Abstract

Past research has provided very inconsistent empirical support for the relationship between aggregate levels of turnover and firm performance. To remedy this controversy, we identify the three main perspectives explaining today’s turnover effect, and theorize that the following constructs constitute potent boundary conditions for these theories: 1) different industry types ranging from efficiency-oriented to innovation-dependent, 2) labor market conditions defining the disparity in knowledge between the leaving employee and the replacement, and 3) the overall learning rates of both the organization and its employees. Each of these constructs plays a significant role in shaping the turnover-performance relationship into either one of the acknowledged patterns in the literature.

ABSTRACT

Past research has provided very inconsistent empirical support for the relationship between aggregate levels of turnover and firm performance. To remedy this controversy, we identify the three main perspectives explaining today’s turnover effect, and theorize that the following constructs constitute potent boundary conditions for these theories: 1) different industry types ranging from efficiency-oriented to innovation-dependent, 2) labor market conditions defining the disparity in knowledge between the leaving employee and the replacement, and 3) the overall learning rates of both the organization and its employees. Each of these constructs plays a significant role in shaping the turnover-performance relationship into either one of the acknowledged patterns in the literature.

Keywords:

Turnover effect; turnover effect patterns; firm performance; exploration

INTRODUCTION
The employee turnover literature is fraught with competing views and theories on how turnover affects a firm’s performance metrics (see figure 1) (Call et al. 2015; Hausknecht, 2013; Park & Shaw, 2013). On the one hand, based on the human capital perspective, a firm’s performance hinges on the accumulated firm-specific human capital. In result, turnover is strictly nefarious to a firm’s performance since it erodes this accumulated human capital. Under the premise that turnover refers to both employee exit and replacement, this effect is further accentuated when replacement employees cannot perform immediately at the same level as the departing employees (i.e. the leavers). Consequently, as turnover increases, performance decreases in a strictly linear negative relationship (e.g. Guthrie, 2001; Kacmar et al. 2006; Ton and Huckman, 2008). However, under the sociological view, “successively higher amounts of turnover […] produce […] successively lower amounts of effectiveness at a decreasing rate” (Price, 1977; p. 119). The underlying logic behind this view is based on the organizational disruption argument (see Katz and Kahn 1978; Staw, 1980); the knowledge of the incumbent employees is already low at high turnover rates, so incremental turnover is only marginally disruptive. Therefore, the organizational disruption view advocates for an Attenuated Negative Relationship between turnover and performance (e.g. Shaw, Gupta, and Delery, 2005; Shaw, Park, Kim, 2013). On the other hand, the organizational behavior framework advocates for an Inverted U-Shaped Relationship (e.g. Glebbeek and Bax, 2004; Siebert and Zubanov 2009); moderate levels of turnover are seen as potentially beneficial to a firm’s performance since they can revitalize workforce innovation and flexibility (Abelson & Baysinger, 1984; Dalton & Todor, 1979).

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Given that these mixed views and findings have rallied significant and practically equal support in the turnover literature (Shaw, 2011), our research aims to offer theoretical boundary conditions that could explain the empirical results of each perspective. We theorize that each turnover effect perspective is only applicable to specific industry and labor market contexts, and is further moderated by specific employee and organizational learning rates. For instance, the human capital and organizational disruption theories are mainly supported in purely efficiency dependent industries where market labor conditions imply very low replacement knowledge relative to that of the departing employees. Inversely, the organizational behavior’s pattern is mostly manifested in innovation-dependent industries where labor market conditions enable hiring employees of similar general knowledge levels as that of the exiting employees.

We adopt a knowledge based view of the firm in a simulation model that illustrates the effect of turnover with replacements on the firm’s accumulated knowledge. We consider that depending on the industry type, firms attempt to reach higher performance through either exploiting the knowledge of its existing employees (e.g. in efficiency dependent industries), or exploring alternative knowledge brought in through turnover (e.g. in innovation-dependent industries), or both. Therefore, for the sake of consistency, we build on March (1991)’s model, and adopt his notions of exploration and exploitation. We illustrate firm performance as its accumulated knowledge through either exploitation or exploration. Then, we incorporate an industry parameter $\gamma \in [0,1]$ that reflects whether the firm’s payoff is dependent mainly on its average employee knowledge (e.g. $\gamma=0$; efficiency), or its organizational knowledge supremacy (e.g. $\gamma=1$; innovativeness), or both (e.g. $\gamma=0.5$). We also account for labor market conditions modeled through a parameter $\alpha \in [0,1]$ that reflects the disparity between the leaver’s knowledge and that of the replacement (e.g. $\alpha = 0$ when the disparity is high, and $\alpha = 1$ when the disparity is
low). Also, in accordance with March’s model, we investigate the effects of $\gamma$ and $\alpha$ for different employee learning rates $p1 \in \{0.1; 0.5; 0.9\}$ mapped to different organizational learning rates $p2 \in \{0.1; 0.5; 0.9\}$. In consequence, we show that depending on the industry type, replacements' knowledge disparity, and different organizational and employee learning rates, different turnover rates paint the dominant patterns of today’s existing turnover effect studies.

We contribute to the turnover literature by offering a closer solution to the turnover effect debate (see, Shaw 2011; Shaw, Gupta, and Delery, 2005). We build further on the recent and emerging research attempting to delimit the conditions for either the positive or negative effects of turnover (Call et al. 2015; Hausknecht, 2013; Park & Shaw, 2013) instead of proving one of the two effects. Thus, to the best of our knowledge, the main two studies that have attempted to do so as of yet, are Call et al. (2015) and Hausknecht (2013). Nonetheless, neither of the two studies accounts for the knowledge intensity of the encompassing industry the firm is situated in. In turn, our research succeeds in replicating the exact theorized patterns in the turnover effect literature based on the very same settings used in each study. Thus, we take the conversation away from a simple homogeneous view of the firm, to the heterogeneous effect that the underlying industry plays in shaping firm performance. Using this approach allows for bridging between the dominant turnover-effect perspectives instead of only testing the effect of new constructs on the turnover-performance relationship.

