Chapter 4: Managing Turnover

This chapter focuses on how evaluate the impact of HR policies and practices on employee turnover. One of the most basic HR responsibilities involves finding and keeping enough employees with the right skills to produce the firm's goods or services. We will focus on the "keeping" side of the effort here, though as will be noted in other chapters, some business metrics are best addressed by some combination of HR efforts. I will present an overview of some unique issues associated with understanding and managing employee turnover, followed by a brief discussion of possible turnover-related business outcome (business metric) measures for use in evaluating HR policies and practices aimed at managing turnover. Finally, I will walk through two real turnover management cases.[1] The first case involves assessing how a personnel selection system might reduce turnover (voluntary and involuntary) and forecast when it will occur among call center telephone operators. The second case examines how to modify a compensation system to reduce voluntary turnover in an existing workforce to "acceptable" levels.

Chapter 4 Goal: To learn how to assess the impact of HR policies and procedures on voluntary and involuntary employee turnover in terms line managers can understand and relate to important business decisions.

Turnover Musings

Sooner or later all employees leave their jobs. The Society for Human Resources Management reported that average annual turnover for all industries was 18% (retail, for-profit service, and not-for-profit service ranked highest at 34%, 24%, and 22%, respectively). Involuntary turnover occurs because the firm ends the employment

[1] I slightly modified real business circumstances to help illustrate alternate ways of assessing HR→business metric relationships.

relationship – you are fired for "cause," you are fired on a whim (yes, managers, like all people, can be arbitrary and capricious at times), your position is no longer needed due to some business change (e.g., "rationalization"), etc. For our purposes, we will call decisions by employees to end employment voluntary turnover.[2] Some small portion of turnover will occur that is neither voluntary nor involuntary due to causes beyond the firm's or employee's control (e.g., severe threats to health, accidental death, etc.). Analysis of termination codes for over 200,000 "leavers" across hundreds of firms over the last 10 years indicates turnover due to health, accidental death, etc. is relatively rare at less than 2%.[3] Because involuntary turnover is by definition controlled by the firm, it is typically not the focus of HR policies and practices aimed at current employees, though it is relevant for HR policies and practices aimed at applicants. Future HR-related turnover costs for an applicant are generally the same regardless of whether that turnover was voluntary or involuntary.[4] As noted on multiple occasions elsewhere in this text, any given business metric is rarely effected by one and only one HR policy or practice. Pre-employment recruiting and selection systems might influence subsequent involuntary turnover, while subsequent training and compensation might influence voluntary turnover. As we see below, HR policies and practices that increase the likelihood of

[2] Since the Age Discrimination Act, as amended, extends protection from age 40 to $+\infty$, no one can be forced to retire at age 65, 70, or any age over 40 (though I suppose it might be within the confines of the Age Discrimination Act to require retirement at 39!). Exemptions exist only for executive level jobs.
[3] This number may under-represent the impact of health issues on employee exit as health issues may influence some individual's decisions to retire.
[4] Differences exist primarily in possible dollars lost due to low performance of individuals terminated for cause. If terminated due to failure to perform, the firm loses the value of performance it could have enjoyed from a satisfactory employee. This value is not lost when employees who are otherwise performing at satisfactory levels voluntarily turn over.

hiring employees who perform the job adequately will, by definition, decrease the number of newly hired employees terminated for inadequate job performance.

Firms can also incur costs when employees decide to quit, though some of this voluntary turnover is simply beyond the firm's ability to either predict or influence. For example, "trailing spouse" turnover occurs when an employee's spouse received a wonderful job offer in some distant locale. After consideration of all economic and non-economic implications for the family, the couple decides the spouse will accept the job offer, the family will relocate, and the "trailing spouse" will resign his/her current job (i.e., the one with your firm) to look for employment in the new locale. HR policies and practices typically cannot influence trailing spouse turnover. HR policies and practices can influence many other reasons for voluntary turnover. I coarsely label these reasons as "push" and "pull" factors, examples of which include:

Dual Careers and Voluntary Turnover. The University of Oklahoma and many other employers have HR policies aimed at helping find employment for trailing spouses of valued recruits. OU's Price College of Business hired a valued colleague of mine because the music department was willing to pay for a portion of her salary in order to hire her spouse as a conductor for the university orchestra. Without this university-wide policy, our budget would not have permitted adding another faculty member.

- Better working conditions/supervision or a promotion from a labor market competitor. (pull)
- Disgust with current working conditions/supervision. (push)
- Better pay from a labor market competitor. (pull)
- Change in desired career path (e.g., public school teachers leaving for jobs in industry) or to return to school. (pull)
- Desire for more leisure time causing resignation from 2nd job while continuing in 1st job. (pull)
- Desire to learn new skills on a new job. (pull)
- Boredom with current job. (push)

Clearly both push and pull factors can simultaneously influence employee decisions to quit. Given this list is not even close to comprehensive, we can safely conclude there are a bunch of reasons why people voluntarily quit their jobs.

