Abstract

Today’s rapid pace of technological evolution requires organizations to seek swift solutions to acquire the needed skills and talents that are vital to maintain a competitive edge. The reallocation of R&D employees between organizations in particular has attracted the attention of many scholars (for example: Almeida and Kogut, 1999; Agrawal et al., 2006) as this reallocation of workers enables a dynamic rejuvenation of knowledge and social capital in the organization, and consequently plays an important role in furthering the firm’s technological performance (Ettlie, 1980). Given this, organizations are in a continuous hiring and separation loop, generating a flow of R&D workers, in an effort to match the skills they need and those that employees provide, as well as to regenerate ideas and knowledge within the organization. It is thus important to understand the effect of the inbound (i.e. hiring) and outbound (i.e. separation) R&D worker flows on firms’ ability to develop new knowledge.

Research on the impact of employee mobility on organizational performance have mostly focused on the performance implications of mobility in terms of quantity (e.g. number of new hires). This extensive literature has provided evidence of a positive relationship between inbound mobility and performance using patent citations as an indicator of knowledge transfer (see for example: Song et al., 2003; Groysberg and Lee, 2010). In that spirit, some studies have also highlighted the negative impact that employees’ separation can have on organizational performance (i.e. rehiring and retraining costs), neglecting the possible reverse knowledge channels that these separated employees can enable (Agrawal et al., 2006). Recent research has in fact suggested that outbound worker flows may have a positive effect on firms’ technological performance (see for example: Somaya et al., 2008; Agrawal et al., 2006). While these studies provide important insights regarding the performance implications of the mobility of employees, they have focused on the levels of either the inbound or the outbound worker flows, assumed a rather linear relationship between mobility and performance, and ignored the composition of these flows. As organizations tend to observe worker flows in both directions simultaneously (i.e. inbound and outbound), and as these worker flows are likely to be characterized by different degrees of heterogeneity in their skills and experiences (Somaya, et al., 2008), the potential firm gains from new hires and/or separations may depend on both the levels and composition of these flows. Focusing merely on either the inbound or the outbound flows, and most importantly neglecting the composition of these flows, may provide a partial understanding of the effects of the R&D workers flows on the firm.
Building on the organizational innovation, and the labor mobility literatures, we conceptualize the effect of R&D worker flows on firms’ ability to develop new technological knowledge as the result of the level, composition and direction of these flows. We first argue that the levels of inbound and outbound worker flows may, through different mechanisms, influence the technological performance of firms, and then, that this effect is accentuated by the degree of diversity of these flows. We then test these expectations using biannual data on 6350 firm-year observations on French firms involved in R&D activities between 2007 and 2013.

Our findings suggest that the levels of inbound and outbound R&D worker flows have a positive impact on organizations’ patenting activities, but only up to a threshold after which, increases in the levels of worker flows engenders a negative effect. At low levels of R&D worker flows a diverse composition of these flows improves performance, while it negatively affects performance at high levels, accentuating the complexity and management costs resulting from the reorganization of working teams.

This study contributes to current research on labor mobility, knowledge diffusion, and organizational innovation by showing, first, how the firm’s technological performance responds to different levels of new hires and exits, and second, how the levels and diversity of these hires and exits interact to influence the firm’s performance. Our results have practical implications to the firm with respect to managing the levels of inbound and outbound workers’ flows, as well as to balancing the levels and diversity of these flows.
Quantity, Variety, or both? “R&D Worker Flows, Diversity, and effects on Technological Performance”

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Abstract

Organizations are in a continuous hiring and separation loop in an effort to match the skills they need and those that employees provide, as well as to regenerate ideas and knowledge within the organization. The R&D worker flows, in terms of levels and variety, enable a dynamic rejuvenation of knowledge and social capital, which play an important role in driving performance. This study conceptualizes the effect of R&D worker flows on the technological performance of firms, as resulting from the levels of these flows, as well as from their degrees of diversity. Using biannual data on 6350 firm-year observations on French firms involved in R&D activities between 2007 and 2013, we suggest that the levels of R&D worker flows (both incoming and outgoing) have an inverted u-shaped effect on technological performance (namely, patent applications). Our findings also suggest that the diversity of these flows (in terms of distinct knowledge backgrounds) moderates this effect, such as at low levels of worker flows (for both inbound and outbound flows), a diverse composition of these flows improves performance, while it negatively affects performance at high levels, accentuating the complexity and management costs of the reorganization of working teams. We discuss the implications of these results for theory and policy.

Keywords: Worker flows, mobility, R&D, diversity, technological performance, inbound mobility, outbound mobility
1. Introduction

Today’s rapid pace of technological evolution requires organizations to seek swift solutions to acquire the needed skills and talents that are vital to maintain a competitive edge. The reallocation of R&D employees between organizations in particular has attracted the attention of many scholars (for example: Almeida and Kogut, 1999; Agrawal et al., 2006) as this reallocation of workers enables a dynamic rejuvenation of knowledge and social capital in the organization, and consequently plays an important role in furthering the firm’s technological performance (Ettlie, 1980). Given this, organizations are in a continuous hiring and separation loop, generating a flow of R&D workers, in an effort to match the skills they need and those that employees provide, as well as to regenerate ideas and knowledge within the organization. It is thus important to understand the effect of the inbound (i.e. hiring) and outbound (i.e. separation) R&D worker flows on firms’ ability to develop new knowledge.

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characterized by different degrees of heterogeneity in their skills and experiences (Somaya, et al., 2008), the potential firm gains from new hires and/or separations may depend on both the levels and composition of these flows. Focusing merely on either the inbound or the outbound flows, and most importantly neglecting the composition of these flows, may provide a partial understanding of the effects of the R&D workers flows on the firm.

Building on the organizational innovation, and the labor mobility literatures, we conceptualize the effect of R&D worker flows on firms’ ability to develop new technological knowledge as the result of the level, composition and direction of these flows. We first argue that the levels of inbound and outbound worker flows may, through different mechanisms, influence the technological performance of firms, and then, that this effect is accentuated by the degree of diversity of these flows. We then test these expectations using biannual data on 6350 firm-year observations on French firms involved in R&D activities between 2007 and 2013.

Our findings suggest that the levels of inbound and outbound R&D worker flows have a positive impact on organizations’ patenting activities, but only up to a threshold after which, increases in the levels of worker flows engenders a negative effect. At low levels of R&D worker flows a diverse composition of these flows improves performance, while it negatively affects performance at high levels, accentuating the complexity and management costs resulting from the reorganization of working teams.

This study contributes to current research on labor mobility, knowledge diffusion, and organizational innovation by showing, first, how the firm’s technological performance responds to different levels of new hires and exits, and second, how the levels and diversity of these hires and exits interact to influence the firm’s performance. Our results have practical implications to the firm with respect to managing the levels of inbound and outbound workers’ flows, as well as to balancing the levels and diversity of these flows.
The remainder of the paper is structured as follows. Section 2 contains a discussion on the levels and the composition of worker flows, and technological performance. Section 3 describes the data. Section 4 presents the results of the regression analyses. Section 5 discusses the results and presents the implications, limitations and avenues for further research.

2. Theoretical Framework

The development and accumulation of knowledge capital through R&D assists firms in developing and maintaining competitive advantage. A particularly important resource in this process of knowledge creation and technological development is R&D employees (Faems and Subramanian, 2013; Merton, 1973; Nelson, 2003). R&D workers hold and transmit valuable skills and technological knowledge as well as key social capital that represent critical inputs for inventive activity (Brown and Eisenhardt, 1995). The management of R&D workers has thus become increasingly important as a mechanism to rejuvenate knowledge and social capital within the firm (Edström and Galbraith, 1977).

