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The impact of employee turnover and turnover volatility on labor productivity: a flexible non-linear approach

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ABSTRACT

This article intends to further unravel the relationship between employee turnover and organizational performance. We test a complex non-linear relationship between turnover and performance, integrating different theoretical views (i.e. theories on human and social capital, operational disruptions and organizational learning) and using polynomial regressions. Based on organizational routines theory, we also consider the role of turnover volatility, i.e. the turbulence in turnover across time. To this end, we make use of longitudinal data of Belgian firms over a period of 10 years (1999–2008). Our results confirm the complex non-linear relationship such that organizations' labor productivity increases at low levels of turnover, reaches a peak and decreases afterwards in a negatively attenuated fashion. Moreover, turnover volatility is negatively associated with labor productivity, suggesting that organizations find it especially difficult to deal with strong and frequent changes in turnover across time. Finally, volatility also moderates the relationship between employee turnover and labor productivity. The higher turnover volatility, the less outspoken the positive results of small amounts of turnover. At high levels of turnover, firms with medium volatility suffer the most negative effects. Both research and practical implications of these findings are considered.

KEYWORDS

Employee turnover; turnover volatility; labor productivity; organizational routines; polynomial regression

Introduction

Traditionally, employee turnover has been assumed to create substantial losses for organizations due to human and social capital depletion, and operational disruptions. It would therefore affect organizational performance negatively (Hancock,

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Allen, Bosco, McDaniel, & Pierce, 2013; Shaw, 2011). A bulk of research has indeed found a negative linear relationship between turnover and several indicators of organizational performance, such as sales, profits, productivity, customer satisfaction and value added (for an overview, see Shaw, 2011). At the same time, some authors questioned the simplicity of a linear relationship arguing that there may be more complex curvilinear relationships masked behind it. Firstly, an inverted-U shaped relationship has been put forward, implying that organizations benefit from small amounts of turnover because there is a reduction of labor costs and an influx of new ideas. Beyond an optimal turnover point, however, performance steadily declines due to turnover costs outweighing its benefits (e.g. Glebbeek & Bax, 2004; Shaw, 2011; Shaw, Gupta, & Delery, 2005). Secondly, an attenuated negative relationship has been proposed meaning that at low to medium levels, turnover is particularly harmful, while at high levels, the marginal impact of additional turnover is lower (e.g. Shaw, 2011; Shaw et al., 2005; Ton & Huckman, 2008).

Relatively few studies have tested these curvilinear relationships. In their reviews, Hausknecht and Trevor (2011) and Shaw (2011) only found 12 papers explicitly examining curvilinear relationships. While some of these studies found support for the inverted-U shaped relationship (e.g. Glebbeek & Bax, 2004; Meier & Hicklin, 2007), others did not find evidence for it (e.g. Batt & Colvin, 2011), and still others found evidence for an attenuated negative relationship (e.g. Alexander, Bloom, & Nuchols, 1994; Shaw et al., 2005). Considering this mixed evidence throughout the years, several authors have recently called for more research examining the exact shape of the relationship between employee turnover and performance, as well as contextual moderators that influence it (e.g. Hancock, Allen, & Soelberg, 2017; Hancock et al., 2013; Hom, Lee, Shaw, & Hausknecht, 2017; Park & Shaw, 2013). This study aims to answer both calls.

A first response to this call has been suggested over a decade ago by Shaw and colleagues (2005). They put forward a more complex non-linear relationship which integrates the inverted-U shaped relationship with the attenuated negative one. This entails a relationship that initially increases, reaches a peak and then continues in a negative but attenuated fashion. The rationale behind this relationship is a combination of existing theoretical views on the turnover-performance relationship, building on notions of human and social capital, operational disruptions and (organizational) learning (Shaw, 2011; Shaw et al., 2005). However, to our knowledge, this perspective has never been tested. Probably because it is impossible to discern through the traditionally used tests of curvilinearity, i.e. adding a quadratic term to regression analyses (e.g. Glebbeek & Bax, 2004). Therefore, a first aim of this study is to take a more flexible non-linear approach to further explore the turnover-performance relationship in a multi-industry setting. We do so by using polynomial regression analyses, a technique that is able to map complex non-linear relationships going beyond curvilinearity.

Secondly, we answer the call for more insights into the relationship between employee turnover and organizational performance by introducing the notion

of turnover volatility. We argue that it is not only the level of employee turnover that has an influence on organizational performance, but also the turbulence or (in)stability in its pattern throughout time. Based on organizational routines theory, we expect both a main effect of turnover volatility and an interaction effect between turnover and turnover volatility. More specifically, we hypothesize that firms with high turnover volatility are, on average, less performant as compared to firms with low volatility, and that firms with high volatility reap less benefits of small amounts of turnover and are less protected against the negative effects of high turnover.

This study adds to turnover research in two ways. Firstly, we dig deeper into the relationship between turnover and organizational performance, by exploring the non-linearity in a more sophisticated manner. This provides more insight into the complexity of the relationship, testing the viability of an integration of different theoretical frameworks. Secondly, we introduce a new theoretical lens to explore the role of turnover volatility, i.e. organizational routines theory. By focusing on turnover volatility, we identify a moderating variable determining the actual shape of the relationship between turnover and performance, and also add to recent studies acknowledging the role of time and changes in turnover (e.g. Call, Nyberg, Ployhart, & Weekley, 2015; Hausknecht & Holwerda, 2013).

Literature review and hypotheses

Employee turnover and labor productivity: exploring its non-linearity

In 2011, merely 12 studies had tested and reported curvilinear relationships between turnover and performance (Hausknecht & Trevor, 2011; Shaw, 2011). Some studies found no evidence of a curvilinear relationship between turnover and firm performance in samples such as teachers (Shevchuck, Leana, & Mittal, 2007) and call centers (Batt & Colvin, 2011). Others found evidence for an inverted U-shaped relationship, yet only in specific samples such as part-time employees of retail stores (Siebert & Zubanov, 2009), employees working in temporary job agencies (Glebbeek & Bax, 2004) and teachers (Meier & Hicklin, 2007). Finally, still others found support for a negative but attenuated relationship among samples of production workers, truck drivers and retail employees (Shaw et al., 2005; Ton & Huckman, 2008). Hence, it was concluded that the existence of a curvilinear relationship was doubtful at best considering the lack of clear and consistent evidence pointing in this direction (Hausknecht & Trevor, 2011; Shaw, 2011). Yet, recent research has rekindled the belief in a non-linear relationship. First, while they did not test this formally, Park and Shaw (2013) interpret the fact that they find sample-specific and different effects of turnover depending on the turnover type as a sign that a curvilinear effect may exist. Second and most importantly, two meta-analyses found support for an inverted-U-curve across a wide range of studies and samples (Hancock et al., 2013, 2017). As a result, there is a new call for

additional research to explore the non-linear nature of the turnover-performance relationship (Hancock et al., 2017; Hom et al., 2017).

Building on Shaw et al.'s (2005) and Shaw's (2011) suggestion, we propose a non-linear relationship taking the shape depicted in Figure 1. This relationship can be theoretically explained through the integration of several existing views on the relationship between turnover and performance. Firstly, we argue that a small amount of turnover outperforms zero turnover. Small changes in staff can prevent an organization from organizational blindness and group-think, and can stimulate innovation and creativity (e.g. Abelson & Baysinger, 1984; Dalton & Todor, 1979; Shaw, 2011). Secondly, small numbers of employees leaving the firm can imply potential efficiency gains if other employees can take over (Abelson & Baysinger, 1984; Shaw, 2011). Finally, although less visible, the retention costs needed to reduce turnover (in extremis to zero), can be excessively high in terms of for example more training, promotions, transfers and staff inflexibility (Abelson & Baysinger, 1984). Hence, stimulating a small amount of turnover can keep these costs under control allowing the benefits to prevail.

However, at some point, the costs of turnover take over, explaining why a reduction in performance occurs. These costs are grounded in human and social capital theory and the organizational disruption framework. Firstly, human capital theory suggests that employees' firm-specific human capital – acquired through their work experience and training within the firm – is an important driver of organizational performance as it strongly contributes to the competitive advantage of the firm by being valuable, rare, inimitable and non-transferable (Shaw, 2011; Shaw, Park, & Kim, 2013; Yanadori & Kato, 2007). Although the theory argues that employees with high firm-specific capital have few incentives to leave organizations, research on determinants of turnover has shown that many other economic, psychological and sociological factors might be in play and incite employees to leave (e.g. Rubenstein, Eberly, Lee, & Mitchell, 2017). Hence, through turnover (for whatever reason), organizations incur losses of valuable firm-specific human capital harming their competitive advantage and decreasing the return they obtain from past investments in this human capital (e.g. firm-specific training) (Dess & Shaw, 2001; Shaw, 2011; Shaw et al., 2013). In addition, replacing these leavers

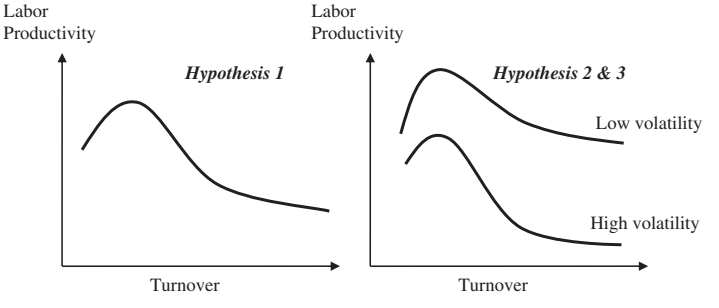

Figure 1. Visualization of hypotheses.

with employees possessing the same level of firm-specific human capital requires substantial investments in terms of money and time (e.g. for recruitment, selection, socialization and training).