So, what can we do about it? I would suggest we first need to ask "Why does it matter if we do anything about it?" In other words, does voluntary or involuntary turnover affect important business metrics and, if so, which ones and how? Extremely disruptive turnover gets everyone's attention, including that of line management. The HR challenge comes in showing line management how HR policies and practices aimed at managing turnover are worthy of management's time and effort when circumstances are not so extreme.

Common Turnover-related Business Metric

Common HR system cost measures are traditionally one of the first business metrics discussed, as they are directly caused by both voluntary and involuntary turnover. Table 1 contains a short list of common turnover-related business metric costs. These typically run between 50% and 200% of employee salaries (Edwards, 2005; Reinfield, 2004; Simmons & Hinkin, 2001; Waldman, Kelly, Arora, & Smith, 2004), though can easily be much

Table 1: Common Turnover-related Business Metrics

Average recruiting cost (C_r) per replacement hired, including costs of: ➢ Print advertisements. ➢ On-line job postings. ➢ HR recruiting staff salaries and benefits.
Average selection cost (C_s) per replacement hired, including costs of: ➢ Tests and scoring. ➢ Travel/relocation. ➢ HR selection staff salaries and benefits. ➢ Search firm commissions and fees. ➢ Line management time needed for candidate interviews.
Lost production/sales due to unfilled openings caused by turnover. Average time-to-hire is often a surrogate measure.
Overtime costs incurred by asking current employees to work longer to maintain production levels, including costs of: ➢ Overtime costs as per Fair Labor Standards Act. ➢ Management time needed for scheduling and coordination.
Orientation and training costs, including costs of: ➢ New employee orientation (actual costs of materials, staff, and worker time). ➢ On- and off-job training. ➢ "Lag" performance loss (i.e., performance decrement incurred while employee moves from "newcomer" to "non-newcomer" status).
Average HR employment processing costs (C_e), including costs of: ➢ Processing required employment forms (W-2s, immigration forms, etc.) for new hires. ➢ Processing required employment forms for exiting employees.

higher when executive search firms perform national or international searches working on a cost plus commission basis.[5]

While typically not a major issue, a certain amount of voluntary turnover may actually be "pre-emptive" involuntary turnover, i.e., poor performing employees who voluntarily quit because they see termination coming. Recall the Taylor-Russell model in Chapter 3 described the likelihood newly hired employees would perform adequately for any combination of criterion validity (r_{xy}), base rate, and selection ratio characterizing a selection system. Likelihood of adequate performance ($p_{adequate}$) using a selection system will never be 100%, so 1 - $p_{adequate}$ is the proportion not expected to perform adequately, leading to involuntary turnover or "pre-emptive" voluntary turnover. A conservatively low estimate of expected cost of performance-related involuntary turnover would be the sum of all the costs described in Table 1 multiplied the number of new hires (n_{s_1}) times 1 - $p_{adequate}$, or:

$$n_{s_1}\left(1 - p_{adquate}\right)\sum_{i=1}^{k} c_i$$

Equation 1

where k = the number of direct costs from Table 1
c_i = actual amount of the i^{th} cost in Table 1

This estimate is low because after replacing those initial $n_{s_2} = n_{s_1}(1 - p_{adequate})$ individuals who turnover due to inadequate performance, 1 - $p_{adequate}$ percent

[5] About 10 years ago generous donor was kind enough to pay $150,000 for the services of an executive search firm to assist our dean search committee on which I was a faculty representative. Given the difficult of this job and the fact that at any given time approximately 33% of all deanships are vacant in accredited U.S. business schools, it was money well spent. Search firms typically charge ~ 20% of base salary for successful referral of applicants for skilled individual contributor positions (e.g., machinist, welder, etc.).

of that second cohort of n_{s_2} replacements is also expected not to perform adequately and have to be replaced. The third cohort of $n_{s_3} = n_{s_2}(1 - p_{adequate}) = n_{s_1}(1 - p_{adquate})^2$ new hires will be needed to replace those who perform inadequately within the second cohort of n_{s_2} new hires. Hence, if n_{s_1} and $1 - p_{adequate}$ are relatively large, actual expected turnover costs when any initial cohort of n_{s_1} is hired could be spread out over as many years as it takes to finally get a full complement of n_s adequately performing employees. Equation 2 estimates total involuntary turnover costs as:

$$C_{involuntary\ turnover} = n_{s_1}\left(1 - p_{adquate}\right)\sum_{i=1}^{k} c_i + n_{s_1}\left(1 - p_{adquate}\right)^2\sum_{i=1}^{k} c_i + n_{s_1}\left(1 - p_{adquate}\right)^3\sum_{i=1}^{k} c_i + \ \ldots$$

or

$$C_{involuntary\ turnover} = n_{s_1}\left(1 - p_{adquate}\right)\sum_{i=1}^{k} c_i + n_{s_2}\left(1 - p_{adquate}\right)\sum_{i=1}^{k} c_i + n_{s_3}\left(1 - p_{adquate}\right)\sum_{i=1}^{k} c_i + \ \ldots$$

Equation 2

where $n_{s_2} = n_{s_1}(1 - p_{adequate})$ = number hired to replace inadequate performers in the first cohort of n_{s_1} hired, and;
$n_{s_3} = n_{s_2}(1 - p_{adequate})$ = number hired to replace inadequate performers in the second cohort of n_{s_2} hired.

