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Learning-By-Being-Acquired: Post-Acquisition R&D Team Reorganization and Knowledge Transfer

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Abstract

In horizontal acquisitions, the post-acquisition integration of the R&D function often damages the inventive labor force and results in lower innovative productivity of acquired inventors. In this paper we study post-acquisition integration in terms of R&D team reorganization—i.e., the creation of new teams with both inventors of the acquiring and acquired firms—and assess the impact of this integration action on knowledge transfer in the period that follows the acquisition. Specifically, drawing on social identity and self-categorization theories, we argue that R&D team reorganization increases the acquired inventors' use of the prior stock of technological knowledge of the acquiring firm after the acquisition. Furthermore, this effect is enhanced if acquired inventors have higher innovation ability relative to their acquiring peers but is weakened for acquired inventors with high pre-acquisition ingroup collaborative strength. We construct a sample of 3,625 acquired inventors implementing the coarsened exact matching (CEM) technique and empirically test our arguments applying a difference-in-differences setup in a longitudinal data setting. We find general support for the hypothesized relationships. This study shows that the social identity perspective helps complementing predictions from the coordination-autonomy perspective.

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ABSTRACT

In this paper we study post-acquisition integration in terms of R&D team reorganization—i.e., the creation of new teams with both inventors of the acquiring and acquired firms—and assess its impact on knowledge transfer in the period that follows the acquisition. Drawing on social identity and self-categorization theories, we argue that R&D team reorganization increases the acquired inventors' use of the prior stock of technological knowledge of the acquiring firm after the acquisition. Furthermore, this effect is enhanced if acquired inventors have higher innovation ability relative to their acquiring peers but is weakened for acquired inventors with high pre-acquisition ingroup collaborative strength. We construct a sample of 3,625 acquired inventors implementing the coarsened exact matching (CEM) technique and empirically test our arguments applying a difference-in-differences setup in a longitudinal data setting. We find general support for the hypothesized relationships. This study shows that the social identity perspective helps complementing predictions from the coordination-autonomy perspective.

INTRODUCTION

Horizontal acquisitions—i.e., acquisitions of firms that operate in the same industry as the acquiring firm—are an important mechanism firms use to access strategic assets and competencies which combined with internal capabilities can create value (e.g., Larsson & Finkelstein, 1999; Schweiger & Lippert, 2005; Valentini, 2012). However, value realization requires that resources of the acquiring and acquired firms are used somehow in conjunction. Post-acquisition integration of the acquiring and acquired operations aims at improving coordination and mutual learning between the two previously separated entities, and thus is a fundamental, yet very challenging process to realize the acquisition's potential for value creation (e.g., Jemison & Sitkin, 1986; Pablo, 1994; Zollo & Singh, 2004). Indeed, despite the potential coordination benefits of post-acquisition integration, the acquisition literature tends to emphasize its costs (Larsson & Finkelstein, 1999). In sum, the literature on post-acquisition integration highlights two main conflicting effects of the integration process: a coordination effect that by aligning procedures, goals and authority between acquiring and acquired firms' knowledge workers facilitates acquiring firms to leverage the acquired firms' knowledge base (e.g., Graebner, 2004; Puranam, Singh, & Zollo, 2006; Puranam & Srikanth, 2007), and a loss of autonomy effect which hinges mostly on acquired inventors through the disruption of their existing routines and motivations (e.g., Paruchuri et al., 2006; Puranam & Srikanth, 2007).

In this study, we propose that social identity and self-categorization theories (e.g., Tajfel, 1974; Tajfel, 1979; Tajfel & Turner, 1979; Tajfel & Turner, 1986) complement the coordination-autonomy perspective and help explaining further the post-acquisition integration impact on acquired inventors. A social identity approach emphasizes how individuals define themselves as members of social groups and, the stronger is their social identification the more their membership is core in their self-concept and, thereby, they accept the group norms and behave in the best interest of their group (e.g., Tajfel & Turner, 1986). When such identification takes place individuals are more inclined to share knowledge with other group members; this is because membership positively associates with ingroup trust, honesty and cooperation (Kane, Argote, & Levine, 2005; Kogut & Zander, 1996). Moreover, while identity threats tend to reduce post-acquisition perceived satisfaction they also facilitate the creation of serendipitous value (Colman & Lunnan, 2011). Given that human factors clearly play an important role in predicting why acquisitions fail or succeed (e.g., Cartwright, 2012; Cartwright & Cooper, 1992), we propose that paying greater attention to the social identity process of acquired inventors will enrich our understanding on the effect of post-acquisition integration.

The extent to which acquired inventors leverage the knowledge base of the acquiring firm in their post-acquisition patenting activity, as reflected by backward patent citations (e.g., Almeida & Kogut, 1999), is an important, yet unexplored, post-acquisition outcomes of acquired inventors. While it is central that acquired inventors stay after the acquisition and continue to innovate, it is also desirable that they will generate innovation that combines their technological knowledge with knowledge and capabilities of the acquiring firm. This process of transfer of knowledge from the acquiring to the acquired inventors emphasizes the full recombination of existing knowledge into new knowledge (Kogut & Zander, 1992). It is a crucial ingredient for the diffusion of ideas and competencies and, thus, for the creation of value after the acquisition (Almeida & Kogut, 1999; Almeida, Song, & Grant, 2002; Rosenkopf & Almeida, 2003). Also, bilateral knowledge transfer and the exposure of acquiring and acquired inventors to each other's knowledge bases increase opportunities to discover 'serendipitous value' (Graebner, 2004). Accordingly, in this study we investigate the effect of post-acquisition integration on the extent to which knowledge of acquiring inventors flows to and is leveraged by acquired inventors after the acquisition. In particular, as for post-acquisition integration action we focus on the reorganization of R&D teams in the period that immediately follows an acquisition. That is the creation of R&D teams composed of inventors of both the acquiring and acquired firms. Team reorganization is an important integration action as R&D teams are the immediate organizational context in which dialogue, discussion, experimentation, and reflection between inventors take place.

Our empirical analysis is based on the patenting activity of 3,625 acquired inventors who continue to work within the new firm after the acquisition (Kapoor & Lim, 2007; Paruchuri et al., 2006) and 25 horizontal acquisitions of sizable firms in medium- and high-tech industries. In each acquisition, the R&D function is a component of the acquired firm's assets and the R&D operations of acquiring and acquired firms are in the same broadly defined technological area. We construct our sample implementing the coarsened exact matching (CEM) technique and empirically test our arguments applying a difference-in-differences setup in a longitudinal data setting. First, we replicate previous findings on the negative effect of post-acquisition integration on acquired inventors' productivity. Second, we find that by triggering a self-recategorization process R&D team reorganization enhances the use of the acquiring firm's knowledge base by the acquired inventors in their post-acquisition patenting activity. Furthermore, since the social identity processes induced by the R&D team reorganization are unlikely to be uniformly beneficial for all acquired inventors we show that the effect of team reorganization on the transfer of knowledge from acquiring to acquired inventors depends on the innovation ability (relative to their acquiring peers) and ingroup collaborative strength of the acquired inventors prior the acquisition. The former individual characteristic triggers group members' ability to switch among multiple identities. The latter enhances group members' identification and limits identity change.

In examining the social identity and self-categorization processes triggered by R&D team reorganization and how they are enabled or prevented by characteristics of acquired inventors, we bridge insights from the coordination-autonomy perspective and contribute to extend our understanding of the multifaceted and complex nature of post-acquisition integration.

THEORY AND HYPOTHESES

Post-Acquisition Integration and Innovation Activity of Acquired Inventors

Post-acquisition integration of the acquired operations is a necessary step to realize synergies and reap the benefits inherent in horizontal acquisitions. In particular, integration actions are necessary to assure close coordination of the previously separated units and facilitate learning processes (e.g., Capron, 1999; Grant, 1996; Grimpe, 2007; Kogut & Zander, 1992; Puranam & Srikanth, 2007; Zollo & Singh, 2004). In line with this view, previous studies have highlighted that post-acquisition integration may generate an environment more conducive to transfer of knowledge between the acquiring and acquired firms (Ranft & Lord, 2002). In particular, Puranam and Srikanth (2007) argue that structural integration enhances coordination through common procedures, goals and authority between acquired and acquiring firms' inventors and, ultimately, favors knowledge transfer from acquired to acquiring inventors. However, while through the ‘coordination effect’ (Puranam & Srikanth, 2007) integration enables the acquiring firm to leverage the acquired firm’s knowledge base, through the ‘loss of autonomy effect’ (Puranam & Srikanth, 2007) it damages acquired inventors’ ability to generate innovations in the post-acquisition period. That is, integration triggers a radical disruption of acquired inventors’ routines and undermines their motivations as they largely loose autonomy. In line with this view, Kapoor and Lim (2007) show that acquired inventors have lower innovation productivity after an acquisition than their matched inventors in non-acquired firms. Moreover, Paruchuri et al. (2006) provide evidence that the negative effects of structural integration on acquired inventors’ innovation productivity are contingent on inventors’ individual characteristics, with the most detrimental effects being experienced by inventors who lose more centrality and social status.

