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ABSTRACT

Labour Turnover and Labour Productivity in a Retail Organization*

We study the impact of labour turnover on labour productivity using a panel dataset of 347 shops belonging to a large UK clothing retailer over1995-1999. For the within-shop link – holding constant the shop's permanent characteristics – we observe an inverted U-shape effect of labour turnover on productivity. The productivity-maximizing rates of FTE-adjusted quits and hires are each about 20% per year, improving productivity by 2.5% compared to the zero turnover level. We explain the difference between this optimal level of labour turnover and its observed average (quits and hires each around 10%) through the costs of hiring estimated at about £600 per hire. By contrast, between shops, there is a positive link between average rates of turnover and average productivity, suggesting that an unobservable management quality factor generates both high turnover and productivity, which we discuss.

JEL Classification: J63, J24, L81

Keywords: labour productivity, labour turnover, matched employee-firm panel data, retailing

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LABOUR TURNOVER AND LABOUR PRODUCTIVITY IN A RETAIL ORGANIZATION

This study investigates the impact of labour turnover on labour productivity in a UK retail organisation over 1995-1999. Retailing is traditionally a sector with high labour turnover, and our organization is no exception, with (headcount) turnover levels in excess of 50% per year. Such levels might seem problematic. However, the research on the consequences of labour turnover is inconclusive, and provides little guidance on how much turnover, if any, is optimal. Our paper analyses this issue using a dataset which offers two particular advantages over previous studies.

The first advantage is an accurate measure of labour turnover. For each of our organisation's 347 shops we have daily data on when a worker is hired or leaves, and on his/her contracted hours. These data allow us to disaggregate labour turnover into its components, separations and hires, which is appropriate because these components respond to different forces – in our dataset their correlation across shop-years is only 0.33. Furthermore, these data also allow us to analyse turnover not simply in terms of headcount, as is the norm, but in terms of full-time equivalents (FTE). We can also make further refinements, in particular computing the actual FTE working hours lost due to each separation. This measure is better suited than a headcount for establishing the link between separations and shop productivity.

The second advantage is the panel nature of our data which allow control for unobservable characteristics, in particular, the management factor. Management quality may affect both shop performance and labour turnover, since some managers will be better than others at choosing good matches, and dissolving bad ones. Then, failure to account for unobservable management practices may result in distorted regression estimates for the impact of turnover which will then partly reflect the impact of management. Our panel dataset offers the opportunity of isolating the management factor, and therefore of detecting the pure effects of turnover on productivity, independent of management quality.

We provide several econometric specifications to isolate the impact of management. The simplest method is to use within-shop variation only, in a fixed effect framework. However, this method removes all time-invariant variables (such as shop space) from the equation, and prevents comparisons between shops. We take an alternative approach, by estimating a production function using the Mundlak (1978) specification. This specification produces the same estimates as the fixed-effects one (and thus free of the distorting influence of the unobservables) and keeps all variables in. It also enables us to make between-shop comparisons, some of which have interesting interpretations in terms of the management factor.

The Literature on Labour Turnover and Firm Performance

The human resource management literature has traditionally viewed labour turnover in a negative light. Human capital theories of labour turnover point to loss of firm-specific human and social capital (Dess and Shaw 2001). Organisational theories point to disruptive changes in organisation (Carroll and Harrison 1998). This negative view is supported by the results of several empirical studies. For example, Huselid (1995) finds high labour turnover negatively linked to labour productivity in his sample of 968 U.S. firms. Also Baron, Hannan and Burton (2001) find turnover to be "disruptive" in their study of hi-tech start-ups in California in the early 1990s. Many studies have concentrated on quits specifically, and have found a negative impact of quits on firm performance, including Mefford (1986) for plants of a multinational manufacturing firm, Alexander, Bloom and Nuchols (1994) for U.S. hospitals, Batt (2002) for U.S. call centres, McElroy, Morrow and Rude (2001) for branches of a U.S. financial company, and Kersley and Martin (1997) for the sample of firms in the 1990 UK Workplace Employee Relations Survey (WERS). The explanations generally revolve around the loss of firm-specific human capital to quits (see Farber 1999 for a survey).

Yet some research reports the opposite finding. Job matching theory (Jovanovic 1979) predicts that workers less suitable for the firm leave earlier; hence, there is room for labour turnover to improve performance by clearing the workforce of poor worker-job matches. McEvoy and Cascio's (1987) meta-analysis of twenty-four reported correlations between performance and turnover concluded that 'good performers are … less likely to leave … than are poor performers', which supports the main prediction of job matching theory (p. 758). Williams and Livingstone's (1994) further meta-study of turnover supported McEvoy and Cascio (1987) and proved an even stronger negative relationship between worker individual performance and voluntary turnover when pay is contingent on performance. Ilmakunnas, Maliranta and Vainiomäki (2005) report a positive impact of turnover on total factor productivity growth in Finnish manufacturing.

Unlike most of the research on the topic, Bingley and Westergaard-Nielsen (2004) look at hires and quits simultaneously in their study of personnel policies and profit in a panel of 7,118 Danish firms over 1992-95. In contrast to the popular result, they conclude that quits increase profit and hires reduce it. They argue, consistently with job matching theory, that the least productive workers are more likely to leave. The finding on hires is interpreted in terms of turnover costs, since hires incur recruitment and training costs. Thus, reconciliation of job matching and human capital theories of labour turnover is assisted by distinguishing between quits and hires, a path we will follow.

It is also important to allow for nonlinearities in the impact of turnover. Arthur (1994) and Guthrie (2001) found a dichotomy in the impact of turnover on productivity depending on the type of human resource management (HRM) system in the firm: negative in "high-commitment" HRM systems, characterised by intensive training, performance-based rewards, employee participation, task diversity and job autonomy, and none in "control" HRM systems. Abelson and Basinger (1984) concluded that there was an "optimal level of turnover", variable across organisations. Glebbeek and Bax (2004) using data from offices of a temporary employment agency in the Netherlands over 1995-98 indeed find an inverted U-shape relationship between worker turnover and performance. The same relationship between labour turnover and productivity is reported in a study of 2,435 workplaces in Australia over 1995-97, by Harris, Tang and Tseng (2002). However, Shaw, Gupta and Delery (2005: 61) report the opposite result for U.S. and Canadian concrete plants and U.S. transportation companies, where they conclude that the relationship between voluntary turnover and workforce performance is 'negative but becomes attenuated as turnover increases'.

Part of the conflict in empirical evidence may be due to failure to control for differences in management quality between firms, which are difficult to observe, yet which influence both labour productivity and labour turnover. Clearly, management affects labour productivity (see, e.g., Bartel 2004). It is also known that neglect of this factor, known as "management bias" in the production function, results in overestimates of production function parameters if the inputs are positively correlated with the management factor (Mundlak 1961; Dawson and Lingard 1982; Alvarez and Arias 2003). At the same time, there is some evidence that management affects labour turnover. Thus, Davis and Haltiwanger (1992) and Hamermesh, Hassink and Van Ours (1996) report on variability of turnover rates across firms within narrowly defined sectors of economy, and their persistency within a given firm, which implies that management practices in these firms affect labour turnover. Burgess, Lane and Stevens (2000: 480) have also argued that some managers will be better than others at choosing good matches, and dissolving bad ones – and might even thrive on high turnover. Other managers, and management practices, will need low turnover. It is possible, therefore, that confounding the impacts of turnover itself and management partly mediated through turnover obscures the true role of labour turnover in firm performance.

Our panel dataset offers advantages here, because when management cannot be observed, one of the solutions to the "management bias" problem is to isolate it into the fixed effect, which requires panel data. This solution has been applied in several studies, for example Bingley and Westergaard-Nielsen (2004), Ilmakunnas, Maliranta and Vainiomäki (2005), and Harris, Tang and Tseng (2002). Here we go one step further and, in addition to the traditional fixed effects, try the alternative Mundlak (1978) specification, which keeps all variables in and allows us to make between- as well as within-shop comparisons.

Part of the conflict in the evidence may also be due to incorporating different industries in one study which makes for difficulties in controlling for industry-specific effects, such as learning curves and skill transferability. In fact, even if the study is confined to a particular industry, between-firm variation due to differences in corporate culture or management practices may be significant (Bertrand and Schoar 2003). As costs and benefits of turnover are industry- or even firm-specific, without adequate statistical provision, regression results may be biased. Our study, which relates to a single firm, does not have this problem.

In studying a single firm, we are following in the footsteps of the classic analysis of Baker, Gibbs and Holmstrom (1994). As these authors note, the single firm methodology allows more control than the study of many firms, since the same personnel policies hold across the firm (in our firm, in particular, all the shops are wholly owned subsidiaries, with no franchises). The disadvantage is that the firm may not be representative. This disadvantage notwithstanding, the single firm personnel economics literature is growing. The literature review in Lin (2005) lists twenty studies of single companies based on personnel records, just like ours. Notable examples are studies by Kahn and Sherer (1990) of management incentives in a mid-West manufacturer, Audas, Barmby and Treble (2004) of wage incentives in a UK financial sector firm, and Bartel (2004) of HRM management and performance in the branches of a Canadian bank.