Note some of the costs in Table 1 will be incurred regardless of subsequent turnover simply due to costs incurred to recruit, hire, and train the original n_{s_1} cohort hired (e.g., recruiting costs, selection costs, etc.), or $C_{HR\ costs\ for\ n_{s_1}} = n_{s_1}\sum_{i=1}^{k} c_i$. Interestingly, if it took 4+ years to fill all n_{s_1} positions with adequate performers, we could estimate the cost of voluntary turnover occurring in this time period for the original cohort of n_{s_1} selected as follows:

$$C_{voluntary\ turnover} = C_{total} - C_{HR\ \ costs\ \ for\ n_{s_1}} - C_{invluntary\ turnover}$$

Equation 3

where C_{total} is the sum of all Table 1 costs incurred during the 4+ years it takes to get a full complement of n_{s_1} adequately performing employees in place.

$C_{voluntary\ turnover}$ and $C_{involuntary\ turnover}$ could be used to evaluate any number of HR policies and practices. For example, I would expect recruiting procedures that yield higher quality applicants to increase the applicant pool base rate, and subsequently, the proportion of applicants expected to perform adequately. As $p_{adequate}$ increases, Equation 2 shows $C_{involuntary\ turnover}$ will decrease. Once we know how much $p_{adequate}$ increases due to a new suite of recruiting practices, we simply plug the $p_{adequate}$ obtained from new and old recruiting systems into Equation 2 along with cost figures from Table 1 to estimate and compare the relative costs of involuntary turnover. If the new recruiting system costs less than the decrease in expected involuntary turnover costs ($C_{involuntary\ turnover}$), we make the tactical HR choice of implementing the new recruiting suite.

Alternatively, we could also evaluate how change in HR policies and practices aimed at current employees reduce cost of voluntary turnover ($C_{voluntary\ turnover}$). One might run a pilot study in a single production facility, implementing higher annual merit pay increases and lower annual bonuses to increase employee membership motivation for a 2-3 year period. If cost of voluntary turnover ($C_{voluntary\ turnover}$) goes down by more than the total cost of operating the new pay system, we know the new pay system is adding more value than it costs. Any HR policy or practice implemented to reduce voluntary turnover could be evaluated for its impact on $C_{voluntary\ turnover}$ if we know $p_{adequate}$ from the Taylor-Russell tables and cost figures from Table 1.

<u>Not-so-Familiar Turnover-Related Business Metrics</u>.

Multiple other turnover business metrics could be developed, limited only by our imaginations and the nature of the target job. For example, high voluntary turnover among customer service call center phone operators might cause ratings of customer satisfaction with service center call experience to go down. Low customer satisfaction would occur when high turnover resulted in a large proportion of call center operators providing relatively poor customer service while in early on-the-job training stages. While not an economic business metric, customer satisfaction ratings may be of extreme strategic importance to executives, making it immediately relevant.

Alternatively, "typical" employee job tenure may not be of concern, though job tenure distribution is a potential problem/opportunity. For example, in the mid-1990's I did a summer faculty internship with a major U.S. retail clothing and house wares chain. Average job tenure across all retail employees was about 18 months, while average job tenure for employees with at least three years on the job was 21 years! In others words, employees who made it past the three year mark generally stay with the firm through retirement. The highest likelihood of voluntary turnover occurred for those with less than three years of job tenure right after the annual end-of-year holiday season and in late August.[6] Discussions with store personnel managers suggested this pattern was due to young retail sales personnel returning to school full time in the fall (August turnover) or spring (early January or late December turnover). Hence, three chronological forms of systematic voluntary turnover occurred, including school-related August quits, school-

[6] Voluntary turnover likelihood relative to employee start date was also examined, though no patterns emerged.

related end-of-year holiday quits, and a small portion of voluntary quits and retirements randomly sprinkled throughout the year.[7]

A small portion of the many entry-level retail sales personnel hired each year is "bit by the retail bug." New hires who become excited by retail careers either stayed with the firm part time while finishing their educations or committed full time to completing school before seeking re-employment. This odd job tenure pattern led to a unique personnel selection opportunity. Table 2 describes the firm's relative desire to hire from five groups of employees. Note the "Yes" with the capital "Y" means high performers expected to turnover in January after less than three years were slightly preferred to the "yes" with the lower case "y" received by high performers expected to turnover in August in less than three years. This preference existed due to the firm's history of problems getting adequate seasonal part-time end-of-year holiday help.

