Hiring on the basis of expected productivity in a South African clothing firm.

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Abstract

Using information from the personnel files of a South African clothing firm, I explore the in- and outflow of weekly-paid workers. These employees form a separate labour market within the company. Data was available concerning both the productivity of current workers, and the characteristics of rejected applicants and fired workers. This makes it possible to identify the characteristics which are screened out at entry and the characteristics that influence productivity. This allows for an empirical analysis of discrimination at job-entry. Hiring decisions were found to be consistent with expected productivity. The observed screening out of African workers at job entry could be explained by statistical discrimination, i.e., the actual productivity of African workers in this firm was found to be significantly lower than the productivity of workers of other ethnic backgrounds. The effect of education on productivity was found to be very small.

1. Introduction

This paper examines the careers of 586 weekly-paid workers in a South African clothing firm.

1 The author would like to acknowledge the support from Casper Schweigman and Max v.d. Kamp from the University of Groningen, the Netherlands. This research was made possible by grants from the University of Groningen and the Dr. Hendrick Muller's Vaderlandsch Fonds. I thank anonymous referees and P. Baldwin for helpful comments.
The data set includes information on the personal characteristics and productivity of a subset of currently employed weekly-paid workers. What makes the data set unusual is that it also includes information on the personal characteristics of a group of job-applicants who were not hired and the personal characteristics of a group of former employees who were fired because their productivity was too low. This data allows us to separate the characteristics that influence the hiring decisions from the characteristics that influence productivity. The focus of the paper is on the hiring decisions of the firm: is the screening of individuals at entry based solely on the expected productivity of applicants, which would indicate statistical discrimination, or is it also based on non-productivity related characteristics, which would indicate real discrimination?

Although this case-study is limited by the fact that a detailed analysis of the internal labour market could only be performed for a subset of workers in one firm, the analyses in this paper have some relevance for several lines of economic enquiry. Firstly, they bear direct relevance to the search and matching literature (for a review see e.g. Ridder and Van den Berg, 1997). Secondly, the analysis is concerned with the internal dynamics of one firm and thus has some relevance for the internal labour market literature (see e.g. Baker, Gibbs and Holmstrom, 1994). Lastly, the results indicate the relevance of statistical discrimination for actual firm policy.

In the second section, the data set is described.

In the third section, an empirical model of the careers of weekly-paid workers is developed and explained. In section four, the empirical results are presented. Section five concludes.
2. Descriptive statistics

The firm under investigation kept extensive records on all individuals who came into contact with it. We will only focus on the records that were kept of weekly-paid employees, who form about 80% of the current workforce. Firstly, the firm kept personnel records of all current and former weekly-paid employees, containing information on personal characteristics and on the careers within the firm (length of experience, wages). Secondly, the company kept separate records on the productivity of current weekly-paid employees over the last 18 months. Also, the company had records of individuals who had applied for jobs, but who were rejected. By combining all these records, a data set was constructed of 586 individuals. In Table 1, the 586 individuals are divided into three groups, reflecting their past and current affiliation to this firm:

Table 1
Statistics of the internal labour market for weekly-paid jobs

<table>
<thead>
<tr>
<th></th>
<th>Weekly-paid current employees</th>
<th>Failed applicants for weekly-paid jobs</th>
<th>Dismissed from weekly-paid</th>
</tr>
</thead>
<tbody>
<tr>
<td>education in years</td>
<td>7.5</td>
<td>8.1</td>
<td>7.4</td>
</tr>
<tr>
<td>st. dev. of educ.</td>
<td>4.9</td>
<td>1.8</td>
<td>2.6</td>
</tr>
<tr>
<td>Wage in 1993 in Rands</td>
<td>223</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>st. dev. of wage</td>
<td>0</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Productivity</td>
<td>92</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>st. dev.</td>
<td>11.5</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td># Females</td>
<td>442</td>
<td>48</td>
<td>54</td>
</tr>
<tr>
<td># African</td>
<td>18</td>
<td>27</td>
<td>2</td>
</tr>
<tr>
<td># Indian</td>
<td>462</td>
<td>25</td>
<td>52</td>
</tr>
<tr>
<td># with productivity known</td>
<td>380</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>N</td>
<td>480</td>
<td>52</td>
<td>54</td>
</tr>
</tbody>
</table>

In general, the data mainly concerns Indian females with a large variation in educational
attainment. There were no whites at all at this wage level and only a few Africans.

