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ABSTRACT

Performance Costs and Benefits of Collective Turnover: A Theory-Driven Measurement Framework and Applications

Building on job matching theory, we model the effect of collective turnover on workplace performance as the total of its costs from operational disruptions and benefits from better job-worker match quality, each component varying with turnover level. The resulting theoretical turnover-performance relationship is generally curvilinear, nesting all the hitherto known patterns – linear, "U-shape" and "inverted U-shape" – as special cases, and lends itself to an empirically estimable regression model from which one can derive the implied costs and benefits of turnover. Applications to data from two retail firms reveal some benefits from turnover in one firm, and none in the other. Turnover costs exceed benefits in both firms.

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INTRODUCTION

The impact of collective employee turnover on workplace performance has motivated a prolific literature in excess of 150 published empirical studies finding a variety of patterns in the turnover-performance relationship (TPR) in different contexts. Surveys of this literature conclude that TPR is negative (Hancock et al., 2011, 2017; Hausknecht & Trevor, 2011; Heavey et al., 2013; Park & Shaw, 2013; Shaw, 2011). This said, an increasing number of studies find evidence of curvilinearity in TPR, suggesting that there are “potential positive, as well as negative implications of collective turnover on organizational performance” (Hancock et al., 2017, p. 81). Calls have been made to “more thoroughly explore this curvilinear relationship” (Hancock et al., 2017, p. 81) and to find “any demonstrable benefits of collective turnover” (Hausknecht, 2017, p. 540). Our study responds to these related calls by developing a theory-driven measurement framework suitable for capturing a curvilinear TPR and estimating the benefits and costs of turnover from commonly available data.

Turnover is costly because it depletes firm-specific human capital, disrupts communications, and takes resources to manage. Yet it may also bring benefits, of which ridding the workforce of poorly performing workers is most frequently mentioned (Abelson & Baysinger, 1984; Dalton & Todor, 1979; Glebbeek & Bax, 2004; Siebert & Zubanov, 2009; Simón et al., 2022; Trevor & Piyanontalee, 2020).[1] As the benefits and costs of turnover often coincide (e.g., the departure of an unproductive worker is good riddance but it may disrupt operations nonetheless), a linear regression of performance on turnover, which is the empirical model choice in many studies (see Table 1 in Shaw (2011) for a summary), would capture the net effect of these two opposing forces averaged over the study sample. Accounting for them separately requires a more flexible measurement framework, one that would allow for a curvilinear TPR backed by a set of convincing and generally applicable theoretical arguments.

Currently, the leading approach to capturing curvilinearity in TPR empirically is to model it as a "quadratic U-shape" and run the corresponding regression of a suitable performance measure on the level and square of turnover rate: $Performance = a_1 \cdot Turnover + a_2 \cdot Turnover^2 + controls$. Computational simplicity and flexibility make the quadratic approximation of a theoretically nonlinear relationship a popular model choice in many research fields (Haans et al., 2016). Focusing on TPR, a quadratic U-shape flexibly represents its different alternative conceptualizations as summarized in Shaw et al., 2005. Thus, one variant of human capital theory assumes no benefits from turnover and predicts a straight negative TPR, corresponding to a special case of the quadratic U-shape with $a_1 < 0, a_2 = 0$, which is the most frequently reported empirical finding. Another variant of the same theory proposes that turnover costs in terms of human capital loss would decrease with turnover, since there is less human capital to destroy when turnover is high – corresponding to an ordinary quadratic U-shape with $a_1 < 0, a_2 > 0$, as found in Shaw et al., 2005 and also in a further 3 out of 37 studies surveyed in Shaw (2011) (Table 1) and later in Bouckenooghe et al. (2016). Yet another theoretical alternative predicts that low-to-medium turnover could benefit performance by revitalizing the workforce, but high turnover is more costly and less beneficial. This prediction corresponds to an inverted quadratic U-shape ($a_1 > 0, a_2 < 0$) found in 35 out of 156 TPR studies surveyed in Hancock et al. (2017) (Table 3) and later in De Stefano et al. (2019); DeWinne et al. (2019); Simón et al. (2022), and in Li et al. (2022). [2]

However, a quadratic U-shape is simply an empirically convenient approximation of a generally nonlinear TPR whose pattern is determined by co-variation in the costs and benefits of turnover with its level. This co-variation deserves careful theorizing and a more precise characterization. A better understanding of how turnover costs and benefits vary with its level is needed to support further progress in empirically exploring curvilinearity in TPR, especially when it comes to comparing (and hopefully reconciling) often conflicting empirical findings across contexts that may differ in the factors shaping performance consequences of turnover. Besides, there is a practical interest in calculating the costs and benefits of turnover from data, which requires some analytical structure to separate the two.

The framework we develop in this study can aid these endeavors. It is grounded in job matching theory (Jovanovic, 1979; Weller et al., 2019) which, in a nutshell, argues that i) workers vary in their match quality with respect to the particular work context, ii) bad matches are more likely to quit than good ones, and iii) match quality may be positively or negatively correlated with worker productivity. We operationalize these arguments for our application with a simple structural model that has three parameters: good/bad match productivity ratio, the likelihood of quit ratio, and the costs of turnover per quit. Our model generates a variety of shapes of TPR, each corresponding to a specific combination of the above model parameters, illustrated in Figure 1. An inverted U-shaped TPR emerges when bad matches are sufficiently less productive and more likely to quit than good ones, and the costs of turnover are sufficiently low. Otherwise, the model implies a negative TPR, monotonic or U-shaped.

The TPR implied by our model can be estimated on commonly available data, and the costs and benefits of turnover can be calculated from the regression estimates. As an illustration, we apply our framework to data from two large retail networks. Our results reveal signs of an inverted U-shape relationship between sales staff turnover and net sales in Firm 1, especially in stores with relatively few above-average productive workers among the leavers. In Firm 2, the TPR is monotonically negative. Manager turnover is followed by lower sales in both firms. On average, counting in the benefits, the net costs of turnover are about zero in Firm 1 and 1% of net sales in Firm 2. Based on the insights we gained from top manager interviews, the difference in TPR we observe appears to be related to differences in the context in which the two firms operate. Firm 2, which faces a negative TPR and larger costs of turnover, relies more heavily on worker knowledge, pays more competitive wages to its sales staff and has more comprehensive training and selection practices, as compared to Firm 1. Accordingly, there are fewer bad matches and greater operational costs from turnover.

The main contribution of our work is in developing a theory-driven, flexible, and widely-applicable empirical tool with which researchers could study performance effects of collective turnover in a variety of settings. We provide a more detailed discussion of this and related contributions and the practical value of our work at the end of the paper.

THEORY DEVELOPMENT

Curvilinearity in TPR: empirical findings and supporting theoretical arguments

We will argue that TPR is generally curvilinear, nesting a linear relationship as a special case. Before we present our theory in detail, it is useful to take stock of the existing empirical findings of a curvilinear TPR, and of the theoretical arguments linked to these findings. In the latest meta-analysis by Hancock et al. (2017) that covers 641 effect sizes from 156 published studies on TPR, 139 effect sizes in 35 studies (a fifth of the total) show evidence for a curvilinear TPR (Appendix B). An earlier meta-analysis by Hancock et al. (2011) identifies a third of studies finding a curvilinear TPR, but the actual frequency may even be higher since not all studies theorize curvilinearity or test for it (Heavey et al., 2013; Park & Shaw, 2013; Shaw, 2011). Of the studies finding a curvilinear TPR, most find an inverted U-shape.

Our reading of the studies searching for a curvilinear TPR suggests that most build their theoretical arguments on the notions of functional and dysfunctional turnover first introduced in Dalton et al. (1982) and later developed into the concept of the optimal turnover level by Abelson & Baysinger (1984). Functional turnover involves workers who are more expensive to retain than to see go, for instance, poor performers whose productivity is below their labor costs. Dysfunctional turnover involves valuable workers whose departure is more costly than retention. When poor performers are more likely to quit, turnover at low levels is mostly functional. However, as turnover increases, the share of valuable workers among the leavers increases as well, making it dysfunctional. This scenario predicts an inverted U-shaped TPR. In the opposite case, when valuable workers are more likely to quit than poor performers, turnover is initially dysfunctional, but becomes less so at higher levels when many valuable workers have already quit. An ordinary U-shaped TPR is predicted in this case. In what follows, we will use job matching theory (JMT) to refine these intuitions and incorporate them into our measurement framework.

Job matching theory in application to TPR

JMT originated in labor economics where it was used to explain a number of empirical facts related to turnover and unemployment (Mortensen & Pissarides, 2011). Outside economics, JMT is closely related to the person-environment (P-E) fit paradigm in organizational behavior research (Edwards, 2008), and in particular to the attraction-selection-attrition (ASA) model (Schneider et al., 1995). Recently, Weller et al. (2019) brought JMT even closer to HRM research agenda by conceptualizing matching as “an essential human resource and talent management mechanism for transforming human capital into economic value” (p. 202). As turnover is intrinsically linked to changes in human capital (Nyberg & Ployhart, 2013), it is appropriate to view its consequences for economic value through the lens of JMT.

Firm-job-worker match quality and individual turnover. According to JMT, heterogeneity among jobs offered by different firms and workers applying for these jobs produces firm-job-worker matches of varying quality. The concept of match quality is worth carefully defining. Mathematical models within JMT define match quality as worker productivity (Jovanovic, 1984, p. 109). P-E fit theories speak of multiple dimensions of match quality involving the fit between a worker's needs, rewards, abilities, external demands, and social environment (Edwards, 2008, p. 168). We lean toward the latter view and treat match quality and productivity as two related but different constructs. Specifically, we recognize that the firm and the worker may have different evaluations of their match and define the metric of match quality as the minimum of the firm's and the worker's evaluations. In this sense, either low productivity (the firm's evaluation of match quality) or low satisfaction with the current job (the worker's evaluation) will make a bad match, and uniformly high/low evaluations by both parties will make a good/bad match.