Table 2: Who Do You Want?

Performance	< 3 years job tenure		> 3 years job tenure
	August turnover	January turnover	
Low	No		NO!
High	yes	Yes	YES!

Experience in other industries suggested we first needed to identify those most likely to not voluntarily turnover quickly. Within that group, we would then try to select applicants predicted to perform well. This HR practice would first forecast who was going to fall in Table 2's far right column, then predict which applicants were most likely to perform well among those most likely to have more than three years of job tenure. This approach would work well if large numbers of applicants were likely to fall in Table 2's "YES!" cell. Unfortunately, the applicant pool characteristics and the retailer's

[7] Less than 4% of all voluntary turnover occurred for reasons other than retirement or return to school.

unique pattern of quits within each year did not encourage that selection sequence. Less than 10% of applicants were likely to end up having long careers with the firm (i.e., more than three years of job tenure). Hence, eliminating all those predicted to be "short timers" from further consideration would likely leave fewer applicants than open positions!

The reality of retail in the existing labor market was that the vast majority of new employees did not pursue a retail career. If the firm was to survive and thrive it had to embrace the temporary employment of those destined for non-retail careers elsewhere. In this instance the best HR approach to managing voluntary turnover was to first identify those applicants expected to perform the job well, then attempt to identify which of those remaining are likely to turnover in August, January, or stick it out for a career. The retailer's selection battery should first screen applicants based on scores optimized to predict job performance. The selection battery should screen remaining applicants on the basis of a second score optimized to predict job tenure. Knowledge of current employees' retirement eligibility combined with accurate forecasts of when recent new hires were likely to turnover told the retailer how to pace its recruiting efforts throughout the year.

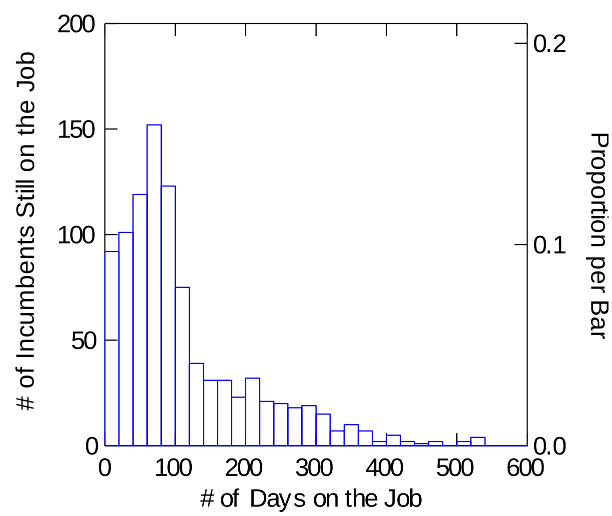
We now turn to two actual business cases examining how HR practices reduced voluntary turnover and influenced key business metrics. The first case examines new Call Center Operators (CCOs) whose median job tenure was just 80 days. The second case examines how a quarry operator might change its pay structure to reduce voluntary turnover costs among existing employees.

Case I: Call Center Operator Turnover at a Financial Services Firm

This case describes how a battery of two personnel selection tests can be used to both increase average job tenure of newly hired Call Center Operators (CCOs) and forecast exactly how many CCOs are likely to turnover up to six months into the future. Analyses reported below estimate relationships between two personnel selection tests and the length of subsequent job tenure among applicants for call center positions at a Fortune 500 financial services firm. Forecasts should be accurate to the extent that future CCO applicants come from the same applicant pool population as participants in this study. I describe below how an applicant's test score profile can forecast how many days s/he is likely to stay on the job. Voluntary and involuntary turnover decisions are examined.

The firm had hired 1348 CCO applicants hired over a three year period between January, 2005 and February, 2008. Median job tenure of those hired and who subsequently turned over was 80 days.[8] Figure 1: Job Tenure FrequencyFigure 1 graphically shows the job tenure frequency distribution of those who turned over in this time period. Visual interpretation of the frequency distributions suggests the highest risk of turnover occurred in the first 120 days (70% turnover within 120 days, while 80% turned over within 180 days).

Figure 1: Job Tenure Frequency



On Medians and Averages. Median job tenure is a measure of central tendency that is unaffected by extreme values, and hence is a more accurate way of describing "typical" job tenure. Average job tenure was 101 days due to a small group of CCOs hired early in the study period that turned over almost 3 years later. Dropping these individuals from the sample caused average and median job tenure to drop to 84 and 79 days,

[8] Median job tenure of those hired who had not yet turned over could not be calculated, simply because they had not yet turned over. This is called "right truncated" data and is discussed in a side bar below.