We also advance a model that confirms previous empirical studies, enables deriving further novel and testable propositions about optimal turnover rates, and offers important managerial implications. For instance, we are able to deduce how a firm’s optimal turnover rate is associated with its organizational learning capability, the expected level of new entrants’ knowledge, the nature of the competition the organization perceives, and the environment’s
turbulence rates. Moreover, in contrast to the existing cumbersome turnover models (see Glebbeek and Bax, 2004), our model enables managers to easily determine whether turnover is indeed beneficial to their company. Managers are able to locate which turnover-performance curve shape they’re on simply based on the type of industry and labor market context they’re located in; then based on their current turnover rate, and idiosyncratic organizational and employee learning rates, they are able to assess how far they are from their optimal turnover rate.

Finally, we draw from the research stream that introduces the individual exploration as a second means to prolong organizational exploration (e.g. Lazer and Friedman, 2007). The main stream in organizational learning builds on March (1991) and attributes the organizational exploration to exploiting the knowledge of new comers whose knowledge is not socialized to the organization yet. However, this logic cannot explain how new knowledge is generated in an organization when no one, anywhere, holds the elements of such piece of knowledge. Accounting for individual exploration resolves this problem. We introduce the notion of “exploration-mix” as a strategic decision about the extent of the organizational resources to be allocated to each exploration mechanism: either transferring the stars’ known knowledge to the organization, or allowing the stars to explore new knowledge individually. Then we investigate how the turnover-performance relationship is further moderated by the specific exploration mix a firm adapts. Organizational directors are thus able to draw more realistic conclusions about the impact of turnover on their firm’s performance given their specific exploration-mix.

THEORETICAL BACKGROUND

“Some Hindus have an elephant to show. No one here has ever seen an elephant. They bring it at night to a dark room. One by one, we go in the dark and come out saying how we experience the animal. One of us happens to touch the trunk. “A water-pipe kind of creature.” Another, the
ear. “A very strong, always moving back and forth, fan-animal.” Another, the leg. “I find it still, like a column on a temple.” Another touches the curved back. “A leathery throne.” Another, the cleverest, feels the tusk. “A rounded sword made of porcelain.” He’s proud of his description.

Each of us touches one place and understands the whole in that way. The palm and the fingers feeling in the dark are how the senses explore the reality of the elephant. If each of us held a candle there, and if we went in together, we could see it.” – Rumi, “Elephant in the Dark,”

The debate on the turnover effect on performance has been, so far, akin to independently investigating an elephant in a dark room (see quote above). Over fifty studies have been allocated to this matter only to result in continuous validation of either one of three perspectives, namely: the human capital view, the organizational disruption logic, and the organizational behavior view (Shaw, 2011; Shaw, Gupta, and Delery, 2005). Most of these studies so far have mainly focused on proving one of the viewpoints, instead of explaining the discrepancy in findings. Some scholars have further attempted to analyze the effect of turnover on performance across a wide range of industries (e.g. Guthrie 2001; Huselid 1995; Messersmith, Guthrie and Ji 2009; Sels et al. 2006; Shaw et al. 2009; Shen and Cannella, 2002; Yanadori and Kato, 2007). These studies, nonetheless, have only provided further support to either one of the existing perspectives instead of trying to bridge between them. As such, in this paper, we contend that the solution to the turnover effect debate lies in acknowledging the veracity of all three perspectives simultaneously while controlling for factors that favor the outcomes of one perspective over the others.

The negative turnover effect views

The human capital theory (Becker, 1975) explains that employees in a firm possess a certain level of human capital that can be either general or firm specific (Coff, 1997). While the general
human capital can be acquired through standard education or training and improves the employee’s productivity regardless of his host organization; the firm specific human capital is only acquired with time through learning a set of the host organization’s knowledge and routines. The human capital logic further argues that since firms require unique resources to create value and generate rents, the firm specific human capital plays a greater role in maintaining a firm’s performance than the general human capital. Consequently, losing employees with high levels of firm specific human capital will engender a strict decrease of performance in the host firm since replacements do not possess the same firm specific human capital as that of the leavers. The turnover of employees implies a strict loss of valuable firm resources that would require time to re-acquire.

In a similar chain of thought, the organizational disruption view advocates that employees perform tasks in dependence of others (Price, 1977). Therefore, the loss of an employee lowers other firm process’s performance, or even halts productivity altogether, until the replacements socialize to the organizational routines. However, in contrast to the human capital loss perspective, the organizational disruption view dictates that continuous higher levels of turnover will result in lower loss of organizational performance (e.g. than at low levels of turnover). At low turnover rates, leavers typically hold a high level of human capital which would require the replacements a long time to attain. Whereas, at high turnover rates, leavers typically didn’t spend enough time to acquire high firm specific human capital, and therefore replacements can easily catch up to their performance level.

