Further Investigation of Credit History as a Predictor of Employee Turnover

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We investigated the validity of job applicant credit history in predicting subsequent employee turnover. Credit history had no validity at differentiating between "negative" (e.g., terminated for dishonesty) vs. "non-negative" (e.g., sickness, relocation) reasons for leaving, and had no validity at distinguishing these employees from those who remained on the job.

Companies use a variety of predictors in an attempt to predict future employee behavior. These predictors include ability tests, interviews, biographical data tests, references and letters of recommendation, college transcripts, and many others, and most often are used to determine whether to offer an applicant a job. Organizations can legally use predictors to make selection decisions and do so without worry unless the predictor results in adverse impact against a protected class (Gatewood & Feild, 2001). Some examples of Federal protected classes include race, gender, religion, age, national origin, and disability. Adverse impact would occur if the predictor causes the percentage of minority applicants hired to be less than 4/5 of the percentage of majority applicants hired. For example, the requirement that applicants pass a strength test is part of getting a job as a firefighter. This predictor results in adverse impact against females because they are less likely to pass the test. Fire departments aren't breaking the law, however, because they are able to demonstrate the strength test to be related to the job and because most publicize their requirements, allowing applicants to train for the physical ability test (Guion, 1998).

Adverse impact itself is not illegal. If a predictor or employment decision causes adverse impact, the organization must be able to demonstrate that the predictor or employment decision is either 1) a Bona Fide Occupational Qualification (BFOQ), 2) a business necessity, or 3) job related (EEOC, et.al., 1978). An example of a BFOQ would be the case where a religious organization requires a candidate for the job of minister to be ordained and a member of that church. This would result in adverse impact against individuals who were not church members, but still be legal (Gatewood & Feild, 2001; American Bar Association, 1997; Equal Employment Opportunity Commission, et. al., 1978).

An example of a business necessity might be the case where an airline requires pilots to retire at a certain age. This mandatory retirement adversely affects older pilots, but has been upheld by courts on grounds of public safety (Gutman, 2000).

The job relatedness of a test is shown by a demonstration that the test is valid. A valid test is one that either 1) measures the same knowledge and skills that are performed on the job or 2) that mathematically predicts performance with sufficient accuracy. Cognitive ability tests, for example, adversely impact minorities. However, these predictors have passed legal challenges because they do mathematically predict performance (Gatewood & Feild, 2001).

Should the predictor or employment decision result in adverse impact and the company fails to demonstrate either the job

Method

Sample and Procedure

For the present study 178 employees spanning six company locations and including several related job positions were randomly sampled. This included 1) 141 active employees and 2) 70 employees who had terminated employment with the company. The average age was approximately 35.

Credit reports (See Appendix A for a short example.) for the sampled employees were then collected. Credit reports were in printed form, with personal information removed and replaced by random numbers. This information was then provided to the researchers, who used the random numbers to match personnel data with credit reports. A small number of the credit reports were missing pages or were unreadable. Thus, the analyses were computed on varying sample sizes, which are indicated in Tables One and Two.

The predictors in the present study were extracted from employee credit history data covering the two years immediately preceding employment at the company. Several specific predictors were used. These included:

- The number of positive accounts in the credit history (e.g., "never late").
- The number of accounts that were not positive.
- The total number of accounts (positive + negative).
- The number of times, across all accounts, that payment had been 30 days late.
- The number of times, across all accounts, that payment had been 60 days late.
- The number of times, across all accounts, that payment had been 90 days late.
- The number of times, across all accounts, that payment had been 120 days late.
- The number of accounts that were turned over to collections.
- The number of accounts that had been written off plus those requiring litigation ("charge offs").
- The percentage of all accounts that were negative (negative ÷ total).
- The total number of times, across all accounts, payment had been late.
- The average number of times late per late account.
- The average number of times late computed across all accounts.

Some of these predictors are transformations of the original variables. This was done because we felt that it might be possible that the non-transformed variables might not adequately assess the constructs (e.g., responsibility) that credit history might reflect. Again, only accounts that were active during the two years immediately preceding employment at the company were used.