The movement of R&D workers into and out of jobs has been termed as the worker flows in the labor economics literature (Burgess et al., 2000). This flow of workers is driven by what Jovanovic (1979) calls job matching (and mismatching). The reallocation of workers is triggered by a process of continuous strive to improve the match between the skills firms demand and those that the employees provide. The literature on labor economics suggests that the quality of this job matching process is a critical determinant of performance, for both the employer and the employee (Jovanovic; 1979). A job match is dissolved if it is of unsatisfactory quality, meaning that either the organization’s needed skills do not match the skills the worker provides, or vice versa (a mismatch). Under these circumstances, the worker is separated from the employer, allowing for a new job match to happen (a new hiring), and creating a flow of workers. Following this logic, as technologies and markets evolve, organizations retaining low levels of worker flows can suffer from increasing mismatches (Jovanovic; 1979) - i.e. from lack
of relevant skills to innovate. In this study, we are concerned with understanding the technological performance implications of the reallocation of R&D workers within firms.

Owing to the important contribution of R&D workers to the firm’s knowledge and social capital assets, several studies have attempted to explain how and why the movement of R&D workers between organizations influences performance. Being carriers of distinct recent experiences, incoming flows of R&D workers may provide established R&D teams with specific knowledge and/or new perspectives on how to overcome bottlenecks in their ongoing projects, with new market insights that permit to review and reframe their ongoing development projects to new market niches, and with connections to relevant partners for their R&D projects (Phillips, 2002; Rosenkopf and Almeida, 2003; Song et al., 2003; Price, 1977). Yet, since, according to the organizational learning literature, organizations are limited in their ability to accommodate large challenges to their resources and routines (Becker and Murphy, 1992; Cohen and Levinthal, 1990), different levels of new hires may have different impacts on the firm’s technological performance. Excessive levels of new hires can increase the complexity of the communication structures between R&D team members (Zenger and Lawrence, 1989) and disrupt the working dynamics of existing teams by initiating a need to redesign existing interactions that are critical for the effective functioning of the team (Price, 1977; Mowday et al., 1982). These disruptions to the R&D team may engender additional coordination and management costs that can become a burden to the firm and eventually have a negative impact on its performance (Becker and Murphy, 1992).

While prior empirical evidence focused mostly on the incoming worker flows, the outgoing flow of R&D workers may also influence the firm’s technological performance. Failure to account simultaneously for the outbound R&D worker flows (separated employees), which are also an active part in workers’ reallocation, limits our understanding of how worker flows influence firms’ technological performance. The few studies that examine workers outflow provided non-consensual evidence on their effect. These studies have conventionally proposed a negative impact of employees’ separation on organizational performance (see for example: Phillips,
2002; Batt, 2002), under the assumptions that as employees leave a firm, they carry key tacit knowledge with them to their next employer, and that separations can trigger significant rehiring and training costs that can disrupt the firm. A number of more recent studies, however, and inline with the network theory, have proposed that the outgoing flow of R&D workers may allow for the establishment of new inter-firm ties, which trigger reverse knowledge and social capital channels (Breschi and Lissoni, 2005; Agrawal et al., 2006).

In the same vein, prior literature has focused on explaining the performance implications of employees’ mobility, without considering the heterogeneity of the “moving employees”. R&D employees are largely different from each other within firms in terms of the knowledge and social capital assets that they hold and have access to (Faems and Subramanian, 2013). New R&D hires for instance are likely to come from a variety of different knowledge areas (e.g. different employers and/or industries) and have access to distinct networks. While new hires may expose the firm to new knowledge sources and networks, the diverse composition of these new hires ensures the breadth and variety of these knowledge and social capital assets (Ahuja and Katila, 2001; Leiponen and Helfat, 2010), which can enable novel combinations of knowledge, and eventually lead to improved technological performance (Cohen and Levinthal, 1990; Bercovits and Feldman, 2011). However, at high levels of worker flows, which can already be problematic for the firm, an increase in the variety and breadth of knowledge can trigger new challenges to the firm. For instance, excessive exits to diverse destinations can engender additional monitoring costs (Goerzen and Beamish, 2005), and may may lead to the risk of overloading (Cohen and Levinthal, 1990; Lin, 2014).

Hence, in this study, we build on the labor mobility and the organizational learning literatures, to examine the effect of the R&D worker flows on firms’ technological performance. The labor mobility literature argues that R&D workers retain knowledge (and social capital), which is founded on their prior professional experiences, that travels with them as they move among firms. Understanding R&D workers as an economic input for new technology development, the labor economics literature focuses on the effect of levels of worker flows, and tends to
argue that retaining a large number of employee-employer mismatches has a negative impact on performance. The organizational learning literature on the other hand suggests that organizations are rather limited in their capacities to absorb new knowledge, and that diverse knowledge assets can lead to additional challenges and costs. In addition, this stream of literature suggests that informal linkages/ties are also valuable in the process of learning and new technological development. Therefore, the effect of worker flows not only depends on the level and composition of new hires, but also on the those of separated employees, owing to the informal ties that are likely to be retained between the focal firm’s R&D workers and the separated employees.

Thus, based on these streams of literatures, we conceptualize the effect of worker flows on the firm’s technological performance as a result of the direction (incoming vs. outgoing), the level, and the composition of these flows. We will argue that the levels of the R&D worker flows have a positive impact on technological performance up to a threshold, after which, higher levels of worker flows negatively impact performance, as the organization needs to readapt its capacity to integrate excessive knowledge and social capital resources. In particular, we will argue for a curvilinear effect on performance for both inbound and outbound worker flows. We will then argue that the effect of these worker flows will be moderated by their degrees of diversity, which shapes the variety of knowledge that these flows can bring to the firm. In particular, we propose that the varied origins of new hires, indicating the diversity of familiarity with different types of organizations, will moderate the impact of the levels of inbound R&D worker flows on technological performance, while the varied destinations of separations, indicating the diversity of new social ties with different types of organizations, will moderate the impact of the levels of outbound R&D worker flows on technological performance.

1 For example, and Hopenhayn and Rogerson (1993), and Autor et al. (2007) found that employee protection programs increase the number of employee-employer mismatches within the firm, leading to negative effects on performance.
2.1 Levels of worker flows and technological performance

The mobility of workers has attracted the attention of many scholars and industry practitioners due to its importance in sharing knowledge and social capital, and consequently, in driving competitive advantage (Barney, 1991; Arrow, 1962; Cappelli, 2000). For instance, using patent data of 74 firms between 1990 and 1995, Rosenkopf and Almeida (2003) suggested that the mobility of inventors facilitate inter-firm knowledge flows. Tacit knowledge, which includes an overall understanding of the patterns of evolution of state-of-the-art technologies, is embodied in individuals (Song et al., 2003). As individuals join a new employer, their tacit knowledge also moves to the new employer (Szulanski, 1996; Song et al., 2003). This movement exposes the organization to new external ideas that can complement the exploitation of pre-existing ideas (Singh and Agrawal, 2011), allowing the firm to overcome performance constraints imposed by depending mainly on “internally grown resources and capabilities” (Singh and Agrawal, 2011; Barney, 1991).

Yet, while new hires can have a positive impact on its technological performance, high levels of inbound worker flows may engender a negative effect by disrupting the functioning of existing R&D teams. Intense and long-established interactions between R&D team members are critical to the creation of common codes through which the individuals interact, communicate and collectively create new knowledge (Price, 1977; Bertolotti et al., 2015; Drach-Zahavy and Somech, 2001). In organizations with excessive levels of incoming R&D worker flows, the structure of the R&D employees is regularly changing in a manner that does not permit the establishment of long-standing interactions among the team members (Price, 1977; Mowday et al., 1982). This lack of intensive, well-established interactions decreases the integration of R&D workers (Price, 1977), and may engender a negative effect on technological performance.

In addition, the cost of coordinating a group of new hires increases as the number of the hires increase (Becker and Murphy, 1992). Likewise, increases in the levels of new R&D workers can result in additional coordination and search costs. The new knowledge and social capital assets
that these new R&D workers bring can broaden the organizational search for new technologies and market opportunities that can lead to the risk of over-searching (Laursen and Salter, 2006). In addition, since organizations are limited in their knowledge processing capabilities (internalizing new knowledge and combining it with the existing knowledge base) (Jantunen, 2005, Cohen and Levinthal, 1990), a large increase in new hires can drain a firm’s knowledge-utilization capabilities and divert its focus in the direction of specific knowledge domains (Herstad et al., 2015), which might engender a negative impact on technological performance, especially in the short-term. Moreover, new R&D hires will likely need to learn the ropes before being totally integrated within the R&D department. This introduces additional training costs that can be substantial at excessive levels of R&D hires.