Secondly, following a similar line of reasoning, turnover implies a potential loss of valuable social capital (i.e. capital and resources which are incorporated in social networks and relationships) built up by leavers (Hancock et al., 2013). For example, when a leaver has many and important social connections within and outside of the organization, the organization may lose a key member of its organizational network and incur performance losses (Dess & Shaw, 2001).

Finally, the operational disruption framework can be used to argue that turnover has strong repercussions for organizational functioning. Turnover disrupts the organization's operations both directly (e.g. by increasing the odds of work undone, of unmet commitments, and missed opportunities due to a decrease in employees or replacement employees being potentially less-experienced and knowledgeable) as indirectly (e.g. through the cost of and time spent on hiring, socializing and training a new employee) (Hausknecht, Trevor, & Howard, 2009; Heavey, Holwerda, & Hausknecht, 2013; Watrous, Huffman, & Pritchard, 2006).

In sum, due to these costs, at medium levels of turnover, it is assumed that turnover starts to harm organizational performance. Yet, based on insights from (organizational) learning, we can assume that this harm would weaken at higher levels of turnover (Shaw, 2011; Shaw et al., 2005). More specifically, as opposed to a situation of high turnover, medium turnover means that a company tends to lose employees that have, on average, worked longer in the organization and have gone through a relatively substantial learning curve, building up valuable and firm-specific human and social capital (Yanadori & Kato, 2007). Hence, the loss of such employees is relatively more disruptive and costly to overcome (in terms of finding a newcomer and training him/her to achieve the same level of human/social capital) (Shaw et al., 2005). In contrast, in the case of high average turnover, employees exit at a faster and higher rate, hence building up relatively less firm-specific human and social capital. As a result, the marginal cost of an extra employee leaving will be relatively lower as opposed to a situation of medium average turnover, considering that relatively less expenses need to be made in terms of bringing a newcomer to the same level as the leaver and that the continuous replacement of employees has become something the organization has learned how to deal with and measures have been taken to keep it from disrupting the organization (Shaw, 2011; Shaw et al., 2005). Hence, from medium to high turnover, we would witness a negatively attenuated relationship.

In terms of organizational performance, we focus on labor productivity because turnover involves changes related to the labor pool of organizations. Accordingly, it has repeatedly been recognized and used as an appropriate measure of firm performance (e.g. Glebbeek & Bax, 2004; Shaw et al., 2005; Siebert & Zubanov, 2009; Yanadori & Kato, 2007) because it is more directly influenced by turnover than, for example, financial performance (Heavey et al., 2013; Shaw, 2011). In addition,

it measures performance in a relatively comparable manner across organizations in a wide range of industries.

Hypothesis 1: The relationship between turnover and labor productivity is inversely U-shaped from low to medium turnover and negatively attenuated from medium to high turnover.

Exploring the role of turnover volatility

Although much work has been done to identify the strategies to keep turnover under control (e.g. by implementing high commitment HR practices and realistic job previews; for an overview, see Hom et al., 2017; Hancock et al., 2017), less insight exists in the strategies through which and conditions under which organizations can control the consequences of turnover. Essentially, organizations need to find strategies to cope with turnover and the uncertainty created by it (Mowday, 1984). Drawing from organizational routines theory, we can label these strategies as 'organizational routines' (Becker, 2004). The concept of routines itself is subject to many definitions and conceptualizations but all definitions have in common that routines refer to 'repeated patterns of behavior bound by rules and customs' (Edmondson, Bohmer, & Pisano, 2001; : 686). These patterns of behavior are a set of interactions between organization members that are triggered by a certain situation, task or problem that needs to be handled (e.g. turnover) (Becker, 2004; Gersick & Hackman, 1990). Routines are functional to the organization in several ways. They allow firms to quickly take action and maintain performance in the case of certain events (e.g. turnover), thereby saving time and energy (Gersick & Hackman, 1990). In addition, they reduce uncertainty in the organization, store knowledge about which course of action to undertake and provide stability for the organization (Becker, 2004).

Applied to the context of turnover, exits of employees can be seen as a trigger for the development and use of organizational routines. Examples of such routines are (1) actively influencing the job demands of the remaining team members to make sure the work gets done, for example by designing a procedure regarding whether, how and to whom work should be delegated after the exit of one employee (e.g. Reilly, Nyberg, Maltarich, & Weller, 2014); (2) stimulating team learning or creating apprenticeships to stimulate knowledge transfer between the employee who is leaving and the person(s) who will have to take over (Knight, 2016); (3) transferring employees from one team to another within the organization based on an employee skills inventory or after cross-training to get efficient replacement from within (e.g. Reilly et al., 2014); (4) increasing efforts towards continuous recruitment, e.g. by building long-term relationships with hiring agencies or universities, to call upon when needed and to be able to quickly find external replacement (e.g. Mowday, 1984; Reilly et al., 2014); (5) introducing a newcomer manual with both general and more specific information about the employee who has left and his/her function or introducing training activities to make sure that the knowledge

transfer towards a newcomer is facilitated, he or she quickly becomes productive and the inefficiency following the leave of an employee is reduced (e.g. Knight, 2016; Mowday, 1984); (6) hiring excess employees such that turnover is covered by this excess and does not create disruptions in the production or service process (e.g. Mowday, 1984); and (7) sustaining a good relationship with the person who is leaving to make sure the organization can count on him/her if needed in the future, for example by organizing an exit interview or a farewell drink (Knight, 2016). These examples show that organizations can gradually develop *turnover routines* to become more efficient and effective in the event of turnover (e.g. Reilly et al., 2014).

In line with this routines perspective, Ton and Huckman (2008) for example showed that organizations can protect themselves from the destructive effects of turnover by creating a set of standardized rules and procedures for employees to follow when executing tasks (which they label as 'a high process conformance approach'). An experimental study by Rao and Argote (2006) produced similar results illustrating that teams working on very structured tasks with a fixed set of guidelines suffered a lower performance decline when faced with turnover as opposed to teams lacking such structure and guidelines. In other words, by creating performance rules and procedures, the organization's human capital partly resides in the routines (as opposed to its individual employees), allowing the firm to quickly bring a newcomer to an adequate level of performance (Ton & Huckman, 2008).

Yet, developing and optimizing functional routines to cope with turnover takes significant time and effort (Becker, 2004; Brauer & Laamanen, 2014; Edmondson et al., 2001). Moreover, routines evolve in a path dependent way. While empirical research has repeatedly shown that routines can change over time (for an overview, see Becker, 2004; Pentland, Hærem, & Hillison, 2011), their evolution is often incremental involving relatively small changes to perfection them or tailor them to small changes in the environment (Becker, 2004). This means that when a substantial change in the environment occurs, organizations will find it difficult to cope with the redesign of organizational routines as it may require a radical change (Brauer & Laamanen, 2014; Gersick & Hackman, 1990). Especially when these changes are strong and frequent, incremental changes in organizational routines may not suffice to uphold productivity in the organization (Gersick & Hackman, 1990). Turnover volatility can be seen as the degree to which strong changes occur in the level of turnover across time. Building on the above reasoning, we can argue that as long as the level of turnover remains stable across years (i.e. low turnover volatility), the development of turnover routines is functional for the organization by coordinating the course of actions that need to be undertaken. In this case, organizations are able to develop and perfection functional organizational routines. In contrast, when the level of turnover faces heavy peaks and lows across different years (i.e. high turnover volatility), the organization will face problems to cope with it and organizational routines will become dysfunctional (Gersick

& Hackman, 1990). In this case, the routines developed in the past to deal with turnover will be disrupted and inefficient because of a mismatch between the current routine and the organizational conditions (Edmondson et al., 2001). These arguments are in line with the work of Hausknecht and Holwerda (2013) who argued that time-dispersed turnover (i.e. spread out across time) does less damage to organizations as opposed to time-restricted turnover (i.e. occurring simultaneously). Specifically, time-dispersed turnover would allow the organization as a whole to better 'handle disruption and meet role demands until newcomers achieve proficiency themselves' (Hausknecht & Holwerda, 2013: 213). Although the authors do not explicitly refer to organizational routines theory and the concept of volatility, there is a clear link. Time-dispersed turnover would eventually result in low turnover volatility within a certain time frame as the departures are spread out (rather equally) over time. Moreover, the stable and functional organizational routines built up in this context might be exactly the reason why organizations are able to handle disruption better in this situation. In contrast, time-restricted departures (i.e. peaks of turnover occurring simultaneously at just a few points in time across a wide time window) can eventually result in high volatility which causes organizations to struggle to develop stable and functional routines to handle the disruptions.