The positive turnover effect views

The Organizational Behavior View
The organizational behavior view adds a positive perspective to the two previous arguments. It stipulates that even if turnover is overall detrimental to the firm’s performance, some level of turnover ought to revitalize workforce innovation and flexibility (Abelson & Baysinger, 1984; Dalton & Todor, 1979). This perspective has been first advanced by Adelson and Baysinger (1984), which builds on the premise that turnover can be both functional and dysfunctional. The functional turnover refers to the departure of less valued employees, whereas the dysfunctional turnover relates to valuable employees quitting voluntarily (Dalton, Tudor, and Krackhardt, 1982). Thus, Adelson and Baysinger (1984) argue that since “the costs of retaining any employee can be excessive, the norms of rationality suggest that organizations could welcome a positive rate of turnover.” (Adelson and Baysinger 1984, p. 332). As such, they define that the optimal turnover rate should potentially minimize the aggregate costs of turnover as well as the costs engendered by retention investments. In consequence, the optimal turnover rate would maximize the firm performance in an inverted U shape manner; whereby turnover rates at either side of the optimal point (e.g. either too low or too high) would result in relatively less firm performance.

**The Organizational Learning View**

In a different vein of research, the organizational learning literature explains employee mobility as a means to boost a firm’s performance through access to external knowledge (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003). External knowledge can help a firm overcome the limitations of incremental advancements and suboptimal solutions; it increases the number and variety of knowledge components available for recombination, and therefore the number of combinatorial possibilities and potential solutions (Fleming, 2001; Rosenkopf and Nerkar, 2001). Moreover, this knowledge transfer between organizations has been shown to be further fostered by geographic concentrations of industrial activity (Jaffe, Trajtenberg, and Henderson, 1993). In
such settings, firms potentially benefit from the external knowledge pool provided by competitors (e.g. through resource mobility or professional service firms (Wagner, Hoisl, and Thoma 2014), as well as from their own knowledge spillovers carried over, via employee mobility, to a competing firm and back (Yang, Phelps, and Steensma 2010).

The underlying logic to this positive effect of resource mobility can be found in the seminal study of March (1991). This study advances the two notions of exploitation and exploration. Exploitation pertains to incremental changes to the organization’s existing rent-generating systems; whilst exploration pertains to radical changes in a firm’s search for better rent-generation possibilities. As such, the study argues for the benefit of employee mobility as a means to sustain and improve the firm’s current performance in the face of turbulent environment, or to reach a more preferred competitive position. In this manner, March (1991) also accounts for the competitive dynamics between firms and argues for the importance of explorative behavior in the face of competition for supremacy. Consequently, exploration is not only instigated by natural resource loss (e.g. employee turnover), but also by the competitors’ explorative actions. In effect, less talented competitors are more willing to sacrifice their average performance in order to increase their chances of winning a superior competitive position. This behavior forces the more talented firms (e.g. the leaders) to do likewise in order to protect their competitive supremacy. Subsequently, the competition shifts into an exploration race in which average performance (due to ability and effort) becomes irrelevant. Therefore, March (1991) succeeds in explaining why, “in general”, it may be more beneficial for firms (in a highly volatile industry) to trade resources, and even relocate to areas that further fosters resource mobility. However, March’s study doesn’t explain the “specific” heterogeneous conditions that favor (or disfavor) employee mobility.
THEORY BUILDING

To mitigate the tension in perspectives and findings of the turnover-effect related research, the argument we bring forth in this paper is as follows. We contend that the outcome of each of the above perspectives will have a different weight given different external contexts a firm is embedded in. For instance, in studies incorporating the human capital loss perspective, the perspectives of both the organizational behavior view and the organizational disruption literature still hold, albeit to a very small degree. Consider, for example, the study made by Kacmar et al. (2006) on turnover among employees of a fast food chain (i.e. Burger King). The study finds that the turnover-performance relationship is a strictly decreasing one, and justifies this finding using the human capital loss perspective. However, just because the findings support this perspective, doesn’t necessarily mean it negates the other ones. As per the organizational behavior view, new employees do still bring new motivation to the team in this case, though the advantages brought in by this turnover are not enough to offset the detriments of losing the firm specific human capital held by the leavers. Similarly, in another example, the study made by Gleebek and Bax (2004), on turnover in Dutch temp firms, finds an inverted U-shaped turnover-performance relationship. As such, the study hails the organizational behavior perspective over the others. Yet again, the inverted U-shaped finding does not exclude the other perspectives. In this case, the fresh generic knowledge and motivation brought in by the new hires, simply overshadows the loss from firm specific human capital. The loss of human capital is still there; it is just of less significance than the gain in generic knowledge.

To explain the causes for this difference in perspective weights, we adopt a knowledge based view of the firm. We consider that firm performance is highly contingent on its overall knowledge. Furthermore, we argue that a firm’s knowledge can be quantified in two ways; either
as the overall organizational code (March, 1991); or as the average knowledge of all firm’s employees. Both types of knowledge indeed converge in time. However, depending on the competitive environment a firm is situated in, the payoff of either type of knowledge will be more significant than the other during a certain observation period. For instance, in a perfectly winner-take-all market, the higher the organizational knowledge (e.g. innovative capability), the higher the return. Whereas, in an efficiency-rewarding market, the higher a firm’s average knowledge (e.g. autonomous employees), the higher the return. However, we acknowledge that firms are heterogeneously endowed with different learning rates, both on the micro employee level (i.e. an individual employee’s speed of learning from the collective knowledge), and on the macro organizational code level (i.e. the speed of the organization’s collective code to learn from the employees). Thus, turnover will affect a firm’s knowledge differently depending on the firm’s inherent learning rates, as well as the exogenous quality of replacements (see figure 2). Accordingly, in innovative industries, where replacements have comparable knowledge to that of the exiting employees, turnover can indeed have positive performance returns; the benefit of learning new ideas from these employees outweigh the costs of training them to the existing organizational routines. However, in efficiency-rewarding industry, turnover will mostly be detrimental to the firm, since the firm has little need for the extra knowledge diversity carried on by the replacements. And therefore, the (time) costs of training them will outweigh any other benefits new employees may bring.