Econometric Model and Estimation Issues

Clothing shops operate in a competitive environment, where those offering better customer service gain larger market share. As Bartel (2004: 183-184) points out, the human factor is particularly important in the services sector, which brings customer and worker together. Better customer service can be provided by employing more labour to operate longer opening hours, and also by carefully selecting workers. Hence, the data-generating process, as we model it, is based on the assumption that the manager at shop i has a sales target in year t, to achieve which he/she chooses the amount and type of labour to be deployed given a commonly available "technology". Apart from the budgetary constraint (for which central HQ sets a target, as noted below, but over which the local manager still has some discretion), the choice of the sales target, and hence the quantity of labour, by a rational manager is influenced by other factors, including the shop's physical capacity, the area's purchasing power, and managerial ability. The manager also determines the shop's workforce characteristics (age, gender, experience), and the allocation of hours throughout the year, which is of particular importance given the seasonal nature of the clothing business. Lastly, because the business involves some uncertainty, the actual sales volume differs from the target one by a random error, independent of the production inputs and their characteristics.

The above description of the data-generating process lends itself to a regression equation based on a production function. We model shop *i*'s sales per hour worked at time *t* ($prod_{it}$) as a Cobb-Douglas function of labour (L_{it}) and capital (K_{it}) inputs (as in Bartel 2004). We further allow output per hour worked to vary with total factor productivity (A_{it}) and the efficiency with which individual inputs are deployed (F_{Lit} and F_{Kit}), depending on observable ($\mathbf{f}_{it}$, $\boldsymbol{\kappa}_{it}$, $\boldsymbol{\eta}_{it}$) and unobservable (c_i) shop, workforce and area characteristics, time period (λ_t), and a random error (e_{it}):

$$prod_{it} = Y_{it}/L_{it} = A_{it} \cdot \exp(\lambda_t) \cdot (F_{Kit}K_{it})^{\alpha} \cdot F_{Lit}^{\beta} L_{it}^{\beta-1} \cdot \exp(e_{it}), \quad \alpha, \beta > 0, \quad \alpha + \beta \leq 1$$

$$A_{it} = c_i \cdot \prod_{l=1}^{n} f_{itl}^{\gamma_l}, \quad F_{Kit} = \prod_{l=1}^{m} \kappa_{itl}^{\delta_l}, \quad F_{Lit} = \prod_{l=1}^{k} \eta_{itl}^{\omega_l}$$

Most of our regression variables (discussed in detail in the next section) are parts of total factor productivity (A_{it}) and the efficiency multipliers (F_{Lit} and F_{Kit}). For instance, managerial ability and area wealth enhance the marginal product of both labour and capital, and therefore belong to A_{it}. Quits and hires, on the other hand, are unlikely to affect the marginal product of capital, but by changing the structure of the labour input may increase or decrease its marginal product; thus, they belong to F_{Lit}.

For the purposes of econometric estimation, it is convenient to divide the observable variables into two groups: time-varying ($\mathbf{V}_{it}$), such as hours worked and workforce characteristics, and time-invariant ($\mathbf{R}_i$), such as shop location and space. Note that since we control for shop space, brand, location, workforce and area characteristics, the remaining time-invariant variable c_i is meant to reflect possible differences in productivity across shops due to unobservable factors, such as local shop management[1]. Thus the econometric equation to be estimated is:

$$\ln(prod_{it}) = \mathbf{V}_{it} \times \mathbf{B}_1 + \mathbf{R}_i \times \mathbf{B}_2 + c_i + e_{it}, \ i=1..\mathrm{N},\ t=1..\mathrm{T} \qquad (1)$$

where $\mathbf{B}_1$, $\mathbf{B}_2$ are estimates for the respective groups. c_i and e_{it} are the two parts of the error term, as neither one, nor the other can be directly estimated. In accordance with our description of the data-generating process and as one of the identifying assumptions for the estimation, we let e_{it} be an idiosyncratic error term following the classical assumptions. However, while e_{it} is uncorrelated with the variables in equation (1) by assumption, c_i may be so correlated thus invalidating the OLS estimation of (1). Indeed, our description of the data-generating process suggests a positive correlation between managerial ability concealed in c_i and labour input since abler managers have higher sales targets to achieve, for which they need more labour.

A straightforward way to control for the bias caused by at least some of the unobservables in c_i being correlated with observable variables is to run a fixed-effects

[1] Time-invariance of c_i is equivalent to no changes in shop management and no improvements in the ability of existing managers, which, given only five years of observations available, is reasonable. We experimented with a stochastic frontier model with time-varying unobserved effects, but found no evidence to suggest c_i varying with time.

estimator. The fixed-effects specification removes the unobservable time-invariant variables from the equation by taking averages out of observations. Zero correlation of the regression variables with the error term, however, is achieved here at the cost of conflating all time-invariant variables with c_i into the fixed effect. As a result, no inferences can be made about the separate impacts of location, shop space, regional management and other observable time-invariant variables. Thus the applicability of estimation results obtained through the fixed-effects transformation is limited to productivity movements within a given shop.

To render inferences applicable to different shops, we have to preserve time-invariant variables in the equation and avoid the omitted variable bias at the same time, which requires a further identifying assumption for c_i. For a static regression model, such as ours, there are two ways to proceed. One is to apply consistent semi-parametric estimators for production functions developed by Olley and Pakes (1996) who proxy c_i by investment level, or Levinsohn and Petrin (2003) who use intermediate inputs instead. However, we are unable to apply either of these estimators because of lack of information on shop-level investment and intermediate inputs.

We use instead a modified random-effects estimator proposed in Mundlak (1978). This estimation procedure involves applying the random-effects transformation to equation (1) and expressing c_i as a linear combination of averages of all time-varying regression variables and a separate error term (u_i) following the usual assumptions:

$$c_i = \text{constant} + \overline{\mathbf{V}_{i\cdot}} \times \mathbf{C} + u_i \tag{2}$$

The random-effects transformation serves to keep time-invariant variables ($\mathbf{R}_i$) in the main equation (1). At the same time, equation (2) attempts to identify c_i through observable variables, that is, the time averages of the shop-specific and area-wide variables. Thus, similarly to Olley and Pakes (1996) and Levinsohn and Petrin (2003), we estimate c_i indirectly rather than assume it purely random.

We apply a random-effects estimator to (1) combined with (2), which amounts to running OLS on equation (1) transformed as follows (Hsiao 2003: 34-38):

$$\begin{aligned}
&\ln(prod_{it}) - \hat{\lambda}\cdot\overline{\ln(prod_{i\cdot})} \\
&= \left(\mathbf{V}_{it} - \hat{\lambda}\cdot\overline{\mathbf{V}_{i\cdot}}\right)\times\mathbf{B}_1 + \left(\mathbf{R}_i - \hat{\lambda}\cdot\mathbf{R}_i\right)\times\mathbf{B}_2 + \\
&+ \underbrace{\text{constant} + \left(1-\hat{\lambda}\right)\cdot\overline{\mathbf{V}_{i\cdot}}\times\mathbf{C} + \left(1-\hat{\lambda}\right)\cdot u_i}_{\left(1-\hat{\lambda}\right)c_i} + e_{it}
\end{aligned} \tag{3}$$

where $\hat{\lambda} = 1 - \sqrt{\dfrac{\hat{\sigma}_e^2}{T\cdot\hat{\sigma}_c^2 + \hat{\sigma}_e^2}}$, and $\hat{\sigma}_e, \hat{\sigma}_c$ are the estimates of the standard deviations of e_{it} and c_i. This transformation is required to have the variance of the error term $\left(1-\hat{\lambda}\right)\cdot u_i + e_{it}$ equal for each observation, as required for the efficiency of estimation.

In this equation, the error term is uncorrelated with $\mathbf{V}_{it} - \hat{\lambda}\cdot\overline{\mathbf{V}_{i\cdot}}$, thus rendering the OLS estimate of $\mathbf{B}_1$ from (3) unbiased and identical to that obtainable under the fixed-effects specification[2]. The unbiasedness of the estimate for $\mathbf{B}_2$ does not depend on the adequacy of (2). This point follows from that the $\mathbf{R}_i$ do not vary in time. Hence, it is impossible to distinguish between the parts of $\mathbf{R}_i$ correlated and uncorrelated with u_i, and the estimate for $\mathbf{B}_2$ is the same whether any of $\mathbf{R}_i$ is correlated with u_i or not. The unbiasedness of **C**, however, hinges on whether or not there are omitted variables in (2). Although the choice of omitted variable tests applicable for (2) is quite limited, we test below for biases in the estimate of **C** due to incorrect functional specification by running RESET tests after regressing $\hat{c}_i = \hat{f}_i - \mathbf{R}_i \times \hat{\mathbf{B}}_2$ on $\overline{\mathbf{V}}_{i\cdot}$.