Further, departing CCO's exit interviews suggested turnover after 6 months of employment was for fundamentally different reasons when compared to turnover during the first 6 months of employment. While median job tenure was 80 days for all those who turned over, those who turned over by failing to return from leave (N = 15) was 179 days and for violations of rules/insubordination (N = 81) was 214 days. There were no apparent seasonal fluctuations in turnover, so the financial services firm was constantly hiring to refill positions as turnover occurred.

Other Prediction Caveats. Any forecasts we make about who will turnover next month, the following month, the month after that, etc. will not be accurate if changes occur in the applicant pool or how the financial services firm (or its competition) draws applicants from the pool. Specifically, changes in recruiting activities (by the firm or its labor market competitors), changes in applicant demand (by the firm or its labor market competitors), changes in applicant supply (quality or quantity), or any other factor that might influence the depth or quality of the applicant pool could cause turnover forecasts to become less accurate.

Before proceeding, it is important to consider how a personnel selection system might realistically increase CCO job tenure. The financial services firm loses half of all newly hired CCOs about 2.5 months (80 days) after being hired and 70% in the first 4 months (120 days) on the job. We are unlikely to find test score → job tenure relationships revealing ways to select CCOs who stay 600 or more days on the job simply because too few CCOs hired in this three year period lasted long enough to reveal such relationships. If the future CCO applicant pool looks just like past CCO applicant pools, we will not find ways of forecasting job tenure much beyond 180 days. Put differently, any test scores or test score combinations found to predict job tenure for CCOs hired over the last 3 years cannot be used to predict CCO turnover 180 days from now, if only because most CCOs who turn over 180 days from now have not yet been hired! Turnover was just happening too quickly to permit detection of how job tenure might increase beyond 180 days.

Regardless, CCOs turning over after more than 180 days seemed to do so for very different reasons than those who turned over before 180 days. Even if the CCO sample examined here was so big that many CCOs with >180 days of job tenure were included, test score → job tenure relationships would probably be different for CCOs who turned over after 180 days. Hence, initial analyses examined only CCOs hired during the three year period and subsequently turned over after less than 181 days of job tenure. Subsequent analyses were also conducted on all CCOs hired as described below.

Predictors. Applicants completed two selection tests prior to accepting job offers, though test scores were not used in deciding who was hired. Applicants' subsequent job tenures were predicted using two personnel selection tests administered but not used to select CCOs during this time period. The first came from personality questionnaire items purchased from a large personnel selection consulting firm and administered to all CCO applicants. Table 3 describes five sample items drawn from the 45 item personality test. Response scales ranged from 1= strongly disagree to 5 = strongly agree. The personnel selection consulting firm computed all applicant scores.

Table 3: Sample Test Items

1. People I know would say that I have a lot of patience.
2. I am known for being committed to my work.
3. I enjoy working in a fast-paced environment.
4. In stressful situations, I generally remain calm and composed.
5. In school or at work, I usually ask my teacher/supervisor for feedback on my performance.

A second experimental test score came from CCO applicant responses to a biographical information inventory, commonly called a biodata inventory. These questions ranged from simple personal history questions such as "How many jobs have you had in the last 5 years?" and "How many months of experience have you had as a call center operator?" to "Bosses I have had in the past did not give constructive feedback well" and "How often did your last 3 bosses look over your shoulder at work?" Each item was paired with a 5-point response scale with 1 = very infrequently, 2 = seldom, 3 = sometimes, 4 = often, and 5 = very frequently. Applicants' biodata responses appeared in 225 columns, one for each response option across the 45 biodata items. Biodata scores resulted from the two steps described below:

1. Calculate Pearson Product Moment Correlations between each response option (scored "0" if not chosen and "1" if chosen by the applicant) and the applicant's job tenure measured in days.
2. The correlations associated with each response option selected by an applicant are added up into a biodata score. Because some response options correlate negatively with applicant job tenure, negative biodata scores were possible.[9]

These scoring steps create a "key" used to score applicant responses to biographical information inventories. The "score" applicants receive from selecting a given response option is determined by the "empirical" relationship between the response option and the target criterion y measure, in this case, job tenure. Not surprisingly, "empirical keying" is the label used to describe this process. In contrast to "2 + 2 = 4" kind of items found in cognitive ability tests, the "right" answers to the current biodata inventory are the ones that best predict job tenure. Evidence suggests it is almost impossible to "fake" or otherwise cheat on a biodata inventory as long as the empirical key remains confidential, which makes biodata inventories very useful in unproctored, internet-based job application settings (Kluger, Reilly, & Russell, 1991).

There is one additional and very important step in using biodata scores called cross-validation. To avoid derailing our discussion of turnover in the current case, the cross validation step appears in an Appendix at the end of the chapter.

<u>Business Metric Criterion Measure y_i</u>

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[9] If negative personnel selection test scores is a cause for concern (e.g., if it is feed back to applicants), biodata scoring processes often simply add 50 points to every applicant's biodata score. Ultimately, it has no effect on biodata score → job tenure relationships under examination.