Despite the clear negative effect of post-acquisition integration on acquired inventors’ productivity, the impact on the acquired inventors’ capability to generate further innovations by exploiting the fruits of the acquiring firm’s inventive efforts remains unclear. The coordination-autonomy perspective offers valuable insights into how post-acquisition integration favors acquiring inventors’ leverage of acquired firms’ knowledge but damages the acquired inventors’ innovation productivity. However, we propose that a focus on social identity and self-categorization theories (e.g., Tajfel, 1974; Tajfel, 1979; Tajfel & Turner, 1979; Tajfel & Turner, 1986) can help to clarify how post-acquisition integration influences acquired inventors’ use of the acquiring firm’s capabilities following the acquisition. As for the acquiring inventors we could expect that the enhanced coordination induced by post-acquisition integration would influence positively also acquired inventors and, thus, increase the transfer of knowledge from acquiring to acquired inventors. However, we cannot exclude that this positive impact will be reduced, or may not even emerge, if the negative consequences predicted by the autonomy effect will prevail.

Social identity is the extent to which individuals categorize themselves and others in a group. Specifically, social identity theory (SIT) and self-categorization theory (SCT) suggest that individuals identify themselves to be members of specific groups on the basis of categories capturing ingroup similarities and intergroup differences. One's self-evaluation is partially determined by categorization, thus, to maintain high self-esteem individuals tend to view their group in a positive light compared to other groups (e.g., Tajfel, 1974; Tajfel, 1979; Tajfel & Turner, 1979; Tajfel & Turner, 1986). Previous work has recognized that the merging of acquired and acquiring firms requires the employees of both organizations to abandon their pre-acquisition group identity and initiate a recategorization process leading to the development of the new superordinate group identity (Amiot, Terry, & Callan, 2007; Haunschild, Moreland, & Murrell, 1994; Terry, Carey, & Callan, 2001; van Knippenberg et al., 2002). In the following section, with the focus on post-acquisition reorganization of R&D teams as integration action, we show how theoretical mechanisms drawn from SIT and SCT complement the coordination-autonomy perspective to explain the effects of post-acquisition integration on knowledge transfer from acquiring to acquired inventors.

Social Identity, Social Categorization and Post-Acquisition R&D Team Reorganization

An inventor's ability to unlock the post-acquisition innovative potential stemming from the realization of knowledge transfer depends on the capacity of his/her R&D team to encourage the coordinated exchange of knowledge, materials, and reciprocal inputs with other team members. R&D team reorganization creates the necessary conditions for different inventors to engage in face-to-face communication and direct observation of each other's work. Also, R&D team reorganization involves redefinition from separate to common tasks, procedures, and goal. Accordingly, post-acquisition R&D team reorganization creates stronger and more frequent connections between acquired and acquiring inventors, fosters more efficient communications between them and enhances the coordination of their inventive activity (Ranft & Lord, 2002). In line with the coordination effect, R&D team reorganization creates a favorable setting for knowledge transfer from the acquiring to the acquired inventors. However, with R&D team reorganization the autonomy structure of the team is likely to change leading to a disruption process. Specifically, on one side, R&D team reorganization might impose that existing routines of the acquired firm are altered to come together with those of the acquiring firm (Kapoor & Lim, 2007; Paruchuri et al., 2006; Puranam et al., 2006). On the other side, acquired inventors might be increasingly exposed to sense of anger and loss, anxiety, lack of motivation, confusion and uncertainty (for a review, see Cartwright, 2012; Seo & Hill, 2005). Thus, in line with the autonomy effect, R&D team reorganization would raise negative feelings and emotions in acquired inventors who, ultimately, are likely to limit their propensity to leverage the acquiring inventors' knowledge after the acquisition. Since the full realization of coordination cannot occur without identity (Kogut & Zander, 1996) that is also an important determinant of knowledge transfer (Kane et al., 2005), we propose that drawing on SIT and SCT helps to understand the balance between the effects of coordination and autonomy on the transfer of knowledge from acquiring to acquired inventors.

We argue that the post-acquisition creation of teams with both acquired and acquiring inventors is an integration action inducing reorganized acquired inventors to conceive a new group categorization that weakens outgroup biases and triggers positive attitudes toward former outgroup people (i.e., acquiring inventors). The emergence of a new collective identity favors the coordination effect (Kogut & Zander, 1996) and the acquired inventors' willingness to accept knowledge from the acquiring inventors in the team (Kane et al., 2005). Our expectation builds on three distinctive mechanisms. First, it is now well established that simply assigning individuals to different groups is sufficient to generate in-group favoritism and induce an individual of one group to favor his/her group members relative to individuals in the other groups (Brewer, 1979; Brewer & Kramer, 1985; Tajfel, 1982). New members get to perceive themselves as part of the new group while considering the old members as outgroup (Moreland, 1985). Therefore, the simple reorganization of an acquired inventor into a team with acquiring inventors is likely to make the distinction between acquired and acquiring inventors less salient. Second, previous work shows that group members have different perceptions of self and others, depending on which comparison group provides the frame for their judgments (Ellemers et al., 2002; Haslam & Turner, 1992; Hogg & Terry, 2000; Van Rijswijk & Ellemers, 2002). Specifically, the disassemble of groups and the creation of a new group is a mechanism that helps group members to break their old categorization schemes and reduces ingroup favoritism and intergroup tension (Haunschild et al., 1994). We suggest that when acquired and acquiring inventors are reorganized into a new team that combines together previously separate inventors the relevant comparison group changes: other newly formed teams of acquired and acquiring inventors become the salient outgroups in the immediate social context. In other words, R&D team reorganization promotes acquired inventors' transformation of their categorized representations of 'us'—acquired inventors—and 'them'—acquiring inventors—to a more inclusive category of 'we' (Haunschild et al., 1994). Accordingly, the creation of a new group of acquiring and acquired inventors performing a collective task brings former outgroup members under the umbrella of a new social identity (Gaertner & Dovidio, 2000). Third, the literature on interpersonal relations and group processes shows that intergroup cooperation reduces ingroup/outgroup biases by developing more positive attitudes toward former out-group members (Gaertner et al., 1990). Cooperation increases knowledge about the other group (Stephan & Stephan, 1984), weakens the cognitive salience of the boundaries among the two groups and promotes acceptance (Tajfel & Turner, 1979). Specifically, cooperation degrades the members' cognitive representations of two separated groups and prompts the group members to recategorize themselves primarily as one larger group (Gaertner et al., 1990). We expect that R&D team reorganization favors the inclusion of outgroup members and the creation of a new identity also because it fosters connections and communication between acquired and acquiring inventors.

Hypothesis 1: The extent of acquired inventors' leverage of the acquiring inventors' technological capabilities is greater after the acquisition if post-acquisition integration involves the reorganization of R&D teams of the acquired and acquiring firms.

Multiple Identities and the Moderating Effect of Acquired Inventors' Relative Innovation Ability

Social identity is often complex and multifaceted in the sense that people can describe themselves and other using diverse, overlapping, and interwoven categories (Crisp & Hewstone, 2007). Group members with high relative individual ability show multiple identities—an individual's simultaneous membership in multiple groups—and are better able to switch to a new social identity (cf. Ellemers, 1993; Shih, Sanchez, & Ho, 2010; Shih, Young, & Bucher, 2013). Indeed, multiple identities relate to multiple categorizations and are beneficial for intergroup relations (e.g., Crisp & Hewstone, 2006). Specifically, multiple identities create opportunities to alter people's judgments of category membership and override group members' devalued perception of an outgroup member (Kang & Bodenhausen, 2015). Urada and colleagues find that two shared identities are sufficient to make a group member's perceptions of an outgroup member becoming identical to those of ingroup members (Urada, Stenstrom, & Miller, 2007). Multiple identities allow for flexible self-definition so that individuals switch to a more favorable sense of self depending on the current context, needs, or goals (e.g., Shih et al., 2010; Shih et al., 2013). In other words, multiple identities create the conditions for moving the dividing line between in- and outgroups (Kang & Bodenhausen, 2015).

We expect that acquired inventors who in the pre-acquisition time period show a higher ability to innovate compared to their acquiring peers—inventors' relative innovation ability—are likely to view themselves as members of many differentiated groups: "I am an acquired inventor", "I am a highly productive inventor", etc. Accordingly, we posit that the extent to which R&D team reorganization induces recategorization schemes and affects knowledge transfer will differ from acquired inventors with high relative innovation ability to low-ability acquired inventors. This difference depends on how high- vs. low-ability acquired inventors are able to switch identity from the old to the new group membership. The process of identity change is partially explained by identity compatibility, which captures how the new identity fits with previously established identities (Iyer et al., 2009). Identity change is detrimental for well-being if individuals' multiple identities are not consistent with the new identity (Iyer et al., 2009). In addition, Hogg and Terry (2000) suggest that individuals adopt a social identity among different because motivated by the need for positive self-esteem and to reduce subjective uncertainty. Therefore, we would expect that the more acquired inventors perceive that the new group identity induced by team reorganization increases their self-esteem and is compatible with their existing identities, the more likely they will take on the new group identity. When acquired inventors have high relative innovation ability—a condition that gives them a relative standing within their peers in the acquiring organization—they will perceive a high level of compatibility with acquiring inventors. In this situation, high-ability acquired inventors experience perceptions of continuity between the old and the present identity, so that survival threats are minimized (for a discussion of identity continuity, see van Knippenberg et al., 2002; van Leeuwen, van Knippenberg, & Ellemers, 2003). Conversely, if low-ability acquired inventors perceive little compatibility with the acquiring inventors, they are less likely to adjust to the social identity of the new reorganized team. R&D team reorganization exposes low-ability inventors to concerns of negative self-esteem. Group members with low ability may find refuge in their acquired inventors' group as a way to compensate for their (innovation) capacity shortcomings (cf. Ellemers, Spears, & Doosje, 2002). Accordingly, they will have a desire to protect their current identity in response to the threat imposed by team reorganization. Also, low-ability inventors would prefer to protect their previous identity since identity discontinuity resulting from the recategorization process is directly threatening their survival (van Knippenberg et al., 2002; van Leeuwen et al., 2003).