There is one more econometric issue to be addressed: simultaneity. Bingley and Westergaard-Nielsen (2004: 560) argue that profit (or productivity) and worker turnover are jointly determined. If this is true, the resulting simultaneity bias will distort the estimation results. Following their approach, we test the endogeneity of quits and hires in equation (1) applying a fixed-effects instrumental variables estimator. We then compare the instrumented fixed-effects regression results with uninstrumented ones. As will be seen, we are able to accept the initial assumption of no simultaneity, so all the estimation results we report in Table 3 are non-instrumented.

The Company

The company is a national retailer of clothing . Our unit of observation is the shop, which works within parameters set by the central company HQ. The HQ has a system of twenty regional managers, who appoint and monitor managers in the approximately 600 shops from which our sample is drawn (the balanced panel is 347 shops). The selection process for managers for the bigger shops is tougher, we were told – which helps ensure that abler managers are assigned to bigger shops. Later we attempt to test if this is indeed the case.

The shop managers' powers in running their shops are limited by HQ rules. Product prices and wages are set centrally[3]. Shop managers also have little discretion over product stocks which are determined automatically using electronic point of sale data. In addition, wage budgets are set, with a target of 14% of previous year's sales. On the other hand, this framework still allows for shop managers' to influence productivity principally via personnel management. By hiring workers to make up for separations they match the workforce to the seasonal pattern in demand (see Figures 1 and 2 below), and also to yearly fluctuations which are quite marked (see below). The managers also motivate the salesforce – "to the workers, the shop's manager is the company", in the words of the company's HR director.

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[2] To prove this, rewrite equation (3) as follows: $\underbrace{\mathbf{Y}}_{\ln(prod_{it})} = \mathbf{V}\boldsymbol{\alpha} + \overline{\mathbf{V}}\boldsymbol{\beta} + \mathbf{R}\boldsymbol{\gamma} + \underbrace{\mathbf{n}}_{constant+errors}$ (i).

Applying the fixed-effects transformation to (i), we derive the estimate for **V**, $\hat{\boldsymbol{\alpha}} = \left[\mathbf{V}'\mathbf{M}\mathbf{V}\right]^{-1}\mathbf{V}'\mathbf{M}\mathbf{Y}$ (ii), where $\mathbf{M} = \mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'$ is the matrix which transforms individual observations into deviations from their shop averages, and $\mathbf{D}' = [1 \quad 1 \quad \ldots \quad 1]_T \otimes \mathbf{I}_N$. Without the fixed-effects transformation this estimate will be $\hat{\boldsymbol{\alpha}} = \left[\mathbf{V}'\mathbf{N}\mathbf{V}\right]^{-1}\mathbf{V}'\mathbf{N}\mathbf{Y}$ (iii), where $\mathbf{N} = \mathbf{I} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}', \mathbf{X} = \left[\overline{\mathbf{V}} \quad \mathbf{R}\right]$. In fact, **N**=**M**, which can be shown by multiplying both of them by **X** and noting that $\mathbf{D}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'\mathbf{X} = \mathbf{X}$ since all variables in **X** are time-invariant. Therefore, (iii) produces the same estimates as (ii). Clearly, the same is true for any $\mathbf{X}^* = \mathbf{X}\boldsymbol{\Omega} \neq \mathbf{0}$ such that $\mathbf{D}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'\mathbf{X}^* = \mathbf{X}^*$, so this result is robust to the random-effects transformation as applied in equation (3).

[3] Workers were paid a standard hourly wage that (during our period of study) differed by four region types (rural, town, city and central London), as well as age (18 or less, and greater than 18), and there were no wage increments for seniority and no rewards for performance.

The company pursues a simple, "low-commitment", personnel policy for its shop assistants. The job is unskilled in the context of our company, since its clothing products do not require expert knowledge to market. Consequently, there is little training, minimal career progression and a simple wage structure (no sales commissions) which does not reflect achievement or reward commitment. There is an emphasis, instead, on careful monitoring by the managers. In these circumstances, high labour turnover can be expected (Shaw *et al.* 1998; Batt, Colvin and Keefe 2002).

The company's turbulent market conditions also affect personnel policy. The average shop employs 7.4 workers in FTE terms (14,642 workerhours/1976 hours per FTE year, Table 1), but this figure regularly varies between 6 and 8 over the seasons (see Figure 1). We can add a further 10% year-on-year variation (the shop average absolute change in employment) to this figure, due to cyclical demand fluctuations. In this environment it is as important to downsize as upsize, hence a personnel policy resulting in a high quit rate can be advantageous. The company employs few staff on temporary contracts (about 5%), so the needed flexibility has to be gained in other ways. One way would be to employ workers for just a few hours a week, which indeed is practiced: 16% of employees work less than 5 hours a week (Table 1). However, this approach is only useful in adjusting the labour input to demand fluctuations within the week. A further approach is the company's low-commitment personnel policy, which is helpful in ensuring that workers do not linger when managers want them to go. (In this context most separations are quits, which is the term we use.) Then, as regards hiring, the shop manager has to develop local knowledge about where to direct his/her hiring efforts when the time comes, and develop "understandings" with various part-time members as to when during the year they will be needed, and when not.

The Data

Our dataset includes detailed information on labour turnover and personnel characteristics. It consists of three parts. The first part includes personnel records of all the employees who worked at any time between 1995 and 1999. Altogether, there are 72,669 records of 32,546 individuals. Individual records include age, gender, date hired and date left employment, and weekly contract hours – which is our measure of hours worked. We thus can observe job matches as short as one day and, as noted (Figures 1 and 2) can accurately adjust labour turnover to full-time equivalent. Since individual productivity data are not available, we then derive employee average data for each shop in order to compute shop average productivity. Hence, to the employee information we match the second part of our data which contains shop information: annual sales, location, type of brand, shop space, number of floors, share of children's products, and the shop's area manager. To avoid dealing with possibly endogenous entry and exit events, we exclude shops which opened or closed down during the1994-99 observation period.

The third part of the data consists of area-wide wage and unemployment data for the county in which each shop is situated. Here, we include the county average earnings rate, the county average shop assistant wages (so we can calculate a relative wage variable for the company), and the county unemployment rate. These data are obtained from the UK Quarterly Labour Force Survey (QLFS), based on samples of individuals 16 to 65 years of age in 63 counties.[4] The resulting dataset includes 1735 observations from 347 shops for 1995-99.

[4] For each year, we discarded the top and bottom 1 percent of the hourly wage distribution in the QLFS, to improve the accuracy of the mean wage calculation.

Our dependent variable is labour productivity per shop-year, measured as (natural log of) sales per worker hour adjusted for inflation. Our explanatory variables are defined as follows. The labour input is measured by total hours worked in a year. Other workforce characteristics include the average employee's age and tenure, the shop's share of male employees; its weekly hours distribution, its average hourly wage, and a dummy variable to account for sharp decrease in hours worked (>20%). Of course, we also include labour turnover variables measured in terms of quit rate (as noted, most separations are quits), and hiring rate. All workforce characteristics are calculated based on employee records adjusting for FTE.

In particular, our FTE-adjusted measure of hires rate is calculated as actual hours worked by the newly hired relative to total shop hours worked during a given year, so that the earlier on in the year they are hired, the more pronounced their impact on productivity should be. Furthermore, the quit rate is calculated using the number of hours leavers *would* have worked had they not left. Hence, if someone quits at the very end of a year the impact of their leaving on labour productivity in that year would be zero, with the converse if they leave at the beginning of the year. Thus, our measures of quits and hires allow both for their real impact in terms of hours, and for their timing.

Figures 1, for the headcounts, and 2, FTE-adjusted, illustrate some aspects of our turnover data. The average yearly intake of employees is about 7 (but 1 in FTE), and about 6 (1 in FTE) leave. There is marked seasonal variation in labour inputs. Quits are reasonably steady at about 0.1 persons a month, but hires vary considerably from 0.05 in the January low season, to 0.15 when the summer season begins. It is clearly important to reduce labour inputs when needed, as noted above, so a high rate of natural wastage has advantages. However, then the manager must be able to hire labour to capture sales where possible. Thus the retail environment is naturally one of high turnover, which it is a major responsibility of shop managers to control: "right person, right time" in the words of company HQ.

Figures 1 and 2.

The capital input is given by the shop space measured in square meters. Other shop characteristics include shop type, location, children's mix, and number of floors. Shop type is represented by a set of dummy variables assigned to a particular brand (six altogether, including the main brand and other, minor ones). Location is coded by dummy variables for shops located in city centres, local shopping streets, in district, regional, sub-regional or out-of-town retail parks, or elsewhere. We also control for the share of children's goods in total sales – since they require more labour per sale – and for the number of floors, since customers may resist climbing floors. Finally, we control for the regional manager by introducing dummy variables corresponding to the twenty manager regions, and for the time period, using year dummies.