Results

Descriptives are presented in Table One. Because the dependent variable was binary, logistic regression was utilized. As presented in Table Two, only five of the 39 analyses were significant, and one was marginally significant. Furthermore, for the comparison of "negative" vs. non-negative terminations, three of the significant predictors covaried considerably because of the transformations performed on them (e.g., Total Number of Times Late and Average Times Late Per Late Account).

The non-significant analyses cannot be attributed to differences of group sample size percentages. Terminated employees comprised between 22% and 52% of the sample for all analyses.

Table One: Descriptives

	"Negative" Terms			Non-Negative Terms			Non-Terms		
Predictor	$\overline{X}$	SD	N	$\overline{X}$	SD	N	$\overline{X}$	SD	N
Number of Positive Accounts	4.35	3.86	26	5.96	5.97	24	5.17	6.10	86
Number of Negative Accounts	4.57	5.22	26	2.54	3.08	24	2.53	2.86	85
Total Number of Accounts	8.92	6.00	26	8.50	5.52	24	7.71	6.54	85
Number of 30-day Late Instances	3.85	8.01	26	1.46	3.89	24	3.02	5.79	86
Number of 60-day Late Instances	2.08	3.97	26	0.96	2.49	24	1.26	2.92	86
Number of 90-day Late Instances	1.31	2.29	26	0.54	1.86	24	1.19	3.71	86
Number of 120-day Late Instances	3.27	9.67	26	0.33	1.43	24	1.09	3.61	86
Accounts Requiring Collection Action	1.38	2.00	26	0.75	1.29	24	0.77	1.39	86
"Charge Off" Accounts	1.04	1.51	26	0.75	1.92	24	0.65	1.55	86
Percentage of Accounts Negative	0.50	0.37	26	0.41	0.40	24	0.40	0.40	83
Total Number of Times Late	10.50	16.76	26	3.29	9.30	24	6.56	12.14	86
Avg. Times Late Per Late Account	1.28	2.65	26	0.35	0.66	24	1.20	2.51	83
Avg. Times Late Per Account	1.76	3.48	26	0.23	0.78	24	0.92	3.65	83

Note: Statistics reflect consumer credit activity over an approximately two-year period.

To summarize the results, only a few of the measures of credit history used for the present sample had any validity in the prediction of termination data. This number is sufficiently small that chance is probably the best explanation.

Discussion

Based on the results herein and that of a previous (e.g., Palmer & Koppes, 2003) study and sample, credit history data should not be used to select employees unless the company demonstrates evidence that such data have validity at predicting employee behavior.

Employers can use any test or predictor they want to use, provided the test or predictor does not result in adverse impact against a protected class. If the test or predictor does result in adverse impact, the employer must demonstrate the test or predictor to be job related. If the test or predictor is not job related and does result in adverse impact, the employer would likely lose any litigation brought against it by a party contesting the test or predictor (Gutman, 2000). For the present study, the existence of adverse impact is unknown because demographic information – race, age, gender, etc. – was not provided to the researchers.

The present study results indicate, in this sample, that credit history data have no validity at predicting employee performance measures. This means that any non-valid use of this predictor that results in adverse impact would be in violation of Title VII of the Civil Rights Act (United States Code, Volume 42, Section 2000e) as well as case law from both Supreme Court decisions (e.g., *Griggs vs. Duke Power*, 1971) and state courts (e.g., *Soroka vs. Dayton Hudson*, 1989) spanning three decades.

There is reason to believe that credit history data does result in adverse impact, which is the position of the EEOC, who based their arguments on demographic and census data (Joel, 1996). Several parties have attempted to ban the use of credit history data by banks, and also by insurance companies, who use the data to determine insurance rates. The argument is that credit history data adversely impacts minorities. The insurance companies defense has been that credit history data predict the likelihood a person will file a claim (Insurance Advocate, 1999). Opponents this year gained a major victory; the state of Washington recently passed legislation, effective 2003, restricting the use of credit history information by insurance companies. Washington state insurance commissioner Mike Kreidler stated "...Washington State now has one of the nation's toughest credit scoring laws...a reflection of an unprecedented grassroots effort...[to] protect consumers from unfair discrimination..." (Office of the Insurance Commissioner, 2002).