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Existing Turnover Models

Despite turnover-effect being a prominent field of research for the past decades, very few studies have yet attempted to conceptualize the effect of turnover on a firm’s performance into a comprehensive model. In fact, the only known study to try to do so was Adelson and Baysinger (1984), albeit their proposed model being very difficult to use or test (Glebbeek and Bax, 2004). The Adelson and Baysinger (1984) model suggests that every firm has a current baseline turnover rate, which the firm should either attempt to reduce or increase until reaching an optimal performance level. Based on this logic, the model provides an extensive guideline that managers could follow to estimate both the firm’s turnover baseline, as well as its optimal rate of turnover. However, since its publication in 1984, the model has received little application in both empirical and theoretical works (Glebbeek and Bax, 2004). One of the main criticisms of the model is that it would require a “massive research program” for the manager to learn about the many determinants of turnover in his/her firm before even being able to estimate its effects (Glebbeek and Bax, 2004). Such research would require “Gigantic quantities of data […] to put all the necessary control variables in place” (Glebbeek and Bax, 2004, p 279) and that it “sets researchers and practitioners an impossible task by linking the application of their model to data that must be obtained outside a given company itself” (Glebbeek and Bax, 2004, p. 279).

March (1991) Model

Interestingly, stepping outside the turnover-effect literature into the organizational learning research, March (1991) has for a long time, proposed a model in which turnover effect on firm performance (e.g. knowledge) can be both positive and negative. The main purpose of the model
was to explain the mutual learning of an organization and the individuals in it, wherein turnover plays a moderating role. He suggests that individuals modify their beliefs by socializing with the organizational code. Individuals’ belief could be modified and changed to the code’s belief based on the effectiveness of their socialization with code. The faster socialization with code, the faster the individual follows the organizational code and changes his beliefs to conform to the code. On the other hand, the organizational code adapts to the beliefs of superior individuals and in this way the knowledge of the code improves by mimicking the beliefs of those individuals. March (1991) identifies these superiors as “individuals whose overall knowledge score is superior to that of the code” (P.74). The probability of code’s adjustment to superiors’ beliefs depends on both the learning rate of the code and the agreement level among superiors. Individuals with low learning rates resist conforming to the code, providing the organization with further chances to learn from them. His model shows that within a closed system having fixed members, eventually the organizational beliefs and individual beliefs converge over time towards an equilibrium state. He also shows how an organization’s stock of knowledge at the equilibrium point is positively influenced by the employee’s slow learning rates and the organization’s high learning rate. At the stable equilibrium state, individuals on average are more knowledgeable (compared with their initial state) and homogeneous. This equilibrium point is the point at which learning is halted for the organization and all individuals in it.

Consequently, March has conceptualized turnover as a means for firm exploration to overcome this firm’s socialization trap. The trap refers to the situation in which superior individuals inside the firm learn too fast from the code, thereby thwarting the code’s opportunity to learn from them; thus the need for turnover. March proposes that turnover, as a means for exploration, is one solution to rejuvenate the diminished diversity caused by the fast socialization
speed. Turnover serves to increase the variance of knowledge, albeit, at the expense of decreasing its mean, since the average knowledge of newcomers may be less than that of the replacements. March suggests that organizations can manage the drawbacks of turnover, i.e., decrease in the average of individuals’ knowledge, via recruitment plans. If the newcomers are hired from a population with similar knowledge average to the existing members’, not only turnover contributes to the increase in higher code’s knowledge, but also it does not decrease the average of individuals’ knowledge. In this case, an organization benefits even more from turnover and reaches higher performance. Furthermore, March’s model implies that firms should make the strategic choice between high turnover (i.e. benefitting the code knowledge at the expense of employee average knowledge) and low turnover (i.e. employee average knowledge) based on the nature of the competition they face. The more competition has a “winner takes all” nature, the more likely is the firm to prefer increased turnover (i.e. code knowledge) over low turnover (i.e. employee average knowledge); and vice versa.

Although, March (1991) succeeds (albeit perhaps unintentionally) in showcasing that the turnover-performance relationship can be both negative or moderately positive (i.e. inverted U-shape), the study limits the replacements’ knowledge to a constant value of one-third of the maximum possible knowledge (i.e. the reality). Thus, in the model, turnover is seen to increase the knowledge variance in the initial iterations without significant effect on the employees’ knowledge average; whereas, in the later iterations, turnover leads to both the increase in the variance of employees’ knowledge and the decrease in the value of the average knowledge of the employees. This is a strong assumption that may not be applicable to all firm contexts. Consequently, the implications of the model on the effects of turnover, require further analysis and extra amendments to the model.
Our Model

In our study, we build on March (1991) model, and incorporate two more context-describing parameters that enable the study of realistic turnover conditions and their subsequent effect on firm’s performance. First, we start by replicating March’s model as our baseline. We model the firm as having 50 employees. The complexity of the reality is modeled as a vector of 30 elements that each receives a random value of either -1 or 1. Employees’ beliefs are initialized by a matrix of 50*30 whose elements receive a random number out of {-1, 0 and 1}. The match between the elements of the columns of the employees’ belief matrix and the vector of reality shapes the matrix of employees’ knowledge. Similar to March, we refer to the proportion of each employee’s knowledge elements which hold the value equal to one, (i.e. the employee’s belief elements which match the reality,) as the knowledge of that employee (which can receive a percentage value between zero and one). Firm’s code is initialized by a vector of 30 elements holding values equal to zero. We reserve $p1$ through $p4$ for the similar dynamics as in March’s model. Each iteration includes a socialization of each element of employees’ knowledge with the codes’ element with a probability of $p1$; an updating of the elements of the firm’s code with that of the dominant belief held by the superior employees with probability of $p2$; a turnover probability of $p3$; and a turbulence (i.e. change in the value of reality) with a probability of $p4$. Moreover, concurrently with March’s model, we set the agreement level among superiors as a boost coefficient to the effect of $p2$ in the code’s socialization.

