider CAPEX an alternative to M&A because both activities may provide similar outcomes in the firm's development (Hanelt et al., 2021). In the context of our study, we expect CAPEX intensity to have the similar effect on post-merger outcomes as ACAP proxies:

H5. The higher a company's CAPEX intensity, the lower the post-merger firm's performance.

Methodology and Data

The empirical section follows a two-step procedure. In the first step, we calculate the adjusted financial performance using the DEA approach to assess how efficiently the target's technology is absorbed. DEA allows one to estimate the efficiency score based on the metrics of the post-merger financial performance of the acquirer weighted for the parameters of the acquired technological base. Then, in the second step, we estimate the regression equation to investigate the relationship between the efficiency score and metrics of ACAP.

DEA Approach: Calculation of the Efficiency Score

DEA is a popular benchmarking technique for the estimation of a relative efficiency score (Lafuente, Berbegal-Mirabent, 2019). In the case of our research, the M&A efficiency score refers to the merged firm's financial performance relative to the technological characteristics of the target firm. The best performing merged firms are mapped as an efficiency frontier. Any merged firm that performs less well is positioned below the efficiency frontier. The radial distance between a merged company's position and the point on the efficiency frontier indicates the degree of inefficiency. Finally, the efficiency score takes a value from 0 to 1 and allows us to compare the outcomes of M&A deals in the sample.

DEA Outputs: Measures of Acquirer's Post-Merger Financial Efficiency

Post-merger financial performance can be measured by accounting- and market-based metrics. However, both types of measurement may provide fragmented estimates of efficiency when used in isolation. For a more comprehensive understanding of post-merger performance, researchers are encouraged to integrate accounting- and market-based measures (King et al., 2021); thus, we measure the efficiency of the deal using a mix of metrics.

The first market-based metric is the abnormal stock return after the deal is measured as CAR (Bettinazzi, Zollo, 2017). CAR is a dominant measure of stock performance in empirical M&A research to catch the short-term effect of the deal – that is, investors' immediate reaction to the M&A announcement (Renneboog, Vansteenkiste, 2019). We estimated CARs within an event window of three days around the announcement of acquisitions ([−1; +1]). We use the short event window based on efficient market theory (Fama, 1970) and the predictive abilities of investors' reactions: a long event window may deliver inconsistent results because

the estimates may be affected by changes in the time correlation of stock and market returns (MacKinlay, 1997). The CARs are calculated over the event period with an estimation window of 180 days. Since DEA operates with positive output values (Cooper et al., 2011), we constructed the variable CAR+1 by adding 1 to the CAR to avoid negative return values.

In contrast with the short-term CARs, the second market-based DEA output captures long-term performance — expectations of investors measured by the forward-looking post-merger M/B ratio (Maditinos et al., 2011). As for the accounting-based indicators, in the context of M&A research, scholars often prefer to measure post-merger efficiency using ROE and ROA (King et al., 2021). However, ROA may provide biased results because an M&A premium raises the asset base of an acquirer, while ROE is less sensitive to the relative size of the deal (King et al., 2021), so we use ROE as the third DEA output.

Thus, we integrate CAR, ROE, and M/B ratio as our DEA output variables. These measures cover different planning horizons, capture several performance aspects, and provide a complex view of a firm's efficiency.

DEA Inputs: Characteristics of the Target's Technological Base

Technology transfer is a multidimensional process and the absorbed technology has several attributes to be measured. R&D expenses are often used as a proxy for a firm's technological depth – which represents the level of technological expertise (George et al., 2001) – and depth is relevant for R&D efficiency (Ahuja, Katila, 2001; Chen et al., 2011; Laursen, Salter, 2006). The number of patents may indicate the technological breadth associated with the number of potential knowledge applications (Boh et al., 2014). At the same time, the CAPEX intensity can be used as a proxy for technological activity, and it is vital for empirical research in the case of missing or vague data on R&D and innovation expenses (Stoneman, 2001; Stoneman, Kwon, 1996). Finally, the M/B ratio is a proxy for potential growth associated with investors' expectations of technological development success (Gu, 2016). Taken together, these indicators represent key innovation stages from technology research (R&D intensity) to its development (patent activity), implementation (CAPEX intensity), and expected commercialization success (M/B ratio).