In line with the aforementioned arguments, we hypothesize that organizations with high turnover volatility, i.e. strong and frequent changes in employee turnover, have more difficulties to develop and change routines, and therefore show lower labor productivity compared to organizations with low turnover volatility.

Hypothesis 2: The direct relationship between turnover volatility and labor productivity is negative.

Moreover, we believe turnover volatility to moderate the relationship between employee turnover and labor productivity. This follows up on previous research which has already identified a few moderating variables. Hausknecht et al. (2009), for example, showed that particularly larger work units and units with a relatively high degree of newcomers found it more difficult to cope with turnover. Shaw et al. (2013) showed the relationship to be contingent on HRM investments, such that higher investments imply a more harmful loss of social and human capital. In their meta-analyses, Hancock et al. (2013, 2017) and Park and Shaw (2013) found several contextual variables to matter. They, for example, concluded that turnover is especially detrimental within the service industry and when it concerns managerial turnover. Finally, Hausknecht and Holwerda (2013) have stressed the importance of turnover properties, arguing that turnover is more difficult to efficiently cope with when all turnover, for example, occurs simultaneously ('time-restricted') and when the remaining employees are novice. Adding to this research, we are the first to look at the moderating role of turnover volatility.

It is often argued that routines are created in a firm-specific way as they are developed and adapted through the learning process of individuals within an organization (Becker, 2004; Helfat & Karim, 2014; Pentland, Hærem, & Hillison,

2010; Zollo & Winter, 2002). Considering this firm-specificity of routines, we argue that firms that are confronted with low to medium numbers of separations will develop other routines than firms confronted with high numbers of exits.

Firms with low to medium turnover will, for example, focus on dispersing knowledge (via team learning or apprenticeships) or cross-training within the firm to make sure that if one individual exits, one of the remaining employees can quickly replace him or her to buy the necessary time to find worthy replacement. Thanks to these knowledge related routines (e.g. knowledge dispersion, cross-training), very small numbers of turnover create not only little costs and disruptions but will also have particularly outspoken benefits for the firm as a newcomer's new and different knowledge will quickly spillover to and be absorbed by existing employees. The higher the amount of leavers, however, the higher the disruption of processes and the more difficult it will get to smoothly replace the leavers. Hence, at medium levels of turnover, labor productivity eventually takes a downturn (in line with hypothesis 1). Yet, this initial benefit of low turnover will only be fully maximized when the firm is confronted with consistently stable low amounts of turnover across time, as only in this situation, the firm has been able to develop stable and functional routines to deal with turnover (cf. also our reasoning above in hypothesis 2). In contrast, when a firm faces heavy alternations between low and high turnover (i.e. high turnover volatility), they will not be able to develop the stable, functional and necessary routines to deal with low turnover. As a result, they draw less value from low turnover in terms of labor productivity. The same holds for the negative part of the curve after the optimal turnover level. This will be more negative in case of high turnover volatility as compared to low turnover volatility.

Conversely, firms with generally high turnover might predominantly focus on creating slack by hiring excess employees to compensate for separations or at least building an excess recruitment pool which the firm can easily call upon (Mowday, 1984). They are thus much more focused on quickly attracting and training newcomers as compared to firms with low to medium turnover. By doing so, they can minimize the negative effect of high numbers of turnover on labor productivity. Yet, in line with our reasoning above (hypothesis 2), they can only fully develop and perfection these routines and minimize this negative effect when their level of turnover is consistently high across time (i.e. low turnover volatility). This is significantly more difficult to achieve in case of heavy turnover volatility, which is why, in this case, firms find it difficult to protect themselves from high turnover, resulting in a stronger decline in labor productivity.

In sum, firms facing heavy turbulence in their turnover pattern from one year to another (i.e. high turnover volatility) will face different consequences in terms of labor productivity as compared to firms with a stable turnover pattern (i.e. low turnover volatility). We expect these firms to draw fewer (if any) benefits from low to medium turnover, and face more destructive consequences from medium to high turnover. In contrast, firms with low turnover volatility are able to develop

stable and functional routines and are thus expected to more fully profit from the benefits of low to medium turnover and be better able to protect themselves from the destructive effect of medium to high turnover.

> *Hypothesis 3*: Turnover volatility moderates the non-linear relationship between turnover and labor productivity such that the initial increase in case of low to medium turnover is more (less) pronounced and the negatively attenuated slope is less (more) pronounced in case of low (high) turnover volatility

Hypotheses 2 and 3 are visualized in Figure 1. Hypothesis 2 is represented by the vertical difference between the two curves as for low volatility we expect generally higher labor productivity. Hypothesis 3 is visualized by the less outspoken positive effects from low to medium turnover and the more outspoken negative effect for high turnover when turnover volatility is high.

Methods

Data

The data are obtained from the Belfirst database (BvDEP, 2010). This database contains balance sheet and income statement data for all Belgian firms that are required to file their annual accounts to the National Bank of Belgium. In addition to the standard balance sheet and income statement data, all firms that employ personnel are required to file a social balance sheet, containing information on the number of employees as well as on the in- and outflow of workers. The outflow of workers is of particular relevance to this study and represents the organization's turnover.

The sample used in the empirical analysis includes data for the years 1999–2008. We include firms from all sectors of activity, except for the sector 'Employment activities', since it includes firms that employ workers on a daily and weekly basis and is hence characterized by unusually high turnover rates. Moreover, for several reasons, we focused on firms that employed at least 50 employees in at least one year. First, most firms employing less than 50 employees are not required to provide detailed information on the outflow of workers.[1] Second, we expect larger firms to be less prone to measurement errors as they are more likely to systematically and accurately keep track of turnover. Moreover, as the denominator of the turnover rate is smaller for small firms, measurement error in the number of outflows creates larger variation in the turnover rate for these firms.

To verify the reliability of our data, we check whether the total number of employees at the end of a particular year is equal to the total number at the end of the previous year plus the inflow of new people, minus the outflow of employees. A substantial difference between both indicates that the organization did not accurately report the in- and outflow of employees. We decided to drop an observation from the data when the difference is larger than 10% of the total number of employees. As a result, 3% of the observations were dropped.[2] Secondly, we

clean for outliers to avoid their distortion of the results. We excluded all firm-year observations that are in the top five percentile of the distribution of the turnover rate, i.e. a turnover rate of 74% of the total number of employees in a given year and above). This results in a final sample of 45,044 firm-year observations for 6,246 firms.

Measures

Labor productivity

We calculated labor productivity as the gross value added divided by the average number of employees (part-time employees are given a weight according to the number of hours they work relative to a full-time employee). In all analyses, we use the natural logarithm of labor productivity to make the measure less sensitive to outliers. Moreover, to control for inflationary changes in labor productivity, we deflate value added using a NACE 2 digit value added deflator obtained from the EU Klems database (see Appendix 1 for more details). Note that labor costs such as wages or severance payments are not part of labor productivity. If, for example, a firm wants to pay higher wages to reduce turnover rates (i.e. retention costs as mentioned by Abelson & Baysinger, 1984), these costs are not included in labor productivity. Most of the costs related to turnover and mentioned in the section on the hypotheses are however indirect costs, such as disruptions in production processes, loss of human capital, or productivity losses due to training, that lead to lower value added for a given number of employees. As such, these are reflected in our measure for labor productivity. Also factors that lead to more employees to generate a particular level of value added, such as larger HR departments (due to more HR employees involved in training and recruitment and selection), are picked up by our measure. Finally, a part of turnover costs, such as costs of posting vacancies, are intermediate inputs and are therefore included in labor productivity as well.

Turnover

Our measure includes the number of workers leaving the organization at their own initiative or due to the end of a fixed term contract. We divided this number in a given year, by the average number of employees in that same year. Turnover in the form of layoffs was excluded from the measure. The generally disruptive nature of employee turnover and its volatility that lies at the heart of the theoretical arguments mentioned above, applies less strongly to layoffs. Discharges are considered to benefit the organization, for example by replacing underperforming employees (McElroy, Morrow, & Rude, 2001; Park & Shaw, 2013). A recent meta-analysis also points towards a low disruptive nature of dismissals by finding no significant relationship between dismissals and firm performance (Park & Shaw, 2013). Therefore, we decided to drop them in the analyses.

Turnover volatility

Volatility is defined as the firm-level standard deviation of the turnover rate over all periods in which the firm was included in the sample and thus measures the within-firm turbulence in the turnover pattern throughout time. The higher the standard deviation, the more the firm faces peaks and lows across time and thus the higher turnover volatility.

Control variables

As control variables, we include firm-level capital intensity, age, and a set of sector and year dummies. Capital intensity is defined as the ratio of real tangible fixed assets over the average number of employees and is usually associated with higher labor productivity (e.g. van Ark, O'Mahony, & Timmer, 2008). The age of the firm is calculated in years using the firm's year of incorporation. The size of the organization is captured by including the number of employees working in the organization in a given year. Size, age and capital intensity are expressed in natural logarithms to make the results less sensitive to outliers. Sector dummies are defined at the NACE three-digit level[3] and pick up sector level differences in labor productivity and turnover rates due to technological differences, variations in skill intensity of the labor force, etc. across different sectors. The year dummies control for cyclical changes in labor productivity and turnover rates.