Basic Statistics and Analysis of Variance

Table 1 reports key descriptive statistics for the dataset variables. An average shop sells £52.78 worth of goods per hour, occupying 143.67 sq m of trading space, working 14,642 hours a year (roughly 7.4 FTE workers). Most shops in our dataset belong to the main medium-priced brand. About a third of an average shop's sales are children's goods. The company's retail network has a large presence throughout the country, covering 302 locations in 63 counties. The majority of shops (40.6%) are located in towns surrounding big cities, and some (11.5%) in city centres.

Table 1

An average shop employs 24.27 people throughout the year. The employees are in their 30s, most of them women working under 15 hours a week, staying on the same job for 3.55 years. However, the FTE-adjusted tenure is 5.33 years, as employees working longer hours tend to stay on the job longer than casual or seasonal workers. The relative pay of shop assistants is only 81.7% (£3.84/£4.70) of the county average rate for a similar job, but as noted, this strategy has advantages when the time comes to pare down the workforce.

There is a significant movement of employees in and out of work, with average annual labour headcount turnover of 56.5% (29% hires + 27.5% quits). The company's quit rate is in line with the 1998 WERS quit rate figure of 23.1% for the UK retail sector as a whole.. Changes in shop employment are generally not matched by changes in staff numbers, as shown by analysing job "churning". In terms of headcount, Table 1 shows that labour turnover is higher than job turnover (the average of absolute changes in staff numbers), hence the average job churn rate of 46.5%[5]. Thus, job turnover would require a labour turnover of only 10% (= 56.5 – 46.5), which is only 0.18 (=(56.5-46.5)/56.5) of observed labour turnover. The proportion of job turnover in labour turnover is considerably lower than the 30% reported in Burgess, Lane and Stevens (2000a: 481) and Hamermesh, Hassink and Van Ours (1996: 29), implying a problematic amount of turnover in our company.

However, when adjusted for FTE, average labour turnover is considerably less, at 24% (10.9% hires + 13.1% quits), which points to a large presence of short-term or seasonal employment, which is indeed the case in our organisation[6]. Moreover, the FTE-adjusted job churn is lower, 16.4%. Now job turnover would require a labour turnover of 0.32 (=(24-16.4)/24) of the 24% observed, indicating less waste. Still, while FTE adjustment is clearly important, labour churn remains high, presumably due to the large seasonal and cyclical fluctuations in retailing already noted.

The shops show a variety of performance results, despite being subject to central control. As can be seen, labour productivity ranges from £21.75 to £111.56 per hour worked. This variety is matched by differences in workforce size (from 2,445 to 80,889 hours a year), and in other workforce variables such as average age (21 to 65.7 years), and tenure (0.86 to 22 years). Presumably, this variety can be explained by permanent (not always observable) shop and area characteristics. We can investigate the importance of within- and outside-shop factors for the key variables using analysis of variance. In particular, we calculate the shares in total variance of log productivity and workforce characteristics explained by shop-, area- and time-specific factors. Table 2 reports the results.

Table 2.

The variance explained at the shop level consists of two parts: that explained at a higher level of aggregation (in our case, the area level) and which is therefore attributable to area-wide factors; and that which is accounted for by factors peculiar to an individual

[5] Job churn is defined as the excess of employment turnover over job turnover, and is here calculated as the difference between the sum of quitting and hiring rates net of the average absolute change in workforce numbers.

[6] Most of the observed reduction in rates is due to job movers' relatively low labour input. Thus, the workers with employment duration less than one year constitute 35.3% of the workforce but contribute only 5.4% to the total hours worked.

shop. One can see that for the majority of variables shop permanent characteristics are the single most important source of variation. Thus, netting out differences at the area level (0.144) roughly half of the variation in log labour productivity (0.651-0.144) is attributable to fundamental differences between shops – space, location, and management, – the individual importance of each to be further determined. For the total hours worked, these differences are even more important explaining 0.967-0.178=0.789 of its variance, which is not surprising. Given constant shop space, staff numbers would tend to concentrate around a given level corresponding to a given space (i.e., capital) to labour ratio which is optimal for the management input. The relative wage, on the other hand, is a notable exception: most of its variance is explained at the area level (0.338), while shop alone explains a modest 0.123 (=0.461-0.338). Again, this is predictable, since shop managers have no say in the company's wage policy, and can influence shop average wage only to a limited extent, by hiring employees above or below age 18.

Shop differences – still netting out area – explain roughly a quarter of the total variance in quits and hires, just under a third of that in job churn, and roughly a fifth in job turnover. The labour turnover result is quite similar to the finding of Burgess, Lane and Stevens (2000) for firm differences in labour turnover (0.28 for non-manufacturing firms, p. 487), while our shop shares of variance in labour turnover (quits or hires) and job churn are considerably less than those reported in the above study (0.54 and 0.52, respectively, p. 487). High shares of variance in labour turnover and job churn explained at the workplace level, as reported in Burgess, Lane and Stevens (2000), mean that persistently high and low levels of these variables exist within groups of otherwise similar firms, which supports their hypothesis of 'different equilibrium personnel policies' 'coexisting within narrowly defined industries' (p.486). Our study shows that once this source of variance has been removed (after all, our company operates many common personnel policies – e.g. wages policy – which affects hiring and retention of employees), the importance of shop management in determining labour turnover reduces dramatically. Still, that the remaining quarter of total variation in quits and hires is explained at the shop level shows systematic differences in the shop conduct of the personnel policies despite the rules sent out by company HQ.

Regression results

Table 3 shows the results of applying various estimators to the productivity equation (1). The benchmark OLS specification provides a starting point for discussion; it also illustrates the dangers of relegating shop-specific unobservable heterogeneity to the error term rather than properly accounting for it. In particular, OLS results tell us that every 10% increase in total hours worked reduce labour productivity by 3.42%, whereas after controlling for the unobservables the true impact of labour proper becomes higher, in the region of 8%. It looks as if some of the unobserved factors are positively linked with workforce size and labour productivity thus causing an upward bias in the OLS estimate for the labour input. As we shall see, a link between better shop management and shop workforce size fits this description rather well.

Table 3.

Because the fixed-effects specification provides for time-invariant unobservable variables simply and completely, by allowing for a shop-specific constant term, we use it to test for the endogeneity of quits and hires (and their square terms and cross-product) for productivity. Following Bingley and Westergaard-Nielsen (2004) we choose the neighbouring shops' averages of workforce characteristics to be excluded instruments[7]. These instruments were found sufficiently correlated with the instrumented variables. Thus, the overall significance statistics of the first-stage IV regressions for quits and hires are high, F(31, 1245)= 7.37 and 7.74, respectively with similar statistics for the square terms and cross-product). They were also found suitable for exclusion from the main equation, as the low value of the Sargan overidentification test statistic (χ^2(10)= 1.97) shows. Given the validity of the instruments, the low Hausman endogeneity test statistic (χ^2 (20)=8.85) can be accepted as showing lack of evidence for the endogeneity of quits and hires for productivity. This result supports the assumption of independence of personnel policies from current productivity performance and permits us to use the more efficient uninstrumented fixed-effects specification which is reported in the second column of Table 3.

However, as we have noted, the explanatory power of the fixed-effects specification is limited to "within" effects only. Thus we can only observe the impacts of our control variables on productivity in a given shop. The "within" effects perform well, explaining 77.2% of the "within" variance of log productivity (that is, the variance remaining after subtracting shop averages as the fixed-effects transformation requires). But as the ANOVA results (Table 2) show, the majority of variance in log productivity (65.1%) remains in the shop averages, and is the joint impact of time-invariant factors such as shop space, location, brand and management. We are unable to incorporate these factors in the fixed effects specification, hence the modest 13.3% overall R^2 for the fixed-effects estimates.

In order to estimate individual impacts of observable time-invariant factors without compromising the consistency of estimation results, we express the unobservable factors concealed in c_i through the averages of workforce and area characteristics (equation (2)). The results are reported in the third column of Table 3 ("Random effects augmented"). Not surprisingly, the estimates for the time-varying variables are almost identical to the fixed-effects ones[8]. The added variables are very significant. The high statistic testing for redundancy of shop averages (χ^2 (13)= 211.18) shows that they must not be omitted. They, together with other time-invariant variables (e.g., space, location), add much explanatory power to our productivity equation, as can be seen by comparing R^2s for the fixed effects and augmented random effects regressions. This result follows because we can now explain the variation in productivity levels between different shops better. Lastly, it is worth noting that the values from both of the two varieties of the RESET test for equation (2) explaining c_i are low: (F(38, 273)=0.88 for the powers of the right-hand-side variables, and F(3, 308)=1.32 for the powers of the left-hand-side variable). These values do not indicate any significant problems with specification, implying that (2) adequately approximates unobservable shop characteristics.

Still, this random-effects specification can be improved by allowing for heteroscedasticity and autocorrelation. High levels of statistics for the likelihood ratio test for heteroscedasticity (χ^2(324)=1338.72) and the Wooldridge test for residual

[7] We thus have 15 instrumental variables for 5 instrumented variables (quits, hires, their squares and a cross-product). For each shop, we calculate averages from other shops in the same county for all 15 time-varying workforce variables: size, 5 turnover components, age, sex, 3 hours distribution components, tenure and its square, shrink, and shop relative wage. In doing so, we exclude six shops that have no other shops in their county.