DEA Model Specifications and Bootstrapping Procedure

We estimate the efficiency using an input-oriented constant return-to-scale model with radial distance for DEA estimation. This model was developed in the original paper of (Charnes et al., 1978) and is called the CCR model. CCR input-oriented models aim to obtain a proportional reduction in the inputs that can produce the current outputs (Bogetoft, 2000; Korhonen et al., 2003). Generally, after obtaining a new technology, any acquirer will be concerned with how

to transform this technology in order to create value for the company and ensure financial performance. We choose several inputs representing stages from research to commercialization. We assume those inputs should be changed proportionally to scale up or down the acquiring technological capacity. At the same time, we are looking at the minimum values of inputs to obtain the desired level of deal efficiency, which justifies the choice of the CCR model for this study.

To address the statistical inference problem with DEA scores (Simar, Wilson, 2000), we use bootstrapping by smoothing the empirical distribution of efficiency scores to obtain the bootstrapped efficiency scores. Bootstrapping includes the following steps. First, we obtain efficiency scores using the DEA CCR model. Then, the smoothed bootstrapping procedure generates a set of bootstrap inputs (Simar, Wilson, 2000). Third, the new DEA is calculated using a set of bootstrap inputs with the same outputs to obtain the DEA-bootstrapped efficiency scores. Finally, we repeat these three steps 3,000 times to generate a set of estimates.

Regression Analysis: What Determines the Efficiency Score

We implemented the econometric analysis to analyze how the efficiency score is influenced by the parameters of the M&A deal and acquirer. The effects are estimated by beta regression, which can be applied if the dependent variable is bound between 0 and 1 (Ferrari, Cribari-Neto, 2004). Beta distribution differs from a normal distribution because it is not necessarily symmetrical and is more heteroscedastic around the mean and less so around 0 and 1. Following Ferrari and Cribari-Neto (2004), we assume that the value of the DEA efficiency score of the i-th firm is drawn from the beta distribution with the mean μ_i. Hence, the beta regression model can be applied:

$$g(\mu_i) = \sum_k^n x_{i,k}\beta_k , \qquad (1)$$

where g is the logit transformation of the mean of the beta distribution — $g(\mu_i) = \ln(\mu_i / (1 - \mu_i))$;

x is a matrix of values of independent variables;

β is a vector of unknown regression parameters.

Thus, we specify the main model as:

$$g(\mu_i) = \beta_0 + \beta_1 Ln(Patents_i) + \beta_2 R\&D_i + \beta_3 Ln(Rel\ Size_i) + \beta_4 Ln(Revenue_i) + \beta_5 CAPEX_i + \beta_6 International_i + \beta_6 Method\ of\ Payment_i + \varepsilon_i \qquad (2)$$

where $Ln(Patents_i)$ is the logarithm of the patent count of the i-th acquirer plus 1;

$R\&D_i$ is the R&D intensity measured by R&D expenses over sales of the i-th acquirer;

$Ln(Rel\ Size_i)$ is the logarithm of the deal size of the i-th deal over the total assets of the i-th acquirer;

$Ln(Revenue_i)$ is the logarithm of the revenue of the i-th acquirer;

CAPEX$_i$ is the capital intensity measured by CAPEX over total assets of the *i*-th acquirer;

International$_i$ is a dummy variable for cross-border deals (1 if the deal is cross-border, 0 – otherwise);

Method of Payment$_i$ is the transaction payment dummy variable (1 if the payment method is cash, 0 – otherwise).