JMT and P-E fit theories both predict that bad matches are more likely to quit than good ones (Burdett, 1978; Jovanovic, 1979, 1984; Kristof-Brown et al., 2005). When a match is bad because of the firm's low evaluation of its quality, the firm will have the incentive to initiate a quit. The quit does not have to be involuntary, since the firm may act to lower the worker's evaluation of the match as well, for example, by denying promotion or worsening job conditions, prompting the worker to quit voluntarily. When a match is bad from the worker's perspective, the worker will look for other alternatives. The likelihood of finding a better match increases with search intensity, which in turn depends on the quality of the current match: the worse the quality, the higher the search intensity (Gertler et al., 2020).

The benefits and costs of collective turnover. The negative relationship between match quality and individual turnover can result in benefits or costs of collective turnover. The ambivalence in its performance consequences has to do with the differences in the quantity and quality aspects of collective turnover as expressed in Nyberg & Ployhart, (2013)'s content-emergent theory. Nyberg & Ployhart (2013) define collective turnover as "the quantity and quality of depletion of knowledge, skills, abilities, and other characteristics (KSAO) from the unit" (p. 112). They argue further that "collective turnover may result in either a net positive or net negative change in the value of the human capital resource, depending on the quantity and quality of the human capital depleted. For example, losing a few low-quality employees may increase the value of the human capital resource, leading to improved unit performance, whereas losing high-quality employees may decrease the value of the human capital resources and hurt unit performance" (p. 113). JMT allows for both of these possibilities.

Collective turnover benefits performance when good matches are more productive than bad ones. Empirically, better matches indeed tend to be more productive (Lazear & Oyer, 2012, pp. 492-497; Nagypál, 2007), more satisfied with their job and less likely to quit (Gesthuizen & Dagevos, 2008), and to earn higher wages (Ferreira & Taylor, 2011). While high match quality is good for both parties, the information available to the parties to evaluate their match at the time of hiring is imperfect (Bangerter et al., 2012), resulting in some bad matches. With time, better information arrives (e.g., through performance evaluation or other feedback), and bad matches tend to be dissolved and replaced with better ones.

Despite supporting empirical evidence, a positive correlation between match quality and productivity is not a given. If bad matches are on average more productive than good ones, turnover harms performance by reducing workforce average productivity. This theoretical possibility follows from a version of JMT that allows for on-the-job search for alternative employment opportunities (Burdett, 1978; Jovanovic, 1984). If more productive workers receive more competing offers, their evaluation of the match with their current job and firm may worsen and they will be more likely to quit – unless the firm extends counter-offers, which is not always the best strategy (Barron et al., 2006). It also echoes with Jackofsky, (1984)'s push-pull model of individual turnover where the worst performers are pushed out of the firm, the average stay, and the best are pulled into other firms, resulting in a U-shaped relationship between individual productivity and the likelihood of leaving. Empirically, although the correlation between worker productivity and the likelihood of quitting is robustly negative, it is nuanced by context,[3] implying that one cannot assume that bad matches are always less productive and should consider both possibilities.

In addition to the possible costs of turnover in terms of losing productive workers, there are likely further, operational costs. Although JMT does not explicitly model them, there is ample empirical evidence for their existence. Examples of these costs are: losses in firm-specific human capital (Coff & Raffiee, 2015; Frank & Obloj, 2014; Kacmar et al., 2006; Kryscynski, 2021), disruptions in communications and operational processes (Chung et al., 2021; Holtom & Burch, 2016; Kuypers et al., 2018), and administration costs (Sagie et al., 2002; Tziner & Birati, 1996). Though their magnitude, understandably, varies by context, the estimated monetary costs of turnover are non-trivial and amount to a sizeable fraction of labor costs (Boushey & Glynn, 2012; Friebel et al., 2022; Kuhn & Yu, 2021; Siebert & Zubanov, 2009; Tracey & Hinkin, 2008). We therefore account for the operational costs of turnover in our model as well.

Separating the benefits and costs of turnover. JMT predicts different dynamics of the benefits and costs of turnover, making it possible to separate the two by measuring performance consequences at different levels of turnover. The benefits, which occur through ridding the workforce of less productive bad matches, decrease with the level of turnover. For an illustration, consider the following thought experiment repeated multiple times. There is a workforce of a given size and match quality distribution. Individual workers quit with probabilities corresponding to their match quality, with bad matches being less productive and more likely to quit. Each time a worker quits, an operational cost is incurred, and a replacement is randomly drawn from the same match quality distribution as that of the workforce.

Given the above setting, the first leaver will more likely be a bad match, and a less productive worker, than a good one, and their replacement will be a better match and a more productive worker. Hence, in expectation, the first quit will improve the average workforce productivity. However, since the number of bad matches is fixed, the probability of every next leaver being a bad match goes down, and the share of bad matches among the leavers decreases. Consequently, performance benefits decrease with the level of turnover. For instance, if the entire workforce quits, the newly hired workers will have the same match quality distribution as the original workforce before any turnover, bringing any benefits from turnover to zero.

Unlike the benefits of turnover, its costs tend to increase with its level. In addition to the mechanically increasing operational costs, if bad matches in our thought experiment are more productive, their departure will further reduce performance by lowering the average workforce productivity.

Summarizing, JMT predicts that turnover costs and benefits depend on the differences in productivity and turnover probabilities between workers of different match quality, as well as on the operational costs of turnover. These dependencies taken together generate different patterns of the implied TPR, plotted in Figure 1, all of which were reported in the existing empirical studies. It turns out that all these patterns can be generated by one simple formal model under different values of its parameters, as we show next.

The formal model

Consider a workplace employing N workers who differ in their match quality, productivity, and propensity to quit. Let us rank the workers by match quality and label the bottom 50% with a below-median match quality as "bad" matches, and the upper 50% as "good" matches. Let the average good match be δ times as productive as the average bad match; that is, if the average bad match produces output B, the average good match's output is $\delta \cdot B$. Lastly, let the odds of the average bad match's leaving be ω times that of the average good match.

We model the workplace's collective performance outcome (e.g., physical output) as a Cobb-Douglas production function of its size N and worker type-specific productivity levels weighed by their shares (0.5 each, under zero turnover), as well as other factors skipped here for brevity but controlled for in the empirical analysis. Thus, under zero turnover, the workplace produces $Y(0) = N \cdot B^{0.5} \cdot (\delta \cdot B)^{0.5} = N \cdot B \cdot \delta^{0.5}$. Taking logarithms,

$$\ln\big(Y(0)\big) = y(0) = n + b + 0.5 \cdot \ln(\delta) \tag{1}$$

Now, suppose share q of the workers quit, incurring operational costs that amount to fraction $c \cdot q$ of the output, and is replaced with new hires drawn from the same match type distribution. Denote the share of bad matches among the leavers as $p(q)$. The after-turnover share of bad matches in the workforce is: their share under zero turnover, 0.5, minus the fraction of bad matches who left, $p(q) \cdot q$, plus the share of bad matches among the replacements, $0.5 \cdot q$, adding up to $s_b(q) = 0.5 - [p(q) - 0.5] \cdot q$. Correspondingly, the share of good matches is $s_g(q) = 1 - s_b(q) = 0.5 + [p(q) - 0.5] \cdot q$, and the post-turnover performance outcome is

$$\begin{aligned} y(q) &= n + b + s_g(q) \cdot \ln(\delta) - c \cdot q \\ &= n + b + 0.5 \cdot \ln(\delta) + \ln(\delta)[p(q) - 0.5] \cdot q - c \cdot q \\ &= y(0) + \ln(\delta)[p(q) - 0.5] \cdot q - c \cdot q \end{aligned} \tag{2}$$

Comparing the performance outcomes under zero and non-zero turnover reveals that the net performance gain from turnover, $\Delta y = y(q) - y(0) = \ln(\delta)[p(q) - 0.5] \cdot q - c \cdot q$, increases to the extent that turnover rids the workforce of less productive bad matches ($\ln(\delta)[p(q) - 0.5] \cdot q$), and decreases with the operational costs of turnover ($c \cdot q$). This accords with the previously developed intuitions. Furthermore, expressing the share of bad matches among the leavers, $p(q)$, as a function of turnover rate q,[4]

$$p(q) = \frac{1 + (q + 0.5)(\omega - 1) - \sqrt{(\omega - 1)^2 (q - 0.5)^2 + \omega}}{2q(\omega - 1)} \tag{3}$$

and plugging the above expression in the performance equation (2) and simplifying, we obtain an explicit functional relationship between performance outcome y and turnover rate q moderated by the odds of bad (below-median) vs. good matches leaving (ω), the productivity differential between the good and bad matches (δ), and the operational costs of turnover (c):

$$\begin{aligned} y(q) &= y(0) + \frac{\ln(\delta)(\omega + 1)}{4(\omega - 1)} \\ &- \frac{\ln(\delta) \cdot \sqrt{(\omega - 1)^2 (q - 0.5)^2 + \omega}}{2(\omega - 1)} - c \cdot q \end{aligned} \tag{4}$$

Graphical illustration

Figure 1 plots the net performance gain from turnover, $\Delta y = y(q) - y(0)$, based on equation (4). The net performance gain is zero at no turnover ($q = 0$) and $-c$ at 100% turnover

($q = 1$) for any values of the model parameters δ, ω, c. This is a useful property of our model allowing it to be applied to measure performance consequences of individual ($t = 0{,}1$) as well as collective turnover; in fact, we use it to measure the effects of manager turnover in the empirical applications later on. For intermediate turnover levels, the model generates straight negative, inverted U- or regular U-shape patterns in TPR, depending on the model parameters, thus nesting all hitherto known TPR patterns as special cases.