Based on the discussion above, we hypothesize the following:

**H1a:** The levels of inbound R&D worker flows have an inverted U-shaped effect on a firms’ technological performance.

When focusing on the effect of outbound worker flows, the evidence and arguments are less straightforward. Conventionally, a negative impact is expected (e.g. Huselid, 1995; Cooper, 2001; Phillips, 2002; Batt, 2002; Wezel et al., 2006). Cooper (2001) for instance stated that “a portion of the firm’s knowledge is embodied in the worker, and thus cannot be retained when the worker leaves”, suggesting that employee-firm knowledge transfer ends when employment ends. Similarly, Wezel et al. (2006) investigated the effect of mobility on performance, namely on dissolution risk, and suggested that employees’ separation, especially in groups, triggers transfer of routines across organizational boundaries, creating a dissolution risk for the former organization.

However, Campbell et al. (2012) suggest that employees with low human capital are more likely to exit a firm than those with high human capital. This implies that the risks associated with the exit of employees with low human capital, who often contribute less to total created value than employees with high human capital, can be negligible. These exits often allow firms to replace
human capital that is deemed to be unable to improve performance (Jovanovic, 1979), suggesting that employees’ separations may have a positive effect on firms’ performance. In fact, a number of studies (e.g. Agrawal et al., 2006; Corredoira and Rosenkopf, 2010; Somaya et al., 2008) have shown that employees’ exits may actually engender a positive impact on firm’s performance. Using the number of outsourced patent applications, Somaya et al., (2008) suggest that outbound mobility, especially to cooperators, can enhance technological performance. Since separated employees are likely to “stay in touch” with former colleagues the social relationships with former colleagues allow knowledge and social capital spillovers from the worker’s new employer, to his/her former employer (Levin, 1988; Agrawal et al., 2006; Somaya et al., 2008). Thus, from a network perspective, worker separation enables new ties between two new nodes (the new and the former employer), of a network. The newly created tie can reduce the distance to other nodes within the same network, allowing for new knowledge exchange opportunities (Breschi and Lissoni, 2005; Singh, 2005). Given the externalities of R&D knowledge production, a piece of knowledge may have different applications, i.e. it can often be utilized by more than one organization simultaneously, without necessarily impacting the originating organization negatively (Arrow, 1962). In this sense, the outbound worker flows trigger a reverse knowledge and social capital spillover effect; from the new employer to the former employer (von Hippel, 1987).

However, despite their ability to create reverse knowledge flows, large levels of employees’ separations can trigger additional challenges to the firm that can have an adverse effect on its performance. These reverse knowledge flows are based on the informal relationship that separated employees maintain with former colleagues (Madsen et al., 2003). At excessive levels of separations, the separated employees’ “former colleagues” at the focal firm are likely to have moved to another employer. In other words, the focal firm needs to keep employees that have previously worked with the separated employees in order to benefit from these reverse knowledge flows. Thus at excessive levels of outbound worker flows, forward knowledge flows (from the focal firm to the employee’s new employer) are likely to outweigh the benefits of the reverse knowledge flows, and eventually lead to an adverse effect on the firm’s performance.
In addition, the coordination and search costs also increase with the number of R&D workers’ exits. Excessive separations may introduce new challenges to organizations. First, since knowledge in general, and R&D knowledge in particular, is embodied in people (i.e. R&D workers) (Cooper, 2001), excessive separations can result in the erosion of existent knowledge stocks. Although organizations can replace separations by hiring new workers, this will perhaps take a substantial amount of time and will introduce important costs and challenges. New R&D hires will likely need to learn the organizational routines and create linkages with their new colleagues before they can fully contribute to the technological performance of the firm. Thus, when facing an extensive drain of R&D workers, the technological focus of the R&D team’s development projects, as well as the form of organizing R&D activities, are likely to change drastically, limiting the swift integration of knowledge that existing employees could gain by getting in touch with their separated colleagues. Moreover, excessive separations can affect the R&D team’s communication, since the remaining R&D workers are likely to lose important collaborators, and reference points. As the communication among the R&D team becomes less informal, the performance of the focal firm’s R&D team may be reduced.

Based on the discussion above, we hypothesize the following:

**H1b:** The levels of outbound R&D worker flows have an inverted U-shaped effect firms’ technological performance.

**2.2 Interaction between worker flows’ levels and diversity**

While the levels of R&D worker flows are critical to the rejuvenation of the firm’s knowledge stocks and social capital, it should be stressed that R&D workers are not homogenous (Becker and Murphy, 1992). As Becker and Murphy (1992) proposed, “The composition of the research work force in terms of knowledge heterogeneity, in addition to its size, matters in determining the production of new knowledge”. Ashby’s (1960) argues that “the internal variety of a system (e.g. an organizations) needs to match the variety of the external environment”. It is thus
important to consider the composition of the R&D worker flows in addition to their levels, when studying the impact of these flows on firms’ performance.

Previous studies suggest that access to broader types of knowledge sources is likely to enhance technological innovations (Laursen and Salter, 2006; Ahuja and Katila, 2001). Diversity in terms of knowledge sources and experience increases the potential for novel associations and hence for new technological developments and innovations (Cox, 1991; Cohen and Levinthal, 1990). With regards to R&D worker flows, knowledge diversity is expressed in the R&D workers’ experiences, and know-how. For instance, new hires are likely to carry specific knowledge and social capital assets acquired from their previous employers (Agarwal et al., 2004). Prior work experience at universities, competitors or in unrelated industrial activities may provide workers with different skills and in particular may shape their analytical frames differently. Similarly separated employees are likely to develop specific skills, access specific knowledge and social capital assets, and mold their analytical frames, based on the new employers they join. Therefore, varied origins of new hires and destinations of exits introduce a diverse spectrum of knowledge and social capital that may support the generation of competitive advantage (Somaya et al., 2008). Unlike other extensively studied diversity features (e.g. age, nationality, etc.) which describe the worker demographics but not their specific professional experience or competences, the experience gained in the prior job (for new hires) or in the next job (for exits) adds to specific competences and analytical frames of the workers (Jackson and Ruderman, 1995).

R&D intensive firms in particular require a diverse range of specialized knowledge and access to wide networks (Tijssen, 2001). Homogenous sources of R&D worker flows are likely to hold overlapping knowledge and social capital (Madsen et al., 2003), which can limit the possibility to access different types of ideas and skills that may be required for technological development. Heterogeneous sources of both inbound and outbound flows can provide the firm with an increased and varied stock of knowledge and social capital, allowing the firm to tap
into diverse markets and technological knowledge (Almeida et al., 2003; Laursen and Salter, 2006; Leiponen and Helfat, 2009).

A firm that hires new employees from different types of employers (for example, from universities, national business enterprises, and international business enterprises) has access to broader and more diverse knowledge sources and networks than a firm that hires from one single knowledge domain (for example, hiring from universities only, or from national business enterprises only). In this sense, diversity in the inbound R&D worker flows enables organizations to access a broader pool of technological opportunities (Madsen et al., 2003). By increasing awareness and capacity to frame different new problems in a variety of forms, diversity of the R&D worker flows increases the organization’s absorptive capacity (Cohen and Levinthal, 1990), improves knowledge sharing, acquiring, and recombining, as well as improves the search for novel combinations (Østergaard et al., 2011). Combining a variety of external knowledge that is acquired through the inbound worker flows, promotes the generation of groundbreaking ideas and assists in linking different knowledge bases (Katila and Ahuja, 2002; Smith et al., 2005), which are likely to improve technological performance.