Second, we also proxy firm’s performance as the firm’s knowledge. However, contrary to March’s model, we differentiate between two types of firm knowledge – namely: its organizational knowledge (i.e. the code knowledge) and the aggregate employee average knowledge (e.g. see equation 1). Based on this definition, we incorporate an industry parameter
\[ \gamma \in [0,1] \] that reflects whether the firm’s performance is dependent mainly on the aggregate employee average knowledge (e.g. \( \gamma = 0 \)), or mainly on organizational knowledge (e.g. \( \gamma = 1 \)), or both (e.g. \( \gamma = 0.5 \)). In competition-related terms, higher \( \gamma \) signals that the nature of competition, a firm is situated in, is a “winner takes all” type. According to March (1991), providing the firm with the opportunity of sustaining high exploration through turnover may have a destructive effect on the average of individuals’ knowledge. Thus, if the competition is for primacy and has a “winner takes all” nature (e.g. in the high-tech and other fast-growing industries), the firm should guide its exploration-exploitation balance more towards variance (e.g. exploration) rather than the mean (e.g. exploitation). On the other hand, when the competition has a “last loses all” nature (e.g. in more mature industries such as trucking) the organization should mainly try to increase the mean performance, i.e., follow the efficiency path. The performance of the firm is thus calculated as in equation 2:

1. \[ \text{EmployeeAverageKnowledge} (t = T) = \]

\[ \frac{(\sum_{t=1}^{T} \sum_{i=1}^{50} \text{Employee}_i's knowledge)}{T} \]

2. \[ \text{Firm performance} (t = T) = \]

\[ Code^\gamma_{(t=T)} \times EmployeeAverageK^{(1-\gamma)}_{(t=T)} \]

We also introduce a parameter \( \alpha \in [0,1] \) that reflects the disparity between the leaver’s knowledge and that of the replacement (e.g. \( \alpha = 0 \) when the disparity is high, and \( \alpha = 1 \) when the disparity is low. See equation 3). \( \alpha \) also reflects labor market conditions of the firm; within the same type of industry (e.g. the locomotive), the pool of human resources a firm can tap into will vary from one region to another. For instance, in the USA, (and particularly, in Silicon Valley),
most firms of a certain industry (e.g. the locomotive) can have access to employees with high expertise to replace the departing ones. However, in other less economically-endowed regions (e.g. Africa), firms of the same industry (e.g. the locomotive) can hardly find qualified replacements for the departing high skilled employees. In other words, whereas employee mobility in high economically-endowed regions (e.g. USA) is bilateral (e.g. firms in the region exchange employees between themselves), employee mobility in less economically-endowed regions (e.g. Africa) is mostly one-way and outward to better economically-endowed regions. Therefore, while employee mobility increases the talent pool in high economically-endowed regions, it drains it in the less economically-endowed regions. Thus the labor market conditions differ even within the same type of industry.

3. \[ \text{expected replacementKnowledge}_{t=t_x} = (\alpha \ast \text{employees average Knowledge}_{t=t_x}) \]

The premise of our model, is that the two parameters \(\alpha\) and \(\gamma\) coupled with March’s inherent parameters (i.e. \(p1, p2, p3,\) and \(p4\)) provide a complete description of a firm’s encompassing context. Only by taking the whole context into account, could we derive complete turnover-effect implications.

RESULTS & ANALYSIS

Cross Industry Analysis

We simulate our model for \(N=80\) firms and across \(i=20\) time iterations for each firm and each value of \(\alpha, \gamma, p1, p2, p3, p4\). Each iteration represents a point in time in which a firm experiences turbulence, a certain level of turnover, then engages in a round of exploration and exploitation. Through turbulence, each element of reality changes with the independent probability of \(p4\). In
the turnover phase, a $p3$ percentage of the firm’s employees are replaced by a new batch of employees with $\alpha$-dependent knowledge (see equation 3). Then in the exploration stage, the firm identifies the stars in the company, and attempts learning from them with the rate $p2$ (e.g. based on March model). At the exploitation phase, all employees in the firm attempt to learn from the firm’s knowledge with rate $p1$ (e.g. based on March model). We repeat this process for the $N=80$ firms, and average the $\gamma$ dependent profit of time $T = 20$ (see equation 2) across all 80 firms. In the end, for each value of $\alpha, \gamma, p1, p2, p3, p4$, we only record the profit of all 80 firms as one observation containing the average across the 80 firms. Overall, the simulation yields 37,422 observations based on the following values of $\alpha, \gamma, p1, p2, p3, p4$:

- 6 values of replacement quality $\alpha \in [0.5, 1]$ with increments of 0.1.
- 11 values of industry type $\gamma \in [0, 1]$ with increments of 0.1.
- 3 values for each of $p1, p2 \in \{0.1; 0.5; 0.9\}$
- 3 values for turbulence $p4 \in \{0; 0.02; 0.04\}$
- 21 values of turnover level $p3 \in [0, 0.4]$ with increments of 0.02.