Straight negative TPR. The net performance gain is linearly negative in turnover when bad matches are as productive as good ones ($\boldsymbol{\delta = 1}$) or when they are equally likely to leave ($\boldsymbol{\omega = 1}$), since equation (4) simplifies to $\boldsymbol{\Delta y = -c \cdot q}$ (the dashed lines in Figure 1) when either $\boldsymbol{\delta = 1}$ or $\boldsymbol{\omega = 1}$. This makes sense: when $\boldsymbol{\omega = 1}$ workers are equally likely to leave regardless of their match quality, and when $\boldsymbol{\delta = 1}$ there are no productivity differences between good and bad matches. There can be no benefits from turnover in either case.

Inverted U-shape TPR. The net performance gain from turnover increases with the productivity difference between good and bad matches $\boldsymbol{\delta}$ relative to the operational costs $\boldsymbol{c}$ ($\boldsymbol{\delta >> 1 > c}$), and with the odds ratio of bad vs. good matches leaving ($\boldsymbol{\omega >> 1}$). Under these circumstances, turnover improves performance by ridding the workforce of the less productive bad matches until it reaches some optimal level past which its benefits become outweighed by costs. The resulting TPR is an inverted U-shape, depicted by the black curves in Figure 1, each curve for a specific combination of $\boldsymbol{\delta, \omega, c}$. The inverted U-shape is the more pronounced, the larger the inter-type differences in productivity and quit likelihood are, relative to the operational costs.

Ordinary U-shape TPR. Turnover is bad for performance when its operational costs $\boldsymbol{c}$ are high and the inter-type differences in productivity and quit likelihood are small ($\boldsymbol{\delta, \omega}$ close to 1), in which case the benefits from turnover are never high enough to outweigh its costs. Its detrimental performance effect is particularly pronounced when bad matches are more productive than good ones ($\boldsymbol{\delta} < \mathbf{1} < \boldsymbol{\omega}$), in which case turnover is costly not only because of disrupting operations but also because of the ensuing losses in human capital quality. The latter effect produces an ordinary U-shaped TPR depicted by the gray curves in Figure 1. Higher turnover brings disproportionally large negative performance effects until it reaches some critical level. Past this level, its negative effects abate because many productive bad matches have already left (recall that $\boldsymbol{\delta} < \mathbf{1}$ in this case), so higher turnover is relatively less of a drain on human capital.

Insert Figure 1 about here

MEASUREMENT FRAMEWORK

We have shown theoretically that TPR is determined by the odds of bad vs. good matches leaving (ω), the productivity differential between the good and bad matches (δ), and the operational costs of turnover (c), in the way captured in equation (4). We now focus on estimating TPR empirically, starting with the choice of regression specification.

The regression specification

Nonlinear vs. linear regression. Equation (4) lends itself directly to a nonlinear regression specification of the same structure and with appropriate controls for $\boldsymbol{y}(\mathbf{0})$ that is, in principle, estimable from data. Since this specification is nonlinear in its parameters $\boldsymbol{\omega}, \boldsymbol{\delta}, \boldsymbol{c}$, a nonlinear estimator is required. We use the nonlinear least squares estimator (NLS) for its relatively light identification assumptions and coding effort involved.[5] Like the commonly used ordinary least squares estimator (OLS), NLS works by choosing parameter values that minimize the sum of squared residuals in the regression model (Davidson & MacKinnon, 2004, chapter 6).

However, unlike OLS, which works with regression models that are linear in their coefficients, there is no exact formula for NLS parameter estimates. As a result, NLS relies on numerical methods in calculating regression parameters through an iterative procedure, and can therefore be prone to computational problems, such as lack of convergence.

Possible computational problems as well as the current lack of applications of NLS in management literature call for a simpler (and currently prevailing) alternative – to approximate the TPR in equation (4) with a quadratic U-shape that is linear in its coefficients and can thus be estimated with OLS:

$$y(q) = \alpha_1 \cdot q + \alpha_2 \cdot q^2 + \text{controls} + \text{residual}, \tag{5}$$

The quadratic U-shape in (5) seems to fit the theoretical TPR implied by our model (recall Figure 1), and, also like our model, it simplifies into a straight line under a given parametric restriction ($\alpha_2 = 0$). There is a deeper link between specification (5) and our model than optics: one can see from equation (2) that approximating the share of bad matches among the leavers, $p(q)$ in equation (3), with a linear function in turnover rate q gives a quadratic TPR. The computation ease of the quadratic U-shape and its structural link with our theoretical model speak in favor of (6) as a valid choice of regression specification.

Which specification to choose? Nonlinear equation (4) works best when bad matches are sufficiently more likely to quit and are less productive than good matches ($\boldsymbol{\omega}, \boldsymbol{\delta} >> \mathbf{1}$) and there is sufficient variation in the quit rates, so that its more complicated structure could be statistically identified. A quadratic U-shape regression like (5) would work under a wider range of the underlying model parameter values, but, since it is an approximation, it may produce less precise estimates.[6] We recommend running both specifications, starting with the quadratic U-shape (equation (5)) because of its computational ease and similarity with the existing approaches to estimating nonlinear TPR.

Allowing multiple worker sub-groups. Our theoretical model operates with a single worker group for which a collective turnover rate and performance outcome can be defined. In some practical cases, however, output is jointly produced by multiple worker sub-groups whose contributions are hard to separate. Aggregating these sub-groups into one may be questionable, since turnover within them may have different performance consequences. For instance, Simón et al. (2022) find different effects of staff and manager turnover, as Siebert & Zubanov (2009) do for full- and part-time workers.

Extending our model to include multiple worker sub-groups is straightforward if one continues to assume that output is generated by a Cobb-Douglas production function (equation (1)) where production factors, such as worker sub-group labor inputs, enter log-additively. In this case, equation (4) or its quadratic U-shape approximation (5) will have separate (and additive) terms for each sub-group.

In the more general case, the effects of sub-group-specific turnover may interact with each other. It is very hard in this case to obtain an analytically tractable, let alone empirically estimable, expression for the effect of turnover on performance like equation (4). However, taking a second-order Taylor series approximation of the original model produces a familiar quadratic U-shape in terms of levels, squares, and pair-wise cross-products of k sub-group-specific turnover rates:

$$y(q_1, \ldots, q_k) = \sum_{i=1}^{k} \alpha_{1i} \cdot q_i + \sum_{i=1}^{k} \alpha_{2i} \cdot q_i^2 + \sum_{i=1}^{k} \sum_{j \neq i}^{k} \beta_{ij} \cdot q_i \cdot q_j + \text{controls} + \text{residual} \tag{6}$$

Siebert & Zubanov (2009) use this specification to find interaction in the effects of full- and part-time worker turnover on performance, and we recommend trying it as well.

Introducing moderators. As we have shown, the TPR implied by our model can take different shapes depending on the underlying parameters which in turn may depend on the context. Controlling for contextual variation is therefore important. In addition to focusing on observations taken from broadly similar contexts (e.g., using data from one firm), one can further account for contextual variation by using moderators in the analysis. It is straightforward to introduce moderator variables in our measurement framework, which can be done in three ways: i) running separate regressions on subsamples with high vs. low values of a moderator (Boyd et al., 2012); ii) interacting the linear and quadratic terms of the quadratic U-shape with moderator variable(s) (Haans et al., 2016); or iii) expressing the parameters of the nonlinear regression specification as functions of moderator(s).

Endogeneity concerns and ways to address them

Factors such as local demand shocks or workplace management style may affect turnover and performance simultaneously, leading to a bias in the estimated effect of turnover on performance when these factors are not included in the regression specification. Existing TPR studies have come up with several ways of addressing these concerns. While none of these ways is perfect, each has advantages and deserves consideration.

Controls. A popular approach to address endogeneity concerns is to include controls for the factors simultaneously affecting turnover and performance. We consider controls for workplace size, workplace- and time-specific fixed effects, and past performance essential. Past performance accounts for past shocks that may have influenced turnover decisions and whose consequences may persist over several periods of time, which is particularly important for relatively high-frequency (quarterly or monthly) observations used in recent TPR studies (De Stefano et al., 2019; Simón et al., 2022) as well as ours. Workplace size controls for the scale of operations which clearly affects output and may also be related to turnover. Fixed effects pick up the workplace- and time-specific "unobservables' that affect sales and performance, for instance, location, management style or seasonality.[7] Other controls for study-specific context, for example, workforce or location characteristics, may be included as well, when available.

Timing of turnover events. In addition to using controls, one could exploit information on the timing of the events leading up to turnover, to identify turnover events that are predetermined with respect to current shocks to performance and are thus quasi-exogenous. One way of doing so is to rely on the practice of advance notice required before a worker leaves the firm. Provided this practice exists and is enforced, the currently observed turnover is the result of decisions influenced by earlier, rather than current, shocks to performance. An example of this approach is the study by Kuhn & Yu (2021) who use the advance notice practice in their study firm to identify the effect of individual sales staff turnover on retail store performance, arguing that "because a worker's departure is essentially locked in after she announces, we can be confident that productivity losses between the announcement and departure are a result, not a cause, of the impending departure" (p. 467).

An alternative is to regress current performance outcomes on past turnover, which would be predetermined even in the absence of advance notice, as is done in De Stefano et al. (2019) and Reilly et al. (2014). We consider this a valid approach not only because it helps partially address turnover endogeneity, but also because the effects of turnover on performance may take time to develop. It is important, however, to carefully choose the lag(s) of turnover to be included in the regression model: too recent turnover is likely endogenous, while turnover occurring in too distant past may have ceased to affect current performance. As theories, including ours, are often silent on this issue, turnover lag length selection is an empirical matter. Reilly et al. (2014) use a sophisticated statistical procedure for lag length selection, choosing a one-month lag in the end (p. 776). We use a simpler version of the same approach, selecting the lag length based on correlations between current performance and lags of turnover.