To test hypotheses, the independent variables include two main parameters of the acquiring companies related to ACAP (R&D intensity and patent count before the M&A deal) as well as acquirer's CAPEX intensity, revenue, and relative size of the deal. The model is controlled for international deals and method of payment. The *International$_i$* defines each deal as a domestic or cross-border M&A. The acquisition of technologies offers opportunities for acquiring companies to enter new markets, and cross-border deals have become a popular domain of business globalization. Specifically, large international technological companies, through M&A, transfer necessary knowledge (Bresman et al., 1999). Cross-border M&A may be the only way to obtain technologies and knowledge protected by patents or domestic regulations (Boateng et al., 2008). Several studies demonstrate that international M&A is associated with high abnormal returns (Seth et al., 2002). Moreover, cross-border M&A deals provide better technological efficiency for acquiring companies (Hagedoorn, Duysters, 2002). Following prior studies (e.g. Du, Boateng, 2015; King et al., 2021), we also included the payment method (cash and non-cash method) as a variable, because acquiring companies are more likely to pay for targets with cash and thus expect an increase in synergy value due to risk reallocation (Danbolt, 2004; Du, Boateng 2015).

The main model is estimated for three specifications of the efficiency score measured by four inputs (patents count, R&D intensity, CAPEX intensity, and M/B ratio) and different sets of outputs. The first specification (General Model) uses three variables as the output (CAR, ROE, and M/B ratio). The second specification (Short-term Model) is based on a single output – the short-term performance measured by CAR. Finally, the third specification (Long-term Model) uses ROE and M/B ratio as outputs in the DEA calculation. Different methods of the DEA score estimation allow us to investigate post-merger efficiency for several planning horizons and simultaneously check for the robustness.

For additional robustness check, we implemented models controlled for industry-related information. We identify three types of M&A deals which differ in the relatedness between the merging firms' industries: horizontal, vertical, and conglomerate deals (Tremblay, Tremblay, 2012). Horizontal M&A indicates acquisitions between partners from the same industry, which usually involves technological overlap. Vertical M&A refers to firms merging with customers or suppliers whose technologies may complement the acquirer. Finally, conglomerate M&A usually exhibit low technological relatedness between the acquirer and target.

Relatedness may be linked to a higher post-merger performance. First, relatedness lowers information asymmetries. Thus, acquirers can better understand their target's technology and find more suitable targets (Hussinger, 2010). Second, relatedness allows merged M&A teams to cooperate better because they can draw on shared language and compatible cognitive structures (Colombo, Rabbiosi, 2014). Similarly, recombining related knowledge may facilitate innovation rather than recombining distant knowledge (Valentini, Di Guardo, 2012). Third, relatedness allows for a higher post-merger scale and scope in innovation management (Hagedoorn, Duysters, 2002).

Thus, we examine differences in the impact of ACAP in three types of deals (horizontal, vertical, and conglomerate), using two specifications of the main model: type of M&A models with and without a structural break. The DEA efficiency score is determined by four inputs (patents count, R&D intensity, CAPEX intensity, and M/B ratio) and three outputs (CAR, ROE, and M/B ratio). In the model without a structural break, we apply beta regressions to the ACAP metrics, control variables used in the main model, and two additional dummy variables: *Vertical$_i$* (1 if the deal is vertical, 0 – otherwise) and *Conglomerate$_i$* (1 if the deal is conglomerate, 0 – otherwise). Finally, we test whether there is any structural break in the relationship between ACAP and adjusted performance in different types of deals in the model, which includes four additional variables: $Ln(Patents_i) \times Vertical_i$, $R\&D_i \times Vertical_i$, $Ln(Patents_i) \times Conglomerate_i$ and $R\&D_i \times Conglomerate_i$.

Data Sample.

We drew the data from the Bloomberg database for M&A deals from 2008 to 2017. A total of 5,176 deals took place during this period between companies listed on stock markets. We then excluded M&A deals for which data on R&D expenses and patents were

Table 1. **Mean/Standard Deviation of DEA Inputs/Outputs**				
Variables	**Main Sample**		**Sample with Types of M&A**	
	Mean	**SD**	**Mean**	**SD**
DEA Outputs				
CAR of the Merged Firm, %	0.230	5.405	0.159	5.432
ROE of the Merged Firm, %	15.456	12.322	15.500	11.267
M/B ratio of the Merged firm	3.698	4.098	3.766	4.179
DEA Inputs				
Patents of the Target	25.467	140.542	24.468	137.684
R&D intensity of the Target, %	6.386	7.993	6.268	7.826
CAPEX intensity of the Target, %	4.515	4.708	4.652	4.843
M/B ratio of the Target	4.388	7.794	4.489	8.248
Source: authors.				