Based on these arguments, we suggest that inventors with high relative innovation ability are more willing to identify with their new team of both acquired and acquiring inventors and experience greater benefits from team reorganization.

Hypothesis 2: Under conditions of R&D team reorganization, the higher the acquired inventors' pre-acquisition innovation ability relative to the acquiring inventors, the greater the extent of acquired inventors' leverage of the acquiring inventors' technological capabilities after the acquisition.

Group Identification and the Moderating Effect of Acquired Inventors' Ingroup Collaborative Strength

We propose that the extent to which acquired inventors identify as members of their social group—i.e., the extent of social identification—is expected to influence the recategorization process triggered by R&D team reorganization and its effect on the acquired inventors. In particular, we expect that acquired inventors with higher levels of ingroup collaborative strength (i.e., they had repeated collaborations with other inventors within the acquired firm prior the acquisition) will show higher levels of identification with their pre-acquisition groups and, therefore, a slower adaptation to the new social identity triggered by R&D team reorganization.

Work on social identity demonstrates that the consequences of a threat for the self and the responses to this threat differ depending on the group member's strength of identification to the group (Ellemers et al., 2002). Group members with strong group identification are more suspicious about changes in group membership that can threaten their social identity; thus, they develop solid feelings of attraction among group members (cohesion) and are motivated to preserve the group from external threat (Haunschild et al., 1994). Ulrich et al. (1989) found that group cohesion restricts the communication and the interaction of employees across two merging companies. Moreover, when they are under threat group members who have already developed a strong identification tend to emphasize higher group cohesiveness and to be less likely to engage in recategorization, also when this choice will improve their status position (Doosje, Spears, & Ellemers, 2002). Group members' motivation and needs to preserve the group identity is enhanced if group identification is high while group identity is further undermined and recategorization promoted if the identification in that group is low (Jetten, Spears, & Manstead, 1999). As a direct behavioral response, members with high identification show a strong desire to clearly differentiate their group from other groups, also by showing discrimination to the outgroup members (Jetten et al., 1999).

Collaborations require shared mental models or systems of meaning that enable individuals to describe, explain, and use knowledge from one another (e.g., Brown & Duguid, 1991; Orlikowski, 1996; Schwenk, 1988). Crucially important is the development of shared language, norms, and goals that can facilitate communication and shared understanding (Edmondson, 2003). Along these lines, the extent of the ingroup collaborative activity of acquired inventors expresses the extent of their relationships with the rest of the acquired inventors, and provides indications of their social identification. This is because inventors that are more interdependent and interact more extensively with each other identify more strongly with their groups. Indeed, if two individuals have worked together on a joint task, when merged with other dyads they show a stronger interdyad bias compared to individuals who have not worked together in their own dyad (Hogg & Terry, 2000). Stronger identification involves the sharing of identity attributes like values, goals, beliefs, and traits, and the more people embody these attributes, the more they identify as member of the collective (Amiot et al., 2007; Ashforth, Harrison, & Corley, 2008). Accordingly, as acquired inventors who have developed extensive ingroup collaborations develop resilient shared values, practices and norms, the homogeneity of these attributes between acquired inventors also reflects a strong ingroup identification (cf. Doosje, Ellemers, & Spears, 1995). If on one side a strong identification results in ingroup members' cognitive coherence which serves the sharing of knowledge, on the other side it also limits the exchange of knowledge between ingroup and outgroup members given the resistance to change practices, norms and values of ingroup members (Nag, Corley, & Gioia, 2007).

Hypothesis 3: Under conditions of R&D team reorganization, the higher the acquired inventors' pre-acquisition ingroup collaborative strength, the lower the extent of acquired inventors' leverage of the acquiring inventors' technological capabilities after the acquisition.

METHOD

The test of the effect of post-acquisition R&D team reorganization on acquired inventors' leverage of acquiring inventors' technological capabilities requires a methodology that takes into account selection effects and unobserved heterogeneity. First, we need to account for the fact that characteristics related to the inventors in the pre-acquisition period could trigger the decision to reorganize teams. Second, inventors exhibit a life cycle in their innovation productivity (Kapoor & Lim, 2007; Levin & Stephan, 1991), with the rate at which they produce innovations varying with the experience that they accumulate. Therefore, it is not sufficient to estimate the effect of

R&D team reorganization solely based on pre and post extent of acquired inventors' leverage of acquiring's capability: this approach would provide no indication of abnormal deviations from what is expected to be observed for an inventor within a similar trajectory. Finally, previous work shows the negative effect of acquisitions on inventor productivity (e.g., Kapoor & Lim, 2007; Paruchuri et al., 2006). Accordingly, to estimate the effect of R&D team reorganization on post-acquisition knowledge transfer, we first need to account for the expected changes in inventors' productivity triggered by the acquisition itself. Not accounting for this effect could lead to biased estimations.

In the attempt to overcome these endogeneity issues, we apply a difference-in-differences setup and compare before and after the acquisition the rate of capability leverage by acquired inventors involved in R&D team reorganization (*treatment group*) with that of inventors who were not exposed to R&D team reorganization (*control group*). For both groups we observe the longitudinal changes in the extent to which they draw from the acquirer's knowledge, based on information referring to the pre- and post-acquisition periods. In order to implement this empirical strategy, we rely on the Coarsened Exact Matching (CEM) technique (Iacus, King, & Porro, 2011, 2012) to estimate the ATT (average treatment effect on the treated) concerning inventors knowledge transfer.

Sample and Data

The sample consists of 3,625 acquired inventors working in 25 firms resulting from horizontal acquisitions undertaken in medium and high-tech industry by large firms headquartered in the European Union (EU). Information about the horizontal acquisitions is based on data collected as part of a research project promoted by the DG Research of the European Commission.[1] Using

[1] This data collection was conducted within the FP5 project "Mergers and Acquisitions and Science and Technology Policy" funded by the European Commission, DG Research (Contract No. ERBHPV2-CT-1999-13).

the 1993 EU Market Share Matrix (MSM), the project identified 59 acquiring leading firms—the five largest EU producers in EU 3-digit medium and high-tech industry in that year—headquartered in EU. 31 firms out of 59 (response rate of approximately 52%) agreed to participate in the study based on a multiple-case design and provided detailed information about 31 acquisitions occurred during the 1987-2001 period. Some acquisitions were domestic, other cross-border and involved acquired firms located in other EU countries as well as in North America. Our choice of selecting acquisitions from the DG research project was dictated by the fact that usually is very difficult to have access to detailed information about post-acquisition integration processes. The DG project data were collected during face-to-face interviews with those who were in charge of or actively participated in the implementation of the acquisition process (in most cases the Vice-President for strategy or corporate development and the Vice-President for R&D or the Chief Technology Officer). We use this information to operationalize the R&D team reorganization and other deal-level control variables used in our empirical exercise.

The second source of data is the *Patent Network Dataverse* database that builds on the United States Patent and Trademark Office (USPTO) and includes information regarding the identification of disambiguated names of individual inventors registered at the U.S. utility patents for the period 1975−2010 (Li et al., 2014). We use patent information to compute the dependent variable and other individual and firm level characteristics.

The following steps describe the construction of our dataset. First, based on the company name we identified all patents filed at the USPTO by the 31 acquired firms in the 5 years prior the acquisition. We removed from the sample five firms with no patenting activity. Second, in some cases the acquisition involved only specific businesses of the acquired firm. Accordingly, we scrutinize the patent data of the remaining 26 acquired firms to retain only information pertaining to the business units and their inventors directly involved in the acquisition[2]. However, in one case the complex structure of the assets of both the acquired and acquiring firms involved in the acquisition did not allow us to uniquely identify businesses and inventors that undoubtedly were part of the acquisition. We removed this case from our sample and remained with 25 deals involving 4,785 unique inventors that actively patented during the pre-acquisition period—i.e., active inventors. Third, we accounted for inventors mobility across firms (Singh & Agrawal, 2011; Younge, Tong, & Fleming, 2015). Specifically, we removed inventors who had patented in a different firm within the five years before and after the acquisition was concluded—the assignee name differs from the name of the acquired firm. After removing these inventors, the sample consists of 3,978 active acquired inventors. We use this sample in the matching procedure.

Measures

The dependent variable, *knowledge transfer*, is measured as the cumulative number of citations that each acquired inventor makes to the acquirer firm's patents (e.g., Almeida & Kogut, 1999; Mowery, Oxley, & Silverman, 1996). More precisely, we look at the backward citations of the patents produced by the acquired inventors to identify if they draw from knowledge and technological capabilities produced by the acquirer firm. The dependent variable is computed based on two time windows. The first window captures the five years before the acquisition[3] and the second window refers to the five years after the acquisition. Moreover, in order to replicate previous findings, we also define the variable *patenting productivity* as total number of granted

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[2] For example, in the acquisition of Westinghouse by British Nuclear Fuels Limited (BNFL) only the nuclear business of Westinghouse was acquired. To identify the inventors that were part of the acquisition, we scrutinized the abstracts and content of all patents filled by Westinghouse and select only those inventors involved in the nuclear business. Similarly, in the acquisition of CytoMed by UCB the deal involved activities of CytoMed in the fields of allergy, asthma and central nervous system. Using the same approach, we selected only CytoMed inventors related to the patents that were part of the deal.