The first column in Table 1 shows the characteristics of the weekly-paid employees actually working in this firm. Information on the average productivity during the previous 18 months was available for 380 of these workers. A peculiarity of the group of weekly-paid workers is that they all received the same industry-negotiated wage and hence there was no wage variation: perhaps to avoid the resentment that many weekly-paid employees have against differential payment which creates differences in local status (see Frank, 1985).

The second column of Table 1 describes the characteristics of a group of individuals who applied for weekly-paid jobs at the firm, but were rejected. We see that the group of rejected applicants contains relatively more Africans. The third column describes the characteristics of a number of weekly-paid workers who had worked for this firm in the past, but who were fired because their productivity was too low.

Before going on to describe the internal labour market further in the next section, some comments on the way productivity of weekly-waged workers was measured in the firm are relevant here. Productivity was measured by averaging the efficiency ratings of a weekly-paid worker over the period October 1991 till April 1993. These efficiency ratings were based on an evaluation of the total amount of clothes that a worker handles and thus represent the amount of faultless clothes that a worker sewed, pressed or examined during this period, compared to the amount that the average worker was found to process in this company in such a time-span.

An example from daily practice may make this clear. Consider the efficiency ratings of a machinist, who makes clothes on a sewing-machine. The number of clothes she manages to make are recorded every day. The clothes were checked for faults and if any faults were found, the clothes were returned to that worker and efficiency points for those clothes were withheld until they were faultless, thus maintaining a consistent quality. The number of faultless clothes made by a worker is then transformed into an efficiency-rating for the day. At
the end of a week, workers with high efficiency ratings are given small, and unfortunately unrecorded, monetary bonuses as an incentive. These bonuses make up about 5% to 10% of the weekly-paid wage bill of the firm.

The estimate of productivity is thus an indicator of the physical quality-adjusted-output of individuals in weekly-paid jobs.
3. The empirical model

The careers of weekly-paid workers have three stages: entry into the weekly-paid segment of the firm, production, and exit from the weekly-paid segment of the firm. Each stage is described. Then an empirical model is constructed with which to analyse the hiring and firing behaviour of the firm.\(^2\)

In the first stage, applicants for weekly-paid jobs are screened at entry with the use of a nimbleness test. If applicants pass this test, it is stated firm policy to offer them a weekly-paid job at this firm. However, when information from the test results is collated with the ensuing hiring decisions, a different picture emerges. Consider the following probit equation which shows the dependence between the probability of being hired, the results of the test, and individual characteristics (education, age, ethnic classification):

\[
P[\text{being hired}] = \Phi(-0.31 + 0.04^{\text{educ}} - 0.004^{\text{age}} + 1.15^{\text{test}} - 2.04^{\text{African}})\]

\[
t-val \quad (0.2) \quad (0.4) \quad (0.1) \quad (4.2) \quad (4.2)
\]

\(N=122\)

\(-2\text{Log}(L)=93.1\)

where the variable “test” denotes a dummy indicating whether the test was followed successfully or not, and where “African” is a dummy denoting whether the applicant was classified as an African or not. \(N\) contains the rejected applicants and a control group containing current workers who applied at the same time as the rejected job-applicants. The results are strikingly

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\(^2\) Given that the empirical literature on the analysis of personnel files is very sparse (for a review see Prendergast, 1996), there are few empirical facts to guide the discussion here (cf. Baker et al., 1994).
at odds with stated firm policy: not only is passing the test important for the chances of being hired, at least as important is not being an African. The practice is that most Africans are screened out at entry. By modelling the hiring policy explicitly, we will ascertain whether the screening of Africans is due to real discrimination or statistical discrimination.

In the second stage, the productivity stage, a weekly-paid worker is set to work and is given some time (about a year) to raise her average productivity above 80.\(^3\) All workers whose productivity remains below 80, or whose productivity falls below 80 for a period, are fired. A worker whose productivity remains above 80 eventually retires, gets promoted, or leaves the firm for personal reasons (no detailed information is available on these non-productivity related exits).