	Variable	Mean	CO	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Ln(Patents)	4.12	2.20	1						
(2)	R&D	5.54	6.27	0.12**	1					
(3)	CAPEX	0.03	0.02	0.26***	−0.14***	1				
(4)	Ln(Rel Size)	−4.40	3.39	−0.33***	0.20***	−0.15***	1			
(5)	Ln(Revenue)	9.30	1.66	0.42***	−0.20***	0.14***	−0.43***	1		
(6)	Method of Payments	0.70	0.46	−0.002	-0.05	0.01	-0.06	0.14***	1	
(7)	International	0.40	0.49	0.01	−0.18	-0.04	0.10**	0.08*	0.36***	1

Table 2. **Descriptive Statistics of Independent Variables**

Note: Level of confidence: *** - 1%, ** - 5%, * - 10%. Number of obs.: 434.
Source: authors.

unavailable. The data on patents were collected from the EPO (European Patent Office) PATSTAT database. The combined dataset mainly contained companies from developed countries. Specifically, up to 40% of acquirers and targets were from the USA, followed by companies from Japan, the UK, Australia, Germany, Canada, and others. In addition, 57% of the deals were national and 43% were international. The overall distribution has been obtained for a sample of 434 deals. However, the SIC codes were incomplete for 55 deals, so we could not determine the M&A type. Thus, we found information on the type of deal for 379 M&As (137 vertical deals, 129 horizontal deals, and 113 conglomerate deals). Table 1 describes the inputs and outputs for two samples: the main sample and the sample with the information on the type of M&A.

Table 2 provides descriptive statistics of the independent variables. Targets tend to have higher level of R&D intensity compared to acquirers. Acquirers, in general, have a higher number of patents. These findings are consistent with the literature stating that R&D-intensive firms are more likely to be targeted, and acquirers have a considerably higher number of patents (Bena, Li, 2014). We can see a generally positive reaction from investors to M&A announcements.

Empirical Results

Figure 1 depicts the distributions of the DEA efficiency score.

The results of the regression estimation are presented in Table 3. The general model is based on several variables as DEA outputs to address the short-term and long-term effects. Additionally, we compare results of the general model with the short-term (CAR as the DEA output) and long-term (ROE and M/B as DEA outputs) models. The type of M&A model includes dummy variables for vertical and conglomerate deals. In contrast, four additional variables expand the type of M&A model with a structural break to test the presence of a structural break in the relationship between ACAP and efficiency in vertical and conglomerate deals compared to horizontal M&As.

The empirical results confirm the significant and negative effect of ACAP measured by R&D intensity: the higher the acquirer's R&D intensity, the lower the post-merger efficiency. Thus, the more technologically advanced acquirer is less efficient after the M&A deal. Importantly, this effect remains stable for both the short- and long-term. However, the number of patents has significant negative outcomes within the long-term model only. As in the case of the main specification, estimates of the types of M&A models confirm the significant and negative effect of ACAP measured by R&D intensity.

In addition, we witnessed the significantly negative impact of the relative size variable which is a robust over all specifications in the regression equation. Revenue also negatively impacts post-merger outcomes, although its effect is insignificant in the long-term model. The effect of CAPEX intensity on the efficiency of technology transfer through M&A is insignificant in all the specifications of the model.

The results show that the efficiency of technology absorption does not depend on the type of deal: the model with the structural break does not confirm the significance of the structural break between vertical, horizontal, and conglomerate deals. At the same time, the type of M&A model without a structural break indicates that the efficiency of vertical deals, on average, is lower than efficiency of technology transfers through horizontal and conglomerate deals.