Analytic approach

To test our hypotheses, we regress log labor productivity on the control variables and the turnover rate. To illustrate our approach and obtain the estimation equation, we characterize the production of a firm by a Cobb-Douglas production function, written in value added form:

$$Q_{it} = A_{it} L_{it}^{\alpha} K_{it}^{\beta} \tag{1}$$

where Q_{it} is the value added of firm i in year t, A_{it} is firm level productivity and L_{it}^{α} and K_{it}^{β} represent labor and capital input respectively. Denoting natural logarithms by lower case variables, we can rewrite the above equation as follows.

$$q_{it} = \gamma + \alpha l_{it} + \beta k_{it} + \omega_{it} \tag{2}$$

Here productivity is decomposed into a factor common to all firms, γ, and firm specific deviations from this average productivity level, ω_{it}. Next, we rearrange the equation such that labor productivity is the dependent variable and bring in the hypothesis that part of the unobserved productivity depends on employees' turnover as well as on the volatility of the measure. Thus, the equation is the following:

$$q_{it} - l_{it} = \gamma + \beta(k_{it} - l_{it}) + \delta l_{it} + \sigma v_i + f\left(\frac{S_{it}}{L_{it}}\right) + \iota y_{it} + D_t + D_J + \omega_{it}^{'} \tag{3}$$

where $q_{it} - l_{it}$ is log labor productivity and $k_{it} - l_{it}$ is the natural logarithm of capital intensity (capital stock per employee). The coefficient on labor picks up the returns to scale as δ can be shown to be equal to $\alpha + \beta - 1$. The $f(.)$ function picks up how the turnover rate $\frac{S_{it}}{L_{it}}$ relates to firm level labor productivity while v_i represents firm level volatility in turnover. We also include a vector of sector dummies, D_j at the NACE 3 digit level to control for sector specific differences in labor productivity and turnover rates. Likewise the year dummies D_t pick up business cycle effects. Finally, we include the age of the firm, y_{it}, as a control variable as both productivity and turnover could be different between young and old firms (Olley & Pakes, 1996).

The error term of this equation consists of unobserved productivity shocks, ω'_{it}. The rate of employees exiting the firm, could be influenced by changes in unobserved productivity making the turnover rate endogenous. For example, an employee working for a firm performing badly – reflected in low values for ω'_{it} – could be more likely to leave the firm compared to a worker employed in a highly productive firm, or a firm with better management practices may have both higher productivity and lower turnover rates. We address these potential endogeneity problems in the robustness checks using lagged values of the turnover rate and recent developments from the productivity literature (Wooldridge, 2009). Appendix 3 provides more details on this estimation procedure.

In the presentation of our results, we first enter only the control variables in step 1, after which we include turnover in step 2. To test the non-linear nature of the relationship between productivity and turnover, we perform polynomial regressions by adding higher order terms of the turnover rate.[4] More precisely, we include up to the 4th power of turnover in the regression. Next, we additionally include the turnover volatility rate to test Hypothesis 2. All regressions are estimated using Ordinary Least Squares using robust standard errors, clustered at the firm level.[5]

Finally, to test hypothesis 3, we perform a multi group analysis and repeat equation (3) for three different groups of firms based on their volatility level. More precisely we define 'Low Volatility' and 'High Volatility' firms as firms with a volatility level respectively one standard deviation above and below the average volatility. The firms within one standard deviation of the average volatility are labeled 'Medium Volatility' firms.

Results

Summary statistics

Table 1 displays the means, and standard deviations of the variables used in the estimation, as well as the correlations between these variables. The number of observations is 45,044. The average firm experiences a turnover rate of 16.6% although there exists substantial heterogeneity across firms as indicated by the high standard deviation (.15). The average turnover rate is highest in the services

Table 1. Correlations and descriptive statistics.

Variable	Mean	Standard Deviation	1	2	3	4	5
1. Turnover rate	.17	.15	1				
2. Turnover volatility	.08	.05	.40***	1			
3. ln(Labor productivity)	4.25	.59	−.10***	−.04***	1		
4. ln(Employment)	4.62	.95	−.08***	−.27***	−.02***	1	
5. ln(Capital intensity)	7.66	1.53	−.05***	−.03***	.34***	.02***	1
6. ln(Age of the firm)	3.07	.79	−.07***	−.10***	−.00	.14***	.06***

*$p < .05$; **$p < .01$; ***$p < .001$.

sector (20%) and lowest in the manufacturing industry (12%). The volatility variable has a mean value of .08 and a standard deviation of .05, again reflecting substantial variation across firms. All variables except for the turnover rate and the volatility measure are expressed in natural logarithms to make the results less sensitive to outliers. The correlation coefficients show that the turnover rate is negatively correlated with labor productivity ($r = -.10$; $p < .001$). In addition, volatility is negatively associated with labor productivity ($r = -.04$; $p < .001$).

Regression analyses

The results of the regression analyses are reported in Table 2. In column 1, the results for the analysis with the control variables are reported. In column 2, we include the turnover rate up to the fourth power.

For ease of interpretation, we graphically represented the estimated link between turnover and labor productivity in Figure 2. The figure also includes a histogram with the distribution of the turnover rate over all firms. The relationship is positive for low levels of turnover. As turnover rises, the *marginal* effect of turnover

Table 2. Regression analysis of labor productivity on employee turnover (ordinary least squares).

	1	2	3	4	5	6
		All	All	Low Vol.	Med. Vol.	High Vol.
Turnover rate		1.32*** [.24]	1.22*** [.24]	2.75** [.85]	.69* [.28]	1.584** [.51]
Turnover rate^2		−10.12*** [1.56]	−9.34*** [1.57]	−17.96* [7.19]	−5.77** [1.89]	−10.13** [3.15]
Turnover rate^3		22.38*** [3.64]	21.05*** [3.68]	38.38* [18.41]	12.23** [4.60]	21.53** [6.88]
Turnover rate^4		−15.72*** [2.71]	−14.98*** [2.75]	−26.45 [14.09]	−8.44* [3.55]	−14.82** [4.88]
Turnover volatility			−.36*** [.11]			
Ln(Employment)	−.02* [.01]	−.02* [.01]	−.02** [.01]	.05* [.02]	−.03*** [.01]	−.09*** [.02]
Ln(Capital Intensity)	.13*** [.01]	.13*** [.01]	.12*** [.01]	.13*** [.02]	.12*** [.01]	.12*** [.01]
Ln(Age)	.01 [.01]	.01 [.01]	.01 [.01]	−.01 [.02]	.01 [.01]	.06** [.02]
N	45,044	45,044	44,784	5215	32,444	7125
R^2	.32	.32	.32	.49	.33	.36

Notes: All analyses include year and sector dummies. The robust standard errors, clustered at the firm level are mentioned between brackets. The indicators 2, 3 and 4 indicate the square of turnover, the third power of turnover and the fourth power of turnover respectively. This is typical for polynomial functions.
*$p < .05$; **$p < .01$; ***$p < .001$.

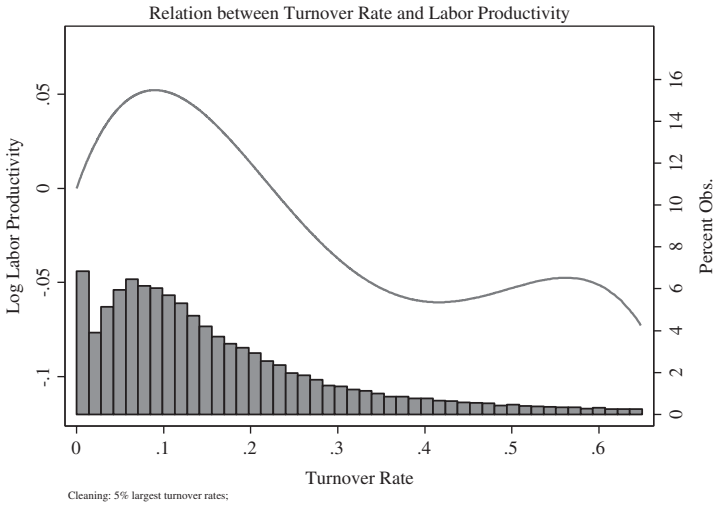

Figure 2. Relationship between turnover rate and labor productivity.

starts to decrease. The optimal turnover rate for the specification in column 4 of Table 2 is 9.0%, which is below the average turnover rate reported in Table 1. This means that a firm with this optimal turnover rate has a productivity premium of 5.3% compared to a firm with zero turnover.[6] At turnover rates higher than this optimal rate, the marginal effect of turnover becomes negative, although the *total* effect on productivity is still positive: only firms experiencing turnover rates larger than 22.4% have lower labor productivity compared to firms with zero turnover. At high rates, the negative marginal effect of the turnover rate attenuates and the marginal impact of turnover becomes close to zero. All in all, the results strongly support hypothesis 1, namely an inversely U-shaped relationship between turnover and labor productivity for low and medium turnover rates, and an attenuated negative effect for high turnover rates.[7]

In column 3 of Table 2, turnover volatility is included. The reported coefficient for turnover volatility is negative and significant ($\beta = -.36$; $p < .01$): an increase by one standard deviation of turnover volatility (.05) lowers labor productivity by 1.9%. This points to a negative impact of volatility on labor productivity. Hence, the results reported lend support to hypothesis 2.