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\(^3\) The number 80 comes from two sources: firstly it is stated firm policy and secondly, there are no current workers with a productivity much below 80 (there are some current workers with productivity slightly below 80 though as it takes a sustained period of below 80 productivity to be fired). The stated policy is therefore assumed to be actual practice.
Constructing an explicit model of these careers, it is assumed that the firm’s actual policy is to take an estimate of the productivity of the applicant as a basis for the decision of whether to hire an applicant or not. This estimate of productivity is denoted by $Z_i$. As all the weekly-paid workers in this category have the same wage, the optimal hiring criterion would be to hire everybody with an expected productivity above a fixed reservation productivity, $R_h$. The same reasoning holds for the firing decision of the firm: as wages are not related to age or experience, it is optimal to fire anyone with a productivity lower than a firing reservation productivity $R_f$. If the hiring reservation productivity is very low, then the firm “tries out” many individuals, which can be optimal if the costs of hiring and firing are low. Similarly, a high hiring reservation productivity would indicate high costs of hiring and firing. The hiring reservation productivity thus gives us some indirect indication of the costs of hiring and firing.

Productivity and the estimate a company makes of that productivity are thus defined:

\[
\text{Prod}_i = \alpha + \beta \text{Educ}_i + \gamma'X_i + \varepsilon_i \\
(1)
\]

\[
Z_i - \tau_i = \alpha + \beta \text{Educ}_i + \gamma'X_i \\
\tau \sim \text{N}(0,\nu^2) \\
(2)
\]

Prod equals productivity, Educ stands for the years of formal schooling.

$X$ is a vector of personal characteristics including age, years of experience, marital status, test, and ethnic classification. $\tau_i$ and $\varepsilon_i$ are assumed to be independently jointly normally distributed. Also, $\sigma^2$ and $\nu^2$ are assumed to be independent of observed

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4 This will hold, assuming for simplicity approximately infinitely long working careers, as long as the expected productivity profile of an individual after entry depends only on expected productivity at entrance. If productivity changed strongly non-linearly over time (for instance through non-linear age profiles), this will not hold. Fortunately, there were no strong non-linearities found, which allows for the above simplification.

5 If the employer can observe productivity related characteristics unavailable in the data set, one can expect $\varepsilon_i$ and $\tau_i$ to be positively correlated. A test for correlation showed that the correlation coefficient between $\varepsilon_i$ and $\tau_i$ was only 0.07 which was insignificant at the 90% confidence level. The assumption of independence is
characteristics.\(^6\)

\((Z_i - \tau_i)\) is the estimate that the company has of a worker's productivity at the moment that (s)he applies for a weekly-paid job, whereby \(\tau_i\) reflects the demand variations at the time of assessment. If there are no demand variations, then the firm should always hire someone with a productivity-estimate greater than \(R_h\), making \(v=0\). Once a worker is hired, that worker will not be fired until her productivity falls below \(R_f\) for a period, where after she is fired.

We now incorporate the possibility of job-discrimination by allowing the hiring reservation to differ for different ethnic and gender groups\(^7\). We model the possibility of job-discrimination by specifying \(R_h = \text{constant} + \theta_0 \text{African} + \theta_1 \text{Male}\)

If \(\theta_0\) is bigger than zero, an African applicant would need to have a higher expected productivity than an Indian applicant and would hence face real discrimination. Similarly, if \(\theta_1\) is greater than zero, males would need to have a higher expected productivity than females to be hired.

A natural question to pose is whether the firing reservation productivity also differs for different workers? There are two reasons why the firing reservation productivity is taken to be constant. The first reason is a practical one: we would have to know the actual productivity of those fired to say with any certainty whether the firing reservation productivity differs according to the characteristics of workers. The personnel files of fired workers do not contain actual productivity data: the personnel files of those workers who were fired only contain information about complaints about the productivity of the individual and the official reasons given for dismissals. Hence the official reasons for dismissals are taken at face value and the productivity of those fired is taken to be below 80.

\(^6\) Several versions of the model were tried which relaxed this assumption. No significant determinants of the variance of productivity and demand were found however.

\(^7\) I thank an anonymous referee for this suggestion.
The second reason why the firing reservation productivity is not endogenised is theoretical: if a firm wants to screen out individuals with certain characteristics, it is much cheaper to screen them out at entry: screening out unwanted characteristics at entry avoids hiring and firing costs. Hence, there is little reason to expect the firing reservation productivity to differ for different groups. Add to this the fact that the stated firing reservation productivity fits well with the observed distribution of productivity in the current group of workers, a constant firing reservation productivity of 80 is taken to be plausible.