However, as the levels of inbound worker flows assume very high levels there is a risk that increased diversity triggers tensions in the firm’s organization that may obstruct knowledge creation (Herstad et al., 2015; Østergaard et al., 2011; Madsen et al., 2003). For instance, Østergaard et al. (2011) suggest that diversity can lead to increased transaction costs due to the difficult interaction and communication between different knowledge bases, which can, eventually, negatively impact performance. As a new knowledge background is added to the range of knowledge backgrounds “x” that the current R&D employees “y” hold, the number of possible knowledge combinations rises to $y^*(x+1)$. Combined with excessive levels of worker flows, diversity increases this number of combinations exponentially, and this can raise additional costs and challenges to the organization, and eventually impede technological performance.
At low levels of inbound worker flows, diversity of the worker flows can accentuate the positive relationship between the levels of these flows and technological performance. Although the integration of a relatively small number of new R&D employees that share similar professional experiences (and thus share overlapping perspectives) can represent a small disruption to the ongoing R&D activities, it generates a relatively small number of opportunities to engage in organizational change, to reconsider current modes of selecting, framing and solving problems, and to restructure existing networks (Madsen et al., 2003; Faems and Subramanian, 2013). While, the proposals from these small and relatively homogenous R&D hires may lead to the questioning of some established practices, which may result in some internal adjustments and improvements or the reinforcement of some internal strategies regarding how and which R&D activities to conduct, the integration of a low number of R&D employees with diverse prior professional experiences may instead propose preferable conditions for knowledge and social capital rejuvenation (Laursen and Salter, 2006). The heterogeneous knowledge bases and social capital that these new employees bring to the firm can fill out lacking knowledge components and/or introduce the firm to formerly inaccessible or unnoticed networks, which can promote the development of new and different ways of approaching R&D projects, and eventually improving the R&D outcome. Thus, the integration of a low number of employees from a variety of origins (in terms of employers) may have a stronger positive effect on technology performance than from less varied origins.

As the number of new hires increases, the costs and the extent of the disruption of the ongoing and planned R&D activities of the firm increases. In such case, heterogeneous prior professional experience of new hires can introduce substantial disruption to the firm’s R&D activities as they (diverse new hires) can exhaust the possible new combinations of the firm’s existing capabilities (Cohen and Levinthal, 1990). For R&D teams, excessive and diverse new hires introduce additional challenges for existing R&D employees to consider the substantial volume of different knowledge and social capital components and their potential relationships simultaneously (Østergaard et al., 2011). The integration of a high number of new R&D employees with a relatively similar prior professional experience may then permit the creation
of a consensual view for a strategic change in the firm. While possessing their individual differences, new hires that come from somewhat similar origins (in terms of previous employers), may share the same views on how technologies and markets evolve, and on the relevant problems to address and the promising opportunities to exploit. These shared views will then cause less disruption than the views of a diverse group of new hires (Herstad et al., 2015; Lin, 2014). For instance, following the hiring of a large number of employees with similar knowledge backgrounds and social capital, the process of recreating the internal work routines and language may be less difficult than if the new hires were highly diverse since the number of alternative modes of working and communication that each employee is used to are different. Thus, the integration of a large number of employees with a similar prior professional experiences may have a stronger positive effect on technology performance than that with diverse prior professional experiences.

Based on the discussion above, we hypothesize the following:

**H2a:** *The inbound worker flows diversity moderates the relationship between the levels of inbound R&D worker flows and technological performance, such that diversity accentuates the positive effect of low levels of inbound worker flows, and the negative effect of high levels of inbound worker flows.*

Similarly, exits to diverse destinations allows for the creation of a variety of new ties, enabling the firm to learn from multiple and diverse new knowledge sources. In such instances, the low levels of worker flows place the firm in a favored condition to leverage the knowledge and social capital assets associated with diversity (since low levels of worker flows do not necessarily trigger substantial coordination or transaction costs). The costs associated with the loss of a small number of employees to diverse types of employers may be relatively small for the focal firm. As these separated employees have previously worked together in the focal firm, their interrelationships, as well as their relationships with their former colleagues in the focal firm, are maintained, allowing for the creation of several, distinct knowledge channels between
their new employers, as well as between the new employers and the focal firm (Somaya et al., 2008). This exposes the focal firm’s R&D workers to a broad selection of approaches, as well as connections, to tackle existing technological bottlenecks, and to handle ongoing and potential projects without exhausting the firm’s absorptive capacity (Cohen and Levinthal, 1990). When the separated employees join very similar employers, they expose the focal firm’s R&D workers to overlapping knowledge and social capital (Madsen et al., 2003). Consequently, the marginal benefit from the reverse knowledge and social capital channels created by separated employees working at diverse new employers are greater than those created by separated employees working at relatively similar employers. Thus, at low levels of the outgoing worker flows, diversity can accentuate the positive relationship between the levels of these flows and technological performance.

At high levels of outbound worker flows, which are already problematic, diversity of these flows may engender additional challenges (e.g. management and coordination costs), and eventually, may accentuate the negative relationship between R&D worker flows and technological performance (Cohen and Levinthal, 1990; Lin, 2014). Excessive exits to diverse destinations will allow the R&D workers at the focal firm to create informal ties with diverse organizations that possess heterogeneous resources and capabilities. As the number of new ties increase, the monitoring costs will also increase, especially if the R&D workers at the focal firm are unfamiliar with the involved organization’s routines and processes (Goerzen and Beamish, 2005), resulting in the exhaustion of their attention and search resources. Moreover, the diverse knowledge assets that are acquired through employees exists will have to be recombined with existing knowledge stocks. If the multiple resources that are coming from the informal ties (enabled by employees exits) are quite diverse in their nature and context of applicability, the R&D workers at the focal firm will be overloaded to process such sizeable and diverse knowledge assets, which can have negative effects on performance (Cohen and Levinthal, 1990; Lin, 2014). Additionally, excessive separations (which are more likely to create forward knowledge channels than reverse ones) to diverse destinations can trigger forward knowledge channels to diverse organizations, including competitors, which may lead to the risk of knowledge erosion.
Based on the discussion above, we hypothesize the following:

**H2b:** The outbound worker flows diversity moderates the relationship between the levels of outbound R&D worker flows and technological performance, such that diversity accentuates the positive effect of low levels of outbound worker flows and the negative effect of high levels of outbound worker flows.

### 3. Data and Sample

The quantitative analysis is based on firm-level data from the “annual survey on resources devoted to research and development in business enterprises” and the “survey on R&D researchers and engineers in business enterprises and institutes of professional and technical studies”, which are conducted by the French ministry of higher education and research based on the Frascati Manual. Both surveys are compulsory and address all business enterprises located in France, including overseas departments and collectivities which carry out research and experimental development work (R&D) for their own account or on behalf of a third party. Permission to access and use the data was granted by the French “Comité du secret statistique” (Statistical Confidentiality Committee).

We merged the data on technological performance and R&D activity from the first survey with data on R&D workers flows from the second survey using the business identification number (French SIREN). The survey on “resources devoted to research and development ...” provides detailed information on firms’ R&D activities (e.g. intramural R&D spending, extramural R&D spending, public R&D funding, etc.) as well as performance indicators (e.g. revenue, patent applications, etc.). The survey on R&D researchers and engineers in business enterprises and institutes of professional and technical studies provides detailed information (level and

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2 The following phrase is copied from the original survey and translated to English: “..., this survey, recognized as being of general interest and of statistical quality, is mandatory”. The same phrase was found in the different survey waves that are used used in this paper.
composition) on the inbound and outbound workers flows. Given that some questions in the survey have changed over the years and some information is not available for the early years, and given that we only had access to data on the R&D worker flows for the years 2007, 2009, 2011 and 2013, and after excluding firms with missing data, our final dataset includes biannual data on 6350 firm-year observations on French firms involved in R&D activities between 2007 and 2013.