Instrumenting turnover. A method to exogenize turnover that does not rely on the availability of controls or the timing of turnover events is to instrument it with variables that affect turnover but are (arguably) unrelated to a focal workplace's performance. The literature on performance consequences of individual turnover counts several studies that instrument turnover with sudden worker deaths or political change (references in Kuhn & Yu, 2021, p. 462), but we could find only one study in the collective turnover literature that uses instruments: Simón et al. (2022).[8] We do not have valid instruments in our data, but we believe instrumenting collective turnover with plausibly exogenous events (for example, unexpected deterioration in worker health leading to quits) could be a promising direction for future research. Our framework can be extended to instrumenting turnover in a straightforward way, provided one uses the quadratic U-shape specification.

Measures

The choice of measures depends on the specific study context. Here, we lay out some considerations that we believe are generally applicable.

Performance. Existing literature has converged on a relatively few types of performance measures linked to collective turnover, comprising output measured in physical or monetary units, and service quality metrics such as customer satisfaction. Our framework can operate with all of these measures, provided they are defined at the same level of aggregation as collective turnover so that they can be clearly linked to the changes in the workforce structure occurring through turnover. In this study, we use sales net of costs of sales as the performance outcome. Net sales is a common performance metric in retail, and our study firms are both retail networks.

Turnover. Our model operates with the share $\boldsymbol{q}$ of the workforce quitting during a given time period. This is a common measure of collective turnover (Hausknecht & Trevor, 2011, p. 358), and we use it in our empirical analysis as well. An alternative measure is the ratio of the number of leavers to the average number of workers employed, typically approximated as the average of the headcount at the beginning and the end of the period (e.g., De Stefano et al., 2019; Shaw et al., 2005). These two measures will be highly correlated when workforce size fluctuations are small, which is likely the case when one uses high-frequency data. One could also correct turnover rates to account for the timing of departures (earlier vs. later during the reference time period, as in Siebert & Zubanov (2009)), but, again, this correction will not greatly affect the resulting turnover measure when time periods are short and departure times are bunched in the middle or end of the period, which they often are, for administrative reasons (Kuhn & Yu, 2021).

There is a case for measuring voluntary and involuntary turnover separately, as involuntary turnover is found to have a more beneficial performance effect than voluntary (Maltarich et al., 2020; Simón et al., 2022). We agree that the two turnover types could have different performance consequences, since there are probably more bad matches among involuntary leavers. However, data on the reasons for leaving may not be available or accurate enough, as managers may be reluctant to fire workers because of potential legal problems, opting instead for putting pressure on the unwanted workers to quit voluntarily. As we have no data on reasons for leaving, we proceed with the aggregate measure of turnover, assuming that involuntary quits are among bad matches.

Time window. What is the length of time (="time window") over which one should measure turnover in order to capture its effect on performance? Some studies measure the effect of a year's worth of turnover on that year's cumulative performance (e.g., Glebbeek & Bax, 2004; Shaw et al., 2005; Siebert & Zubanov, 2009); others use monthly time windows for performance and turnover (e.g., Reilly et al., 2014; Simón et al., 2022). No substantial justification for these choices is provided other than data availability.

Data availability should not be the only consideration, however. The time window should not be too wide lest the effects of earlier turnover peter out, and not too short lest there be not sufficient variation in turnover to identify its performance effect (turnover observed over short time periods is naturally low, and with many zeros). The time windows for performance and turnover do not have to be of the same length: for instance, Ton & Huckman (2008) regress monthly performance outcomes on cumulative turnover over the preceding three months in most of their specifications. We follow their approach. It helps preserve the performance information in our monthly data records while providing sufficient variation in turnover rates to identify our model parameters. The choice of the three-month time window for turnover is also supported by our preliminary analysis (skipped for brevity but available on request): monthly sales are more highly correlated with turnover over three preceding months than for any other time window.

Calculating the costs and benefits of turnover from the regression estimates. Equation (4) conveniently separates the net performance gain from turnover, $\boldsymbol{\Delta y = y(q) - y(0)}$, into the benefits (or costs) in terms of improving (or worsening) job-worker match quality,

$$B(\delta, \omega, q) = \frac{\ln(\delta)(\omega + 1)}{4(\omega - 1)} - \frac{\ln(\delta) \cdot \sqrt{(\omega - 1)^2 (q - 0.5)^2 + \omega}}{2(\omega - 1)},$$

and the operational costs,

$$C(c, q) = c \cdot q$$

If one runs the nonlinear regression specification corresponding to (4), one can compute their values for each individual observation i, $\hat{B} = B(\hat{\delta}, \hat{\omega}, q_i), \hat{C} = C(\hat{c}, q_i)$, as well as sample averages:

$$\hat{B} = \frac{1}{NT}\sum_{i=1}^{NT} B\left(\hat{\delta}, \hat{\omega}, q_i\right) \qquad \hat{C} = \frac{1}{NT}\sum_{i=1}^{NT} C\left(\hat{c}, q_i\right), \tag{7}$$

where NT is the number of observations in the data set. The standard deviations of these quantities, needed to assess their statistical significance, are also calculable.[9] The same can be done based on the quadratic U-shape specification (5):

$$\begin{aligned}\hat{C} &= \frac{1}{NT}\sum_{i=1}^{NT}(\hat{\alpha}_1 + \hat{\alpha}_2)\cdot q_i \\ &= (\hat{\alpha}_1 + \hat{\alpha}_2)\cdot \bar{q}\end{aligned} \qquad \begin{aligned}\hat{B} &= \frac{1}{NT}\sum_{i=1}^{NT}\begin{bmatrix}\hat{\alpha}_1 \cdot q_i + \hat{\alpha}_2 \cdot q_i^2 \\ -(\hat{\alpha}_1 + \hat{\alpha}_2)\cdot q_i\end{bmatrix} \\ &= \hat{\alpha}_2 \cdot \left(\bar{q^2} - \bar{q}\right)\end{aligned} \tag{8}$$

Analogously, for the extended quadratic U-shape specification (6) that includes interactions between worker group-specific turnover rates, the total costs and benefits of turnover in all k worker groups are

$$\begin{aligned}\hat{C} &= \frac{1}{NT}\sum_{i=1}^{NT}\sum_{j=1}^{k}\left(\hat{\alpha}_{1j} + \hat{\alpha}_{2j}\right)\cdot q_{ij} \\ &+ \frac{1}{NT}\sum_{i=1}^{NT}\sum_{j=1}^{k}\sum_{p\neq j}^{k}\beta_{jp}\cdot q_{ij}\cdot q_{ip}\end{aligned} \qquad \begin{aligned}\hat{B} &= \frac{1}{NT}\sum_{i=1}^{NT}\sum_{j=1}^{k}\begin{bmatrix}\hat{\alpha}_{1j}\cdot q_{ij} + \hat{\alpha}_{2j}\cdot q_{ij}^2 \\ -\left(\hat{\alpha}_{1j} + \hat{\alpha}_{2j}\right)\cdot q_{ij}\end{bmatrix} \\ &= \sum_{j=1}^{k}\hat{\alpha}_{2j}\cdot\left(\bar{q_j^2} - \bar{q_j}\right)\end{aligned} \tag{9}$$

Calculating the costs and benefits of turnover by worker group from the above specification is more complicated, so we leave this matter for further study.[10] One can also calculate the implied costs and benefits of turnover per quit by dividing the above quantities by the number of quits taking place within a given period of time.

EMPIRICAL APPLICATIONS

Research setting

We apply our measurement framework to data from two firms whose names cannot be revealed for reasons of confidentiality. Both firms are East-European mid-range retail networks operating comparable numbers of stores in their respective countries, but they differ in the size and scope of operations, and in their HR policies. We gained access to their store-level personnel and sales data and to their top management teams whom we interviewed for insights into the firms' business models and management practices. Additionally, we use the survey of store managers in Firm 1, conducted in September 2016 for an unrelated and yet unpublished project, to support further analysis. (No similar data are available for Firm 2.) Our focal performance outcome for both firms is store sales net of costs of sales ("net sales").

Firm 1. Over the observation period running from May 2015 to May 2017, Firm 1 operated 245 grocery stores.

Table ***1*** reports descriptive statistics and correlations. An average store generates about 67K Euros worth of net sales per month on the trading space of 643 square meters and employs 23 workers supervised by one store manager. Just over half of the stores are located in big towns, defined as urban areas of above-average size for the country (about 50K).

Insert

Table *1* about here

In our analysis of Firm 1, we focus on estimating the impact of turnover among store sales staff and managers.[11] Sales staff comprise 80% of the headcount in an average store. Most of their working time is shared between operating cash registers, filling the shelves, cleaning the store, and, occasionally, helping newly hired employees with onboarding. Sales staff are hired after an interview with the prospective store manager, followed by general training and two days' worth of job shadowing for successful applicants. Selection is not tough: we were told that it took 2.5 applicants to fill an average position, but this was because not all invited applicants ended up accepting the offer. Sales staff earn close to the country's minimum wage plus a bonus based on their store's sales performance. Their average total net earnings are 420 Euros per month for a full-time position, which is 53% of the average wage in Firm 1's country of operation in the same time period. Sales staff's average turnover rate is 19% per three-month period, which is relatively high: for comparison, the average turnover rate in U.S. retail trade in the same time period was about 14% (Bureau of Labor Statistics, 2017). According to the store manager survey, about two-fifth of leavers are above-average productivity workers.[12] The correlation between sales staff turnover and net sales is nearly zero.