The last three columns repeat the analysis for the three different groups, namely low, medium and high volatility firms. Again, for ease of interpretation, Figure 3 plots the estimated relation between turnover and productivity for these groups. The graph also represents the main effect of volatility as the intercept of each group is now the average volatility of the group times the coefficient on volatility in column 3 of Table 2. We found the initial productivity gain to be highest in firms that experience low turnover volatility (12.1%) as opposed to high turnover volatility (8.1%), which is in line with hypothesis 3. Apart from this more pronounced optimum, the shape of the relationship is relatively similar for firms facing high

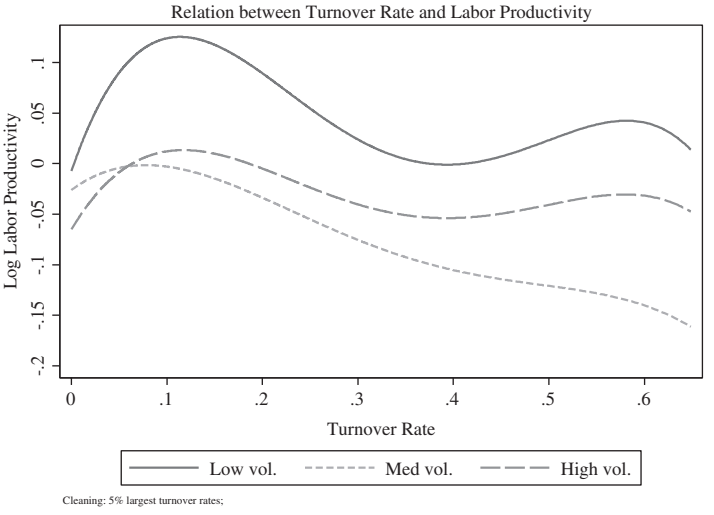

Figure 3. Relationship between turnover rate and labor productivity: different volatility levels.

and low turnover volatility. Although we expected the negative attenuated slope to be less pronounced in case of low volatility as compared to high volatility, the results do not show this. Hypothesis 3 is therefore only partially confirmed. It is actually the group of firms facing medium volatility which deviate strongly, experiencing only a very small benefit of low turnover (2.5% as compared to 12.1% for low volatility and 8.1% for high volatility) and suffering quite strongly from higher levels of turnover. As opposed to the firms experiencing low and high turnover volatility, labor productivity dives below the point of zero turnover and, for example, between a rate of zero and 50% turnover, productivity losses amount to 9.1%.

Robustness checks

We performed several robustness checks. First, we replicated our main results using a different and stricter cleaning procedure following a definition of outliers suggested by Tukey (1977). More precisely, we define U as $U = x_{75} + \frac{3}{2}(x_{75} - x_{25})$ where x_{75} and x_{25} are the 75th and 25th percentile of the turnover rate respectively. Subsequently, we drop observations for which the turnover rate is larger than $U(.53)$.Following a similar reasoning, a lower bound of the turnover rate can be defined but no observations fall below this lower bound. This results in the same conclusions as our original cleaning method (see Table and Figure B1 in Appendix 2).

Second, Trevor and Nyberg (2008) show how layoffs and voluntary turnover may be related. To make sure our results are not confounded by the effects of layoffs, we include the layoff rate, i.e. the ratio of layoffs over employment, as an extra control variable. The results are reported in Table B2 and Figure B2 in the Appendix. The findings are highly similar to our main results.

Third, as highlighted in earlier work (e.g. Glebbeek & Bax, 2004; Koys, 2001; Shaw et al., 2005), reverse causality and simultaneity problems are possible. For example, employees might be less likely to quit more productive firms, which offer a higher degree of job security and better working conditions. This problem is exacerbated by the fact that we measure firm's performance and its turnover at the same point in time. However, note that this type of endogeneity cannot explain the initial positive effect and subsequent negatively attenuating effect of turnover. To control for these potential endogeneity problems we execute a number of extra robustness checks.

First, we exploit the longitudinal character of our data-set and control for the simultaneity problem by regressing labor productivity on *lagged values* of the turnover rate. We therefore re-estimate the relation between turnover and productivity, but now each time for the turnover rate lagged one period. Results are reported in Table B3 (column 1–3) and Figure B3 (the upper graph) in Appendix 2. The conclusions drawn from the reported coefficients are qualitatively and quantitatively the same compared to the base specification where we include the contemporaneous turnover rate. Moreover, the findings indicate that the impact of turnover is not only immediately visible, but that it could also take some time before its impact diminishes.

It is however possible that the first approach does not resolve the endogeneity issues completely, due to unobserved heterogeneity in firm level idiosyncratic performance that is fixed or serially correlated over time. Therefore we introduce a second approach, using a recently developed methodology from the productivity literature, i.e. the Wooldridge (2009) correction (see also. Levinsohn & Petrin, 2003; Olley & Pakes, 1996). The methodology relies on a number of strong assumptions, but has become the standard in productivity literature. The technical details of this Wooldridge correction are beyond the scope of this article, yet are explained in Appendix 3. The results from applying this correction are reported in Table B3 and Figure B3 (the lower graph) in Appendix 2. The coefficients for the turnover rate are jointly highly significant ($p < .001$) and point to the same conclusions as the base specification reported above.

Third, in column (3), we experimented with a regression including firm fixed effects which controls for firm specific heterogeneity that is constant over time. Our main findings concerning the shape of the relation between the turnover rate and labor productivity are again confirmed. The effect sizes are smaller though. A possible explanation could be measurement error combined with persistency in the turnover rate, which would lead to estimates biased towards zero (Griliches & Hausman, 1986).

As a final robustness check, we defined our measure for volatility as the standard deviation of the volatility rate computed from the previous three yearly observations. The advantage is that, in this case, the volatility is time varying. Doing so, we relax the assumption that the firm faces a constant volatility over time, which is implicitly present in our analyses. Moreover, future turnover rates are no longer

used for the computation of volatility and the prediction of labor productivity. The disadvantage is that this measure is a less efficient estimate to capture an underlying constant volatility level (the correlation between the volatility measures is .67). The results are reported in the final column of Table B3 in Appendix 2. Again, we find the volatility of the turnover rate to be negatively related to labor productivity.

Discussion

The main purpose of this study was to further increase insights in the relationship between turnover and firm performance, taking into account the potentially complex non-linearity of the relationship and the role of turnover volatility. To test the nature of the relationship, we made use of a flexible non-linear approach based on data from an industry-wide and representative sample of organizations in Belgium. This allowed us to fully grasp the exact shape of the curve and draw conclusions on the viability of the integration of different theoretical views on the turnover-performance relationship. Our results support the assumption of a complex non-linear shape of the relationship. They show a combination of an inverted-U shaped curve and a negatively attenuated relationship, such that for low levels of turnover, the marginal impact of the turnover rate on labor productivity is positive. As turnover increases, the marginal impact of tunover flattens off and becomes negative in an attenuated fashion.

These results suggest that empirical research can benefit from testing more advanced flexible, non-linear patterns of the relationship between turnover and firm performance. Restricting the analyses to traditional regressions including only turnover and its square, would have led us to falsely conclude in favor of a linear relationship. Only by including higher-order terms, the true pattern is uncovered. This is mainly due to the finding that at intermediary levels of turnover – which covers the majority of observations – turnover is negatively related to labor productivity. Yet, low levels of turnover show to be functional for an organization as opposed to zero turnover. Across all industries and organizations, we find an optimal turnover level of 9.0% at which point firms can obtain a 5.3% productivity gain as opposed to zero turnover. Moreover, we established that only at a threshhold level of 22.4.% turnover becomes dysfunctional as opposed to zero turnover. Finally, at high rates, the negative marginal effect of the turnover rate attenuates and the marginal impact of turnover becomes close to zero.

On a theoretical level, these results call into question the ability of one single theoretical framework to capture the relationship between turnover and firm performance. Instead, they suggest that an integration of the different theoretical views on the relationship between turnover and performance is better able to predict the exact shape of the relationship.

On an empirical level, the initial positive impact of turnover on labor productivity conflicts with prior research that tested a curvilinear relationship, yet did not find this positive impact (e.g. Shaw et al., 2005, 2013; Ton & Huckman,

2008). The national context of the study, i.e. Belgium, could account for this as it may have driven the degree to which organizations can derive benefits from a limited amount of turnover. One such benefit is the avoidance of costly involuntary dismissals of poor performing employees (Abelson & Baysinger, 1984). Belgium has a particularly rigid labor market in which the cost of individual dimissals is relatively high. As a result, the voluntary leave of a poor performing employee can strongly benefit the organization by avoiding those costs. In more flexible labor markets where employees (can) more easily change jobs (e.g. the US; Cuñat & Melitz, 2012) these benefits may be lower resulting in attenuated negative relationships between turnover and performance (e.g. Shaw et al., 2005, 2013; Ton & Huckman, 2008).