We run an initial regression analysis across the whole set of 37,422 observations. In the first model, we regress the effect of all values of $p1, p2, p3, p4, p3$ squared, $\alpha$, and $\gamma$ on the firm’s performance (see table 1) and plot the performance as a function of $p3$ (see figure 3). We derive the plot by fixing all other parameters except turnover ($p3$) and turnover squared at the overall average. We then use the regression coefficients to plot firm’s performance as second order function of turnover. From the results of the first regression analysis, we see that overall some level of turnover ($p3$) is beneficial to the firm. However, this analysis can be said to be biased towards an organizational learning perspective in which the socialization rate between the firm and its employees is either average or above ($p1, p2 \geq 0.5$). The analysis is also biased towards
the organizational behavior view, in which most of replacements have an above average firm specific knowledge ($\alpha \geq .75$).

\[\text{Insert table 1 about here}\]

\[\text{Insert Figure 3 about here}\]

**Negative turnover-performance relationship**

Based on previous studies (e.g. Hausknecht, Trevor, and Howard, 2009; Kacmar et. al. 2006; Sels et al. 2006), we select the widely analyzed case pertaining to the human capital perspective. In this case, the firm is based in an efficiency-dependent industry (e.g. $\gamma<0.5$); its competitive advantage depends on large firm specific knowledge accumulated through time that leads to a relatively low socialization rate (e.g. $p1 = 0.1$); and has little to learn from its employees ($p2 = 0.1$). The results from our second model (table 1) demonstrate a strictly decreasing turnover-performance relationship (see figure 4). However, this data subset includes the cases in which replacements may have high firm specific knowledge (e.g. $\alpha$ is unrestrained). This is unrealistic in a human capital loss perspective. Thus, we refine the data subset further to exclude replacement employees who have high firm specific knowledge (e.g. $\alpha$ is low). Figure 5 plots the regression coefficients pertaining to this case as illustrated in model 3. Concurrently with the human capital loss perspective, when the firm has a sizeable stock of knowledge (e.g. $p1=0.5$) the effect of turnover on firm performance is strictly negative (model 4). However, if the firm’s stock of knowledge is too large (e.g. $p1=0.1$), the turnover-performance relationship becomes slightly attenuated (model 5). This is in support of the organizational disruption perspective. In
this case (e.g. $p1 = 0.1$), employees need a long time to socialize to the firm’s knowledge, and higher levels of turnover result in decreasing impact on firm’s performance.

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Insert Figure 4 about here
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**The Inverted U-Shaped Relationship**

In a setting where firms have an efficient knowledge exchange system between the firm and the employees (e.g. high $p1$ and $p2$), and have access to highly talented recruits with large industrial experience (e.g. $\alpha > 0.8$), a moderate level of turnover can be positive for the firm. (see figure 6 and 7). A high $\alpha$ reflects settings in which the new recruits have a high level of knowledge relevant (although not specific) to the firm. This is typical of technological parks (e.g. Silicon Valley), where firms can tap into a large pool of talented employees with high industrial expertise for their own business domain (e.g. Facebook hiring Google employees). A high $p2$ reflects an efficient mechanism the firm has in place that helps enhance idea exchange between the new recruits and the incumbent teams (e.g. gatekeeping). A high $p1$ reflects little need for the new recruits to learn new knowledge at the recipient firm prior to being productive (e.g. R&D employees with high industry experience). Figure 6 illustrates that high $p2$ (figures 6B and 6C) is more important than high $p1$, but when both are high, turnover can yield a much higher firm profit (e.g. in comparison with the baseline). Figure 7 illustrates that firms embedded in more innovation dependent (having a winner-takes-all nature of competition) industries benefit slightly more from turnover. A low $\gamma$ pertains to firms in which the performance of the company is highly dependent on the individual knowledge of its employees (e.g. service firms). A Moderate $\gamma$
reflects companies whose performance depends on both organizational knowledge and individual average knowledge.

Insert Figure 6 about here

Insert Figure 7 about here

**Best Turnover Rate (turnover as a strategic decision)**

As can be seen through the previous analysis, depending on the context, there exists a certain level of turnover that maximizes firm performance. We refer to this level of turnover as “best turnover rate”. For each value of \( p1, p2, p4, \alpha, \gamma \), we deduce the maximum performance across all levels of turnover \( p3 \in [0, 0.4] \). Then, we deduce the “best turnover” as the level of \( p3 \) that generates this maximum performance for this particular context combination of \( p1, p2, p4, \alpha \) and \( \gamma \). Next, we regress “best turnover rate” over \( p1, p2, p4, \alpha \) and \( \gamma \) both on the whole data and on some subsamples of the data that constitute meaningful contingences in turnover patterns (see table 2). The positive association between a variable and “best turnover” rate, under certain contingences, reveals the greater functionality of turnover under those conditions (i.e. the optimal performance happens at relatively higher turnover rates). Also, we further provide testable propositions for future empirical studies based on the analysis.

Insert Table 2 about here

In model 1, we see that all of \( p1, p2, \alpha, \) and \( \gamma \) enhance the positive effect of turnover. \( P1 \) and \( p2 \) can both reflect the organizational learning perspective as well as the human capital view.
In the former case, higher $p1$ and $p2$ can mean a high efficiency in exchanging knowledge between the firm and employees. $P2$ in particular addresses the organizational capability in changing the individuals’ knowledge to the organizational knowledge. In a human capital perspective, a high $p1$ signifies a low accumulated firm knowledge (e.g. a startup), and a low $p2$ signifies that the firm has little to learn from its employees.