Store managers oversee daily operations (procurement, logistics, customer interactions), and also in charge of financial reporting, ensuring compliance with firm-wide operational standards, and general administration. Additionally, they are engaged in store-level HR activities, including employee selection, training, workforce coordination, and shift scheduling. Half of the store managers are hired externally, the rest promoted from sales staff. Their average monthly earnings, including bonuses, are 970 Euros, an above-average salary in the country. Store managers are much less likely to quit than sales staff: their three-month average turnover rate is 4.4%. There is no correlation between their turnover rate and net sales.

Firm 2. Firm 2 is much bigger in size and scope than Firm 1. Its 232 stores, operated during our observation period from January 2017 to August 2020, carry a wide range of products including clothing and household appliances, as well as groceries. Table 2 reports the descriptive statistics and correlations. The average store is 5.6K square meters large, generates around 600K Euros per month in net sales, and employs 106 full-time sales staff. All of Firm 2's stores are located on the outskirts of big cities, reflecting the size of the market required for its operations, as well as the availability and price of suitable land slots.

Insert Table 2 about here

Firm 2's stores are organized into departments by product category. In our empirical analysis, we focus on the department managers and sales staff, who are the two largest store employee groups (on average 74% and 21% of the total, respectively).[13] The responsibilities of Firm 2's sales staff are similar to those of Firm 1's when it comes to routine tasks like shelving or cleaning. An important difference is that Firm 2's sales staff provide customer advice, especially in the departments that sell products like clothing or household appliances that are higher-value and require more specific knowledge to sell than typical groceries. Sales staff are hired through a centralized selection procedure involving assessment tests, background checks, and at least two interviews. Newly hired sales staff receive foundational training, administered centrally, as well as specific job training offered within their departments. The average wage of Firm 2's sales staff (407 Euros per month) is close to that of Firm 1 (420 Euros) in nominal terms, but is higher in relative terms, corresponding to 65% of the country's average wage. Consistent with the more rigorous selection procedure and higher relative wage, sales staff turnover in Firm 2 (11.3% per three months) is lower than in Firm 1 (19%), and its correlation with net sales is negative and significant (-0.167).

Firm 2's department managers have the same responsibilities as store managers in Firm 1, except that their numbers are higher and they are not in charge of the HR and administrative activities, all of which are centralized at the store or company level. Department managers' average earnings, 646 Euros per month, are significantly lower than what Firm 1's store managers make (970 Euros). Their average turnover rate is 6.0% per three months, exceeding store managers' turnover rate in Firm 1 (4.4%). Like sales staff's, managers' turnover is negatively correlated with net sales (-0.118).

Results

We run the same sequence of regression specifications for each firm: linear, followed by the simple and extended quadratic U-shapes (5) and (6), and finally the nonlinear specification (4). The outcome variable is log monthly net sales, and the key regressor is turnover rate over three preceding months (and its square, where applicable). Each specification includes month and store fixed effects and controls for past sales and other store and workforce characteristics as detailed in the notes to the regression Tables Table *3* and

Table *4*. The estimated average costs and benefits of turnover and their standard errors, in percent of net sales and clustered at the store level, are reported at the bottom of the regression tables.

Baseline regressions. The upper part of Table Table ***3*** presents the regression results for Firm 1. The estimates from the linear specification (column 1) imply a significantly negative link between net sales and both sales staff and manager turnover. The departure of a store manager within the preceding three-month time window is followed by about 1% lower net monthly sales, and the implied losses from turnover of the entire sales staff at any time within the last three months are 3.6% of net monthly sales.

Insert Table 3 about here

The quadratic regression results (columns 2 and 3) offer directional support to the inverted U-shape TPR in the case of sales staff turnover. (We cannot estimate a curvilinear TPR for managers because there is only one manager per store, so the manager turnover rate is either 0 or 1.) The coefficient on sales staff turnover rate is positive (0.04) and that on its square is negative (-0.113), both individually insignificant. However, the implied optimal turnover rate, $-\frac{a_1}{2a_2}$, is positive and significant ($0.17, p = 0.055$), lending some support to the inverted U-shape TPR for sales staff in Firm 1.[14] There is no significant interaction between the sales staff and manager turnover rates, suggesting that turnover in the two worker groups has independent effects on performance.

The estimates of the structural parameters of the nonlinear regression (4) (column 4) suggest that bad matches among sales staff are more likely to quit than good ones: the odds ratio

$\omega = 6.047$ significantly differs from 1, $p < 0.01$. The productivity ratio $\delta = 1.23$ suggests that the average good match is about a quarter more productive than bad, but it is not significantly different from 1 ($p = 0.19$). The operational costs of turnover parameter $c = 0.066$ ($p < 0.05$) is considerably higher than the estimate produced by the linear model (3.6%), owing to the linear specification estimating the net effect without separating the costs and benefits of turnover, but the difference is not statistically significant.

The regression results for Firm 2 are listed in

Table *4*. The linear specification (column 1) shows a strong and negative link between net sales and both sales staff and departmental manager turnover rates. In the simple quadratic regression (5) (column 2), the coefficients on the turnover rate and its square are both negative, implying a monotonically negative TPR for any non-zero turnover for both worker groups. The borderline-significance of sales staff turnover-squared in column 2 hints at the possibility of sales staff turnover having benefits as well as costs. However, this result is not robust to specification; it disappears as we move to the extended quadratic regression (6) that allows for turnover in the two worker groups to interact (column 3). The results in column 3 reveal that turnover among sales staff and departmental managers reinforces each other's negative effect on net sales: the interaction term is negative and significant (-0.78, $p < 0.01$), whereas the remaining terms containing turnover rates are insignificant, individually or jointly ($p = 0.84$).

Insert

Table *4* about here

We could not obtain parameter estimates of the nonlinear model (4) for Firm 2 because the numerical estimation procedure failed to converge. As we noted earlier, nonlinear regressions may be prone to computational problems, especially when quits are low and the differences between good and bad matches in productivity and odds of leaving are small. Besides, the nonlinear model (4) is not equipped to handle interactions in the effects of turnover in different worker groups. The strong interaction between sales staff and departmental manager turnover, found in Firm 2 but not in Firm 1, could be another reason why we failed to estimate this model on Firm 2's data.

The estimated costs and benefits of turnover. The lower parts of Tables Table *3* and

Table *4* report the costs and benefits of sales staff and manager turnover for Firms 1 and 2, respectively, for the average store-month, as implied by the regression results and the actual quits, and calculated with equations (7), (8) or (9) as appropriate. Starting with Firm 1, the linear specification results (column 1) imply that the average store loses 0.7% of net sales per month to turnover, which is the net effect of its operational costs and benefits. Accounting for the operational costs and benefits of turnover separately (columns 2-4) reveals that sales staff turnover brings operational costs averaging at 1.4% of net sales per month, and manager turnover costs a further 0.04%. The costs of manager turnover in percent of net sales are deceptively small because managers quit much less frequently than sales staff: in fact, when calculated per quit, the implied operational costs of turnover are about 700-800 Euros for sales staff, depending on the specification, and twice as much for store managers.[15]

The estimated average benefits of sales staff turnover in Firm 1 are commensurate to costs, leading to an economically and statistically insignificant net effect of turnover on performance ($p > 0.45$ in all specifications). However, while economically sizeable, the benefit estimates have large variances and consequently are only borderline-significant ($p = 0.17$ for the quadratic U-shape and 0.14 for the nonlinear specification). Turnover benefits are estimated less precisely than costs because the benefits depend on the productivity differential δ that is not statistically significant.

In the case of Firm 2, the costs of turnover are larger. Although the benefit estimates are substantial in magnitude, they are not statistically significant and disappear completely in specification (6) where we allow for interaction in the effects of turnover in different worker groups, which proves highly significant. Based on this latter specification, the net effect of sales staff turnover is a loss of about 1% of net sales, or 13K Euros per quit, which is much higher than in Firm 1.

Moderators. We now probe the sensitivity of our results to variations in context by interacting a selection of possible moderators with the quit and quit-squared terms in the quadratic U-shape regression **Error! Reference source not found.** (Haans et al., 2016) and testing whether these interactions are significant. For Firm 1, we use as moderators store size in headcount, location (big vs. small town), local unemployment rate, and the share of above-average productivity workers calculated from the survey of 129 store managers in September 2016 (details in footnote 12). For Firm 2, we only use store size because all of its stores are located in big towns and we have no data on other moderators. It is worth noting that we have no strong theoretical priors regarding the moderators, except perhaps the share of productive workers among the leavers, and present this part of the analysis only as an illustration of our method. A more comprehensive moderation analysis is left for future research.

Insert

Table *5* about here

Of the potential moderators we have considered, only the share of above-average productivity workers among the leavers in Firm 1 is statistically significant ($p = 0.065$, details available on request). Table 5 reports estimation results from the quadratic U-shape and nonlinear regressions (5) and (4) obtained on sub-samples of Firm 1's stores with the shares of above-average quits at or below and above the median (0.33). On the at-or-below-median sub-sample, that is, in stores with relatively few above-average productive leavers, we observe a significant inverted U-shape TPR. The costs and benefits of turnover in terms of net sales are both significant ($p < 0.05$), and are about the same size, producing a zero net effect. On the above-median sub-sample, there is no inverted U-shape. The nonlinear regression estimates imply that, while bad matches are more likely to quit ($\omega = 4.5$), they are as productive as good matches ($\delta = 1.02$). Consequently, there are no benefits of turnover, just costs of close to 1% of net sales in the average store-month.[16]

DISCUSSION AND CONCLUSION

We have devised a theory-driven framework for capturing a potentially nonlinear TPR, discussed attendant estimation issues, and presented two applications producing different results. In this section, after comparing the results from our two study firms, we outline the contributions of our work to research and practice, as well as its limitations.