[3] We consider the year of the acquisition as part of the pre-acquisition period.

patents filed by an inventor with the acquired firm during the pre- and post- acquisition periods. Also this dependent variable is computed based on the two aforementioned time windows.

In order to test the hypothesized relationships we operationalize the following variables. The variable *R&D team reorganization* is a dummy that takes value 1 if R&D teams of both the acquiring and the acquired firms have been reorganized after acquisition, which imposes the creation of R&D teams composed of inventors of both the acquiring and acquired firms. The variable *inventor's relative innovation ability* is the cumulative number of patents of the focal acquired inventor divided by the cumulative average number of patents of all active inventors in the acquirer firm in the pre-acquisition time period. We capture the *inventor's in-group collaborative strength* as the number of unique ties (other inventors) with who the focal inventor had repeated (at least two) collaborations before the acquisition.

We control for a number of individual- and acquisition-level characteristics. We control for the divergence between the acquired inventor's expertise and the acquired firm's stock of knowledge. Similar to a measure proposed by Parachuri et al. (2006) we first identify all patents that had been produced by the acquirer firm within the five years before the acquisition. Then, we observe the main class related to each of those patents in order to identify the field in which the acquirer has been mostly active prior to the acquisition. Subsequently, we look at the patents that each inventor in the acquired firm has produced and compute *inventor's knowledge divergence* as the ratio between the inventor's patents within the acquirer's main technological area and the total patents produced within the same period and subsequently inverted by subtracting it from one. The variable *inventor's technological diversity* measures the heterogeneity of the knowledge inventors have accumulated in different technological fields within the five year prior to the acquisition. It is computed based on a Herfindahl index calculated using the main technological fields (3-digit class) to which the inventor patents are assigned (Hoisl, 2007). All variables concerning acquisition-specific characteristics are measured at the deal level and subsequently shared by inventors working in the same firm. A first group of controls captures other post-acquisition integration decisions that are likely to correlate with the probability of observing R&D team reorganization and also to affect the innovative behavior of acquired inventors. Specifically, the turnover of top managers responsible for the acquired R&D function after the acquisition is captured by the dummy *replacement of acquired R&D top manager*. We define the dummy variable *R&D divestiture* that equals 1 if acquired R&D laboratories have been closed after the acquisition. The dummy *specialization of R&D tasks* takes value 1 if the post-acquisition integration has imposed more specialization of the R&D tasks between the acquired and acquiring firms. Finally, we control for the overall level of integration of systems, products and procedures after the acquisition (Zollo & Singh, 2004). The variable *overall integration* is calculated as average of the dichotomous scores (i.e., 0 = no; 1 = yes) of the following four items (source: DG research project): (1) Transfer/sharing of R&D physical equipment from the acquired to the acquiring firm; (2) Transfer/sharing of R&D physical equipment from the acquiring to the acquired firm; (3) Transfer/sharing of patents, methods, other blueprints, etc., from the acquired to the acquiring firm; and (4) Transfer/sharing of patents, methods, other blueprints, etc., from the acquiring to the acquired firm. The second group of acquisition-specific control variables captures the general characteristics of the deal and of the firms involved in the deal. Differently motivated acquisitions can implement more or less invasive integration processes and aim at different levels of knowledge transfer after the acquisition. During the DG research project, interviewed people were asked to assess the importance of the following innovation related motives, on a five-point Likert scale ranging from “not important at all” to “very important”: (1) realize economies of scope in R&D; (2) obtain access to assets, skills and capabilities of technological nature of the merging companies; (3) obtain access to knowledge and other technical resources embedded in the environment of the merging companies. Based on this information, we compute the variable *knowledge sourcing motives* as a single composite measure based on the loadings from a principal component factor analysis[4] of the three indicators of innovation related motives (Cronbach's alpha = 0.93). We also control for the acquired firm's industry by including the dummy variable *high tech* which equals 1 for high-tech industry and 0 otherwise. We control for *cross-border* acquisitions by using a dummy variable that indicates whether the acquiring and acquired firms are from different countries. The variable *hostile* takes value 1 if the acquisition is the product of a hostile takeover and 0 otherwise. The existence of previous interactions or relationships between the acquired and the acquiring firm should supposedly lower the uncertainties among R&D personnel in the acquired firm. Therefore, we control for the variable *technological links* that equals 1 if acquiring and acquired firms have experienced one or more technological alliances (i.e., equity joint ventures, license agreements, minority shareholding) with one another before the focal acquisition. We also control for the technological similarity that refers to the extent to which acquiring and acquired firms operate in the same technological fields. The variable *technology similarity* is defined using the index proposed by Makri, Hitt and Lane (2010)[5]. Finally, we control for *relative size* defined as the ratio between the total sales of the acquired and acquiring firm.

Coarsened Exact Matching

We use the CEM procedure to create the treatment and control sample with balanced characteristics in terms of several pre-treatment covariates (Iacus et al., 2011, 2012). This matching technique works through a process of data pruning in which the CEM algorithm creates a set of strata that must contain at least one treatment and control observation, which allows to

[4] Factor loadings: item 1 = 0.91; item 2 = 0.98; item 3 = 0.86; Eigenvalue = 2.55; variance explained = 99%.
[5] Our measure differs from the one of Marki et al. (2010) in terms of the time window used (i.e., five years). The original measure is based on a single year.

subsequently run the analysis in the original (pruned) data (Blackwell et al., 2009). The outcome of this matching process ensures a reduction in the overall imbalance between treated and control groups in terms of the matching characteristics while relaxing several assumptions that are required to produce unbiased estimates of the treatment effects (Aggarwal & Hsu, 2014; Iacus et al., 2011, 2012).

To run the CEM algorithm we first split the 3,978 acquired inventors in terms of treatment and control groups. It is interesting to note that in the case of 15 merged firms—2,083 (52.36%) inventors—the R&D team reorganization is implemented after acquisition while it does not occur in 10 merged firms—1,895 (47.64%) inventors. In order to prune the data, we match inventors in the treatment and control groups using pre-treatment observables pertaining to inventor-level characteristics, which the literature on post-acquisition management suggests to correlate with post-acquisition integration and inventors' innovation behavior (e.g., Paruchuri et al., 2006). First, we define the variable *inventor tenure* that is the number of years between the date of the first patent that the inventor produced with the acquired firm as the assignee and the acquisition date. Second, because the status of an inventor before the acquisition can also affect his post-deal innovative behavior and reaction to team reorganization, we also match both groups using a dummy variable indicating if an individual is a *star inventor*. We identify as star inventors those individuals for which the pre-acquisition patenting productivity is one standard deviation above the mean of the other inventors observed within the same firm. The third variable is *inventor's last patenting* calculated as the number of years passed since the last time the focal inventor patented before the acquisition. Fourth, to ensure that the treatment and control group are similar in terms of their performance in the pre-acquisition period, we also consider the variable *number of pre-patents* which is the total number of patents each inventor produced within the five years prior to the year that his/her firm was acquired. This last variable increases the confidence that the deviations in the trajectory between individuals in the treatment and control group are likely to be due to the treatment, as their ex-ante performance should be comparable. Finally, we use three period dummies to match the inventors in the treatment and control groups around the same years that their firms were acquired.

The CEM matching produced a significant improvement of the imbalance in our data, with the overall imbalance provided by the L1 statistic moving from L1=0.40 to L1= 0.27 (for a detailed discussion on the interpretation of the L1 statistic, see Blackwell et al., 2009; Iacus et al., 2011). After the matching procedure none of the four matching criteria exhibited significance differences for the two groups. During the matching process, 353 inventors (approximately 9% of the original sample) were removed from the sample because the CEM algorithm was not able to match those observations in a strata including at least one inventor from the treatment and one for the control group. By dropping these dissimilar observations between inventors that experienced the treatment and the ones that did not, CEM reduced the sample to 3,625 observations that will serve as the sample in which we will test our hypotheses. Among these observations, 1,781 belong to the treatment group and 1,844 to the control group. Given that we are not using a one-to-one matching solution we employ *CEM weights* to compensate for the differential strata size (Blackwell et al., 2009).

A Difference-In-Differences Approach for Examining the Effects of R&D Team Reorganization

The difference-in-differences approach exploits the fact that we observe the leverage of the acquiring firm's stock of knowledge by the acquired inventors (i.e., knowledge transfer) not just in the post-acquisition period but also in the period that precedes it. Although the post-acquisition differences in the treatment and control groups confound inherent differences between the two groups, we can partially disentangle these effects by reducing the imbalance between the two groups based on "observables" and tracking them in the pre- and post-acquisition periods. We use the following equation to implement this logic:

$$Knowledge\ transfer_{j,t} = f\,(\psi_R\, treatment\ group_j + \psi_{R\,P}\, treatment\ group_j \times post\text{-}acquisition_{j,t} + \psi_P\, post\text{-}acquisition_{j,t} + \psi_x\, X_j + \delta_{t\,-\,pre\text{-}acquisition\,(j)} + e_{j,t})$$

For each inventor j whose R&D teams are reorganized after acquisition, the dummy variable *treatment group* takes value 1 and value 0 if the inventors belong to the control group. In this model, ψ_R captures the systematic differences between the treatment and control groups that exist before the acquisition. The interaction term *treatment* × *post-acquisition* should capture the net effect (net of the average acquisition effect) that the treatment has on the treated group. Based on our theoretical argumentation, the coefficient of interest, $\psi_{R\,P}$, should be positive and significant. The final variable *post acquisition* takes value 1 for both the treatment and control groups only when observed in the post-acquisition period. Therefore, ψ_P consists of the *counterfactual* in the knowledge transfer for the post-acquisition period in the case R&D team reorganization has not happened.