On the contrary, the few previous studies which did establish an inversely u-shaped curve and reported the optimal level, found it to range from 6.3 to 16.2% (Glebbeek & Bax, 2004; Meier & Hicklin, 2007; Siebert & Zubanov, 2009). This range can be attributed to the specific samples which were investigated such as retail stores, schools and temporary job agencies. In each organization or industry, the balance between retention and turnover costs might be different, leading to different optimal turnover levels (Glebbeek & Bax, 2004). Nonetheless, in support of Hancock et al.'s (2013, 2017) findings, we offer additional empirical evidence for the existence of an optimal level of turnover and, more importantly, show that it is not restricted to specific samples of organizations or industries.

Finally, the attenuated negative relationship between employee turnover and labor productivity at higher levels of turnover is in line with previous research (e.g. Shaw et al., 2005).

Next, we are the first to consider the role of turnover volatility. The majority of turnover research has nearly exclusively looked at the absolute level of turnover, thereby neglecting the potential role of changes in turnover pattern. An exception is Call et al. (2015) who showed that an increase in the level of turnover from one quarter to the next is more damaging to unit performance when that unit initially experienced low turnover in the previous quarter. We extended their work arguing that not only changes from one time period to the next matter, but also the frequency and intensity of these changes across a larger time period (i.e. 10 years).

Firstly, we found that turnover volatility affects labor productivity in a negative manner. This is consistent with organizational routines theory. The lack of opportunities to develop stable and functional routines or the disruption of existing routines triggered by high turnover volatility can explain why labor productivity declines as turnover volatility increases. As such, an important contribution is that we show that not only the level of turnover in the current time period affects organizational performance but also an organization's history of turnover. This supports the need for theory and research on turnover which transcends the typical focus of turnover research on one time period of six months to one year (Hausknecht & Holwerda, 2013). Herein lies an additional contribution of our study since we showed that organizational routines theory can offer such valuable

insights. This theory assumes that organizational efficiency and productivity is in part dependent on the organization's ability to create functional routines to deal with recurring events such as turnover (Becker, 2004). A high degree of turnover volatility thwarts this process leading to productivity losses.

Secondly, we found turnover volatility to influence the relationship between turnover and labor productivity. We found the initial productivity gain to be highest in firms that experience low turnover volatility in their turnover rates (12.1%) as well as substantially higher as opposed to firms facing high volatility (8.1%). This is in line with organizational routines theory and supports the idea that firms can particularly draw benefits from turnover when a stable turnover environment allows them to develop and perfection functional routines to deal with turnover. Yet, apart from this, we find little support for differences between high and low turnover volatility. Interestingly, the group of firms experiencing medium volatility are the ones who deviate from the general non-linear shape we found across all firms. They experience only a very small productivity gain from small amounts of turnover (i.e. 2.5%) beyond which point they experience fully negative consequences of turnover, diving relatively quick below the point of zero turnover. This suggests that organizations find it particularly difficult to cope with turnover when they experience average fluctuations in their turnover level across years.

At a first glance, this contradicts our initial expectations based on organizational routines theory. Yet, these findings might result from a greater predictability of changes in turnover patterns in case of high turnover volatility. The degree to which organizations can cope with frequent and strong changes in the level of their turnover, will depend on the flexibility and adaptability of their routines. The 'abilities to reconfigure a firm's resources and routines in the manner envisioned and deemed appropriate by the firm's principal decision makers' (Zahra, Sapienza & Davidsson, p. 924) or 'to address changing environments' (McKelvie & Davidsson, 2009, p. s65) is called the dynamic capability of the firm. To create this dynamic capability, i.e. continuously questioning, adapting or recreating exiting routines, decision makers' cognitive effort, willingness and ability are required (Becker, 2004; Brauer & Laamanen, 2014; Zahra, Sapienza, & Davidsson, 2006). Brauer and Laamanen (2014) suggest that cognitive effort is more likely to be present when decision makers (1) feel a strong sense of urgency and thus motivation to develop flexible routines (in this case to cope with different levels of turnover, e.g. by developing a wide range of routines, some to deal with low turnover, others to deal with high turnover), and (2) have the necessary time and resources to adapt or recreate routines. The frequency of changes in turnover and the degree to which they are predictable will matter in this regard. If turnover fluctuates constantly and heavily, actors will feel this sense of urgency to respond to the changes. On the other hand, as there are constant changes, organization will get better in foreseeing the changes (e.g. based on historical patterns of turnover) and actors involved in the routines will have the necessary time to pro-actively engage in (re-)creating a

set of routines and to trigger the appropriate routines (Brauer & Laamanen, 2014). This predictability is higher in the case of high volatility as compared to the case of medium volatility, which could explain why medium volatility organizations suffer most from turnover.

An alternative explanation might be that medium turnover volatility can result from occasional occurrences of CEO or managerial turnover. Turnover among managers can have a snowball effect among other managers or employees as well (Krackhardt & Porter, 1986), which might explain exceptional, unexpected and disruptive occurrences of high turnover as are typical for medium volatility. The replacement of managers, be it by new managers or professional service firms, can subsequently have consequences for the quality of management and management policies. If these replacements do not go smoothly, they can have a negative impact on labor productivity, above and beyond the negative effects of the loss of human and social capital.

Directions for future research

Studying an economy-wide sample allowed us to pronounce upon the general shape of the turnover – labor productivity relationship. Yet, several moderating variables – next to turnover volatility – might play a role and enhance our insights in the relationship. First, the optimal level as well as the negative impact of moderate to high levels of turnover may differ between industries. Regarding the optimal level, previous studies establishinig an inverse u-shaped curve found optimal levels ranging from 6.3 to 16.2% depending on the sample (Glebbeek & Bax, 2004; Meier & Hicklin, 2007; Siebert & Zubanov, 2009). Next, Park and Shaw (2013) found a more detrimental effect of turnover in industries that rely heavily on human capital to obtain high performance (e.g. service industries) compared to industries relying less on human capital (e.g. manufacturing). As such, we would encourage future research to look into non-linear relationships between turnover and organizational performance at the industry level to unravel potential significant differences. Second, as mentioned before, national context could play a substantial role. The (in)flexibility of labour markets, laws regarding governing dismissals, traditions in compensation policies, etc. can all have their impact on dismissal, retention, training and hiring costs, thereby influencing the relationship. Therefore, we encourage future research to explore the turnover-performance relationship in a wide range of labor market contexts. Third, also the occupation in which the turnover occurs could matter a great deal. In Belgium, for a fair amount of occupations, there is a substantial shortage on the labor market due to high demands from organizations and/or supply shortages on the labor market (e.g. nurses, engineers, teachers…). As a result, if turnover is mainly situated in these professions, it will have a more profound negative impact on organizations as replacing such an employee is relatively hard and time-consuming. As such, in these cases, the positive impact of low turnover could be called into question

and the negative impact of high turnover will probably be even stronger. In sum, important to discern in future research is under which conditions the general shape we found, holds and to which degree. Finally, firm size could play a role, although both theoretically and empirically, evidence is mixed. Whereas large organizations are expected to have more buffers (i.e. time, resources) to cope with human and social capital losses due to turnover, small organizations are more flexible and might therefore be more efficient in coping with turnover (Hancock et al., 2013; Park & Shaw, 2013). Accordingly, Hancock et al. (2013) only found medium-sized firms to suffer from turnover. In contrast, however, Park and Shaw (2013)'s results point towards more detrimental consequences for small firms. Future research could thus benefit from further unraveling which type of firm is better protected against turnover and why.

Next, since we were unable to directly observe the (disruption of) organizational routines due to turnover volatility in this study, future research can benefit from studying this more closely. We know little about which routines organizations develop when faced with turnover, which actors are involved in these routines and how and to what degree these routines develop or change over time depending upon changes in turnover patterns. The latter issue is crucial since the degree to which organizations can cope with frequent and strong changes in the level of their turnover, will depend on the flexibility and adaptability of their routines. Literature on dynamic capabilities might be helpful here.

Practical implications

Research on the relationship between turnover and organizational performance has practical significance as it helps organizations to gain insight in the consequences of turnover and whether they can benefit from reducing it. Our results show that low levels of turnover can benefit the organization in terms of labor productivity. This implies that organizations should not aim to fully eliminate turnover as this creates unnecessary high costs (e.g. retention costs) and significantly reduces the chances of obtaining benefits from turnover (e.g. the infusion of new ideas, avoiding dismissal costs). Instead, they should aim towards obtaining a low amount of stable turnover to optimally profit from these benefits. Organizations should thus look for strategies that reduce (but not eliminate) turnover and keep the level of turnover stable across time. This will allow them to develop stable and functional organizational routines to deal with turnover without incurring losses in terms of labor productivity.

Notes

1. There are a number of criteria that determine which firms have to file full or abbreviated accounts, one of which is the number of employees. Firstly, all firms with over 100 employees have to file a full account. Secondly, if the firm has exceeded more

than one of the following ceilings over the last two financial years, the firm has to file a full account: (1) 50 employees, (2) 7,300,000 euro revenue and (3) 3,650,000 euro balance sheet total. The criteria can be found on the website of the National Bank of Belgium (www.nbb.be; 17/04/2011).