Results in Firm 1 vs. Firm 2

We find an inverted U-shape TPR in Firm 1, especially in stores where managers report relatively few above-average productive quits. The implied net effect of turnover on performance is about zero, and the implied per-quit costs in terms of lost net sales are about 800 Euros for sales staff and 1600 Euros for store managers, or just under twice the respective monthly wage. In contrast, the TPR in Firm 2 is monotonically negative, resulting in a loss of about 1% of net sales in the average store-month, with per-quit costs more than ten times higher than in Firm 1. Why is this difference?

The insights we gained from management interviews allow us to connect the TPRs we observe in the two firms to their operations and HR practices. As we stated earlier, Firm 2 carries products that require more specific knowledge to sell (e.g., clothing or household appliances) as compared to Firm 1 (groceries). The greater importance of specific knowledge magnifies the operational costs of turnover Firm 2 faces, since knowledge depletion is costly, resulting in a more negative TPR – an effect also found in Meulenaere et al. (2021)'s study of a large sample of Belgian firms. Relatedly, as Firm 2 pays higher wages to its sales staff and runs more comprehensive selection and training procedures than Firm 1, it may have fewer unproductive bad matches. Put in terms of our model, there may be a lower productivity differential between good and bad matches (δ), which is consistent with our finding of no curvilinearity in TPR for Firm 2.

Research contributions

We have carried out this project in response to the calls to explore curvilinearities in the turnover-performance relationship (TPR) and to delineate between the costs and benefits of collective turnover (Hancock et al., 2017; Hausknecht, 2017). As a contribution to research on these important issues, we offer a flexible, theory-driven and widely applicable framework for measuring TPR, so that its potential curvilinearity can be captured and the implied costs and benefits estimated. Our framework is flexible in that it makes no structural assumptions regarding TPR pattern, allowing one to be estimated from data instead. This flexibility is driven by a general yet parsimonious theoretical model we have derived from job matching theory. Minimalistic data requirements render our framework potentially widely applicable, as we have illustrated with two applications on commonly available firm-worker data. (There are limitations, of course, which we discuss later.)

Beyond developing a tool to measure TPR, our study makes further contributions. First, we extend the research on nonlinear TPR found in some empirical studies (e.g., De Stefano et al., 2019; Glebbeek & Bax, 2004; Siebert & Zubanov, 2009; Simón et al., 2022). Though not as prevalent empirically, nonlinearities in TPR continue to excite researchers thanks to their theoretical appeal (Abelson & Baysinger, 1984; Shaw et al., 2005). In terms of theory, we show that job matching theory can generate all hitherto known TPR patterns, each emerging under a certain combination of the values of a small set of underlying parameters. By this, we by no means exclude other theoretical perspectives on TPR, but rather propose a simple theoretical argument based on which can reconcile the variety of existing empirical findings. In fact, we have argued theoretically, and found empirically, that TPR is not universally nonlinear or nonmonotonic. Specifically, our finding that TPR depends on the share of above-average performers among the leavers is consistent with existing research findings on the moderating role of workforce characteristics in TPR (e.g., De Stefano et al., 2019; Simón et al., 2022).

Second, we strengthen the case for the use of the quadratic U-shape regression in searching for nonlinear TPR. So far, researchers have employed the quadratic U-shape as an approximation to a possibly nonlinear TPR, without a more precise characterization of its true shape as implied by the underlying theory. (All of the studies allowing for a nonlinear TPR used quadratic U-shape, except Li et al. (2022) who used piece-wise linear, or “V-shape” regression, and DeWinne et al. (2019) who used a higher-degree polynomial.) This approach could potentially lead to incorrect inferences, for example, mistaking a nonlinear but monotonic function like $y = a + b \cdot \log(x)$ for a nonmonotonic U-shape (Simonsohn, 2018). We show that a quadratic U-shape is a valid approximation of the TPR implied by our model under a wide range of circumstances.

Why is a more precise theoretical characterization of TPR useful? In addition to bringing the empirics closer to the underlying theory, one advantage of having a more precisely stated "formula" for TPR is the possibility to empirically estimate meaningful quantities that are functions of TPR parameters, such as the benefits and costs of turnover. Our third contribution is in showing how one can estimate these quantities from commonly available data in a theory-driven way. We believe this is an interesting alternative to the approaches currently applied in studies estimating turnover costs, such as relying on expert opinions (Boushey & Glynn, 2012; Tracey & Hinkin, 2008), analyzing linear performance-turnover correlations (Friebel et al., 2022) or tracking individual turnover events (Kuhn & Yu, 2021).[17]

Practical implications

The ability to produce estimates of the costs and possible benefits of turnover from commonly available personnel and sales data makes our measurement framework readily applicable in practice. One potential application is to inform cost-benefit calculations behind HR policies aimed at managing employee turnover. At a more strategic level, our study implies that not all turnover is necessarily detrimental to performance at the workplace level. This idea is not new and has been presented in every study finding a nonlinear TPR that we cited. Yet, the mainstream approach in HR management still seems to be the one that argues that turnover is bad and should be kept to a minimum, through active employee retention policies if necessary (see references in Li et al., 2022, for examples).

Why are the majority of HR management practitioners so unenthusiastic about a possibly curvilinear TPR? First, notice that a curvilinear TPR is still a “fringe” finding obtained in a minority of studies and in the context of relatively low-skilled jobs. Second, even in this context, a curvilinear TPR is malleable and can be transformed into a monotonically negative one by powerful moderators such as leavers’ job-specific knowledge or productivity. Third, and least discussed so far, finding a non-zero optimal turnover rate at the workplace level does not imply its existence at the firm level, which is what matters for HR policy. While the benefits from turnover through better match quality are likely to accrue at the level at which the focal employee group operates, its costs may be felt at different organizational levels. For instance, the costs of turnover in terms of time spent dealing with turnover by HR, payroll and other firm-level departments[18] will not be registered at the workplace level. As a result, a workplace-level study like ours will fail to measure the full cost of turnover. This reasoning, together with our finding that the average net effect of turnover on workplace sales is at best zero (Firm 1), helps understand why many firms, including our two study firms, perceive employee turnover as a problem, despite some empirical evidence that it may be beneficial at some levels.

Limitations and further research

The inability to estimate the full costs of turnover at all levels within the firm is a notable limitation of our approach, as well as of any other TPR study that focuses on a particular organizational level. Further research should adopt a more multi-level perspective in quantifying the costs of turnover. Data limitations are clearly an issue here, especially for single-firm studies like ours, but combining, as we did, results from rigorous data analysis (e.g., workplace-level operational costs of turnover) with expert estimates calculated less methodically (firm-level administrative costs of turnover) seems to be a workable strategy.

There are other limitations to our method in general, as well as specific to the applications featured in this study. Starting with the specific limitations, first, we study TPR in two firms within the same broad industry (retail), which limits the applicability of our findings to other contexts. Second, we lack data on some potentially important moderators of TPR in our study firms, such as individual performance metrics or reasons for leaving, both of which variables were previously found to be important moderators of TPR (Call et al., 2015; Simón et al., 2022). We look forward to seeing more studies of TPR carried out in a greater variety of settings and on more complete data sets, and, hopefully, using our measurement framework.

More generally, among the technical limitations of our method are its computational complexity, parameter identification issues, and inability to produce an analytically tractable TPR in the case of multiple worker groups and one, shared, performance outcome (the case of Firm 2). The failure of the estimation procedure for the theoretical TPR in equation (4) is one consequence of these problems. This said, the conventional quadratic U-shape, which, as we showed, approximates the theoretical TPR under a wide range of parameter values, remains a workable option. Further research should use quadratic U-shape regression for more routine testing of nonlinearities in TPR.

CONCLUSION

Applying our novel measurement framework to data from two retail firms, we find clear evidence that turnover is costly for performance. The benefits of turnover are less certain and more context-specific. Turnover is never beneficial to performance in net terms. This result, together with the other costs that accrue at the firm rather than workplace level (e.g., administration), leads us to conclude that firms are probably right to try to reduce employee turnover. This said, it is still important to appreciate potential benefits from turnover in terms of improving job-worker match quality, and to take these into account in designing HR policies to deal with turnover.

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TABLES

Table 1: Descriptive statistics and correlation matrix for Firm 1

	Pairwise correlations Mean	Std Dev	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)Net sales, '000 Euros	67.028	49.816										
(2)Store area, sq.m	642.798	372.402	0.865									
(3) Store workers headcount	22.747	16.868	0.960	0.902								
(4) Sales staff average wage, Euros	420.620	36.736	-0.113	-0.204	-0.201							
(5) Store managers' average wage, Euros	967.488	214.002	0.472	0.458	0.473	-0.076						
(6) Sales staff average tenure, months	2.965	1.715	0.054	0.056	0.046	0.251	0.106					
(7) Store managers' average tenure, months	7.868	4.684	0.026	0.049	0.006	0.080	0.063	0.238				
(8) Store workers' turnover rate	0.193	0.156	0.043	0.082	0.070	-0.208	-0.017	-0.406	-0.096			
(9) Store managers' turnover rate	0.044	0.205	0.001	0.006	0.010	-0.054	-0.066	-0.035	-0.088	0.098		
(10) Share above-average productive leavers	0.427	0.388	-0.075	-0.145	-0.084	0.097	0.009	0.095	-0.085	-0.066	-0.011	
(11) Location in big city	0.530	0.499	0.314	0.191	0.306	0.017	0.145	-0.180	-0.099	0.138	0.018	0.121
Observations	5793											
Number of stores	245											