Separating the industries with relatively higher extents of efficiency-based nature of competition from the ones with higher extents of winner-takes-all nature of the competition through Models 2 and 3 provides us with further insights. The sign of the estimated coefficient for turbulence differs between these two models. The comparison of these models reveals that the negative association of turbulence and the optimal turnover rate is particularly related to the industries with efficiency-based nature of competition. The absolute coefficient of $p4$ in Model 2 (limited to the efficiency-based industries) is around five times greater than in Model 1 (the full sample). Model 2 and 3 reflect how for low $\gamma$, higher turbulence ($p4$) decreases the positive effect of turnover, and for high $\gamma$, higher turbulence calls for higher turnover (albeit not significantly). This is especially so, since turnover gives the firm a chance to bring variance into its knowledge pool, and thus catch up with the external disturbance. However, when $\gamma$ is low, the firm’s performance is mainly dependent on its employee’s high knowledge. Hence, even if turbulence increases, it is best for the firm to give its employees time to enhance their knowledge. In other words, even as turbulence increases, the firm is better off exchanging fewer employees and let the remaining ones learn new knowledge from the few new recruits.

The positive association coefficient for $p4$, emerged in Model 3, gets significance through Models 4 and 5. In model 4, when $p1$, $a$, and $\gamma$ are high, the effect of $p2$ becomes marginal. This is the case of technological startups in which the firm’s performance depends mostly on the tacit
knowledge of the new recruits, and higher turbulence requires the firm to hire new personnel with updated knowledge. Finally, model 5 reflects the case when $p4$ has the strongest effect on increasing the positive impact of turnover. This is typical of technological incumbents (e.g. Google) that ought to be very reactive to external change (e.g. $p4$); even more so than startups (e.g. model 4).

From the above analysis, we theorize:

**Proposition 1:** The optimal turnover rate is positively associated with)

a. organizational learning capability, b. expected level of knowledge of new entrants, c. the extent of the winner-takes-all nature is in the competition the organization perceives.

**Proposition 2:** The turbulence and pace of change in the industry is negatively related to the optimal turnover rate for the efficiency-based industries.

**Proposition 3:** The turbulence and pace of change in the industry is positively related to the optimal turnover rate for the winner-takes-all industries.

**Proposition 4a:** The positive association between optimal turnover rate and turbulence in winner-takes-all industries is positively moderated by the expected knowledge of new entrants.

**Proposition 4b:** The positive association between optimal turnover rate and turbulence in winner-takes-all industries is accentuated for the entrepreneurial ventures.

**Proposition 4c:** The positive association between optimal turnover rate and turbulence in winner-takes-all industries is accentuated for the mature organizations which have high levels of organizational learning capabilities.
It is particularly important to mention that the negative coefficient of $p2$ in Model 5 which is limited to the organizations with relatively high $p2$ is not surprising and only reveals the concave relation between $p2$ and the best turnover rate.

**Exploration Mix**

So far, we have considered turnover as the only key mechanism for organizational exploration. Organizational exploration is achieved by the exploitation of the newly entering stars whose elements of knowledge is at least partially new to the organization. Through this logic of exploration, an element of knowledge can be acquired by an organization only if an individual already holds it. The organizational learning literature, however, has also introduced the concept of individual exploration through which a researcher may acquire knowledge individually (e.g. Lazer and Friedman, 2007). Consequently, we amend our model to account for two types of possible exploration means for the organization: 1. turnover, and 2. Individual exploration (e.g. research). We model the merge between the two types of explorations as resource allocation tradeoff; The star’s time and effort are a limited resource which the organization needs to decide on which type of exploration it is allocated to (e.g. which percentage of the stars’ efforts should be devoted to transferring their individual knowledge to the organization, and which percentage should be self-managed to increase their personal knowledge individually.) Furthermore, we extend the premises of the turnover as a strategic decision to a pair of joint strategic decisions including optimal turnover rate and the optimal exploration mix: boosting exploration through exploiting stars’ knowledge versus boosting organizational exploration by stars’ individual explorations.

In our model, we introduce “$p5$” as a parameter reflecting the extent of organizational resources devoted to the “stars’ individual exploration”. The knowledge elements of the stars
change to reality with a probability of $p_5$ in each iteration of individual exploration. To account for the tradeoff nature of decision over the $p_5$, we introduce the effective organizational learning rate, $p_2^*$, as follows:

4. $p_2^* = p_2 - M \times p_5$

where, $M$ is a magnifying factor that accounts for a greater uncertainty in individual exploration relative to the stable transfer of individually known knowledge to the organization.

Equation 4 reveals the tradeoff nature of the decision about how to allocate the stars’ efforts to the two different important activities that can, ultimately, boost organizational exploration. This decision about $p_5$ is particularly important for the organizations that are competing at the edge of technology and perceive a winner-takes-all nature of competition (e.g. firms in Silicon Valley). Thus, we limit our sample to such type of firms (e.g. high $\alpha$, $\gamma$, and $p_2$); and we target our subsequent analysis at exploring the effects of $p_5$ on both the best performance these organization achieve and the turnover rate that leads to the best performance. We simulate the turnover rates in the range of [0,0.4]; we set the magnifying factor at $M=3$; and dial $p_5$ in the range of [0,0.3] with steps of 0.05. The maximum value of $p_5$, is at $p_5 = 0.3$, at which all of the organizational learning resources are allocated to individual exploration, and the effective organizational learning rate, $p_2^*$, is thus decreased to zero.