2. We also experimented with a stricter criterion, namely dropping observations for which the deviation is larger than 1%. Our results were not affected by this stricter procedure.
3. NACE is the standard sector classification used in the European Union. Up until the 3-digit level, its structure is comparable to that of the International Standard Industry Classification (ISIC).
4. This is a similar approach to other disciplines in which the 4th order polynomial is often chosen when estimating an unknown function by the use of polynomials (see for example Olley & Pakes, 1996). We also experimented with higher-order terms, but it appeared the fourth order polynomial was flexible enough as the shape of the relation between turnover and productivity did not change when using higher order polynomials. This was also reflected in the Bayesian Information Criterion, which levelled off from the 4th order polynomial onwards.
5. We chose not to use fixed effects for several reasons. First, the fixed effects specification would make it impossible to identify the coefficient on the time-invariant volatility measure. Second, the use of fixed effects would make it, in our view, more difficult to interpret the coefficients on the turnover rate. As fixed effects basically boils down to identifying the turnover rate effects using within-firm time variation, the regression would be less in line with our hypotheses. The regression would relate the deviation from the average firm level turnover with the deviation from the average labor productivity, which goes more in the direction of the volatility or turnover rate change. In one of the robustness checks we do however include fixed effects.
6. The difference in log labour productivity between an observation at the optimal turnover and an observation at zero turnover is equal to .052, so the percentage difference in labor productivity is equal to $\exp(.052) - 1 = 5.3\%$.
7. To check whether our results are not due to overfitting, we also ran a regression with only the linear term on the subsample with turnover rates smaller than .10 (i.e. below the optimum value of turnover). The coefficient on the turnover rate is positive and statistically significant (coefficient is equal to .82, $p < .01$). When executing the same regression on the subsample for which the turnover rate lies between .1 and .3, the coefficient on the turnover rate is equal to −.307 and significant ($p < .01$). For the subsample with turnover rates higher than .3, the coefficient is equal to −.148 ($p < .01$) and highly significant. These results are consistent with the results obtained using the polynomial to fit the effect of the turnover rate on productivity.

Disclosure statement

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Appendix 1. Deflators

To obtain real values of value added and tangible fixed assets (capital), we rely on price indices obtained from two different sources. For value added, we use price deflators obtained from the EU KLEMS database. Producer price indices are available for all two-digit sectors of the Belgian economy between 1970 and 2007. Sectors in the EU KLEMS database are classified as NACE Rev. 1.1 sectors. However, the NACE classification was revised in 2008 and firms in Belfirst 2010 are classified according to NACE Rev. 2. Hence, to obtain a price deflator for the NACE Rev. 2 codes used in Belfirst, we use a concordance table from Eurostat (Ramon server) to translate NACE Rev. 1.1 codes into NACE Rev. 2 codes. To obtain price indices for 2008, which are not available in the EU KLEMS database, we apply the growth rates of the available indices between 2006 and 2007. An economy-wide price index for capital is obtained from Eurostat.

Appendix 2. Robustness checks

Table B1. Regressions using the Tukey (1977) cleaning method.

	1	2	3	4	5	6
	All	All	All	Low Vol.	Med Vol.	High Vol.
Turnover rate		1.85*** [.24]	1.67*** [.33]	2.66* [1.07]	1.02** [.39]	1.23 [.70]
Turnover rate^2		−16.12*** [1.56]	−14.51*** [2.90]	−19.60 [11.68]	−7.98* [3.42]	−11.55* [5.86]
Turnover rate^3		44.55*** [9.16]	39.90*** [9.20]	48.63 [40.44]	17.39 [10.96]	35.42* [17.52]
Turnover rate^4		−40.40*** [9.36]	−35.90*** [9.43]	−41.34 [43.70]	−12.43 [11.43]	−34.83* [17.17]]
Turnover volatility			−.38** [.15]			
Ln(Employment)	−.01 [.01]	−.02* [.01]	−.02** [.01]	.04* [.02]	−.03** [.01]	−.07*** [.02]
Ln(Capital intensity)	.13*** [.01]	.13*** [.01]	.13*** [.01]	.12*** [.02]	.12*** [.01]	.14*** [.01]
Ln(Age)	.01 [.01]	.01 [.01]	.01 [.01]	−.01 [.02]	.01 [.01]	.06** [.02]
N	45,044	45,044	44,784	6306	29,927	6824
R^2	.32	.32	.32	.47	.32	.39

Notes: All analyses include year and sector dummies. The robust standard errors, clustered at the firm level are mentioned between brackets.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table B2. Regression controlling for layoffs.

	1	2	3	4	5	6
		All	All	Low Vol.	Med. Vol.	High Vol.
Turnover rate		1.06*** [.24]	.93*** [.24]	2.68** [.86]	.37 [.28]	1.25* [.54]
Turnover rate^2		−8.68*** [1.59]	−7.78*** [1.60]	−17.55* [7.18]	−3.90* [1.88]	−8.56** [3.29]
Turnover rate^3		19.44*** [3.69]	17.85*** [3.72]	37.47* [18.35]	8.33 [4.56]	18.68** [7.12]
Turnover rate^4		−13.74*** [2.74]	−12.82*** [2.78]	−25.85 [14.04]	−5.77 [3.51]	−13.04** [5.01]
Turnover volatility			−.31*** [.11]			
Ln(Employment)	−.02* [.01]	−.02** [.01]	−.02** [.01]	.05* [.02]	−.03*** [.01]	−.09*** [.018]
Ln(Capital intensity)	.12*** [.01]	.12*** [.01]	.12*** [.01]	.13*** [.02]	.12*** [.01]	.12*** [.01]
Ln(Age)	.01 [.01]	.01 [.01]	.01 [.01]	−.01 [.02]	.00 [.01]	.06** [.02]
Layoff rate	−.17*** [.04]	−.16*** [.04]	−.20*** [.04]	−.05 [.06]	−.30*** [.05]	−.15** [.06]
N	45,044	45,044	44,784	5215	32,444	7125
R^2	.32	.32	.32	.49	.33	.36

Notes: All analyses include year and sector dummies. The robust standard errors, clustered at the firm level are mentioned between brackets.
* $p < .05.$; ** $p < .01.$; *** $p < .001$.

Table B3. Lagged turnover rate, Wooldridge (2009) estimator and time varying volatility.

	1	2	3	4
	Lagged turnover rate	Wooldridge	Fixed Effects	Time varying volatility
Turnover rate	.92*** [.24]	1.97** [.77]	.44** [.15]	1.22*** [.26]
Turnover rate^2	−7.38*** [1.65]	−17.19** [6.11]	−2.93** [.99]	−9.92*** [1.18]
Turnover rate^3	16.18*** [3.97]	42.96** [16.51]	6.44** [2.30]	21.29*** [4.34]
Turnover rate^4	−11.25*** [3.03]	−32.95* [13.81]	−4.47** [1.72]	−14.92*** [3.32]
Turnover volatility		−.31** [.11]		−.14* [.06]
Ln(Employment)	−.01 [.01]	−.21*** [.01]	−.17*** [.01]	−.01 [.01]
Ln(Capital intensity)	.12*** [.01]	.05*** [.01]	.062*** [.01]	.12*** [.01]
Ln(Age)	.00 [.01]	.01 [.01]	.121*** [.02]	.00 [.01]
N	37,435	37,224	45,044	32,544
R^2	.34		.06	.33

Notes: All analyses include year and sector dummies. The robust standard errors, clustered at the firm level are mentioned between brackets.
* $p < .05$; ** $p < .01$; *** $p < .001$.

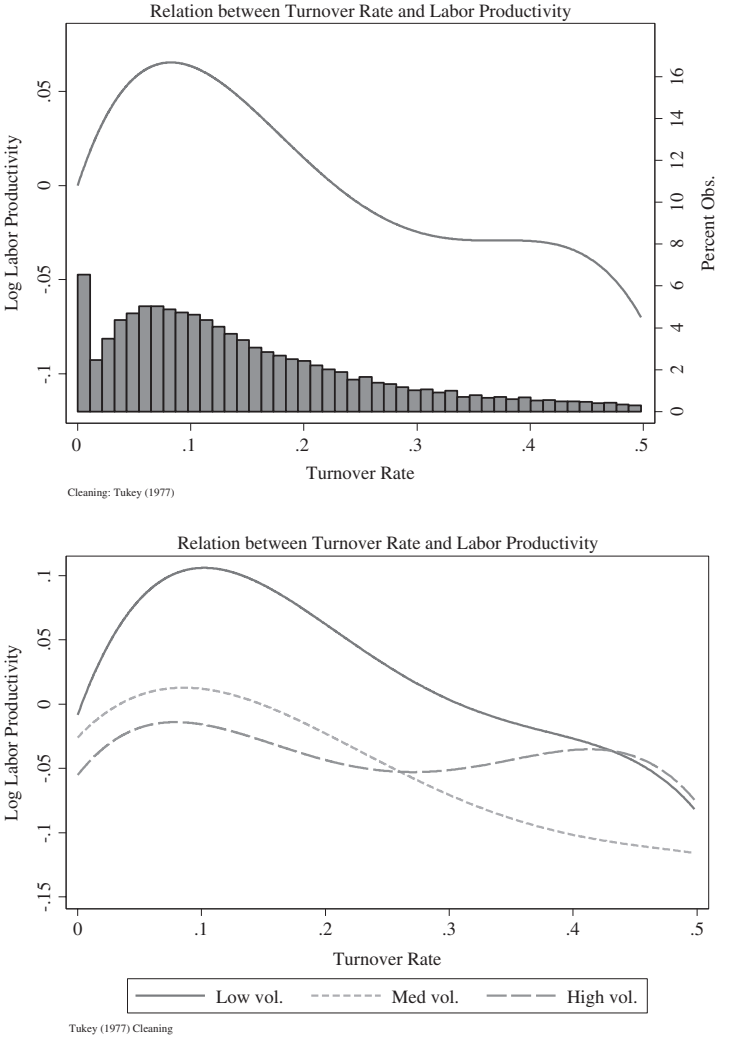

Figure B1. Relation Between Turnover Rate and Labor Productivity (Tukey (1977) Cleaning).