Table 2: Descriptive statistics and correlation matrix for Firm 2

	Pairwise correlations Mean	Std Dev	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)Net sales, '000 Euros	594.754	347.33										
(2)Store area, sq.m	5600.57	1490.8	0.408									
(3) Store workers headcount	106.580	28.197	0.566	0.619								
(4) Sales staff headcount	78.822	25.025	0.548	0.597	0.986							
(5) Department managers' headcount	21.083	3.517	0.554	0.612	0.704	0.640						
(6) Sales staff average wage, Euros	407.147	81.177	-0.010	-0.006	-0.011	-0.011	-0.006					
(7) Dpt. managers' average wage, Euros	645.696	136.98	-0.012	-0.006	0.001	-0.020	-0.027	0.124				
(8) Sales staff average tenure, months	32.091	19.398	0.433	0.356	0.456	0.419	0.471	-0.012	-0.013			
(9) Dpt. managers' average tenure, months	43.626	25.058	0.436	0.371	0.515	0.484	0.497	-0.014	-0.012	0.891		
(10) Sales staff turnover rate	0.113	0.066	-0.167	-0.137	-0.244	-0.209	-0.194	-0.072	0.001	-0.369	-0.348	
(11) Dpt. managers' turnover rate	0.064	0.069	-0.118	-0.093	-0.184	-0.157	-0.231	-0.011	-0.009	-0.217	-0.262	0.393
Observations	8394											
Number of stores	232											

Table 3
Estimation results for Firm 1

	Dependent variable: Log net sales			
	(1)	(2)	(3)	(4)
Sales staff turnover rate	-0.036	0.039	0.039	
	(0.022)	(0.400)	(0.400)	
Sales staff turnover rate squared		-0.114	-0.114	
		(0.167)	(0.173)	
Sales staff and managers' turnover interaction			0.003	
			(0.938)	
Productivity differential (δ)				1.230
				(0.000)
Odds ratio (ω)				6.047
				(0.001)
Cost of Turnover (c)				0.066
				(0.040)
Average costs of sales staff turnover	-0.007	-0.014	-	-0.013
	(0.021)	(0.055)		(0.039)
Average benefits from sales staff turnover	-	0.015	-	0.011
		(0.166)		(0.137)
Average costs of managers turnover	-0.000	-0.000	-	-0.000
	(0.103)	(0.103)		(0.134)
Average total effect from turnover	-0.007	0.000	0.000	-0.002
	(0.016)	(0.961)	(0.964)	(0.541)
Costs per quit of sales staff, ’000 Euros	392.546	818.646	-	724.496
	(0.021)	(0.055)		(0.039)
Costs per quit of store managers,’000 Euros	1680.555	1668.623	-	1543.262
	(0.103)	(0.103)		(0.134)
Costs per quit of all store workers,’000 Euros	-	-	891.412	-
			(0.029)	
Observations	5793			

Notes: From this Table onwards, standard errors are clustered by store, p-values in parentheses. Estimates in column (1) are based on the linear regression of log net sales on sales staff and store manager turnover rate. Column (2) - equation (5), column (3) - equation (7), column (4) - equation (4). Controls in all specifications: time and store fixed effects, lagged dependent variable, log hours worked, share of female employees, deviation of the actual from the expected number of quits, as defined in Call et al. (2015), employee average tenure and wage.

Table 4
Estimation results for Firm 2

	Dependent variable: Log net sales		
	(1)	(2)	(3)
Sales staff turnover rate	-0.117	-0.013	-0.033
	(0.000)	(0.866)	(0.661)
Department managers' turnover rate	-0.071	-0.031	0.024
	(0.000)	(0.514)	(0.632)
Sales staff turnover rate squared		-0.337	-0.043
		(0.150)	(0.867)
Department managers' turnover rate squared		-0.158	0.103
		(0.360)	(0.597)
Sales staff and managers' turnover interaction			-0.781
			(0.008)
Average costs of sales staff turnover	-0.013	-0.040	-
	(0.000)	(0.036)	
Average costs of department managers' turnover	-0.004	-0.012	-
	(0.000)	(0.150)	
Average benefits from sales staff turnover	-	0.032	-
		(0.148)	
Average benefits from department managers' turnover	-	0.009	-
		(0.359)	
Average total effect from sales staff turnover	-0.013	-0.007	-
	(0.000)	(0.176)	
Average total effect from department managers	-0.004	-0.003	-
	(0.000)	(0.059)	
Average total costs from turnover	-0.018	-0.052	-0.010
	(0.000)	(0.009)	(0.649)
Average total benefits from turnover	-	0.041	-0.002
		(0.077)	(0.956)
Average total effect from turnover	-0.018	-0.011	-0.010
	(0.000)	(0.060)	(0.087)
Costs per quit of sales staff, ’000 Euros	2.661	7.938	-
	(0.000)	(0.036)	
Costs per quit of department managers, ’000 Euros	5.992	15.977	-
	(0.000)	(0.150)	
Costs per quit of all store workers, ’000 Euros	-	-	13.927
			(0.005)
Observations	8394		

Table 5
Moderation analysis for Firm 1

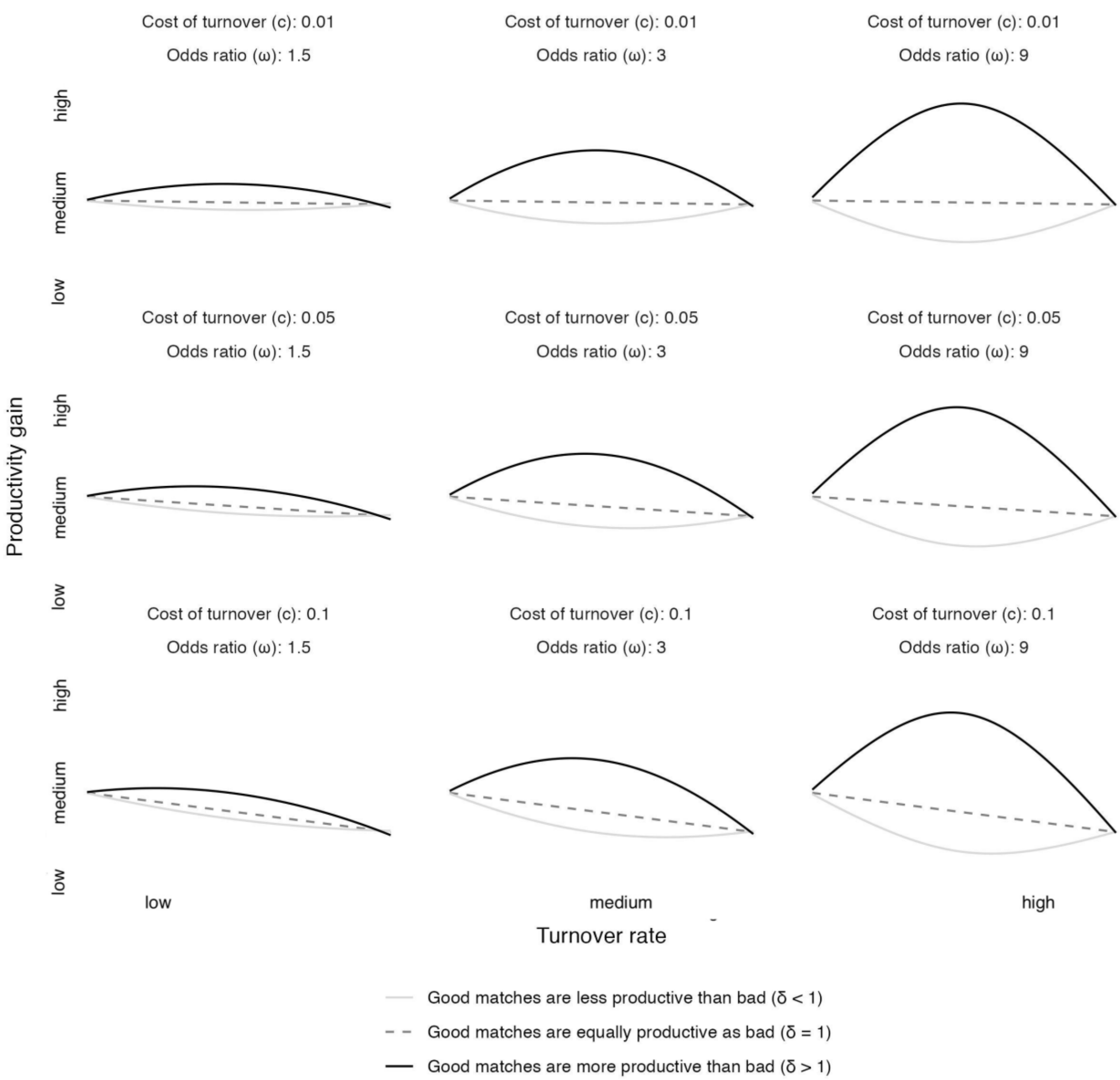
	Dependent variable: Log net sales			
	Stores with few productive quits		Stores with many productive quits	
	(1)	(2)	(3)	(4)
Store managers' turnover	-0.005	-0.005	-0.014	-0.014
	(0.493)	(0.511)	(0.212)	(0.225)
Sales staff turnover rate	0.072		-0.050	
	(0.106)		(0.296)	
Sales staff turnover rate squared	-0.132		0.021	
	(0.035)		(0.754)	
Productivity differential (δ)		1.160		1.017
		(0.000)		(0.000)
Odds ratio (ω)		8264000.319		4.420
		(.)		(0.005)
Cost of Turnover (c)		0.064		0.040
		(0.016)		(0.224)
Average costs of sales staff turnover	-0.014	-0.014	-0.006	-0.008
	(0.019)	(0.014)	(0.345)	(0.219)
Average benefits from sales staff turnover	0.020	0.016	-0.003	0.001
	(0.031)	(0.010)	(0.752)	(0.931)
Average costs of managers turnover	-0.000	-0.000	-0.001	-0.001
	(0.491)	(0.509)	(0.207)	(0.221)
Average total effect from turnover	0.006	0.001	-0.009	-0.007
	(0.308)	(0.749)	(0.129)	(0.206)
Costs per quit of sales staff, ’000 Euros	658.852	703.060	322.305	441.020
	(0.019)	(0.014)	(0.345)	(0.219)
Costs per quit of store managers, ’000 Euros	1069.208	994.913	2835.667	2821.661
	(0.491)	(0.509)	(0.207)	(0.221)
Observations	1711		1475	

Notes: All specifications are exactly the same as in Table 3, except they are estimated on subsamples with the share of above-average productive workers among the leavers above and below the median (0.33).