Summarising, the likelihood of the observations for this model can be formulated as:

\[
L = \prod_{i \in H} P[\text{not being hired}] \prod_{i \in J} P[\text{hired and fired}] \cdot \prod_{i \in L} P[P_{\text{rod},i} > 80 - Z_i > 80] \cdot f(P_{\text{rod},i} | \text{hired and retained})
\]

\(i \in H\) denotes a worker who was not hired

\(i \in J\) denotes a worker who was hired and later fired

\(i \in L\) denotes a worker who was hired and retained

As \(f(.),\) the density function of the productivity distribution, and \(Z\) are assumed to be normally distributed, this likelihood reduces to:

\[
L = \prod_{i \in H} \Phi(R_{\text{h}} - \alpha - \beta \text{Educ}_1 - \gamma' X_i, \frac{\sigma}{\nu}) \prod_{i \in J} \Phi(\frac{\alpha + \beta \text{Educ}_1 + \gamma' X_i - R_{\text{h}}}{\nu}) \cdot \prod_{i \in L} \Phi(\frac{P_{\text{rod},i} - \alpha - \beta \text{Educ}_1 - \gamma' X_i}{\sigma}, \frac{\sigma}{\nu})
\]

(3)

The first element of this likelihood \((i \in H)\) denotes the likelihood of observing those individuals who were not hired, on the basis of their observed characteristics. This equals the likelihood that their expected productivity is below the hiring reservation productivity level. The second
part of the likelihood \((i \in J)\) denotes the likelihood of observing the workers who were fired, which equals the likelihood that they had an actual productivity below the firing reservation productivity, conditional on the fact that their expected productivity was above the hiring reservation productivity. The third and last element of the likelihood function denotes the probability of observing the productivity of the active weekly-paid workers given that their hiring productivity is above the hiring reservation productivity. The estimates of the parameters of equation (3) are presented in the next section.
3. Empirical estimates

Table 2 shows the empirical results for equation (3) and compares them with a simple OLS on the productivity of current workers.

Table 2
Hiring, firing and productivity in a South African clothing company in 1993*

<table>
<thead>
<tr>
<th>Determinants of Productivity</th>
<th>ML Productivity(1)</th>
<th>OLS Productivity (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>72.17 (22.5)</td>
<td>74.62 (11.5)</td>
</tr>
<tr>
<td>Years Of Experience</td>
<td>1.87 (5.2)</td>
<td>2.27 (3.6)</td>
</tr>
<tr>
<td>YOE²</td>
<td>-0.06 (2.6)</td>
<td>-0.08 (2.4)</td>
</tr>
<tr>
<td>Education in years</td>
<td>0.53 (2.7)</td>
<td>0.46 (1.3)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.07 (1.2)</td>
<td>-0.002 (0.02)</td>
</tr>
<tr>
<td>σ</td>
<td>10.82 (33.4)</td>
<td></td>
</tr>
<tr>
<td>ν</td>
<td>4.55 (59.2)</td>
<td></td>
</tr>
</tbody>
</table>

| Dummies:                    |                     |                      |
| Test                        | 3.58 (7.9)          | 4.31 (0.9)           |
| Gender                      | 4.25 (1.0)          | 3.00 (1.0)           |
| Married                     | -0.15 (0.2)         | 0.08 (0.06)          |
| African                     | -16.64 (3.9)        | -13.15 (3.4)         |
| No-test-score               | 5.26 (4.0)          | -1.12 (0.6)          |

Determinants of the hiring reservation productivity:

<table>
<thead>
<tr>
<th></th>
<th>ML</th>
<th>OLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>70.42 (21.5)</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>7.73 (1.7)</td>
<td>380</td>
</tr>
<tr>
<td>African</td>
<td>-11.66 (2.5)</td>
<td>0.151</td>
</tr>
<tr>
<td>N</td>
<td>486</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>3120</td>
<td></td>
</tr>
</tbody>
</table>

* Absolute t-values in parenthesis. Experience includes tenure and previous experience.

Looking at the ML-results first, we can see that the standard deviation of the hiring-residual is a lot smaller than the standard deviation of productivity as reported in Table 1, and is considerably smaller than the unexplained residual from the productivity model. This suggests that although the expected productivity of an applicant is not enough to explain hiring decisions (as v would be 0 in that case), hiring decisions are better explained by observable
characteristics than actual productivity. This good fit indirectly validates the assumption that the firm uses expected productivity as the criterion for hiring an applicant.