Predicting the likelihood of filing a claim and predicting employee work performance and turnover, however, are quite different matters. Even if credit history data predict the likelihood of filing a claim, there is no evidence that the data predict work performance and turnover, and the results of the present study indicate it does not. One possible reason credit history may predict filing a claim (assuming it does), but not predict work performance and turnover is that there may be much to gain by filing an insurance claim, whereas there is much to lose (one's job) by performing poorly at work. This is true whether a person has a good credit history or a poor one; very few people want to lose their job. In other words, filing a claim would be very tempting to a person who is in debt or financial trouble, but performing poorly would not be a temptation.

There is another argument, in addition to the legal and mathematical ones, for not using a non-valid test or predictor. Use of a non-valid test to select employees and predict their performance is practically no different than selecting employees randomly. Predictors can be expensive to develop and implement (Guion, 1998). Consequently, using a non-valid predictor wastes company financial resources.

Conclusion

The results raise the question: exactly what is a credit report measuring? Those who favor using credit history data as a predictor

Appendix A: Sample (Abbreviated) Credit Report

CURRENT ADDRESS REPORTED 01/2000
5000 ICE AVENUE
GLACIER, ANTARCTICA. 12345

SOCIAL SECURITY NUMBER: 123-45-6789
PHONE: 123-4567

FORMER ADDRESS REPORTED 01/2000
1000 TUNDRA STREET
COCONUT FOREST, ANTARCTICA 54321

EMPLOYMENT DATA REPORTED:

ANTARCTICA
DATE REPORTED: 12/1998

ANTARCTICA SWIMWEAR
POSITION: MODEL
DATE REPORTED: 03/1998

CREDIT INFORMATION

THE FOLLOWING CREDIT SUMMARY REPRESENTS THE SUBJECT'S TOTAL FILE HISTORY

PUBLIC RECORDS:	3	CURRENT NEGATIVE ACCTS:	3	REVOLVING ACCTS:	13
COLLECTIONS:	4	PREVIOUS NEGATIVE ACCTS:	4	INSTALLMENT ACCTS:	8
TRADE ACCOUNTS:	19	PREVIOUS TIMES NEGATIVE:	15	MORTGAGE ACCTS:	4
CREDIT INQUIRIES:	6	EMPLOYMENT INQUIRIES:	2	OPEN ACCTS:	0

	HIGH CRED	CRED LIMIT	BALANCE	PAST DUE	MNTHLY	AVAIL
REVOLVING:						
INSTALLMENT:	$19.9K	$	$11.6K	$0	$550	
MORTGAGE:			$778	$776	$	
TOTALS:	$19.9K	$	$13.4K	$776	$550	

THE FOLLOWING ITEMS ARE COLLECTION RECORDS:

GENERAL COLL: M 2376B009 OPEN ACCOUNT
PLACED FOR COLLECTION

VERIF'D	3/1998	BALANCE:	$894	INDIVIDUAL ACCOUNT
OPENED	2/1993	MOST OWED:	$894	PENGUIN GENERAL HOSPITAL
CLOSED	4/1995			

STATUS AS OF 4/1999: COLLECTION ACCOUNT

THE FOLLOWING ACCOUNT INFORMATION IS PRINTED IN ORDER BY MOST NEGATIVE MANNER OF PAYMENT (MOP) AND DATE MOST RECENTLY UPDATED:

BANK OF ANTARCTICA M 2376B009 OPEN ACCOUNT

VERIF'D	6/1998	BALANCE:	$0	INDIVIDUAL ACCOUNT
OPENED	2/1997	MOST OWED:	$456	CREDIT LIMIT: $2000
PAID OFF	12/1995			

STATUS AS OF 4/1999: 120 DAYS PAST DUE
IN PRIOR 08 MONTHS FROM DATE VERIF'D 1 TIME 30 DAYS LATE, 3 TIMES 90 DAYS LATE

THE FOLLOWING COMPANIES HAVE REQUESTED A COPY OF THE SUBJECT'S CREDIT REPORT:

DATE	SUBCODE	SUBSCRIBER NAME
05/07/1998	G 12345	ANTARCTIC BELL TELEPHONE
02/01/1999	E 98765	POLAR CAP BANK & TRUST

THE FOLLOWING COMPANIES HAVE REQUESTED THE SUBJECT'S FILE FOR EMPLOYMENT USE:

DATE	SUBCODE	SUBSCRIBER NAME
02/11/2000	T 33345	WALRUS TANNING SALON