Discussion and Conclusion

This research concerns the assessment of the efficiency of interorganizational technology transfer and its determinants. Instead of a single performance measure, the efficiency score of technology transfer through M&As is estimated using the DEA approach which has not previously been applied for this purpose in the academic literature. The methodology of DEA allows one to construct a multidimensional metric based on key characteristics of the M&A deal participants. Since the success of technology transfer assumes the commercial exploitation of the absorbed technology, we measure the efficiency using post-merger financial indicators weighted by the technological parameters of a target.

Empirical estimates of the study contribute to the discussion on the impact of ACAP metrics on the tech-

Figure 1. **Distribution of DEA Scores on different models**
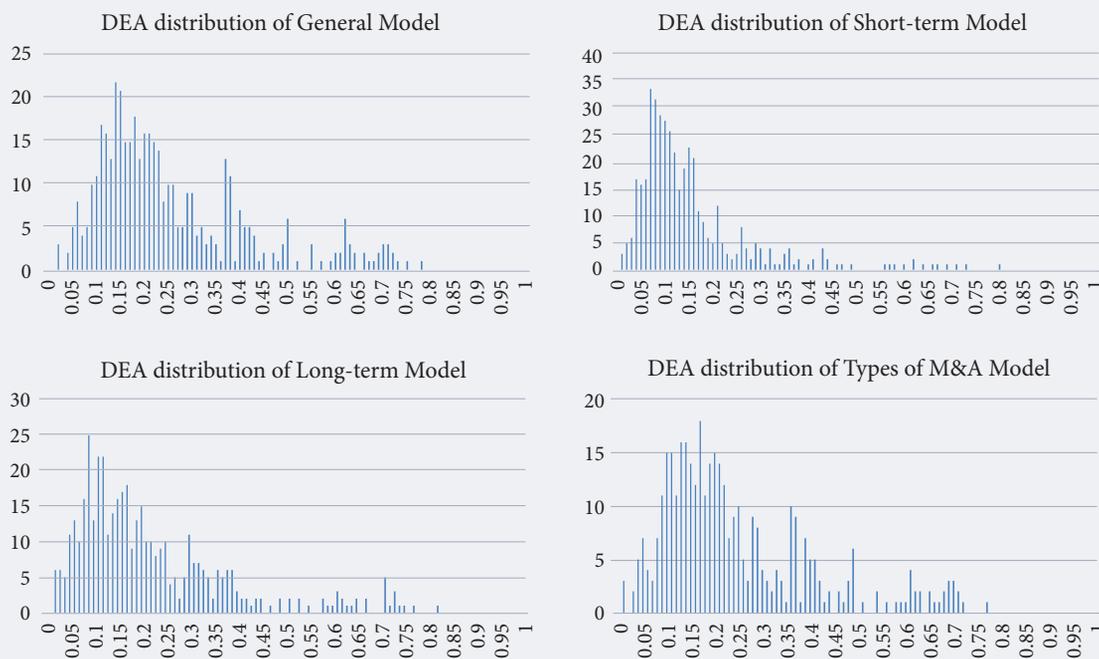
Source: authors.

Table 3. **Results of the Econometric Analysis**

Variable	General model	Short-term Model	Long-term Model	Types of M&A model	Types of M&A model with a structural break
Intercept	−0.632***	−1.155***	−1.036***	−0.647***	−0.556**
Ln(Patents)	−0.020	0.015	−0.044**	−0.016	−0.028
R&D	−0.018***	−0.023***	−0.015**	−0.015**	−0.019*
Ln(Rel Size)	−0.062***	−0.084***	−0.044***	−0.067***	−0.067***
Ln(Revenue)	−0.069***	−0.103***	−0.032	−0.069**	−0.072***
CAPEX	1.953	1.788	2.014	1.877	1.779
Method of Payments	0.019	0.021	0.071	0.159*	0.169*
International	0.048	-0.003	0.052	−0.027	−0.027
Number of observations	434	434	434	379	379