[8] The slight variation is due to excluding the shop averages of quits and hires squared and their cross-product, as they caused symptoms of multicollinearity. By comparing the "Random effects augmented" and "Fixed effects" results, we found we could do so with little cost to the consistency of our estimates, as the low Hausman test statistic χ^2(21)=1.87 demonstrates.

autocorrelation (F(1,452)=397.824) indicate the presence of these data problems. We correct for these problems and, accordingly, base our inferences on the estimates from the augmented random-effects specification with panel-corrected standard errors (PCSE) (the final column in Table 3).

Simplifying equation (3), we obtain:

$$\ln(prod_{it}) = \mathbf{V}_{it} \times \mathbf{B}_1 + \mathbf{R}_i \times \mathbf{B}_2 + \underbrace{\text{constant} + \overline{\mathbf{V}}_{i\cdot} \times \mathbf{C} + u_i}_{c_i} + e_{it} \qquad (4)$$

Thus the explained variance in log productivity consists of three parts: that explained by variation in time-varying factors ($\mathbf{V}_{it} \times \mathbf{B}_1$), observable time-invariant factors ($\mathbf{R}_i \times \mathbf{B}_2$), and unobservable time-invariant factors, such as shop management ($\overline{\mathbf{V}}_{i\cdot} \times \mathbf{C}$). Below we discuss individual impacts of variables from each group holding all other factors constant.

Time-varying factors

Here we make within-shop comparisons, that is, holding time-invariant variables constant. The production process is characterised by decreasing returns to scale: every 10% increase in total hours worked reduces productivity by 8.45%, equivalent to an increase in sales of only 1.55%. This low estimate, however, is not surprising. As the company's managers explain, shops are staffed at busiest times first, so that any increase afterwards brings fewer sales per worker hour employed. Still, with wage-to-sales targets set at about 14%, employing the observed numbers of worker hours makes economic sense, since the marginal product of extra labour (0.155*x%) is then just about equal to its marginal costs (0.14*x%).

We observe a non-linear, inverted U-shape effect of labour turnover on productivity, just as in Harris, Tang and Tseng (2002) and Glebbeek and Bax (2004). Admittedly, our findings on quits and hires contradict Bingley and Westergaard-Nielsen (2004). However, because they use a linear specification, we cannot directly compare our results. The finding of quits and hires having a nonlinear effect on productivity supports the view that turnover has benefits and costs to the firm, and that initially the benefits of turnover outweigh the costs (Abelson and Basinger 1984). For quits, the initial positive impact on productivity appears to be in accord with the view that less productive workers are more likely to quit (McEvoy and Cascio 1987; Williams and Livingstone 1994). But there comes a point when the positive effect of improved job-worker match through quits becomes offset by the loss of firm-specific human and social capital (Dess and Shaw 2001).

For hires, the initial positive impact on productivity supports the idea of newly hired workers performing just as well as their more experienced colleagues, which is consistent with our earlier finding of the learning curve being flat. Although worker tenure does have a weakly positive effect on productivity, the learning curve does not seem to be steep enough to offset the benign influence of high enthusiasm and drive characteristic of newly hired workers. But at some point the organisational capabilities reach their limit in digesting new hires who lack experience and need guidance, which results in more hires reducing overall productivity.

In our study, a 10% increase in the quit rate improves labour productivity by (0.1*0.117-0.01*0.256)*100%=0.9% compared to the zero-quit level. However, the negative effect of quits squared drives the productivity gain down as quits rise, until at some point the overall effect of quits becomes negative. Hires follow similar dynamics, being positively related to productivity, though at a decreasing rate. A 10% increase in hires from zero improves labour productivity by (0.1*0.122-0.01*0.331)*100%=0.9%. Further increases yield progressively less improvement, until at some point excessive labour turnover reduces productivity. Our regression results show that the productivity-maximising levels of quits and hires are each about 20%, and together they can improve productivity by 2.5% on average (£1.30 per each hour worked per year), compared to the zero-turnover level. In fact, our calculations show that if all shops had achieved the productivity-maximising rate of turnover rather than kept to their actual rates, productivity gains would have ranged from 0 to 10.8%, averaging at approximately 1.1% (£0.57) per hour worked per year.

Our estimated optimum rates of quits and hires are around twice as high as the observed averages of about 10% each (Table 1), which might seem problematic. However, we can show that this difference plausibly reflects hiring costs. Let us assume profit maximisation, so that the marginal revenue product of hires equals marginal hiring cost, and the observed average hiring rate, 0.1, is profit maximising. Then, using Table 3's coefficients, the marginal revenue product (= marginal cost) of hires equals 0.122-2*0.331*0.1=0.056, and total hiring costs are 0.56% of total sales (assuming total costs of hiring to be linear and equal to zero in the absence of hires). Therefore, for an average shop making £772,819 (=52.78£/hour*14642 hours) and hiring 7 people per year, the implied recruitment and training costs would be £618.3 (= £772,819*0.0056/7) per newly hired shop assistant. This result is plausible, since it is close to contemporary practitioner estimates (IPD 1997) of hiring and training costs for unskilled labour, £841.

Looking briefly at the other variables, we see that age and experience increase labour efficiency, as shown by positive and significant estimates for average age and tenure, although their impacts are small. Thus the learning curve looks flat. So, we would expect relatively low costs of labour turnover and less of a need to retain trained shop assistants by offering them higher wages. Furthermore, we find no empirical support for the impact of higher relative pay on productivity because log relative pay has an insignificant coefficient (-0.011), although the lack of its significance may primarily be due to the lack of within-shop variance (see Table 2).

Finally, we see a negative coefficient on area average pay, which might seem strange, since we would expect higher productivity in wealthier areas. However, coefficients of the year dummies (only maximum and minimum are reported in Table 3 to save space) show that, all else equal, labour productivity in 1999 was 17.4% higher than in 1995. The negative coefficient of the area pay implies that the improvement in productivity has been uneven: greater percentage gains were made in poorer areas than in richer ones, which is understandable.

Time-invariant factors

Now, we make comparisons between shops. With sizeable persistency in labour productivity across shops, time-invariant characteristics are of major importance. Let us begin with the shop and area averages, then turn to other time-invariant variables such as shop space. The most important shop average is the five-year average total hours worked variable. In fact, we see that the impact of average hours worked on labour productivity is opposite to that of hours worked (i.e., labour input) proper. While employing more labour in a given shop in a given year reduces productivity, shops employing more labour on average increase productivity, all else equal. In other words, if two otherwise identical shops, A and B, employed the same number of worker-hours in a given year, but A had 10% higher 5-year-average labour-hours than B, A would be 5.8% more productive than

B in that year. The positive impact of average workforce size on labour productivity points to the importance of varying organisational capabilities of administering workers. Thus, it appears that the manager at shop A will manage a given number of shop assistants in a more productive way than his/her colleague from an otherwise identical shop B.

The last observation implies that abler managers are assigned to bigger shops – which company HQ expects, and for which some theoretical underpinnings exist. The static profit maximisation conditions would hold management input in a fixed proportion with other inputs, hence the better managers should be allocated to the bigger shops. Also, managerial hierarchy theory (Qian 1994; van Zandt 1999) argues that because the ability and skills of a manager affect the performance of their subordinates, a competitive firm would assign abler managers to workplaces with more subordinates. Similarly, Jovanovic (1982) found that more efficient firms have higher chances of survival, produce more, and hence require more labour given constant production technology. Empirical evidence in support of the link is presented in Meagher (2001), who finds that, controlling for the usual wage factors, a worker's salary is positively related to the level in the firm's hierarchy at which they are employed. He argues that 'since managers affect everyone below them, higher effort and ability are required of higher level managers' (p. 444).

Although, apart from the estimation consistency considerations (since all shop averages must be included in the Mundlak specification), there is little theoretical justification for the inclusion of shop averages other than workforce size in equation (2), they might still pick up differences in organisational "style" relevant to productivity performance. For example, Bertrand and Schoar (2003) track individual top managers as they change companies and find that manager fixed effects account for a significant part of the unexplained variation in a wide range of business practices, from financial policy to organisational strategy. Therefore, we might be able to conceive of different management "styles" affecting labour turnover and other shop variables.

As regards labour turnover, productivity appears to be negatively associated with average quit rate, and positively with average hiring rate, which is consistent with several scenarios. The negative sign on average quits may suggest that worker retention is characteristic of a well-managed shop. For its part, the positive sign on average hires may point to a different good practice – rotating workers in constant search of better job matches[9]. These two may coexist, in which case for every 10% increase in average quit and hiring rates the shop would gain 4.1% in labour productivity due to better worker-job matching, and lose 2.5% due to the resulting decrease in staff retention. The net result, however, is small, 4.1%-2.5%=1.6%, and is not significantly different from zero (the restriction test statistic for average quits + average hires = 0 is $\chi^2(1)=1.04$, p-value = 0.309).