Job tenure is the primary business metric criterion used in analyses reported below. It deserves brief mention because it contains a particular kind of inaccuracy. Specifically, all employees will turnover sooner or later due to voluntary or involuntary reasons. Simply measuring turnover as a dichotomous variable where 0 = turned over and 1 = not turned over results in loss of information, e.g., it fails to distinguish between those who turned over in their 3rd week and those who turned over in their 3rd year. Job tenure, a simple count of the number of days between date of initial employment and date of turnover, recaptures that lost information while simultaneously injecting a new source of systematic measurement error.

The systematic error occurs because most studies of turnover, including this one, use employee samples containing both individuals who have turned over and individuals who have yet to turnover (but who will at some unknown point in the future). Job tenure of those who have turned over is accurately known, while job tenure of those who have yet to turnover cannot be known with certainty. All one knows for sure is that job tenure of those still employed will be at least one day longer then the difference in days between the date on which turnover data was gathered and the date any remaining employees started employment. Hence, while the true job tenure measure y_i for these individuals will be the number of days between their hire date and (future) turnover date, a conservative estimate of job tenure for those who have yet to turnover is "Date of data acquisition – Hire date + 1." This is how the "job tenure" measure was created for CCOs who had yet to turnover in analyses reported below.

Right-truncated Job Tenure Data. About 20% of CCOs hired during this three year period remained employed at the time of the study. Those interested in pursuing a more sophisticated analytic approach that would include "right truncated data," i.e., CCOs who had not yet turned over, should examine "survival analysis" or Cox regression (Cox, 1970).

Analyses and Results

Job tenure was regressed onto 1) the predictor score derived from the personality and biodata tests and 2) a seasonal "dummy" variable to estimate how well Equation 4 predicted job tenure:

$$\hat{y}_{job\ tenure} = b_0 + b_1 x_{personality} + b_2 x_{biodata} + b_3 X_{season}\,;\, \mathrm{R}_{\mathrm{y}-\mathrm{x}_1\mathrm{x}_2\mathrm{x}_3}$$

Equation 4

where x_{season} = 1,2, 3, or 4 depending on whether the applicant was hired in the winter, spring, summer, or fall, and $\mathrm{R}_{\mathrm{y}-\mathrm{x}_1\mathrm{x}_2\mathrm{x}_3}$ is the multiple regression equivalent of the Pearson Product Moment Correlation when there is more than one predictor x variable (see Chapter 2's discussion of the Cleary model of test bias). When this was done for just the N = 937 applicants hired who had actually turned over, $\mathrm{R}_{\mathrm{y}-\mathrm{x}_1\mathrm{x}_2\mathrm{x}_3} = .13$ ($p < .01$), though the regression coefficient b_3 for the x_{season} did not significantly contribute to prediction (a fancy way of saying the hypothesis H_0: $b_3 = 0$ was not rejected). When the same analysis was done on all applicants in the sample (i.e., including those who had yet to turnover), $\mathrm{R}_{\mathrm{y}-\mathrm{x}_1\mathrm{x}_2\mathrm{x}_3} = .15$ ($p < .01$) and the season dummy variable became significant. The difference in contribution of the seasonality factor suggests something different, possibly related to season of the year in which the CCO was hired, contributed to prediction of applicants' decisions to stay on the job ($R_{y-x_1x_2x_3} = .15$ with "stayers" in sample) versus leave early ($R_{y-x_1x_2x_3} = .13$ when only "leavers" were in the sample). Finally, Equation 4 was estimated separately for CCOs who voluntarily turned over (N = 646), who were terminated due to poor performance (N = 112), and who were terminated for rules violations (N = 81) or excessive absences (N = 71). Estimates of $R_{y-x_1x_2x_3}$ ranged between .12 and .17 ($p < .05$), while comparisons of b_0, b_1, b_2, and b_3 did not significantly differ (b_3 was not significant in any instance, meaning season in which hiring took place did not predict job tenure among those who turned over regardless of reason for turnover). In other words, the relationship of job tenure to the two selection tests and "season" were not meaningfully different for CCOs who resigned or were terminated for cause.

Table 4 compares job tenure descriptive statistics associated with each stated "reason for turnover." Recall the median job tenure among all those who turned over was 80 days, with 70% turning over within 120 days. Results reported in Table 4 suggest those who turned over after 120 days did so for substantively different reasons (i.e.,

Table 4: Job Tenure by Reason for Turnover

Job Tenure	Excessive Absences	Poor Perform	Rules Violation	Failure to Return from Leave	Failed Background Check	Resigned
N	70	112	81	15	13	646
Mean	104	86	176	214	18	109
Median	74	94	176	169	15	74
SD	89	50	102	139	22	97