FIGURES

Figure 1

Turnover-performance relationship (TPR) in different contexts



Notes: This figure plots different patterns in TPR depending on the values of the three underlying parameters in our model (equation **Error! Reference source not found.**): the productivity ratio between good and bad matches (δ), the likelihood of quit ratio between bad and good matches (ω), and the operational costs of turnover (c).

FOOTNOTES

[1] Other possible benefits may be improving workforce adjustment to demand fluctuations (De Stefano et al., 2019; Siebert & Zubanov, 2009), or bringing hard-to-access knowledge from other firms that comes with new hires replacing the leavers (Stoyanov & Zubanov, 2012, 2014). We acknowledge these possibilities but do not focus on them in this study.
[2] To be precise, Li et al. (2022)estimated a piece-wise linear regression with varying slopes depending on turnover level, that is, an inverted V- rather than U-shape. capture TPR with a 4th-degree polynomial in turnover, finding an inverted U-shape pattern.
[3] The meta-analysis by McEvoy & Cascio (1987) finds a negative performance-turnover correlation across 24 different studies. More recent research tends to find support for a U-shaped relationship with an attenuated effect for high performers and moderated by culture (Sturman et al., 2012), performance history (Becker & Cropanzano, 2011), performance bonus received (Salamin & Hom, 2005), and gender (Hochwarter et al., 2001). Again, the linear correlations between performance and turnover are negative in all of the above studies.
[4] To derive the expression for p(q), let x be the number of bad matches among the $\mathrm{q} \cdot \mathrm{N}$ leavers, so the share of bad matches among the leavers is $\mathrm{p(q)} = \frac{\mathrm{x}}{\mathrm{q} \cdot \mathrm{N}}$. By definition, the odds ratio of bad vs. good matches leaving is

$$\omega = \frac{\frac{\text{bad matches leaving}}{\text{bad matches staying}}}{\frac{\text{good matches leaving}}{\text{good matches staying}}} = \frac{\mathrm{x}}{0.5 \cdot \mathrm{N} - \mathrm{x}} \cdot \frac{0.5 \cdot \mathrm{N} - (\mathrm{q} \cdot \mathrm{N} - \mathrm{x})}{\mathrm{q} \cdot \mathrm{N} - \mathrm{x}}$$

$$= \frac{\frac{\mathrm{x}}{\mathrm{q} \cdot \mathrm{N}}}{\frac{0.5 \cdot \mathrm{N}}{\mathrm{q} \cdot \mathrm{N}} - \frac{\mathrm{x}}{\mathrm{q} \cdot \mathrm{N}}} \cdot \frac{\frac{0.5 \cdot \mathrm{N}}{\mathrm{q} \cdot \mathrm{N}} - \left(1 - \frac{\mathrm{x}}{\mathrm{q} \cdot \mathrm{N}}\right)}{1 - \frac{\mathrm{x}}{\mathrm{q} \cdot \mathrm{N}}} = \frac{\mathrm{p(q)}}{0.5 \cdot \frac{1}{\mathrm{q}} - \mathrm{p(q)}} \cdot \frac{0.5 \cdot \frac{1}{\mathrm{q}} - (1 - \mathrm{p(q)})}{1 - \mathrm{p(q)}}$$

Solving the above equation for p(q) and choosing the solution corresponding to $0 \leq p(q) \leq 1$ gives the expression in equation (3). This result corresponds to a well-known approximation of the mean of the extended hypergeometric distribution (e.g., Eisinga & Pelzer, 2011)). This distribution is used in statistics to model the probability of finding k objects of a given type in a random sample of size $\mathrm{n} \geq \mathrm{k}$ drawn from a population with a known type structure when sampling probabilities are type-specific (Johnson et al., 2005, pp. 293-295). In our application, the "objects" are bad matches, the "sample" are the leavers, the "type structure" is given by the shares of good and bad matches in the workforce (0.5 each), and the "type-specific sampling probabilities" are given by the odds ratio $\omega = \frac{p_b/(1-p_b)}{p_g/(1-p_g)}$, where p_b, p_g are the type-specific probabilities of quitting.
[5] Unlike maximum likelihood-based estimators, NLS requires no distributional assumptions with respect to the regression residuals. The conditional independence assumption between the residuals and the regressors is still required, as with any other regression estimator. NLS is implemented in all major software programs, including Stata `nl` package that we have used.
[6] The coefficients α_1, α_2 in the quadratic specification are nonlinear functions of the model parameters δ, ω, c, and this nonlinearity can blow up the variances of α_1, α_2. We leave a more thorough exploration of this issue for another study, but, to illustrate the problem, suppose δ, ω, c have means 1.5, 2, 0.02 and standard deviations 0.2, 0.5, 0.01, respectively, and are uncorrelated; so one would reject the null hypothesis of no curvilinearity in TPR ($\delta = 1$ or $\omega = 1$) at the conventional 5% significance level in this setting. However, the quadratic U-shape coefficients α_1, α_2, estimated on simulated data based on the above parameter values, would have means 0.04, −0.05 and standard deviations 0.04,0.03, respectively, leading one to incorrectly accept the null of no curvilinearity in TPR under the same significance level of 5%.
[7] In the context of a linear regression, such as the quadratic U-shape specification **Error! Reference source not found.**, fixed effects are time- and workplace-specific dummy variables. For nonlinear regressions, such

as **Error! Reference source not found.**, including a large number of dummy variables may be quite taxing computationally, especially when one has many workplaces in the data set. An alternative approach is to proxy workplace- or time-specific unobservables with the corresponding averages of the regression variables. Mundlak (1978)developed this approach for the linear regression model. Recently, Hsu & Shiu (2021) and Wooldridge (2021) generalized it to nonlinear models such as ours. We adopt this latter approach.

[8] Simón et al. (2022) instrument involuntary turnover in a given workplace and month with deviations from the sample-average involuntary turnover in that month. It can be shown that instrumenting turnover in a given unit with its deviation from the period average is equivalent to adding time fixed effects in the regression model (Hansen, 2022, chapter 17.28), which we also do.

[9] We recommend using Stata `margins` command with option `expression` that allows evaluating the point estimate and standard error of nearly any expression in terms of regression coefficients and data. For instance, quantity $\hat{C}$ in equation **Error! Reference source not found.** can be evaluated with `margins, expression(-_b[/c]*q)`.

[10] The complication owes itself to the presence of the shared interaction term $\beta_{jp} \cdot q_j \cdot q_p$ corresponding to every pair of worker groups (j, p) that needs to be split between j and p in calculating the costs and benefits of turnover specific to those groups. One intuitive possibility is to split it proportionally to the variances of group-specific turnover rates.

[11] The remaining employee groups are unit managers, who assist store managers in their tasks, and "specialists" who work in specialized store units such as the bakery or fishmongers. They are not focal to our analysis in this study because they are relatively few and not present in all stores and are thus unlikely to affect overall sales strongly enough for the impact of their turnover to be detected. We add turnover rates in these employee groups as controls in our regressions, but they are not significant.

[12] The store manager survey was conducted in September 2016 for an unrelated and yet unpublished project. The exact questions were: 1. "Over the last three months, how many sales staff quit your store?" 2. "Of those sales staff who quit over the last three months, how many would you say were above-average in individual performance?" Our measure of the share of above-average productivity leavers is the ratio of the answers to questions 2 and 1. We have usable data from 129 out of 245 stores.

[13] The other store employee groups in Firm 2 are cash register operators who are not part of the department sales staff (3%), and store general managers and their support staff (2%). Cash register operators work in the checkout zone and do not do any other tasks. Store managers are in charge of the administration, including financial reporting and compliance. We do not focus on these employee groups, but we control for their turnover rates in our regressions, finding none to be significant.

[14] We calculated the variance of a nonlinear combination of two random variables, a_1 and a_2, $-\frac{a_1}{2a_2}$, using Delta method. Similar to the case of a linear combination of regression coefficients, in calculating the variance of a nonlinear combination, Delta method takes into account covariances. This is why a (non)linear combination of individually insignificant regressors may end up significant.

[15] We calculate the operational costs of turnover per quit as the average costs per store-month in % of net sales ($\hat{c}$) times the average net sales divided by the average number of leavers within a given worker group per store-month. For example, if the average store in Firm 1 loses 1.4% of its net monthly sales (67K Euros, Table 1) to sales staff turnover happening at a monthly rate of 0.193/3=0.064 among 18.3 of its sales staff, the implied costs per quit are $\frac{0.014 \times 67{,}000}{0.064 \times 18.3} = 800$ Euros.

[16] The split-sample results in

Table *5* are fragile owing to much smaller sample size. The failure of the nonlinear estimator to estimate the variance of the odds ratio parameter ω on the subsample of stores with a below-median share of productive leavers is a reminder that nonlinear estimation can be tricky. Yet, the nonlinear and quadratic U-shape estimation results are reassuringly close.

[17] To our knowledge, the only other study that attempted to apply theory to estimating the costs of turnover is Siebert & Zubanov (2009) who used a microeconomic argument of profit maximization to back out the implied costs of turnover from the observed difference between the sales-maximizing turnover level and the observed average turnover level (assumed profit-maximizing). While this is a sound argument, it does impose an additional assumption on the turnover cost calculation, which our method does not.

[18] Friebel et al. (2022) estimate the firm-level administrative costs of retail worker turnover at about 250 Euros per quit, or 70% of the monthly salary.