Our regression tests confirm that accounting for individual star learning, as a means to explore, affects the turnover-performance relationship. Accounting for individual star learning also introduces important implications for the firm’s resource allocation between organizational learning and individual star learning. In fact, these two strategic decisions have to be made jointly in order to assess the best turnover rate. The first regression test (Table 3) shows that from
small to moderate \( p5 \) the optimal decision is to shift the organizational learning resources to stars’ individual exploration. Inversely, for greater values of \( p5 \), the optimal decision is to shift back the organizational learning resources towards the transfer of the stars’ knowledge to the organizational code. The results also suggest that accounting for individual exploration as a means of organizational exploration offers the organizations the possibility to manage the costs of turnover (i.e. the decrease in employees’ average knowledge) and achieve greater performance. The second regression table (Table 4) confirms this finding and shows that \( p5 \) negatively affects the best turnover rate.

**Proposition 5:** Turnover rate and exploration mix interact to optimize the organizational performance. The decision about optimal turnover rate and exploration mix should be made jointly.

**Proposition 6:** The higher the extent of individual exploration in the exploration mix, the lower the optimal turnover rate.

**DISCUSSION**

The theoretical framework and analysis of our paper had one main purpose which is to bridge between the contradicting turnover effect perspectives cleaving the literature so far. To do so, our analysis showed that turnover effect is very context-dependent. Any theoretical framework can outweigh another given a specific underlying firm context. Thus, our study argues for, and shows the utility of, performing turnover effect research based on a distinct turnover-effect model, instead of relying on one subset perspective to do so.

Furthermore, we theorize that in the long run, as firms adjust their turnover level to increase their performance, turnover can no longer be regarded as a static variable affecting a
firm’s performance, but rather as a firm’s performance enhancing strategy. In support of this argument, we contend that there are numerous strategies to stop employee mobility, yet many firms do not necessarily employ any of them. For instance, firms can simply outbid the competitor’s offer for the target employee; or choose to retaliate against competitors through lawsuits (Gardner, 2002, 2005; Schwartz and Salamone, 1999); build a reputation for tough litigation (Agarwal, Ganco, and Ziedonis, 2009); or leverage the positive effects of employee embeddedness (Mitchell, Holtom, Lee, Sablynski, and Erez 2001). However, in many instances some firms choose to instead openly embrace turnover. Such is the case for the majority of firms located in Silicon Valley - one of the largest technological clusters, where employee mobility is a common phenomenon. Consequently, it stands to reason that turnover rates are strategically dialed by firms for optimum performance. Therefore, turnover effect on performance at \( t_i \) itself guides the firm into more accurate estimations of the parameters of the model, therefore affecting the turnover-performance relationship at \( t_{i+1} \).

The paper also opens new avenues for future studies. The empirical investigations of our propositions motivate further research. The multi-facet nature of the turnover issue, and simultaneous multi-parameter interactions demonstrated in propositions 4a through 4c, in particular, call for in-depth case study analyses.

**CONCLUSION**

In this research, we hope to advance the understanding of the turnover effect, and help solve the conflicting findings observed so far in this body of literature. We also encourage future researchers to base both theoretical and empirical works on a turnover model that can shed more light on the complexity of the turnover phenomenon. Furthermore, given that an optimal level of turnover can exist for each firm context, it makes sense to study turnover as a performance
enhancing strategy. Performing a cross analysis of the effect of turnover on an aggregate number of firms does not capture how each individual firm may be seeking its own optimal level of turnover with time.
REFERENCES


TABLES AND FIGURES

TABLE 1
Regression analysis on firm performance

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Number of obs       37422   3780    630     315     315
Adj R-squared       0.7361  0.7710  0.9479  0.8605  0.9555

*p < 0.05, ** p < 0.01, *** p < 0.001

TABLE 2
Regression analysis on best turnover

<table>
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Number of obs       37422   13608  17010   2835   3150
Adj R-squared       0.6188  0.6713  0.5689  0.1034  0.6630

*p < 0.05, ** p < 0.01, *** p < 0.001
### TABLE 3

Regression analysis on best profit

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Number of obs 9072  
Adj R-squared 0.7308

*** p < 0.001

### TABLE 4

Regression analysis on best turnover

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Number of obs 9072  
Adj R-squared 0.4654

*** p < 0.001
FIGURE 1
Turnover patterns as illustrated in Shaw, Gupta, and Delery (2005; p. 54).

FIGURE 2
Theoretical model

P1: Employee learning rate
P2: Organization learning rate
A: Average Knowledge
C: Code Knowledge
Performance
Quality of replacements
Competitive environment (e.g. winner-take-all market, vs efficiency-rewarding market)
FIGURE 3
Plot of firm performance as a function of turnover. Coefficients based on regression analysis of all values of p1, p2, p3, p4, p3 squared, α, and γ.

FIGURE 4
Plot of firm performance as a function of turnover. Omitting the turnover squared term.
α > 0.5; γ < 0.5; p2 = 0.1; p1 = 0.1; p4 = 0.

FIGURE 5
Plot of firm performance as a function of turnover. α < 0.8; γ < 0.2; p2 = 0.1.
- : p1 = 0.1 & 0.5.
- : p1 = 0.5.
- : p1 = 0.1. 
FIGURE 6
Plot of firm performance as a function of turnover. $\alpha > 0.8; \gamma > 0.8$; Dark: baseline.

A: $p_2 = 0.5; p_1 = 0.5$

B: $p_2 = 0.9; p_1 = 0.9$

C: $p_2 = 0.9; p_1 = 0.5$

D: $p_2 = 0.5; p_1 = 0.9$
FIGURE 7
Plot of firm performance as a function of turnover. $\alpha > 0.8$; $p_2 = 0.9$; $p_1 = 0.9$; Dark: baseline.

8A: $\gamma = 0.5$

8B: $\gamma < 0.3$

8C: $\Gamma = 0.9$