Violation of Rules/Insubordination and Failure to Return from Leave) compared to those turning over within the first 4 months on the job. Curiously, the significant "season" dummy variable suggests those who had not yet turned over tended to be hired earlier in the year (winter and spring). Combined, these findings suggested "stayers" who remain on the job or turnover late (> 120 days) on the job did so for substantively different reasons than those who turnover early (< 120 days) on the job. Regardless

As most turnover occurred within the first 120 days of employment, we can only forecast when CCO applicants hired during the last ~180 days (6 months) would turnover. Any forecasts of when those hired more than 180 days ago might turnover ("stayers") could not be as accurate due to 1) problems with measures of job tenure for those still employed (i.e., they haven't turned over yet), 2) extremely small sample size for those with more than 180 days of job tenure, and 3) the apparent fact that different things led to their turnover. Recalling how the biodata inventory was scored, different reasons for turning over might cause different response option → turnover relationships from those who turnover within 120 days, resulting in biodata scale scores that do not predict job tenure beyond 120 days.

Table 5 Forecasts. So, where do Table 5 "counts" come from? Mechanically, I started with Equation 4 below:
$\hat{y}_{job\ tenure} = b_0 + b_1 x_{personality} + b_2 x_{biodata} + b_3 X_{season}$

I estimated b_0, b_1, b_2, & b_3 using all CCOs who actually turned over (Model A) and using all CCOs hired regardless of whether they had turned over or not (Model B). For the N = 206 CCO hired since January, 2005, who were still employed I plugged $x_{personality}$, $x_{biodata}$, and x_{season} into Model A to come up with predicted job tenure $\hat{y}_{job\ tenure}$ in number of days. I did the same thing using b_0, b_1, b_2, & b_3 from Model B. Then I added the predicted # of days of job tenure to each remaining CCO's start date to come up with a predicted turnover date. Of the 206 CCOs still employed, Model A predicted 17 would be turning over in March, 2008, while Model B predicted 34 would be turning over in March, 2008. The average months of job tenure across these 17 and 34 individual IF they actually turned over in March, 2008, would have been 29 months.

Forecasts were made of each successful applicant's future turnover date from Equation 4 estimated from all applicants ("stayers" and "leavers") and just those applicants who had turned over ("leavers"). Given the prior conclusion that those who haven't turned over and/or who turned over after 120 days of job tenure do so for different reasons, it is not surprising that forecasts differed for the two prediction models. Specifically, forecasts made from a model derived from all applicants hired between January, 2005 and February, 2008 yielded an average expected job tenure of 179 days. In contrast, Equation 4 predicted 110 days of average job tenure when derived from just those applicants who had turned over during this period. Unfortunately, we cannot know which of the current employees are likely to be "quick turnovers" (i.e., those who turnover in less than 120 days) versus "stayers" (i.e., those who stay longer than 120 days and, when they do turnover, do so for different reasons).[10] Regardless, use of the two selection tests is expected to increase job

[10] Note, additional analyses were performed to determine whether "early leaver" versus "stayer" status could be predicted. Significant prediction of this coarse, artificially dichotomized turnover outcome did not occur.

tenure substantially beyond the current median of 80 days. For purposes of prediction, the first three columns of Table 5 present forecasted turnover frequency for the next 6 months drawn from models derived from 1) just CCOs who had turned over (Model A), 2) all CCOs hired between January, 2005 and February, 2008 (Model B), and 3) an average of the Models A and B. Note, Model A forecasts are particularly low because it predicts most individuals hired since January, 2005, would have turned over some time prior to February 1, 2008. In fact, many did, though Table 5 only makes forecasts for the N = 206 CCOs still employed.[11]

[11] The financial services firm already knows which CCOs have already turned over. Table 5's purpose was to help the firm know when to recruit in the future. Unless the firm plans to increase CCO total, current CCOs job tenure will be the sole determinant of future recruiting efforts.

Table 5: Predicted Turnover for New Hires Remaining since January, 2005

	Predicted # Turning Over if Hired Since 1/1/2005 (N = 206)			Ft. Meyers (N = 145)			Raleigh (N = 3)			Tucson (N = 45)			Sioux City (N = 13)		
Average[1]	Ave. Months on Job[1]	E(#) Turn Over Model A[2]	E(#) Turn Over Model B[3]	Ave. Months on Job[1]	E(#) Turn Over Model A[2]	E(#) Turn Over Model B[3]	Ave. Months on Job[1]	E(#) Turn Over Model A[2]	E(#) Turn Over Model B[3]	Ave. Months on Job[1]	E(#) Turn Over Model A[2]	E(#) Turn Over Model B[3]	Ave. Months on Job[1]	E(#) Turn Over Model A[2]	E(#) Turn Over Model B[3]
March, 2008	29	17 8%	34 17%	33	10 7%	27 19%	7	0	1 33%	6	4 9%	6 13%	6	3 23%	0
April, 2008	17	44 22%	50 25%	12	19 13%	45 31%	0	0	0	5	15 33%	5 11%	10	10 77%	0
May, 2008	30	10 5%	29 14%	16	4 3%	23 16%	5	1 33%	0	13	6 13%	6 13%	0	0	0
June, 2008	23	1 1%	20 10%	19	1 1%	11 8%	0	0	0	9	0	6 13%	12	0	3 23%
July, 2008	2	0	45 22%	1	0	21 15%	0	0	0	1	0	14 31%	14	0	10 77%
Sept, 2008	0	0	9 4%	0	0	3 2%	9	0	1 33%	0	0	6 13%	0	0	0