3.1 Measures

3.1.1 Dependent variable – Patent application
In line with previous studies (Faems and Subramanian, 2013; Belderbos et al., 2010), we measure the technological performance of firms using patent applications’ count. Patents with several applications (i.e. French National Institute of Intellectual Property, European Patent Office, United States patent and trademark office, …) are counted as one application. We used a lagged patent applications’ count at year $t+1$ to, first, alleviate potential endogeneity problems of our dependent variable and second, to capture the effect of the worker flows and account for possible lags between performance and filing for a patent.

3.1.2 Independent variables

**R&D worker flows:** Following Burgess et al. (2000) and Ilmakunnas et al. (2005), the inbound R&D worker flows, $IF$, variable measures all movements of workers into a given organization in a given year, while the outbound R&D workers flow, $OF$, measures all movements of workers out of a given organization in a given year. In order to test for the curvilinear relationships, we include the quadratic terms of both variables ($IF$ and $OF$).

**Worker flows diversity:** Worker flows diversity refers to the distribution of differences in the worker flows’ professional experiences just before or just after the focal firm, which reflect the skills, interests and the mind frames of workers. Thus, our measure of inbound diversity captures the distribution of differences in the new hires’ former employers just before joining

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3 We used the annual survey on R&D researchers and engineers in business enterprises and institutes of professional and technical studies to obtain the lagged variable
the focal firm, while outbound diversity captures the distribution of differences in the separated employees’ new employers just after leaving the focal firms. The survey on “R&D researchers and engineers …” provides detailed information on the origin of new hires (e.g. Inflow of R&D researchers or engineers directly following the completion of their highest degree; R&D carried out in a French public body; Inflow from other business enterprise outside the company and located abroad, etc.), and the destination of separated employees (e.g. R&D carried out in a French public body; outflow from other business enterprise located in France and outside the company, etc.). This categorization captures the differences in the knowledge bases, analytical frames, and social capital that new hires and separated employees have access to. For example, freshly graduated new hires will have a much more scholastic perspective of the creative problem than new hires that were former R&D employees in national public organizations. Similarly, exits to organizations within the same activity as the focal firm (e.g. R&D) bring in different knowledge than exits to organizations in different activities.

Using information on the origins of new hires and destinations of exits, we adopted Shannon’s (1948) entropy statistic to measure worker flows’ diversity. The Shannon’s entropy statistics measures the randomness of a distribution and takes into account both variety and balance (Stirling, 2007). This measure is commonly used in innovation studies for diversity (e.g. Østergaard et al., 2011; Frenken and Nuvolari, 2004; Rijnsoever et al., 2015; Petersen et al., 2016). The entropy statistic is calculated using the following formula:

\[
\text{Shannon’s diversity} = - \sum_{i=1}^{n} p_i \ln p_i = -1 \times (p_1 \ln p_1 + p_2 \ln p_2 + p_3 \ln p_3 + \cdots + p_n \ln p_n)
\]

Where \( n \) is the total number of different types of organizations that new hires come from or separated employees go to, and \( p_i \) is the proportion of \( n \) made up of the \( i^{th} \) type of organization. Accordingly, worker flows with no diversity at all (\( n=1 \)) has an index of 0, and as diversity increases, Shannon’s index increases. Using the formula stated above, we calculated the diversity of both inbound and outbound R&D workers’ flows.

\[\text{4 See Appendix 1 for a detailed overview of the origins and destinations used in calculating the diversity measures}\]
3.1.3 Control variables: We tried to account for alternative explanations for technological performance, by including a series of controls. The innovation literature has shown that R&D intensity and R&D outsourcing are important drivers of patenting (Somaya et al., 2008; Ahuja and Katila, 2001; Somaya et al., 2007). We thus control for *R&D intensity*, defined as a firm’s R&D expenditures divided by total sales, and for *extramural R&D spending*, using the ratio of extramural R&D spending to total R&D spending. Since access to external R&D funding can affect the organization’s performance (Faems and Subramanian, 2013), we included a binary variable that captures whether the organization received external R&D funding (public or private) or not within a given year. R&D employees are composed of researchers and engineers, technicians, and other administrative staff. Since it is the R&D researchers and engineers who mainly contribute to the knowledge stocks of R&D firms, we control for the portion of *researchers and engineers* defined as the number of researchers and engineers divided by the total number of R&D employees within a firm. Finally, since inventive capabilities may be associated with the size of the firm (Herstad et al., 2015; Somaya et al., 2008), we added a variable that controls for firm *size*, defined as the number of employees in the organization (in logs). Since the share of inventive firms varies between industries and throughout time, we used separate industry and year dummies to control for industry-specific effects and time-specific effects, respectively. The summary statistics and correlations are contained in Table 1, while the distribution of the sample by industry is contained in Table 2.

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Insert Table 1 about here

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Insert Table 2 about here

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3.2 Empirical setting

The analysis is performed on panel data comprised of bi-annual observations between 2007 and 2013. The total number of patent applications is a non-negative count variable with a positively skewed distribution, thus, both Poisson models and negative binomial models are good candidates to analyze our data (Hausman et al., 1984). Fixed effects models in non-linear models are generally inconsistent in short panels (in our case T=4) with large “N” due to the incidental parameters bias (Wooldridge, 2011; Greene, 2003; Hsiao, 1986). In our model, the incidental parameters problem is caused by having T=4 observations to estimate each individual effect, so that as “N” grows, the estimate of the individual effect remains random (this is a specific issue of non-linear models where contrary to the linear models this randomness does not get “averaged out”). We conducted a Hausman’s (1978) test to compare the fixed and random effects models’ estimators. Hausman’s test suggests that the random-effects model is more appropriate. Therefore, and in line with the literature (see, e.g. Hottenrott and Lopes-Bento, 2015; Somaya et al., 2007; Wang, 2016), we analyze the data using Poisson regressions5 with random effects estimated using xtPoisson procedure in the Stata 13.0 statistical package. The Poisson estimator is consistent for panel data models even under misspecification of the distributions as long as the mean specification is accurate (Gourieroux et al. 1984). The negative binomial estimators however are inconsistent if the true distribution of the errors is not as hypothesized (Gourieroux et al. 1984).

4. Results

Table 3 reports the results of the random-effect Poisson panel regression. Model 1 represents the basic model, which includes only our concerned control variables. Model 2 adds independent variables pertaining to the worker flows to Model 1. Particularly, Model 2a

5 xtpoisson is also more flexible and robust than xtnbreg (Zucker et al., 2007; Kennedy, 1998).
includes the variable for the inbound worker flows and its quadratic term, while Model 2b includes the variable for outbound worker flows and its quadratic term. Model 3, which represents our full model, adds independent variables pertaining to the diversity measures to Model 2. In particular, Model 3a includes the inbound worker flows’ diversity, while Model 3b includes the outbound worker flows’ diversity.

In Models 2a and 3a in Table 2, the coefficient of the levels of the inbound workers’ flow is positive and significant (p<0.001), and the coefficient of the square term of the level of inbound worker flow is negative and significant (p<0.001). In Models 2b and 3b, the coefficient of the levels of the outbound workers’ flow is positive and significant (p<0.001), while the coefficient of the square term of the level of outbound worker flow is negative and significant (p<0.001). These results provide statistical support for hypotheses 1a and 1b, which predict that the levels of inbound, as well as of outbound, worker flows, respectively, have an inverted u-shaped relationship with the firm’s technological performance.

In model 3a, the coefficient of the interaction between the inbound worker flows’ diversity and levels are negative and significant (p<0.001), while the coefficient of the interaction between the inbound worker flows’ diversity and the quadratic terms for inbound worker flows is positive and significant (p<0.1). In model 3b, the coefficient of the interaction between the outbound worker flows’ diversity and levels are negative and significant (p<0.001), while the coefficient of the interaction between the outbound worker flows’ diversity and the quadratic terms for outbound worker flows is positive and significant (p<0.05). These results support Hypotheses 2a and 2b, which predict that the inbound worker flows’ diversity, as well as the outbound worker flows’ diversity, moderates the relationship between the levels of inbound,
and outbound, R&D worker flows, respectively, and technological performance. The control variables are significant in all of the models, and their effects point in directions that are consistent with prior research.