Following previous studies (e.g., Meyer, 1995; Younge et al., 2015), we test our hypothesized moderating effects by extending the basic difference-in-differences model using three-way interactions between the term *treatment* × *post-acquisition* and each variable of interest.

Results

Table 1 reports the means, standard deviations, minimum, maximum and Pearson correlation coefficients for all variables (*unweighted*) used in the study, based on the CEM-matched sample of 3,625 unique inventors observed across two period (pre- and post-acquisition), for a total of

7,240 observations[6]. Apart from the dependent variable and the variable *post-acquisition* the others variables are time invariant, and vary within the sample only when interacted with the *post-acquisition* variable.

[*Insert Table 1 here*]

Our empirical analysis is conducted at the inventor-period level. As such, each inventor is observed and recorded both in the pre- and the post-acquisition period. As a first step, we expect to confirm a negative effect of post-acquisition integration on acquired inventors' productivity (Paruchuri et al., 2006; Puranam & Srikanth, 2007). Accordingly, we first consider *patenting productivity* as dependent variable and run a difference-in-differences estimation. Table 2 reports the means for the dependent variable *patenting productivity* based on four subsamples: R&D team reorganization (treatment) pre-acquisition, R&D team reorganization (treatment) post-acquisition, control group pre-acquisition and control group post-acquisition. We observe that the inventors of both groups had a substantial decline in their patenting productivity: around 57% for the control group and 70% for the treatment group. The post-acquisition mean values for the patenting productivity in the control and treatment groups are 1.036 patents and 0.732 patents, respectively, and the difference is statistically significant ($p<0.01$). These preliminary results already provide an indication of the negative effect of team reorganization on inventors' patenting productivity. Nevertheless, following the difference-in-differences logic, we obtain the final estimate by subtracting the second difference from the first ($-0.303 - 0.054 = -0.358$). The resulting value is negative and statistically significant ($p<0.01$). Accordingly, we replicate previous findings on a negative effect of integration on acquired inventors' productivity in the

[6] The variable *relative size* shows some correlation with *R&D team reorganization* and *R&D divestiture*. We tested the stability of the estimation coefficients by removing *relative size* from our models. This procedure showed no variation of the estimated coefficients of our explanatory variables.

case of R&D team reorganization as integration decision. This finding also increases the faith validity of our data.

[*Insert Table 2 here*]

To test our hypotheses, we now focus on *knowledge transfer* as dependent variable and follow the procedure just described. On Table 3, we observe that in the pre-acquisition period the difference in knowledge transfer of acquired inventors in the treatment (0.046) and control group (0.165) is statistically significant (difference value = −0.120; p<0.01). From the pre- to the post-acquisition period, acquired inventors in the treatment group have increased their knowledge transfer in the order of 48% (difference value = 0.022) while those in the control group show a decline in their knowledge transfer of 42% (difference value = −0.069). Following the difference-in-differences logic, we subtract the second difference from the first (−0.028 − 0.120 = *0.092*) and find that the difference in differences value is positive and statistically significant (p<0.01). This finding lends preliminary support for hypothesis 1.

[*Insert Table 3 here*]

The rest of the analysis consists of estimating a negative binomial model using a difference-in-differences setup (see Table 4). We include the variables *R&D team reorganization*, *post-acquisition*, and the variable *treatment* that is the interaction between *post-acquisition* and *R&D team reorganization*. Around 25% of the observations across the two periods have a positive outcome for the variable *treatment*. We model unobserved heterogeneity at the inventor level with random effects. Finally, while we match the treatment and control groups on inventor-level characteristics, we attempt in removing undesirable residual heterogeneity by adding several control variables at the individual-, deal- and firm-level. Model 1 shows the estimated coefficients of all control variables. The coefficient of the variable *post-acquisition* is negative and significant (p<0.01), this result is aligned with previous work suggesting that acquisitions are generally detrimental for inventors' innovative behavior (Kapoor & Lim, 2007). In Model 2 we add the variable *treatment* and confirm Hypothesis 1: the coefficient of *treatment* is positive and significant ($p<0.01$). In Models 3-5 we test the moderation hypotheses adding first separately and then jointly the three-way interaction terms of treatment with each moderating variable. We confirm Hypothesis 2 since the coefficient of the interaction *inventor's relative innovation ability* × *treatment* is positive and significant ($p<0.01$) (see Model 3). Also, as we predicted by Hypothesis 3, in Model 4 we find that the coefficient of the interaction *inventor's ingroup collaborative strength* × *treatment* is negative and significant ($p<0.01$). In Model 5 we test the stability of the results adding both interaction terms. Our results are confirmed.

[*Insert Table 4 here*]

To rule out potential alternative explanations, we conducted a number of robustness checks (estimates available upon request). First, we test if our results are biased by omitted time-invariant individual level characteristics by estimating Models 1-5 with inventor-level fixed effects. The results are fully comparable to the ones reported above. Although a fixed effect model could potentially introduce a form of sample selection—all observations where the acquired inventors did not leverage the acquiring's capabilities neither in the pre- or in the post-acquisition period are dropped—these results help reducing concerns associated with time-invariant inventor-level unobserved heterogeneity. Second, an additional source of bias could be time-invariant unobserved heterogeneity at the deal (acquisition) level. To investigate this issue, we re-estimated Models 1-5 adding deal dummies. Also these new estimations confirmed our initial findings. Finally, we also tested if allowing the other integration related variables to vary in the pre- and post-acquisition periods would affect our results. We performed this check by adding to Models 1-5 the interactions between variables *R&D divestiture*, *replacement of R&D top manager*, and *specialization of R&D tasks* and *post-deal*. It could be argued that these interaction terms partially capture time-variant unobserved heterogeneity correlated with R&D team reorganization. No significant changes from the results reported in Table 4 are observed.

DISCUSSION AND CONCLUSIONS

In relation to the effect of horizontal acquisitions on innovative performance, research shows that the post-acquisition integration, although necessary to realize synergistic benefits, imposes several challenges on the inventive labor force of the acquired firms which, ultimately, can harm innovation (Ernst & Vitt, 2000; Puranam et al., 2006; Ranft & Lord, 2000; Ranft & Lord, 2002). Looking at the reorganization of R&D teams after the acquisition, we contribute to this work about the relationship between post-acquisition integration and inventors' innovation behavior both theoretically and empirically.

We propose that the understanding of the effects of post-acquisition integration on acquired inventors is incomplete if we refrain from complement predictions from the coordination-autonomy perspective with those suggested by the social identity approach. First, we replicate previous findings and confirm that the negative effect on innovation productivity of acquired inventors after the acquisition is greater if post-acquisition integration is implemented (Paruchuri et al., 2006; Puranam & Srikanth, 2007). To complement this result, however, we show that R&D team reorganization has a positive effect on the transfer of knowledge from acquiring to acquired inventors. From the coordination-autonomy perspective we know that the loss of autonomy effect may realize through two different mechanisms. One relates to the disruption of acquired inventors experience due to the need to adapt to new routines, norms and values resulting from the integration. The other mechanism reflects that the loss of autonomy may create in acquired inventors a sense of uncertainty about their status and career (e.g., Paruchuri et al., 2006; Walsh, 1989) and exacerbate their feeling of submission and inferiority (e.g., Hambrick & Cannella, 1993). The lower productivity of acquired inventors is consistent with the effect predicted by the loss of autonomy faced by acquired inventors. However, the positive effect of R&D team reorganization on acquired inventors' leverage of the acquiring firm's knowledge suggests that additional balancing mechanisms other than the disruption of acquired inventors' morale might be at work. We propose that SIT and SCT help explaining our findings. Specifically, R&D team reorganization induces a new group categorization that mitigates acquired inventors' uncertainty and feeling of dislocation while triggers positive attitudes toward acquiring inventors. This situation maintains the morale of acquired inventors and through the coordination mechanism favors their commitment to learn via knowledge transfer. Accordingly, consistently with both the coordination-autonomy perspective and the social identity approach, we find that the adaptation to new routines, norms and values is time consuming. Acquired inventors may underestimate the amount of extra learning necessary to effectively take on the new shared mental models, indeed the convergence on new routines develops out of salient shared experiences (Nelson & Winter, 1982). This is likely to explain the direct negative effect on the overall productivity of the focal inventor. On the other hand, the emergence of a new collective identity induced by the R&D team reorganization is likely to weaken that sense of disruption, resentment, and hostility that aggravates the working conditions of acquired inventors who, consequently, show greater propensity to learn from their acquiring peers.