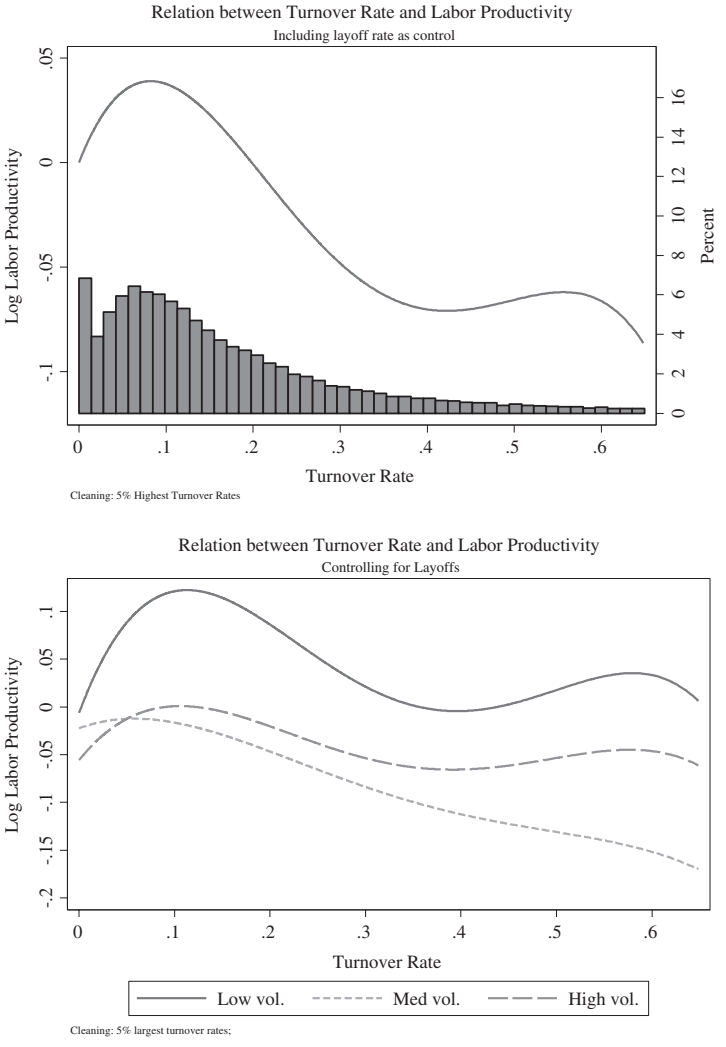

Figure B2. Relation Between Turnover Rate and Labor Productivity (Tukey (1977) Cleaning).

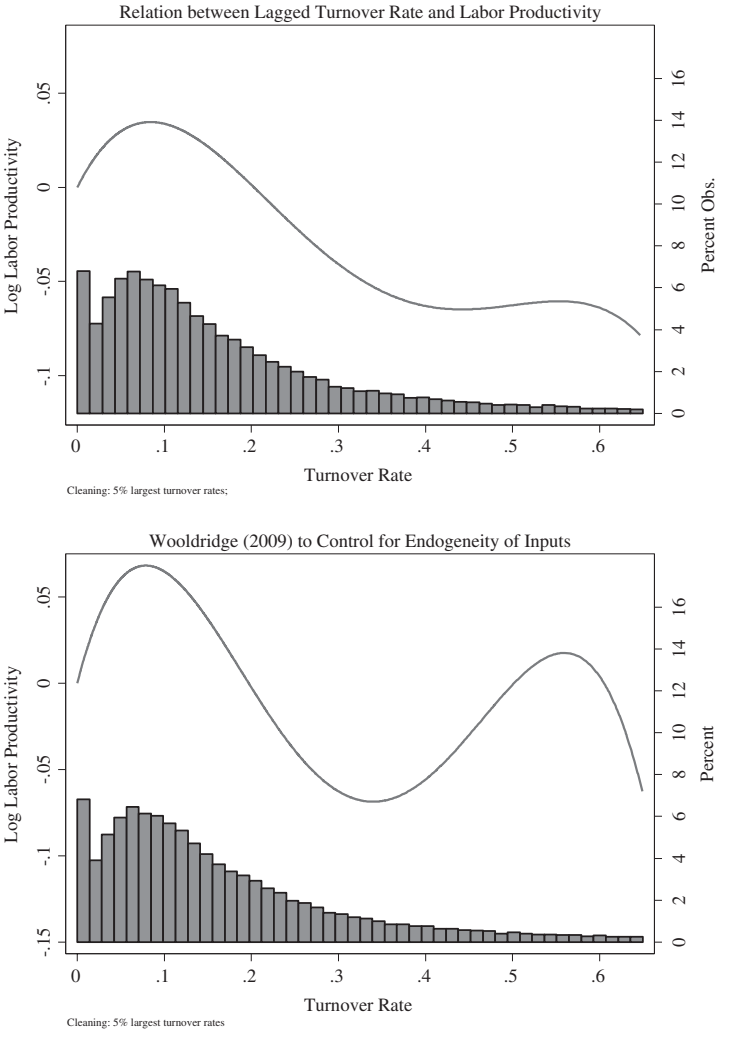

Figure B3. Robustness Checks to control for endogeneity.

Appendix 3. Wooldridge Correction for Endogeneity

Recall the estimation equation introduced in the main text (ignoring the control variables for brevity):

$$q_{it} - l_{it} = \gamma + \beta(k_{it} - l_{it}) + \delta l_{it} + \sigma v_i + f\left(\frac{S_{it}}{L_{it}}\right) + \omega^*_{it} + \varepsilon_{it} \quad (1)$$

Where we decomposed error term of this equation into productivity shocks, ω^*_{it} which are unobserved to the econometrician but taken into account when the firm chooses its optimal value of capital and labor, and ε_{it} which is not considered to influence firm choices. Moreover, the rate of employees exiting the firm, can very well be influenced by changes in unobserved productivity making the turnover rate endogenous. For example, an employee working for a firm performing badly – reflected in low values for ω^*_{it} – could be more likely to leave the firm compared to a worker employed in a highly productive firm. Consequently, OLS estimates for

coefficients on the turnover rate are potentially biased. To control for this, we rely on recent developments in the literature on production function estimation. More precisely, we use the insight that optimal input demand holds information on productivity ω_{it} and can be used to control for it (Levinsohn & Petrin, 2003; Olley & Pakes, 1996; Wooldridge, 2009). We refer to these papers for a more thorough discussion of the methodology while we discuss the general idea here below.

The setting is as follows: each period, a firm chooses its optimal material input after observing its current productivity level ω_{it}^{*}. Consequently material demand by firm i in period t is a function of productivity and other state variables such as the capital stock. If material demand is monotonically increasing in productivity, the function can be inverted and productivity can be written as a function of materials and capital, $\omega_{it}^{*} = h\left(k_{it}, m_{it}\right)$.

Next, we assume productivity to follow a first-order Markov process, namely productivity in period t is a function of productivity in the previous year plus a productivity shock ξ_{it} which was unforeseen in the previous period. As a result, ω_{it}^{*} can be written as a function of lagged capital and materials plus ξ_{it}:

$$q_{it} - l_{it} = \gamma + (\delta - \beta) l_{it} + \beta k_{it} + \alpha v_i + f\left(\frac{S_{it}}{L_{it}}\right) + g\left(k_{it-1}, m_{it-1}\right) + \xi_{it} + \varepsilon_{it} \qquad (2)$$

We estimate equation (2) using Generalized Method of Moments. Appropriate instruments depend on assumptions concerning how freely adjustable inputs are. In line with other papers, we allow firms to adjust their labor stock to unforeseen productivity shocks. Consequently, we instrument labor with its lagged value. Moreover, we allow employees to react to these shocks as well and instrument the turnover variables with their lagged values. Concerning the capital stock, we assume it takes some time before new capital goods are delivered and installed in the firm. As such, the capital stock is uncorrelated with unexpected shocks to productivity and contemporaneous capital stock can be instrumented by itself. We approximate the unknown $g()$ function with a 4th order polynomial in lagged capital and materials. Each element of the polynomial can serve as its own instrument.

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