In order to further understand how the worker flows’ diversity moderates the effect of different levels of worker flows on technological performance, we plotted the average marginal effects of different levels of worker flows at different degrees of diversity, while keeping all other covariates at their means. Figures 1 and 2 plot the marginal effects of inbound and outbound R&D flows, respectively, on performance (The left side of the graph is a zoom-in of what is happening at low levels of the graph on the right).

Figure 1 clearly shows that diversity improves technological performance at low levels of inbound worker flows. As the levels of inbound worker flows increase, higher degrees of diversity engender an adverse effect on performance. The marginal effects’ plot thus shows support of hypothesis 2a, which predicts that diversity accentuates the positive effect of low levels of inbound R&D worker flows on technological performance, and the negative effect of high levels of inbound worker flows.

Figure 2 shows that diversity improves the effect of low levels of outbound mobility on technological performance. However, as the levels of outbound worker flows increase, diversity engenders an adverse effect on performance. This supports hypothesis 2b, which predicts that diversity accentuates the positive effect of low levels of outbound R&D worker flows on technological performance, and the negative effect of high levels of outbound worker flows.

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Insert figure 1 about here
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Insert figure 2 about here
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4.1 Robustness Checks

We submit our results to several sensitivity analyses. All of the results of these analyses are available upon request from the authors. First, we used other estimation techniques. We estimated pooled-data negative binomial, and zero-inflated negative binomial models\(^6\) clustering the standard errors at the level of the firm. The results from both negative binomial and the zero-inflated negative binomial models, which supplements a count density with a binary process for zeroes, provide similar results to the ones presented in Table 3.

Second, considering that many of the firms in our sample did not apply for any patents, and since the panel data option in STATA 13.0 is not available for zero-inflated poisson (and zero-inflated negative binomial) models, we re-estimated our main model using probit regressions with random effects in order to predict a firm’s propensity to apply for patents. We re-coded our dependent variable to a binary variable and followed the same steps as in our main analysis. Results show support of our hypotheses 1a, and 1b. These findings suggest that the inbound and outbound R&D worker flows, respectively, positively affects the propensity to apply for a patent, but only up to a threshold after which, an increase in these flows decreases the propensity to apply for patents. Results also show support of hypothesis 2b, suggesting that diversity of the outbound workers flows has a significant impact (p<0.05) on the relationship between the levels of the outbound flows and the propensity to apply for patents. We found no

\(^6\) We compare the negative binomial models (both standard and zero-inflated) to the poisson models (both standard and zero-inflated) using Stata’s function “countfit”, which compares the residuals of user-specified count models. Results indicates that the pooled negative binomial models are better at estimating our model than the pooled poisson models. We then compare the zero-inflated negative binomial model to the standard negative binomial model using the same Stata function. Results indicates that the standard negative binomial model is better than the zero-inflated model. The results of Vuong’s (1989) test however indicate that the standard negative-binomial model is rejected in favor of the correspondent zero-inflated model. We thus also report the estimation results of the standard negative binomial regressions.
support for our hypotheses 2a\(^7\). We then re-estimated our main models after excluding the organizations that did not apply for any patents. Results show support of all our hypotheses.

Third, given that the distribution of our dependent variable is very skewed, we recoded our dependent variable into an ordinal variable that takes values from 0 to 5 and re-estimated our model using random-effects ordered probit models. Results are overall similar to our main findings.

In addition, we re-estimated our main model after sub-sampling the organizations into small and large enterprises. Results are consistent with our findings for large organizations but not for small organizations. First, results suggest that the relationship between the outbound flows and technological performance is rather negative for small firms. Moreover, results suggest that the diversity of the outbound worker flows has a negative impact on performance\(^8\), indicating that small firms face additional challenges when separated employees join diverse employers. This is not surprising as small organizations performance is often more reliant on the skills of their workers than large firms. In addition, if small organizations suffer large turnovers, the employees that left will know very few people working in the organization (i.e. none of their former colleagues will be in the organization). Concerning inbound R&D worker flows, while the results do not suggest a u-shaped relationship between inbound flows and performance, the findings indicate that for small firms, excessive levels of hiring have a negative impact on technological performance. This is again not surprising, small firms experiencing a large number of intakes will face greater disruptions than larger firms in order to integrate the knowledge and social capital assets that excessive hires can potentially bring. In addition, results indicate that the diversity of the inbound workers’ flow has a positive effect on performance, and that diversity moderates the relationship between the levels of this flow and technological performance.

\(^7\) Results show that diversity of the inbound R&D worker flows has a statistically significant effect (p<0.01) on the propensity to apply for patents. However, we found no proof that diversity moderates the relationship between the levels of these flows and the propensity to apply for patents.

\(^8\) We plotted the marginal effects to interpret the interaction between the levels and diversity of the outbound flows.
performance, such that at low levels of inbound flows, diversity improves technological performance, while at higher levels of inbound flows, diversity has an adverse impact of performance.

We also re-estimated our model after sub-sampling the organizations into high/medium-high tech firms, and medium-low/low tech firms. This classification follows the ISIC, Rev. 4’s classification of technology intensity manufacturing firms. We found support of our hypothesis\(^9\) in both high/medium-high and medium-low/low tech industries subsamples.

Finally, we test whether these results hold independently of the internal diversity already exiting in the firm. We first re-estimated our main model while controlling for different internal diversity characteristics that are commonly used in the literature (see for example: Faems and Subramanian, 2008; Østergaard et al., 2011). We thus control for both demographics characteristics (age, gender, and nationality) and cognitive characteristics (education and knowledge area). Results are consistent with our main findings. Further, we subdivide our sample of firms into three groups according to their level of internal diversity. Internal diversity is measured as the average of a firm’s gender diversity, age diversity, nationality diversity, level of education diversity, and knowledge area diversity. Results are overall consistent with our main findings only for the firms with medium and high internal diversity. This is unsurprising since unlike firms with low internal diversity, firms with medium/high levels of internal diversity are more familiar with handling diverse knowledge and social capital stocks. Internally diverse firms have more varied knowledge assets that enable them to widen the possible links they can make with the knowledge and social capital assets that a diverse worker flow can bring (Cohen and Levinthal, 1990).

\(^9\) Results show that diversity of the outbound R&D worker flows has a statistically significant effect (p<0.001) on technological performance. However, we found no proof that diversity moderates the relationship between the levels of these flows and firm’s performance for Medium low & low tech industries.
5. Discussion

This study set up to contribute to a better understanding of the effect of R&D worker flows on the firms’ technological performance. Previous studies linking the mobility of R&D workers’ mobility to firms’ technological performance have neglected that the inbound and outbound worker flows occur simultaneously within the firm, and that these R&D workers’ flows may be characterized by different degrees of heterogeneity in the skills and social capital of the workers. Building on the labor mobility and organizational learning literatures, we have investigated this effect by focusing on the direction (inbound/outbound), the levels, as well as the composition of the R&D worker flows. In particular, we look at how the levels of inbound and outbound R&D worker flows, respectively, affect technological performance, and how the composition of these flows moderate these relationships.

Using a panel of 6350 firm-year bi-annual observations in the period between 2007 and 2013, our evidence supports the claim that both the levels and composition of the R&D worker flows play a major role in shaping the firm’s technological performance. First, we found that there is an inverted u-shaped relationship between the levels of R&D worker flows and technological performance, independently of their direction. This extends prior literature, which argues for a linear effect of the worker flows on firms’ performance (e.g. Song et al., 2003; Rao and Drazin, 2002. Somaya et al., 2008; Agrawal et al., 2006). This finding suggest that although the movement of R&D workers in and out of an organization can rejuvenate its knowledge stocks and allow access to wider networks, excessive “knowledge and social capital rejuvenation” may trigger additional costs that can have an adverse effect on technological performance.