The main implication of the results on the determinants of the hiring reservation productivity is the fact that the discrimination of Africans at job entry can be attributed to statistical discrimination: the hiring reservation productivity is lower for Africans than for Indians, implying a bias in favour of Africans. Hence, the screening out of Africans at entry can be attributed to their lower expected productivity in this firm. This expectation rests however entirely on the fact that the few Africans working in this company have a low average productivity. If African workers find it more difficult to operate in this firm (for instance because of difficulties of communicating with co-workers across cultural barriers), then the low productivity of Africans is the effect of the fact that they form a small minority in this firm. Given the fact that they are the minority in this firm and that their average productivity is significantly lower, it would seem optimal to screen out Africans at entry.

Another interesting aspect about the hiring reservation productivity is that it is lower for all applicants than the firing reservation productivity. This means that the firm knowingly hires many applicants whom it expects to have to fire after a while in the hope that the productivity of these applicants is unexpectedly high: as $\sigma$ is almost 11, only about 1 in 4 applicants with an expected productivity of 70 will eventually be retained by the firm. This means that the transaction costs of hiring and firing are low enough to make it optimal for the firm to “try out” many different employees. Given the absence of labour laws preventing dismissals in South Africa in 1993, this would seem plausible. Hiring costs were indeed low, as workers could start almost immediately and required little administrating. Firing costs included some severance pay (1 to 3 months pay), but required no long procedures. Trying out many employees was also possible in 1993 as the unemployment in the clothing industry provided a large pool of potential workers. Obviously, if firing and hiring transaction costs were to be increased, for instance through central legislation, the reservation hiring productivity would increase. The
firm would then try out less workers, leading eventually to a lower average productivity. The results on the hiring reservation productivity also show that males have to obtain a higher productivity to be hired for weekly-paid positions than females. There is some qualitative evidence to support this: when prospective workers apply for positions in the firm, mostly females are considered for the weekly-paid positions. Men do apply for such positions but are hardly ever considered for them. Thus gender discrimination applies at job entry, only this time in reverse of the normal pattern in South Africa (see e.g. Kraak, 1991; Innes et al., 1993; Bird, 1992, who argue that in South Africa, the jobs that women do are usually low-paid and low-status because they are done by women).

As to the characteristics influencing productivity, we see that the ML model, which allows for selectivity effects, has increased the OLS-estimate of the relationship between education and productivity only very slightly and the coefficients remain very small: 10 years of education adds about 6% to a weekly-waged worker's productivity, which would lead to a very low social rate of returns for weekly-paid workers. Thus productivity and education are only weakly related for the weekly-paid employees.

Secondly, the profile of productivity according to experience suggests that productivity increases until 15 years of experience has been achieved and thereafter it decreases, probably reflecting the difficulty that older employees have in adapting to new equipment, new clothing patterns and new methods.

Comparing the simple OLS-regression on current workers with the ML-model, we see that the experience profile is less pronounced and the education profile is more pronounced in the ML-model. The difference in the effect of observable characteristics on productivity is insignificant however. The main advantage of the ML-model is thus the opportunity it offers to investigate hiring and firing policies.
In this paper a small model was constructed with which the careers of weekly-paid workers in a South African clothing firm were analysed. The analysis concentrated on the hiring policies of the firm. Because all weekly-paid workers earned the same industry negotiated wage, it was predicted that all job-applicants with an expected productivity greater than a hiring reservation productivity would be hired and that all those who did not achieve a firing reservation productivity would be fired. It indeed turned out that the expected productivity of an applicant was a good predictor for the decision to hire an applicant or not.

From an analysis of the determinants of the hiring reservation productivity, it was found that there was no real discrimination against African workers: the reservation hiring productivity of African workers was even lower than that of Indian workers. The observed screening out of Africans at entry is hence explained by statistical discrimination, i.e., by the fact that the average productivity of Africans in this firm was lower than the productivity of Indians. It must be noted though that this result rests on the low average productivity of the few African workers in the firm. If they face high transaction costs with the Indian majority in this firm due to cultural differences, the results might not have been the same if the majority of weekly-paid workers in this firm had been African.

Considering the characteristics that influence expected productivity, a weak but significantly positive relationship between education and productivity was found. The reason for the weak relationship might be that few of the skills acquired in education are used for weekly-paid jobs for which productivity data is available.

**Literature**