To further illustrate how SIT and SCT help to complement the prediction of the coordination-autonomy perspective, we evaluate how the relative innovation ability and the ingroup collaborative strength of the acquired inventors prior the acquisition moderate the main effect of R&D team reorganization on acquired inventors. From the coordination-autonomy perspective, one could argue that the positive influence of the coordination effect triggered by R&D team reorganization will be reduced when acquired inventors with high relative innovation ability are involved in the integration process. High-ability acquired inventors are those who used to enjoy more autonomy in the acquired firm before the acquisition. In fact, it is quite common that when individuals perform well they get rewarded with increased responsibilities and more autonomy. Accordingly, we would expect that high-ability acquired inventors experience the greater loss from possible autonomy reduction induced by the R&D team reorganization and suffer mostly from the integration process. Our results show that the effect of R&D team reorganization on acquired inventors' leverage of acquiring knowledge increases with the relative innovation ability of acquired inventors. This is in line with arguments drawn from SIC and SCT that acquired inventors with high relative innovation ability will be better able to switch to the new social identity stemming from the recategorization triggered by the R&D team reorganization.

We also find that the ingroup collaborative strength has a negative moderation effect on the relationship between R&D team reorganization and the acquired inventors' leverage of the acquiring firm's knowledge base. Since a stronger fit between values, norms, and practices in use between group members indicates also a strong ingroup identification, from a SIT and SCT perspective it is likely to expect that acquired inventors who have developed strong group routines in the acquired firms through their repeated collaborations will show a slower adaptation to the new social identity triggered by R&D team reorganization. This prediction reinforces that of the coordination-autonomy perspective that accounts for a negative impact of repeated collaborations on knowledge transfer. The routinization enforced by repeated collaboration creates inertia and rigidity to change and imposes additional stress and negative emotions to acquired inventors who need to adapt their routines in response to the integration implementation (e.g., Paruchuri et al., 2006).

This study is not without limitations. We cannot entirely rule out the possibility that individual level performance can drive the decision to reorganize teams. However, we have reasons to believe that our empirical setting reduces concerns in this direction. First, we use as a matching criteria inventor level patenting productivity. In other words, individual inventors in the control and treatment group are statistically comparable in terms of their ex-ante performance. Second, while the average performance of inventors in the same firm could trigger the decision to reorganize R&D team, we take care of deal- and firm-level heterogeneity using control variables. Consequently, it is not obvious that characteristics pertaining single inventors in our sample should drive their selection into the treatment group. Finally, the use of a longitudinal dataset with a difference-in-difference approach moves us a step closer to cope with the potential endogeneity in our treatment. Similar to previous studies examining the effect of acquisitions on individual inventors, we have a relatively small number of deals in our sample. Ideally, one would have a large number of acquisitions connected to individual inventors to explore cross-deal variation. We partially overcome this limitation by looking at individual level characteristics interacted with deal level information. Furthermore, despite the relatively small number of observations, we still observe significant variation at the deal level in our sample.

Despite these limitations, we hope our work will encourage future research to further examine how other post-integration actions affect transferring knowledge between acquiring and acquired inventors and expand the boundaries of the social identity approach to provide a more complete explanation of the effect of post-acquisition integration on acquired inventors' outcomes.

REFERENCES

Aggarwal, V. A., & Hsu, D. H. 2014. Entrepreneurial exits and innovation. ***Management Science***, 60: 867-887.

Almeida, P., & Kogut, B. 1999. Localization of knowledge and the mobility of engineers in regional networks. ***Management Science***, 45: 905-917.

Almeida, P., Song, J., & Grant, R. M. 2002. Are firms superior to alliances and markets? An empirical test of cross-border knowledge building. ***Organization Science***, 13(2): 147-161.

Amiot, C. E., Terry, D. J., & Callan, V. J. 2007. Status, equity and social identification during an intergroup merger: A longitudinal study. ***British Journal of Social Psychology***, 46: 557-577.

Ashforth, B. E., Harrison, J. S., & Corley, K. G. 2008. Identification in organizations: An examination of four fundamental questions. ***Journal of Management***, 34(3): 325-374.

Blackwell, M., Iacus, S., King, G., & Porro, G. 2009. CEM: Coarsened exact matching in Stata. ***Stata Journal***, 9(4): 524-546.

Brewer, M. B. 1979. Ingroup bias in the minimal intergroup situation: A cognitive-motivational analysis. ***Psychological Bulletin***, 86: 307- 324.

Brewer, M. B., & Kramer, R. M. 1985. The psychology of intergroup attitudes and behavior. ***Annual Review of Psychology***, 36: 219-243.

Brown, J. S., & Duguid, P. 1991. Organizational learning and communities-of-practice: Toward a unified view of working, learning, and innovation. ***Organization science***, 2(1): 40-57.

Capron, L. 1999. The long-term performance of horizontal acquisitions. ***Strategic Management Journal***, 20: 987-1018.

Cartwright, S. 2012. Individual response to mergers and acquisitions. In D. Faulkner, S. Teerikangas, & R. J. Joseph (Eds.), ***The handbook of mergers and acquisitions***: 372-391. Oxford, UK: Oxford University Press.

Cartwright, S., & Cooper, C. L. 1992. ***Mergers and acquisitions: The human factor***. Oxford, UK: Butterworth/Heinemann.

Colman, H. L., & Lunnan, R. 2011. Organizational Identification and Serendipitous Value Creation in Post-Acquisition Integration. ***Journal of Management***, 37(3): 839-860.

Crisp, R. J., & Hewstone, M. 2006. ***Multiple social categorization: Processes, models and applications***. Hove, England: Psychology Press.

Crisp, R. J., & Hewstone, M. 2007. Multiple social categorization. ***Advances in Experimental Social Psychology***, 39: 163-254.

Doosje, B., Ellemers, N., & Spears, R. 1995. Perceived intragroup variability as a function of group status and identification. ***Journal of Experimental Social Psychology***, 31: 410-436.

Doosje, B., Spears, R., & Ellemers, N. 2002. The dynamic and determining nature of group identification: Responses to anticipated changes in the status hierarchy. ***British Journal of Social Psychology***, 41: 57-76.

Edmondson, A. C. 2003. Speaking Up in the Operating Room: How Team Leaders Promote Learning in Interdisciplinary Action Teams. ***Journal of Management Studies***, 40(6): 1419-1452.

Ellemers, N. 1993. The influence of socio-structural variables on identity management strategies. ***European Review of Social Psychology***, 4: 27-57.

Ellemers, N., Spears, R., & Doosje, B. 2002. Self and social identity. ***Annual Review of Psychology***, 53: 161-186.

Ernst, H., & Vitt, J. 2000. The influence of corporate acquisitions on the behavior of key inventors. ***R&D Management***, 30(2): 105-119.

Gaertner, S. L., & Dovidio, J. F. 2000. ***Reducing intergroup bias: The Common Ingroup Identity Model***. Philadelphia: Psychology Press.

Gaertner, S. L., Mann, J. A., Dovidio, J. F., Murrell, A. J., & Pomare, M. 1990. How Does Cooperation Reduce Intergroup Bias? ***Journal of Personality and Social Psychology***, 57(4): 692-704.

Graebner, M. E. 2004. Momentum and serendipity: how acquired leaders create value in the integration of technology firms. ***Strategic Management Journal***, 25: 751-777.

Grant, R. M. 1996. Toward a knowledge-based theory of the firm. ***Strategic Management Journal***, 17(Winter special issue): 109-122.

Grimpe, C. 2007. Successful product development after firm acquisitions: the role of research and development. ***The Journal of Product Innovation Management***, 24: 614-628.

Hambrick, D. C., & Cannella, A. A. 1993. Relative standing: a framework for understanding departures of acquired executives ***Academy of Management Journal***, 36(4): 733-762.

Haunschild, P. R., Moreland, R. L., & Murrell, A. J. 1994. Sources of Resistance to Mergers Between Groups. ***Journal of Applied Social Psychology***, 24(13): 1150-1178.

Hitt, M. A., Hoskisson, R. E., Ireland, R. D., & Harrison, J. S. 1991. Effects of acquisitions on R&D inputs and outputs. ***Academy of Management Journal***, 34(3): 693–706.

Hogg, M. A., & Terry, D. J. 2000. Social identity and self-categorization processes in organizational contexts. ***Academy of Management Review***, 25(1): 121-140.

Hoisl, K. 2007. Tracing mobile inventors—The causality between inventor mobility and inventor productivity. ***Research Policy***, 36(5): 619-636.

Iacus, S. M., King, G., & Porro, G. 2011. Multivariate Matching Methods That Are Monotonic Imbalance Bounding. ***Journal of the American Statistical Association***, 106(493): 345-361.

Iacus, S. M., King, G., & Porro, G. 2012. Causal Inference without Balance Checking: Coarsened Exact Matching. ***Political Analysis***, 20(1): 1-24.

Iyer, A., Jetten, J., Tsivrikos, D., Postmes, T., & Haslam, S. A. 2009. The more (and the more compatible) the merrier: multiple group memberships and identity compatibility as predictors of adjustment after life transitions. ***British Journal of Social Psychology***, 48: 707–733.

Jemison, D. B., & Sitkin, S. B. 1986. Corporate Acquisitions: A Process Perspective. ***Academy of Management Review***, 11(1): 145-163.