Additionally, our study moves beyond previous mobility studies by taking into account not only the levels of the worker flows, but also their composition in terms of access to distinct knowledge bases and social capital based on the origins of new hires and destinations of exits. We found that the diversity of the worker flows affects the relationship between the levels of inbound or outbound R&D worker flows and the firm’s technological performance. For both
inbound and outbound worker flows, our findings suggest that diversity accentuates the effect of worker flows levels on technology performance. Diversity is advantageous at low levels of these flows, when knowledge coordination and management costs are reasonably low, while at high levels of inbound and outbound flows, when knowledge coordination and management costs are exorbitant and when absorptive capacity is near saturation, diversity accentuates the negative impact of these flows on performance. These findings support the claim that excessive diversity can results in “knowledge overload” which can engender additional transaction costs that may cause diminishing and negative rates of performance (e.g. Herstad et al., 2015; Østergaard et al., 2011).

Moreover, and in line with previous studies (e.g. Østergaard et al., 2011; Cohen and Levinthal, 1990), our additional analyses suggest that internal diversity is important to improve technological performance. Our results suggest that organizations with a diverse composition of employees are better able in reaping the benefits of the workers’ flows diversity, proposing that these internally diverse organizations possess enhanced capacities to handle diverse knowledge sources. Our additional analyses also suggest that large and small firms respond differently to distinct levels and compositions of worker flows. In particular, our findings suggest that the outbound worker flows have a linear and negative impact on the performance of small firm, and that the diversity of these flows accentuates this negative relationship. This proposes that small firms may, lack the resources to monitor the separated employees’ new employers, and that the more diverse the new employers are, the more challenges these small firms will face. Our findings also suggest that small firms face more challenges in integrating sizeable and diverse knowledge through inbound worker flows, and that excessive levels of new hires, especially if they are diverse, can have adverse effects on performance for these firms.

5.1 Implications

Our study has several theoretical contributions. First, borrowing from the organizational learning literature, which stresses on the importance of routines restructuring as well as on the processes of internal knowledge creation and recombination in accommodating external
challenges, this study contributes to the labor mobility literature by conceptualizing and investigating the effect of labor mobility considering both incoming and outgoing labor flows, in terms of both levels and diversity. Most of the studies regarding the effect of employees’ mobility on innovation have ignored the organizational capacity of the firm in managing large R&D worker flows; they look at inbound mobility and assume a positive effect of total mobility on performance. In addition, these studies have focused on either incoming or outgoing worker flows and considered them independent processes. Furthermore, these studies have mostly neglected the composition of the worker flows. Our findings suggest that neglecting either the direction, the levels, or the compositions of the worker flows when examining their impact on firms’ performance provides a partial view of the story.

Second, this study contributes to the literature on knowledge diffusion by conceptualizing and providing evidence of possible reverse knowledge spillovers triggered by the exits of R&D employees. We extend previous studies (e.g. Corredoira and Rosenkopf, 2010; Agrawal et al., 2006) by providing evidence that the relationship between employee separations and technological performance is not necessarily linear, but rather curvilinear, as well as that this effect depends on the degree to which the organizations that the separated employees join are heterogeneous.

Following these lines, we thus add to previous works on worker flows by developing the concept of flows diversity, defined as the distribution of differences in the worker flows in terms of access to distinct knowledge bases and social capital. While previous diversity studies (For example: Faems and Subramanian, 2013; Østergaard et al., 2011) have provided important insights regarding the performance implications of diversity within the existing workforce, we contribute to the organizational innovation literature by showing that the diverse origins of new hires, as well as the diverse destinations of exits, can significantly alter the knowledge and social capital gains that these hires and separations can potentially bring to the firm.
Our research also holds important implications for how managers strategically manage their human resources. First, our findings suggest that managers need to avoid excessive hiring and separations as they can trigger adverse effects on performance due to the possible challenges (e.g. increased coordination costs, increased training ... etc.) that the new hires and exits can raise within the organization. Second, our findings suggest that managers need to reconsider the effect of employees’ separations. Conventionally, exits have been considered as a “loss” by managers due to the potential forward knowledge flows they create. Our findings suggest that exits, although they are a “loss” at excessive levels, can also allow for reverse knowledge flows and can expand the former employer’s networks. While this claim is not promoting outbound mobility, our findings suggest that low levels of outbound worker flows can facilitate knowledge and social capital exchange, which may enhance technological performance. Third, our findings suggest that managers need to recognize that the firm’s performance can be shaped by the destinations of exits and the origins of new hires. In line with Somaya et al.’s (2008) suggestion, we believe that managers need to move beyond the “individual-level attributes” of new hires and exits, and recognize the origins of these new hires (i.e. the former employer) and the destinations of the exits (i.e. the new employer) and what social ties they can bring to the firm.

Moreover, our findings suggest that managers need to make a trade-off between the diversity of the inbound and/or outbound worker flows, and the levels of these flows. Although heterogeneous origins of new hires and destination of exits can create new knowledge channels and new social ties, combined with high levels of worker flows, heterogeneity can introduce additional challenges that can hamper a firm’s performance.

Finally, we believe that our findings can be provide rich insights to policy makers in the design of effective labor market policies that can strengthen the national environment for technological growth. While labor market flexibility can foster the diffusion of knowledge and encourage technological growth, our study suggests that policy makers need to establish a balanced national labor market that supports the mobility of labor, promotes and rewards the development of a diversified set of competences, not only through education but also through training, and avoids, to a reasonable extent, the promotion of rigid career (education and
professional experience) paths that individuals should follow.

5.2 Limitations and future studies
Although our data allows us to see the origins of new hires and destinations of exits, our analysis suffers from some limitations. First, we do not have detailed data on the specific organizations, as well as their R&D focus, that the inbound and outbound worker flows come from and go to. We thus cannot address whether these flows come from/go to organizations with the same or a different R&D focus. Worker flows from/to organizations with the same R&D focus can hold “redundant” knowledge and social capital, but can also hold key firm-specific knowledge that can assist in creating a competitive advantage. Worker flows from/to organizations with different R&D focus on the other hand can hold “peripheral knowledge” that can disrupt a firm’s technological progress, yet this peripheral knowledge can also challenge the firm’s existing patterns and promote novelty and originality. Additionally, due to data limitations, we were unable to examine the conventional diversity attributes – i.e. demographics (age, nationality, and gender) and cognition (education, knowledge background) of new hires and exits. We encourage future studies to construct a more comprehensive understanding of the effect of worker flows on performance by addressing these points. For example, future research can investigate how the R&D worker flows from/to organizations with the same/different research focus affects technological performance.

Second, this study uses patent applications as an indicator of the inventive output. However, not all inventions are patented, not all the patents lead to innovation, and not all patent applications are equal innovations (Arundel and Kabla, 1998; Griliches, 1990). Future research can test our results using different technological performance measures, and investigate whether our findings can be extended to innovative performance.

Third, our study relies on data on firms located in France, that are subject to the French labor market regulations. Future research is needed to assess whether results hold in different institutional contexts. We thus encourage future researchers to try to replicate our findings in different contexts (e.g. different countries with distinct labor market regulations).
Despite the above constraints, this study is an attempt to examine how the R&D worker flows influence the firm’s ability to create knowledge that fosters its performance. We regard our analysis as improving our understanding of the impact of worker flows’ levels and composition on technological performance.