Interestingly, a number of estimates for the averages of shop and area characteristics used to control for unobservable time-invariant factors are significant, even though their time-varying counterparts are not. Particular examples are average area unemployment rates and average area log relative pay. The negative impact of average area unemployment (-1.47) makes sense: it is more difficult to sell in a high

[9] One could argue that because we measure worker turnover in FTE these suggestions may not be valid, because the same number of people hired and quitting could correspond to different levels of hires and quits depending on the time hired or left and weekly contract hours. However, running the same regression with the averages of unadjusted quitting and hiring rates we obtain estimates of the same signs as before, though of diminished significance.

unemployment area. But as the insignificance of time-varying area unemployment rate in the panel above implies, temporary fluctuations in unemployment do not affect the demand. It is persistently high or low unemployment that matters.

We also see that persistently higher pay relative to that for similar jobs in the area increases labour productivity, presumably because it enables shops to attract better quality workers. Thus, two otherwise identical shops with a 10% persistent difference in relative pay will also differ by 4.6% in terms of labour productivity over time. Assuming shop assistants' wages initially are 14% of sales, a 10% relative pay rise would increase profit, provided the share of value added in total sales is 0.14*0.1/0.046=30.6% or higher. From the company's accounts for the late 90s, the value-added share is around 40%. So, paying shop assistants more might have been a good investment then. However, the insignificance of the time-varying effect of relative pay suggests that raising relative pay is a strategic decision rather than a quick solution to the productivity problem.

Of the remaining shop averages, the variables showing shops with high percentages of part-timers (working less than 15 hours a week) are the easiest to interpret. Productivity thrives on part-time workers, because their hours can be better arranged to coincide with the shop's busiest periods. But part-time workers as such are no more productive than those working full-time, otherwise the time-varying hours dummies in the upper panel would have been significant, and they are not. Presumably, it is good shop managers who can hire a pool of part-timers and fine tune their working hours that achieve the best returns to labour. Their ability to do so is captured by the positive and significant impacts of the shop averages of the shares of part-time workers.

Finally, turning to the other time-invariant variables in the bottom panel, we see that the impact of capital input proxied by shop space is significant: every 10% increase in trading area adds 1.8% to labour productivity, all else equal. However, contrary to the belief of the company's management, shops with more than one floor are no less productive – the numbers of floors variables are insignificant. We also find that productivity depends on the share of children's clothing sold in a shop: every 10% increase here sends labour productivity 3.6% down.

Shop location (individual estimates not shown in Table 3) is another source of systematic variance in labour productivity. As might be expected, out-of-town and city centre locations are most productive. Also, the regional manager is an important factor: productivity differences between shops located in different manager regions can be as high as 28% or as low as -8% of the base region. Shop brand, on the other hand, does not seem to matter for productivity.

The role of unobservable factors for labour turnover and labour productivity

Equation (4) suggests that the full effects of time-varying variables on productivity are represented by $\mathbf{V}_{it} \times \mathbf{B}_1$. Nevertheless, it could be argued that when calculating the total impact of a change in a given time-varying factor, V_k, one should consider its time-invariant part, $d\overline{V}_{ki\cdot} \cdot C$, as well as time-varying one, $dV_{kit} \cdot B_1$. The time-varying part of the impact is caused by a change in the variable itself, but since its average also changes, the time-invariant part comes into play. Therefore, the true impact of a variable is the sum of its time-varying and time-invariant impacts. For example, an extra 10% total hours worked reduces productivity by 8.4% in a given year (time-varying part), but also increases its average by 10%/5 years=2%, which corresponds to 0.583*2%=1.2% permanent increase in productivity; thus the total impact is -8.4%+1.2%=-7.2%, less than reported before.

This logic, however, has two faults. First, it does not apply to within-sample predictions for a given shop, since the average labour input is already defined. Indeed, it would be misleading to claim that every further increase in total hours worked in a given shop is less detrimental to productivity than the one before – the opposite is true. Second, it would not *necessarily* apply in the case of two shops employing different amounts of labour but otherwise identical, because, for instance, they might have different managers and thus employ production inputs with different efficiency. Therefore, since we have used shop averages of time-varying variables to account for unobservable factors concealed in c_i, such as management, the two parts of the change in a given time-varying variable V_k (i.e., dV_{kit} and $d\overline{V}_{ki.}$) should be considered separately, since they represent the influences on productivity of two different factors.

Given the strong statistical link between the unobservables in c_i and shop averages, it is instructive to analyse the differences between the impacts of variable V_k proper (dV_{kit}) and that of unobservable factors mediated through its average ($d\overline{V}_{ki.}$). Let us consider two examples, labour input and labour turnover, in two otherwise identical shops. Holding the unobservables (most importantly, management) constant, the shop with higher labour input in a given year will be less productive (solid thin line in Figure 3). On the other hand, holding labour input constant in a given year, the shop employing more labour on average will be more productive (dashed thin line in Figure 3). However, if the two shops employed different amounts of labour both in a given year and on average, the two effects would apply: the loss of productivity due to higher labour input, and the gain in productivity due to larger average workforce size, which, as we have discussed, may be positively associated with the management input. The total of the two effects is depicted by the solid thick line in Figure 3.

Figure 3.

These two effects can be illustrated with a hypothetical example of two otherwise identical shops one of which has employed 10% more labour on average (i.e., in each year). In this case, this shop is also expected to have higher unobservable term c_i due to larger average workforce size (see equation (2)), and hence better management, as discussed above. So, in any given year it should be only 8.4%-5.8%=2.6% less productive than the other one. Hence, the loss of efficiency due to increased labour intake can be largely offset when adequate management is employed at bigger shops. This result is consistent with the finding of Alvarez and Arias (2003) that diseconomies of size (as we observe in our shops) can be reduced by 'a large enough increase in managerial ability' (p. 141).

We can apply the same logic to labour turnover. Holding c_i constant, the impact of labour turnover on labour productivity is given by the inverted U-shaped curve (the thin curve in Figure 4). However, holding labour turnover constant in a given year, shops with higher average turnover tend to be somewhat more productive on average (dashed thin line in Figure 4). Compared to a shop having no labour turnover at all, the one having non-zero labour turnover gains in that year from the reshuffling of the staff, and (permanently) from with the increase in c_i due to higher average labour turnover. Thus the total observed difference in productivity levels between a shop with positive turnover and one with zero turnover, stemming from the impact of labour turnover proper and unobservable factors channelled through it, is given by the thick solid curve.

Figure 4.

However, the fact that higher value of the unobservable part of shop productivity is associated with higher average labour turnover does not mean a revision of the previously reported optimal quitting and hiring rates. It simply shows that because there is a (slight) positive association between average quit and hiring rates and labour productivity, unobservable differences between shops may distort the observable impact of turnover on productivity. Clearly, in a given shop, a further improvement in productivity may be achieved through better management of labour turnover. The thick solid curve in Figure 4 shows a maximum gain in productivity of about 6.5% at a level of turnover of about 67%. If, however, every shop manager had kept to the optimum turnover rate of 22.8% (quits) + 18.5% (hires) = 41.3% thus gaining up to 2.46% in productivity on top of its respective c_i, the new pattern would have looked like a straight line placed at least as high as the observed one (the thick dashed line in Figure 4). The area between this "ideal" line and "actual" thick solid curve serves as a graphical interpretation of the total gain in productivity to be had from bringing all shops' labour turnover from their actual to the optimum rate. But of course, hiring costs would prevent our company from reaping all these gains.

Conclusions

Empirical research on the relationship between labour turnover and productivity has been inconclusive. Most studies have been aggregate, and have faced difficulties in controlling both for industry differences in the importance of specific human capital, and for unobservables including management. This paper analyses the shops of a large UK clothing retailer. We have collected an original longitudinal dataset on productivity in 347 shops. The personnel information for these shops allows detailed measures of hiring and separation rates, adjusted for FTEs. These measures are an improvement on the headcounts generally used.

The econometric results show that the within-shop relation between productivity and labour turnover – that is, holding constant the shop's permanent characteristics – is an inverted-U. The productivity-maximising rates of FTE-adjusted quits and hires were both about 20%, and at the optimum would raise productivity by about 2.5% compared to the zero-turnover level. In fact, observed rates of quits and hires are about half this optimum, a difference which we can explain by introducing hiring costs. These we estimate at about £600 per hire, which is reasonable. The finding of quits and hires having a non-linear effect on productivity supports the view that the less productive workers are initially the ones more likely to quit. However, there comes a point when the improved worker-job matches permitted by quits become offset by the loss of firm-specific human and social capital. For hires, our finding that increased hires initially positively impact productivity implies quick learning on the job in the retail environment. Eventually, however, organisational capabilities reach their limit in digesting the new hires, and productivity falls.