Jetten, J., Spears, R., & Manstead, A. S. R. 1999. Group distinctiveness and intergroup discrimination. In N. Ellemers, R. Spears, & B. Doosje (Eds.), ***Social Identity: Context, Commitment, Content***: 107-126. Oxford: Blackwell.

Kane, A. A., Argote, L., & Levine, J. M. 2005. Knowledge transfer between groups via personnel rotation: Effects of social identity and knowledge quality. ***Organizational Behavior and Human Decision Processes***, 96: 56-71.

Kang, S. K., & Bodenhausen, G. V. 2015. Multiple Identities in Social Perception and Interaction: Challenges and Opportunities. ***Annual Review of Psychology***, 66: 7.1-7.28.

Kapoor, R., & Lim, K. 2007. The impact of acquisitions on the productivity of inventors at semiconductor firms: a synthesis of knowledge-based and incentive-based perspectives. ***Academy of Management Journal***, 50(5): 1133-1155.

Kogut, B., & Zander, I. 1996. What firms do? Coordination, identity, and learning. ***Organization Science***, 7: 502-510.

Kogut, B., & Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. ***Organization Science***, 3: 383-397.

Larsson, R., & Finkelstein, S. 1999. Integrating Strategic, Organizational, and Human Resource Perspectives on Mergers and Acquisitions: A Case Survey of Synergy Realization. ***Organization Science***, 10(1): 1-26.

Levin, S. G., & Stephan, P. E. 1991. Research productivity over the life cycle: Evidence for academic inventors. ***American Economic Review***, 81: 114-132.

Li, G. C., Lai, R., D'Amour, A., Doolin, D. M., Sun, Y., Torvik, V. I., Yu, A., & Fleming, L. 2014. Disambiguation and co-authorship networks of the US patent inventor database (1975–2010). ***Research Policy***, 43(6): 941-955.

Makri, M., Hitt, M., & Lane, P. J. 2010. Complementary technologies, knowledge relatedness and innovation outcomes in high-technology M&As. ***Strategic Management Journal***, 31(6): 602-628.

Meyer, B. D. 1995. Natural and Quasi-Experiments in Economics. ***Journal of Business & Economic Statistics***, 13(2): 151-161.

Moreland, R. L. 1985. Social categorization and the assimilation of "new" group members. ***Journal of Personality and Social Psychology***, 48(5): 1173-1190.

Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1996. Strategic alliances and interfirm knowledge transfer. ***Strategic Management Journal***, 17(Winter Special Issue): 77-91.

Nag, R., Corley, K. G., & Gioia, D. A. 2007. The intersection of organizational identity, knowledge, and practice: Attempting strategic change via knowledge grafting. ***Academy of Management Journal***, 50(4): 821-847.

Nelson, R., & Winter, S. 1982. ***An evolutionary theory of economic change***. Cambridge, MA: Harvard University Press.

Orlikowski, W. J. 1996. Improvising organizational transformation over time: A situated change perspective. ***Information System Research***, 7: 63-92.

Pablo, A. L. 1994. Determinants of acquisition integration level: A decision making perspective. ***Academy of Management Journal***, 37: 803-836.

Paruchuri, S., Nerkar, A., & Hambrick, D. C. 2006. Acquisition integration and productivity losses in the technical core: disruption of inventors in acquired companies. ***Organization Science***, 17(5): 545-562.

Puranam, P., Singh, H., & Zollo, H. 2006. Organizing for Innovation: Managing the Coordination-Autonomy Dilemma in Technology Acquisitions. ***The Academy of Management Journal***, 49(2): 263-280.

Puranam, P., & Srikanth, K. 2007. What they know vs. what they do: How acquirers leverage technology acquisitions. ***Strategic Management Journal***, 28: 805-825.

Ranft, A. L., & Lord, M. D. 2000. Acquiring new knowledge: The role of retaining human capital in acquisitions of high-tech firms. ***The Journal of High Technology Management Research***, 11(2): 295-319.

Ranft, A. L., & Lord, M. D. 2002. Acquiring New Technologies and Capabilities: A Grounded Model of Acquisition Implementation. ***Organization Studies***, 13(4): 420–441.

Rosenkopf, L., & Almeida, P. 2003. Overcoming local search through alliances and mobility. ***Management Science***, 49(6): 751-766.

Schweiger, D. M., & Lippert, R. L. 2005. The critical link in m&a value creation. In G. K. Stahl, & M. E. Mendenhall (Eds.), ***Mergers and acquisitions: Managing culture and human resources*** 17-43. Stanford, CA: Stanford University Press.

Schwenk, C. 1988. The cognitive perspective of strategic decision-making. ***Journal of Management***, 25: 41-55.

Seo, M.-G., & Hill, N. S. 2005. Understanding the human side of merger and acquisition an integrative framework. ***The Journal of Applied Behavioral Science***, 41(4): 422-443.

Shih, M., Sanchez, D. T., & Ho, G. C. 2010. Costs and benefits of switching among multiple social identities. In R. J. Crisp (Ed.), ***The Psychology of Social and Cultural Diversity***: 62-83. Oxford, UK: Wiley-Blackwell.

Shih, M., Young, M. J., & Bucher, A. 2013. Working to reduce the effects of discrimination: identity management strategies in organizations. ***American Psychologist***, 68(3): 145-157.

Singh, J., & Agrawal, A. 2011. Recruiting for Ideas: How Firms Exploit the Prior Inventions of New Hires. ***Management Science***, 57(1): 129-150.

Stephan, W. G., & Stephan, C. W. 1984. The role of ignorance in intergroup relations. In N. Miller, & M. B. Brewer (Eds.), ***Groups in contact: The psychology of desegregation***: 229-257. San Diego, CA: Academic Press.

Tajfel, H. 1974. Social identity and intergroup behaviour. ***Social Science Information***, 13: 65-93.

Tajfel, H. 1979. Individuals and groups in social psychology. ***British Journal of Social and Clinical Psychology***, 18: 183 - 190.

Tajfel, H. 1982. Social psychology of intergroup relations. ***Annual Review of Psychology***, 33: 1-39.

Tajfel, H., & Turner, J. C. 1979. An integrative theory of intergroup conflict. In W. G. Austin, & S. Worchel (Eds.), ***The social psychology of intergroup relations***. Monterey, CA: Brooks/Co.

Tajfel, H., & Turner, J. C. 1986. The social identity theory of intergroup behavior. In S. Worchel, & W. J. Austin (Eds.), ***Psychology of Intergroup Relations***: 7-24. Chicago: Nelson-Hall.

Terry, D. J., Carey, C. J., & Callan, V. J. 2001. Employee adjustment to an organizational merger: An intergroup perspective. ***Personality and Social Psychology Bulletin***, 27: 267-280.

Ulrich, D., Cody, T., LaFasto, F., & Rucci, T. 1989. Human resources at the Baxter Healthcare Corporation Merger: A strategic partner role. ***Human Resources Planning***, 12: 87-103.

Urada, D., Stenstrom, D. M., & Miller, N. 2007. Crossed categorization beyond the two-group model. ***Journal of Personality Social Psychology***, 92(4): 649-664.

Valentini, G. 2012. Measuring the effect of M&A on patenting quantity and quality. ***Strategic Management Journal***, 33: 336-346.

van Knippenberg, D., van Knippenberg, B., Monden, L., & de Lima, F. 2002. Organizational identification after a merger: A social identity approach. ***British Journal of Social Psychology***, 41: 233-252.

van Leeuwen, E., van Knippenberg, D., & Ellemers, N. 2003. Continuing and changing group identities: The effects of merging on social identification and ingroup bias. ***Personality and Social Psychology Bulletin***, 29: 679-690.

Walsh, J. P. 1989. Doing a deal: Merger and acquisition negotiations and their impact upon target company top management turnover. ***Strategic Management Journal***, 10(4): 307-322.

Younge, K. A., Tong, T. W., & Fleming, L. 2015. How anticipated employee mobility affects acquisition likelihood: Evidence from a natural experiment. ***Strategic Management Journal***, 36(5): 686-708.

Zollo, M., & Singh, H. 2004. Deliberate learning in corporate acquisitions: Post-acquisition strategies and integration capability in U.S. bank mergers. ***Strategic Management Journal***, 25: 1233-1256.