References


### Table 1. Descriptive statistics and correlations

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<th>Variable</th>
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<th>SD</th>
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<th>Max</th>
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<th>(2)</th>
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<th>(7)</th>
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<td>(2) Inbound Flow (IF)</td>
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<td>1.54728</td>
<td>0.0684*</td>
<td>0.194*</td>
<td>0.083*</td>
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<td>0.052*</td>
<td>0.0532*</td>
<td>0.078*</td>
<td>0.069*</td>
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</tr>
<tr>
<td>(8) Public funding</td>
<td>0.39118</td>
<td>0.48805</td>
<td>0</td>
<td>1</td>
<td>0.0866*</td>
<td>0.127*</td>
<td>0.085*</td>
<td>0.1411*</td>
<td>0.115*</td>
<td>0.020*</td>
<td>0.117*</td>
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<tr>
<td>(9) Researchers ratio</td>
<td>0.55964</td>
<td>0.26049</td>
<td>0.01</td>
<td>1</td>
<td>-0.007*</td>
<td>0.067*</td>
<td>0.056*</td>
<td>0.0519*</td>
<td>0.038*</td>
<td>0.008*</td>
<td>0.109*</td>
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<td>(10) Number of employees (log)</td>
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### Table 2. Distribution of the sample by industry

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<tr>
<td>Textile, clothing industries, leather and footwear</td>
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<tr>
<td>Wood, paper and printing industries</td>
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<tr>
<td>Coke and refined petroleum products</td>
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<tr>
<td>Chemicals</td>
<td>780</td>
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<td>Pharmaceuticals</td>
<td>721</td>
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<tr>
<td>Rubber and plastic products</td>
<td>353</td>
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<tr>
<td>Other non-metallic mineral products</td>
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<td>Metallurgical industry</td>
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<tr>
<td>Metal products, except machinery and equipment</td>
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<tr>
<td>Components, electronic cards, computers, peripheral equipment</td>
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<td>Communication equipment</td>
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<td>Instruments and apparatus for measuring, testing and navigation; watchmaking</td>
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<td>Equipment for medical irradiation, electromedical and electrotherapeutic equipment</td>
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<td>Electrical equipment</td>
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<tr>
<td>Machinery and equipment n.e.c.</td>
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<td>Other transport equipment n.e.c.</td>
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Table 3. Poisson regressions with random effects results

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<td>(0.00000)</td>
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<td></td>
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<tr>
<td>OF * OF diversity</td>
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<tr>
<td>OF^{2} * OF diversity</td>
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<tr>
<td>R&amp;D intensity</td>
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<td>-0.00018****</td>
<td>-0.00022****</td>
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<td>(0.00004)</td>
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<td>0.58303****</td>
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<td>0.19461****</td>
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<td>Yes</td>
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<td>-0.54889****</td>
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<td>-17898.348</td>
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<td>1670.20****</td>
<td>1621.57****</td>
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<tr>
<td>Wald Chi-square</td>
<td>1270.49****</td>
<td>1670.20****</td>
<td>1621.57****</td>
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</table>

Significance levels: * p<0.1, ** p<0.05, *** p<0.01, ****p<0.001.

Figure 1. Average Marginal Effects plots of the moderating effect of the inbound worker flows diversity.

Figure 2. Average Marginal Effects plots of the moderating effect of the outbound worker flows diversity.
## Probit regressions with random effects results

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Significance levels: * p<0.1, ** p<0.05, *** p<0.01, ****p<0.001.

Notes – Robust standard error in parentheses. N= 6350. Group variable for random effects: firm, 3070groups.
### Poisson regressions with random effects - Organizations that applied for patents only

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Significance levels: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001.

Notes - Standard error in parentheses. N= 2,317. Group variable for random effects: firm, 1291 groups.
## Additional Robustness checks

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Significance levels: * p<0.1, ** p<0.05, *** p<0.01, ****p<0.001.

Noes - Robust standard errors clustered by firm in parentheses. N= 6350.
### Ordinal Probit regressions with random effects results

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Significance levels: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001.
## Poisson Regressions with Random Effects using small vs. large firms

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Significance levels: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001.

### Poisson regressions with random effects using high vs. low tech subsamples

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Significance levels: * p<0.1, ** p<0.05, *** p<0.01, ****p<0.001.

### Poisson regression with random effects using internal diversity sub-samples

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<td>OF</td>
<td>-0.00411</td>
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<td>0.01172**</td>
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<td>(0.04739)</td>
<td>(0.01625)</td>
<td>(0.00124)</td>
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<td>-0.00149**</td>
<td>-0.00004*</td>
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<tr>
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<td>(0.00073)</td>
<td>(0.00001)</td>
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<td>0.41803****</td>
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<td>1.35074****</td>
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<tr>
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<td>(0.07799)</td>
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<td>Researchers ratio</td>
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<td>(0.18008)</td>
<td>(0.18135)</td>
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<td>(0.12090)</td>
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<tr>
<td>Industry fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
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<td>-2.42629****</td>
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<tr>
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<td>-2660.7045</td>
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<tr>
<td>Wald Chi-square</td>
<td>521.68****</td>
<td>508.50****</td>
<td>487.76****</td>
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</tbody>
</table>

Significance levels: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001.

### Poisson regressions with random effects — controlling for internal diversity

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
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<tbody>
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<td>0.01464***</td>
<td>0.01584***</td>
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<td>-0.00003**</td>
<td>-0.0007***</td>
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<td>0.08806***</td>
<td>0.41750***</td>
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<td>-0.01491***</td>
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<td>IF² * IF diversity</td>
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<td>0.00002</td>
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<td>OF</td>
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<td>0.01584***</td>
<td>0.00007**</td>
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<tr>
<td>OF²</td>
<td>-0.11150*</td>
<td>-0.11150*</td>
<td>-0.08815</td>
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<tr>
<td>OF diversity</td>
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<td>0.85835***</td>
<td>0.85835***</td>
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<tr>
<td>OF * OF diversity</td>
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<td>0.77165***</td>
<td>0.77165***</td>
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<tr>
<td>Gender diversity</td>
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<td>-0.14728**</td>
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<td>0.91468****</td>
<td>0.85835***</td>
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<td>Age diversity</td>
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<td>0.30447***</td>
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<td>Education diversity</td>
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<td>0.06105**</td>
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<td>Knowledge area diversity</td>
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<td>0.00011***</td>
<td>0.00012***</td>
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<tr>
<td>External R&amp;D intensity</td>
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<td>0.31290****</td>
<td>0.50255****</td>
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<td>Researchers ratio</td>
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<td>0.18257***</td>
<td>0.17471***</td>
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<td>Number of employees</td>
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<td>-0.04637****</td>
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<td>Public funding</td>
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<td>0.07100****</td>
<td>0.07777***</td>
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<td>Industry fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Time fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
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<td>-0.55144***</td>
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<tr>
<td>Log likelihood</td>
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<td>-17727.857</td>
<td>-17408.925</td>
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<tr>
<td>Wald Chi-square</td>
<td>1928.44**</td>
<td>1928.44**</td>
<td>2464.72***</td>
</tr>
</tbody>
</table>

Significance levels: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001.

### Appendix 1. Origins on inbound R&D employees and destination of outbound R&D employees

<table>
<thead>
<tr>
<th>Origins of inbound R&amp;D employees</th>
<th>Destinations of outbound R&amp;D employees</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Individuals who arrived in the R&amp;D activity of the company during the year “20XX” and come directly from the educational system</td>
<td>1. Individuals who left the R&amp;D activity of the company during the year “20XX” to go to another company of the group abroad</td>
</tr>
<tr>
<td>2. Individuals who arrived in the R&amp;D activity of the company during the year “20XX” and who come from another company in France that is outside the group</td>
<td>2. Individuals who left the R&amp;D activity of the company during the year “20XX” to go to another company in France that is outside the group</td>
</tr>
<tr>
<td>3. Individuals who arrived in the R&amp;D activity of the company during the year “20XX” and who come from research in a public body in France (including defense)</td>
<td>3. Individuals who left the R&amp;D activity of the company during the year “20XX” to go to research in a public body in France (including defense)</td>
</tr>
<tr>
<td>4. Individuals who arrived in the R&amp;D activity of the company during the year “20XX” and who come from another company abroad (or public body) that is outside the group</td>
<td>4. Individuals who left the R&amp;D activity of the company during the year “20XX” to go to another company abroad that is outside group (or public body)</td>
</tr>
<tr>
<td>5. Individuals who arrived in the R&amp;D activity of the company during the year “20XX” and whose previous situation is other</td>
<td>5. Individuals who left the R&amp;D activity of the company during the year “20XX” whose next situation is not known</td>
</tr>
</tbody>
</table>