These results are within-shop, the between-shop results are different. We adopt here the Mundlak approach, which constructs shop averages of workforce size and other workforce characteristics including turnover. These averages represent persistent personnel factors operating on the shop, and are used – in conjunction with more obvious time-invariant factors such as shop space and location – to explain differences between shops. Within this framework, we then find that shops which are (persistently) larger have higher productivity, other things being equal. Since larger shops will have better managers, this result gives an insight into the unobserved manager quality factor which must be underlying between-shop comparisons. This insight helps explain our finding that the between-shop relationship between turnover and productivity is positive and linear: shops with persistently higher labour turnover tend to have higher productivity, other things equal. More research will be needed to understand the mechanism behind this finding, which could be due to the better managers using higher turnover both to make better job matches, and to match labour inputs more closely to seasonal fluctuations in trade. Be this as it may, it is important to remember that it is only when we control for between-shop differences in unobservables – that is, consider the average manager – that we observe the inverted-U link between turnover and productivity.

Can we be sure, then, that in retailing there is an optimum (high) level of labour turnover for the average shop? Our results do not only depend on the econometric model. The nature of the clothing shop assistant's job is unskilled, with low hiring costs (as suggested by our £600 per hire estimate) and low losses in productivity due to quits. Further, when we consider the large seasonal variation in required labour, and also the impact of the business cycle which each year causes a 10% absolute variation in the average shop's labour input, we can appreciate the advantage of a mobile workforce. Our company needs to maintain a personnel policy that supports a naturally high level of quitting, permitting swift down-sizing. Alert managers can then counteract the employment outflow by hiring new workers to capture sales when conditions improve. What we have found is a high optimum level of labour turnover, which follows from a personnel policy required to accommodate the turbulence of the retail business.

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Table 1. Descriptive statistics.

Variable		Comments	mean	std. dev.	min	max
sales per hour worked		in constant 1999 prices, GBP	52.781	14.201	21.754	111.559
total hours worked		total hours worked	14642	11159	2445	80889
quit rate		leavers as a proportion of total employment, FTE	0.131	0.108	0	0.799
		same unadjusted for FTE (headcount)	0.275	0.133	0	0.636
hires rate		newly hired workers as a proportion of total employment, FTE	0.109	0.089	0	0.628
		same unadjusted for FTE (headcount)	0.290	0.154	0	0.833
job churn		excess of worker turnover over the absolute change in workforce numbers, FTE	0.164	0.135	0	0.913
		same unadjusted for FTE (headcount)	0.465	0.257	0	1.273
average age		shop based, measured in years, adjusted for FTE	31.972	7.133	20.943	65.678
average tenure		shop based, measured in years, adjusted for FTE	5.328	2.743	0.856	21.872
		same unadjusted for FTE (headcount)	3.551	2.089	0.608	19.86
share of male employees		adjusted for FTE	0.119	0.123	0	0.824
shares of employees working	<5hrs/wk	headcount data	0.165	0.163	0	0.753
	<15 hrs/wk		0.422	0.179	0	1
	<30 hrs/wk		0.23	0.139	0	0.8
	>= 30 hrs/wk		0.183	0.117	0	0.75
shrink		1 if hours worked decreased by >20% in a given year	0.134	0.341	0	1
average wage		average hourly pay in a given shop	3.84	0.249	3.258	5.027
average wage of shop asst.		county level, measured from QLFS, adjusted for inflation	4.701	0.488	3.199	6.76
county average pay			8.244	0.957	6.233	10.435
unemployment rate			0.068	0.025	0.024	0.172
main brand		shares of shops belonging to the specified category	0.836	0.371	0	1
other			0.164	0.371	0	1
city centre		shares of shops in the specified location	0.115	0.319	0	1
local area			0.098	0.297	0	1
district			0.153	0.360	0	1
regional			0.144	0.351	0	1
sub-regional			0.406	0.491	0	1
out-of-town			0.020	0.141	0	1
other			0.064	0.245	0	1
space		shop space, in square metres	143.674	79.336	40.17	489.76
share of children's goods		share of children's wares	0.328	0.197	0	0.98
one-floor trading area		shares of shops with 1, 2 and 3 floors	0.749	0.434	0	1
two-floor trading area			0.236	0.425	0	1
three-floor trading area			0.014	0.119	0	1
observations			1735			

Table 2. Analysis of variance.

Variable	shop	area	time
ln(sales per hour worked)	0.651	0.144	0.100
total hours worked	0.967	0.178	0.002
quit rate	0.307	0.059	0.032
hires rate	0.330	0.067	0.046
job churn	0.393	0.088	0.027
job turnover, FTE	0.224	0.038	0.016
average age	0.911	0.249	0.005
share of male employees	0.864	0.366	0.002
share of employees working <15 hrs/wk	0.765	0.236	0.031
relative wage (average in a shop divided by county average wage of a shop assistant)	0.461	0.338	0.008

Table 3. Regression results for the productivity equation (1).

dependent variable	OLS		Fixed effects		Random effects augmented		Random effects PCSE	
ln(sales per hour worked)	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
Time-varying variables								
ln(total hours worked)	-0.342***	0.017	-0.823***	0.019	-0.822***	0.019	-0.845***	0.020
quit rate	0.140	0.113	0.109*	0.057	0.109*	0.056	0.117*	0.063
hires rate	0.079	0.149	0.103	0.074	0.105	0.073	0.122**	0.055
quit rate squared	-0.313	0.257	-0.349***	0.127	-0.352***	0.126	-0.256**	0.127
hires rate squared	-0.374	0.375	-0.467**	0.187	-0.486***	0.186	-0.331*	0.173
quit rate times hires rate	0.461	0.422	0.215	0.208	0.229	0.207	-0.089	0.241
average age	0.001	0.001	0.002**	0.001	0.002**	0.001	0.003***	0.001
average tenure	0.010*	0.006	0.019***	0.007	0.015**	0.006	0.010**	0.005
average tenure squared	0.000	0.000	-0.001**	0.000	-0.001**	0.000	0.000	0.000
share of male employees	0.020	0.055	0.058	0.048	0.058	0.048	0.044	0.045
share of emp.<5hrs/wk	0.295***	0.06	0.034	0.048	0.036	0.048	0.015	0.04
<15 hrs/wk	0.297***	0.057	0.061	0.047	0.064	0.047	0.023	0.038
<30 hrs/wk	0.127**	0.061	0.012	0.054	0.013	0.054	0.021	0.045
shrink	0.030*	0.016	0.016**	0.008	0.016**	0.008	0.022***	0.006
ln(relative wage)	0.083	0.054	-0.024	0.029	-0.023	0.029	-0.011	0.02
ln(county average pay)	-0.160**	0.075	-0.196**	0.096	-0.197**	0.096	-0.161**	0.069
unemployment rate	-0.790***	0.280	-0.070	0.266	-0.077	0.265	-0.080	0.200
year	-0.165*** to -0.030***		-0.168*** to 0.010		-0.169*** to 0.010		-0.174*** to 0.013**	
Time-invariant variables: shop and area averages								
ln(total hours worked)	none		none		0.568***	0.042	0.583***	0.030
quit rate					-0.203	0.245	-0.254*	0.134
hires rate					0.302	0.314	0.406**	0.168
average age					-0.003	0.003	-0.004**	0.002
average tenure					0.002	0.007	0.003	0.004
share of male employees					-0.028	0.138	0.075	0.074
shares of emp.<5hrs/wk					0.359**	0.154	0.335***	0.090
<15 hrs/wk					0.318**	0.144	0.253***	0.078
<30 hrs/wk					0.211	0.152	0.123	0.079
shrink					-0.153**	0.075	-0.143***	0.035
ln(relative wage)					0.348*	0.203	0.458***	0.107
ln(county average pay)					0.071	0.192	0.066	0.109
unemployment rate					-1.130	0.693	-1.470***	0.485
Other time-invariant variables								
ln(space)	0.226***	0.019	none		0.159***	0.038	0.184***	0.023
shop brand	-0.030 to 0.034				-0.012 to 0.066		0.023 to 0.083***	
shop location	-0.177*** to 0.222**				-0.125** to 0.139*		-0.134** to 0.102**	
share of children's goods	-0.395***	0.053			-0.340***	0.106	-0.361***	0.058
two-floor trading area	-0.017	0.013			-0.017	0.026	-0.009	0.014
three-floor trading area	-0.172***	0.044			-0.137	0.088	-0.066	0.043
regional manager	-0.090*** to 0.254***				-0.115 to 0.237***		-0.081*** to 0.281***	
constant	6.459***	0.229	12.033***	0.288	5.926***	0.496	5.867***	0.258
Regression statistics and tests								
R^2 within	0.447		0.772		0.772		0.583 (quasi R^2)	
R^2 between			0.094		0.366			
R^2 overall			0.133		0.527			

Notes: Stata was used to carry out regression estimations. Option *xtpcse* was used to correct for shop-specific heteroscedasticity and shop-specific first-order correlation.
Estimates significant at 1%, 5% and 10% significance level are marked ***, ** and *, respectively.