TABLES

Table 1. Descriptive Statistics and Correlations Coefficients (N = 7,240; Units= 3,625)

	Variables	Mean	S.D.	Min	Max	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
[1]	Knowledge transfer	0.10	0.73	0	20										
[2]	Treatment	0.25	0.43	0	1	-0.022									
[3]	Post deal	0.5	0.50	0	1	-0.024	0.571								
[4]	R&D team reorganization	0.49	0.50	0	1	-0.052	0.581	0.000							
[5]	Inventor's relative innovation ability	1.23	1.28	0	18.21	0.022	0.152	0.000	0.262						
[6]	In-group collaborative strength	1.39	3.06	0	34	0.010	0.040	0.000	0.068	0.617					
[7]	Inventor’s knowledge divergence	0.91	0.27	0	1	-0.032	0.123	0.000	0.212	0.003	-0.077				
[8]	Inventor’s technological diversity	0.64	0.43	0	1	-0.048	-0.07	0.000	-0.12	-0.637	-0.577	0.016			
[9]	Replacement of acquired R&D top manager	0.16	0.36	0	1	-0.001	0.092	0.000	0.159	0.016	0.027	-0.136	-0.039		
[10]	R&D divestiture	0.44	0.50	0	1	-0.062	0.357	0.000	0.614	0.274	0.066	0.167	-0.111	-0.061	
[11]	Specialization of R&D tasks	0.90	0.30	0	1	0.036	-0.084	0.000	-0.145	0.017	-0.081	-0.084	0.074	-0.477	-0.110
[12]	Knowledge sourcing motives	0.02	1.01	-0.36	3.44	-0.027	-0.199	0.000	-0.343	-0.037	0.248	-0.244	-0.039	-0.154	-0.066
[13]	Overall integration	2.26	0.58	0	4	-0.038	-0.083	0.000	-0.143	-0.016	0.269	-0.182	-0.079	0.197	0.023
[14]	High tech	0.08	0.27	0	1	-0.021	-0.037	0.000	-0.064	0.000	0.260	-0.221	-0.045	0.157	-0.247
[15]	Cross border	0.89	0.31	0	1	0.044	0.111	0.000	0.191	0.057	-0.208	0.165	0.003	-0.063	0.304
[16]	Hostile	0.69	0.46	0	1	0.006	-0.056	0.000	-0.097	0.062	0.043	0.064	0.019	-0.577	0.021
[17]	Technological links	0.07	0.25	0	1	-0.015	-0.072	0.000	-0.124	0.002	-0.06	-0.281	0.037	0.617	-0.239
[18]	Technology similarity	0.61	0.17	0	0.91	0.033	-0.284	0.000	-0.488	-0.081	0.125	-0.078	-0.025	-0.345	-0.143
[19]	Relative size	146.06	92.7	0	280.55	-0.047	0.411	0.000	0.708	0.307	0.068	0.150	-0.086	-0.335	0.741

	Variables	Mean	S.D.	Min	Max	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]
[11]	Specialization of R&D tasks	0.90	0.30	0	1								
[12]	Knowledge sourcing motives	0.02	1.01	-0.36	3.44	0.096							
[13]	Integration investments	2.26	0.58	0	4	-0.154	0.750						
[14]	High tech	0.08	0.27	0	1	-0.038	0.615	0.502					
[15]	Cross border	0.89	0.31	0	1	0.290	-0.591	-0.58	-0.608				
[16]	Hostile	0.69	0.46	0	1	0.228	-0.139	-0.311	0.053	-0.069			
[17]	Technological links	0.07	0.25	0	1	0.090	-0.079	-0.109	0.182	0.096	-0.408		
[18]	Technology similarity	0.61	0.17	0	0.91	0.167	0.143	0.147	0.119	0.120	0.487	-0.288	
[19]	Relative size	146.06	92.7	0	280.55	0.279	-0.219	-0.286	-0.119	0.311	0.389	-0.198	-0.096

Table 2. Differences in acquired inventors' patenting productivity for the pre- and post-acquisition periods

	Average Patent Count at the Inventor level					
	Pre-acquisition		Post-acquisition			
Treatment Group *(Acquisition with R&D team Reorganization)*	Subsample mean:		Subsample mean:		First difference (row):	
	Patent Count=	2.443	Patent Count=	0.732	Patent Count=	-1.711
	(N= 1,781)	(0.057)	(N= 1,781)	(0.057)	(N= 3,562)	
Control Group *(Acquisition with no R&D team Reorganization)*	Subsample mean:		Subsample mean:		First difference (row):	
	Patent Count=	2.389	Patent Count=	1.036	Patent Count=	-1.353
	(N=1,844)	(0.056)	(N=1,844)	(0.056)	(N= 3,688)	
Differences	***First difference*** *(Column)*		***First difference*** *(Column)*		***Difference-in-differences:***	
	Patent Count=	0.054	Patent Count=	-0.303***	Patent Count=	-0.358***
	(N= 3,625)	(0.080)	(N= 3,625)	(0.080)		(0.113)

* p<0.10, ** p<0.05, *** p<0.01. Standard errors in parenthesis.

Table 3. Differences in acquired inventors' Knowledge transfer for the pre- and post-acquisition periods

	Average Knowledge integration at the Inventor level					
	Pre-acquisition		Post-acquisition			
Treatment Group *(Acquisition with R&D team Reorganization)*	Subsample mean:		Subsample mean:		First difference (row):	
	Knowledge transfer =	0.046	Knowledge transfer =	0.068	Knowledge transfer =	0.022
	(N= 1,781)	(0.016)	(N= 1,781)	(0.016)	(N= 3,562)	
Control Group *(Acquisition with no R&D team Reorganization)*	Subsample mean:		Subsample mean:		First difference (row):	
	Knowledge transfer =	0.165	Knowledge transfer =	0.096	Knowledge transfer =	-0.069
	(N=1,844)	(0.016)	(N=1,844)	(0.016)	(N= 3,688)	
Differences	***First difference*** *(Column)*		***First difference*** *(Column)*		***Difference-in-differences:***	
	Knowledge transfer =	-0.120***	Knowledge transfer =	-0.028	Knowledge transfer =	0.092***
	(N= 3,625)	(0.023)	(N= 3,625)	(0.023)		(0.032)

* p<0.10, ** p<0.05, *** p<0.01. Standard errors in parenthesis.

Table 4. Panel negative binomial regression models with random effects for acquired inventors' knowledge integration

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Treatment		0.793***	1.042***	0.777***	1.007***
		(0.289)	(0.339)	(0.289)	(0.338)
Inventor's relative innovation ability x Treatment			0.811**		0.736**
			(0.330)		(0.329)
Inventor's relative innovation ability x R&D team reorganization			-1.122***		-0.848**
			(0.314)		(0.357)
Inventor's relative innovation ability x Post deal			0.044		-0.002
			(0.080)		(0.116)
In-group collaborative strength x Treatment				-0.362***	-0.360***
				(0.107)	(0.107)
In-group collaborative strength x R&D team reorganization				-0.332***	-0.171
				(0.085)	(0.124)
In-group collaborative strength x Post deal				0.085*	0.056
				(0.046)	(0.065)
Post deal	-0.601***	-0.739***	-0.752***	-0.869***	-0.820***
	(0.110)	(0.123)	(0.123)	(0.146)	(0.157)
R&D team reorganization	-4.927***	-5.165***	-5.905***	-4.859***	-5.597***
	(1.212)	(1.206)	(1.189)	(1.224)	(1.250)
Inventor's relative innovation ability	0.304***	0.305***	0.422***	0.331***	0.374***
	(0.067)	(0.067)	(0.085)	(0.076)	(0.095)
In-group collaborative strength	-0.087**	-0.086**	-0.076**	0.103	0.099
	(0.037)	(0.037)	(0.038)	(0.064)	(0.067)
Inventor's knowledge divergence	-0.675***	-0.646***	-0.566***	-0.529***	-0.538***
	(0.199)	(0.199)	(0.200)	(0.201)	(0.202)
Inventor's technological diversity	-0.823***	-0.827***	-0.775***	-0.735***	-0.749***
	(0.171)	(0.171)	(0.181)	(0.183)	(0.187)
Replacement of acquired R&D top manager	2.246***	2.099***	2.552***	2.486***	2.681***
	(0.733)	(0.731)	(0.747)	(0.733)	(0.749)
R&D divestiture	-0.370	-0.345	-0.452	-0.359	-0.416

	(0.646)	(0.651)	(0.644)	(0.649)	(0.655)
Specialization of R&D tasks	2.485***	2.432***	2.416***	2.541***	2.610***
	(0.689)	(0.691)	(0.685)	(0.696)	(0.701)
Knowledge sourcing motives	-1.570***	-1.563***	-1.640***	-1.547***	-1.583***
	(0.432)	(0.429)	(0.421)	(0.437)	(0.431)
Overall integration	-1.270	-1.219	-1.078	-1.203	-1.149
	(0.987)	(0.988)	(1.084)	(1.021)	(1.092)
High tech	4.744***	4.728***	4.801***	4.790***	4.858***
	(0.672)	(0.669)	(0.670)	(0.670)	(0.676)
Cross border	-0.208	-0.127	0.151	0.269	0.227
	(1.719)	(1.697)	(1.849)	(1.780)	(1.875)
Hostile	-4.139***	-4.045***	-3.944***	-4.007***	-3.966***
	(1.247)	(1.229)	(1.284)	(1.274)	(1.308)
Technological links	-6.829***	-6.631***	-6.937***	-6.931***	-7.096***
	(1.161)	(1.151)	(1.151)	(1.166)	(1.172)
Technology similarity	2.156	2.070	1.696	1.899	1.655
	(2.398)	(2.388)	(2.573)	(2.457)	(2.590)
Relative size	0.012	0.011	0.015**	0.012	0.015*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	0.855	0.772	-0.257	-0.108	-0.326
	(2.420)	(2.397)	(2.658)	(2.520)	(2.682)
Ln (r) Constant	1.044***	1.043***	1.099***	1.111***	1.105***
	(0.145)	(0.146)	(0.153)	(0.156)	(0.154)
Ln (s) Constant	0.430	0.445	0.535*	0.600**	0.565*
	(0.298)	(0.298)	(0.300)	(0.302)	(0.298)
Number of Observations	7.240	7.240	7.240	7.240	7.240
Chi2	334.619***	349.364***	391.062***	384.642***	392.052***
Log Likelihood	-1537.904	-1534.132	-1519.457	-1516.604	-1512.073

* p<0.10, ** p<0.05, *** p<0.01. Standard errors in parenthesis.