Table 3 continued

Variable	Types of M&A model	Types of M&A model with a structural break
Conglomerate	−0.108	−0.321
Vertical	−0.280***	−0.287
Ln(Patents) × Conglomerate		0.053
R&D × Conglomerate		−0.001
Ln(Patents) × Vertical		−0.011
R&D × Vertical		0.010
Number of observations	379	379

*Level of confidence: *** - 1%, ** - 5%, * - 10%; Logit link function is applied; Multicollinearity is not present. Dependent variable: Bootstrapped DEA score.*

Source: authors.

nology transfer's efficiency. Overall, we discovered that the acquirer's ability to acquire and value external technology (measured by R&D intensity) negatively affects post-merger M&A efficiency. These empirical results are robust over various horizons of planning. At the same time, we found mixed results for the impact of the ability to exploit the absorbed technology (measured by the number of patents). While some prior research found the insignificant effect of patent count on efficiency (George et al., 2001), we distinguish between the short- and long-term effects and document the significantly negative impact of patent count in the long run. Thus, we argue that the accumulation effect of ACAP significantly depends on the technology transfer channel. The efficient absorption of external knowledge requires studying factors influencing the outputs of the transfer process. Within the knowledge-based view of the firm, research on the non-linear relationship between efficiency and ACAP found that a higher

level of prior knowledge is not always a predecessor of successful assimilation and exploitation of external technologies (Lichtenthaler, 2016; Wales et al., 2013). Furthermore, increasing the knowledge base raises the costs associated with knowledge management (Berchicci, 2013).

Another determinant of the interorganizational technology transfer's efficiency is the relative size of the deal: the research confirms the significant and negative effect of the ratio of the deal value to total assets. Since the deal value captures financial and technological characteristics of the target, this result may indicate that the acquisition of the firm with a large technology base reduces the efficiency of technology transfer. The increase in the scale of the acquirer's business also negatively impacts post-merger outcomes and constitutes an obstacle to technology transfer, although the effect of this factor is insignificant in the long-term model. The impact of CAPEX intensity on the efficiency of the technology transfers through M&A is insignificant in all specifications of the model.

Taken together, our results support the proposition that the costs of absorbing a new technology significantly decrease the efficiency of technology transfer across organizational boundaries. The negative impact of the scale of the acquirer's business, R&D intensity, and relative size of the deal may indicate that for large listed companies post-merger efficiency is negatively affected by the higher costs of searching for appropriate external technologies and higher organizational costs for incorporating the acquired R&D into an already established R&D process. A high ability to transform and exploit outside technology (patent count) does not constitute a significant competitive advantage in the short term and only has a delayed negative effect.

The practical implications of this study can support decision-makers when they are considering whether to engage in technologically motivated M&A. Our results suggest that companies may benefit from acquiring technologies despite a low level of pre-merger technological strength. Due to the overall negative impact of the acquirer's prior knowledge base on M&A efficiency, we may conclude that firms with a smaller stockpile of capabilities to exploit external knowledge should pursue external technology absorption through M&A deals despite a possible lack of ACAP. This is in line with the conclusions of Sears and Hoetker (2014), who found that the lack of ACAP and technological overlap does not always harm M&A technology-related efficiency due to the novelty of the acquired technologies. On the other hand, large-scale firms with greater technological capabilities should be more careful with their acquisitions strategy since the absorption of external technologies may be less efficient, especially in the case of the acquisition of a substantial body of external knowledge.

Our results could also be evidence of the substitution effect in technology acquisition, which is in line with several studies on post-merger M&A efficiency (Haucap et al., 2019). Another possible rationale behind the negative implication of ACAP is that, at least on the part of acquirers, the strategic goal of the M&A deal is not the technology acquisition itself but the elimination of competitors. However, those hypotheses require additional empirical testing. First, we assume that all patents and R&D expenses are homogenous in their efficiency impact. However, in some cases acquirers might be ready to pay for the whole knowledge base of target companies in order to gain access to one specific piece of knowledge. Second, we have mainly concentrated on the market or industry similarities for different types of M&A. However, the technological similarity is beyond the scope of this research, leaving potential for this issue to be explored in future studies.

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