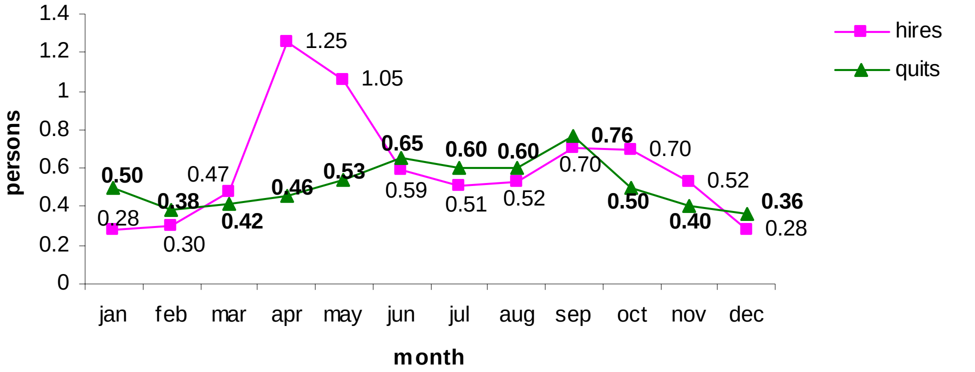

Figure 1: Hires and quits by month, headcount (average shop)

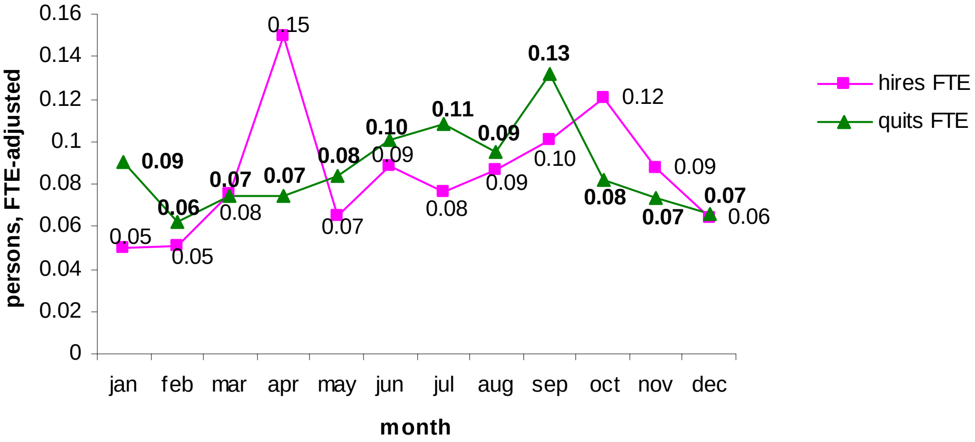

Figure 2: Hires and quits by month, FTE-adjusted (average shop)

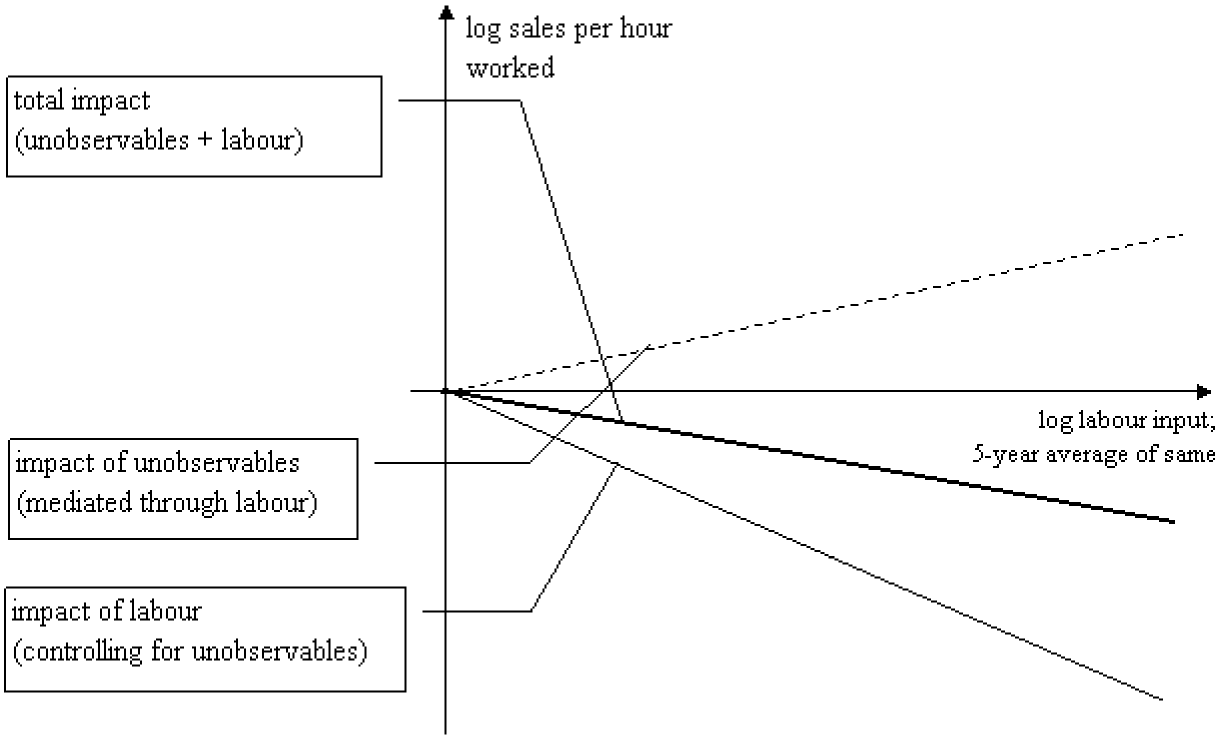

Figure 3. The impacts of labour and management on productivity (not drawn to scale).

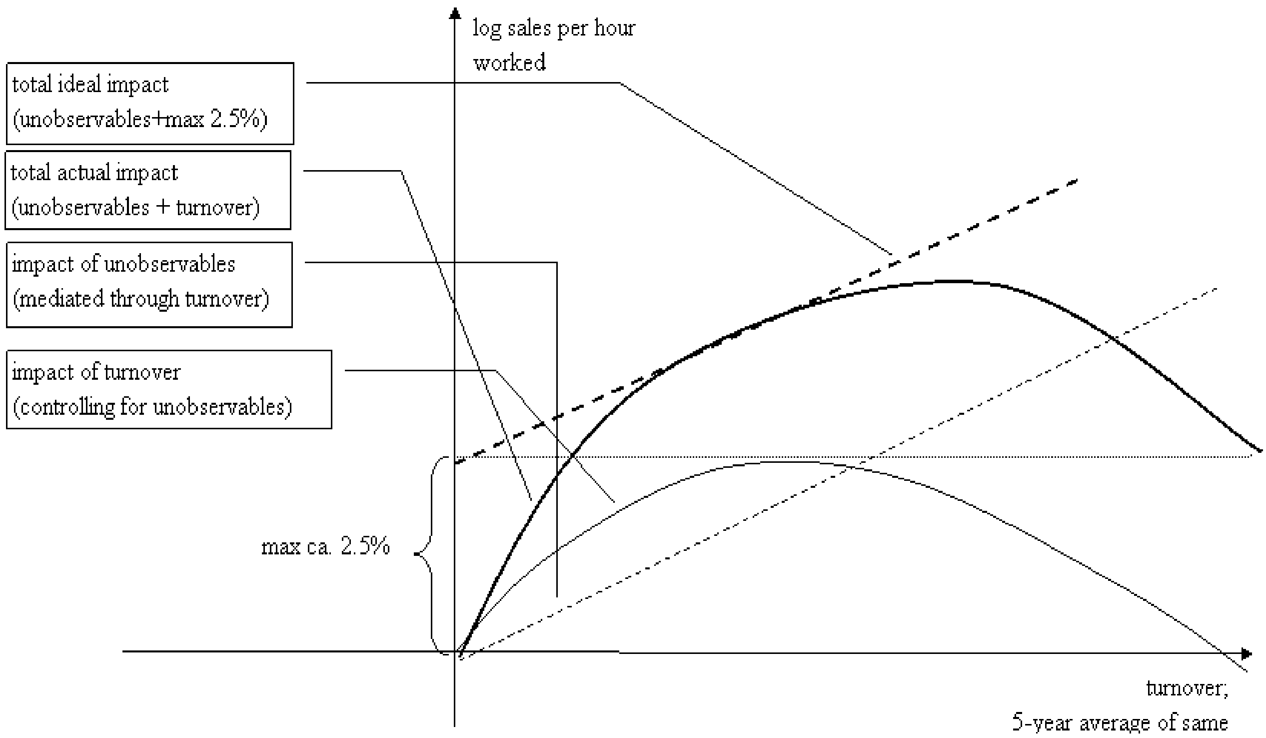

Figure 4. The impacts of labour turnover and management on productivity (not drawn to scale).