1. Average month of turnover based on average forecasted job tenure of Models A and B. The first three cells in the table indicate Model B forecasted 34 CCOs to turnover in March, 2008, Model A forecasted 17 CCOs to turnover in March, 2008, and the average number of months of job tenure for these 17 & 34 individuals is expected to be 29.
2. Model A derived from only those individuals who were hired and turned over between January, 2005 and February, 2008.
3. Model B derived from all individuals hired between January, 2005 and February, 2008.

The last 12 columns of Table 5 forecast turnover frequencies and average job tenure of those leaving for various specific office locations for the next six months. In fact, Table 5 is a snap shot of output from an Excel spreadsheet developed to create a constant rolling 6-month turnover forecast by location. As new employees are hired, Equation 4 forecasts each CCO's job tenure using her/his personality, biodata score, and the season s/he was hired. Excel then updates Table 5 using each newly hired CCO's forecasted job tenure automatically. The corporate office and local call centers use the latest Table 5 to plan recruiting and hiring efforts over the next 6 months. High average number of months of those predicted to turnover would suggest a problem at one or more locations that needs exploration - a sudden spike in high job tenure CCOs turning over suggests something is going on. Or, as my more academic colleagues would say, it suggests some discrete change occurred at that location worthy of investigation.

Finally, we examined relationships between recruiting source and job tenure. Table 6 contains job tenure descriptive statistics for each recruiting source. Curiously, Past Employees have the lowest median job tenure. Applicants referred from the Arizona Republic and Yahoo.com where the only source of applicants with median job tenure greater than 100 days for those who had already turned over. AOL and Monster.com had the highest median job tenure for those who had yet to turnover, while the job tenure of their recruits who had turned over was fairly short (65 and 67 days, respectively).

HR Policy and Practice Implications

It remains to be seen whether Model A or B predicts best or if prediction is consistent across locations. However, by August, 2009 we will know how well the first 12 monthly Table 5 forecasts compare to actual number of CCOs turning over and average job tenure of those who did turn over. At that time we might examine whether some weighted combination of Model A & B predictions performs better than either one alone. Once we identify a preferred forecasting model or combination of models, we would modify the Excel spread sheet tool used to generate monthly Table 5 predictions to reflect the revised forecasting method.

Finally, seven recruiting sources all had median job tenures for CCOs who turned over that were at least 10

More on Recruiting Source. An alternative approach that immediately takes into account recruiting source would use a procedure called analysis of covariance (ANCOVA). This analysis tool permit us to see how well continuous predictors (e.g., CCO applicant test scores) and discrete predictors (e.g., recruiting source) together predict business metrics of interest. With the current CCO data, I would drop the "Research" recruiting source with extremely infrequent applicants. If results suggested Recruiting Source contributed significantly to predicting job tenure, HR professionals at the financial services firm will need to increase applicant flow from high job tenure recruiting sources. Increasing CCO applicants beyond the N =25 recruited from Yahoo.com might be possible and be a viable source for all CCO locations. The *Arizona Republic* newspaper is likely not a viable source of applicants for all CCO locations. However, given referrals from current employees also yields CCO applicants with almost 94 days of job tenure, I would also attempt to generate as many CCO applicant referrals from those hired through Yahoo.com, the *Arizona Republic*, and any other hire job tenure applicant source.

days longer than the 80 day median found in the entire sample. Yahoo.com exhibited the highest median job tenure of 127 days for those who subsequently turned over. We could estimate Equation 4 separately for high volume recruiting sources. Separate estimates of Equation 4 forecasts for each recruiting source might increase overall prediction accuracy. The "More on Recruiting by Source" sidebar briefly describes how a more advanced statistical procedure called analysis of covariance (ANCOVA) does this.

The next case addresses voluntary among current employees in a quarrying operation. The HR policy examined in Case I's financial services firm involved two selection tests used on all applicants. Predictions of voluntary versus involuntary turnover were examined simply sample sizes were large enough to permit their examination separately.[12] Results suggested use of the two selection tests could predict job tenure regardless of subsequent reason for turnover. In contrast, the HR intervention of choice in Johnson Granite and Quarry (i.e., change in pay) only affected

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[12] Involuntary turnover typically does not occur with often enough to yield sample sizes needed to find x→y relationships even when such relationships exist.

current employees, and no information was provided on employees who were terminated for cause.

Table 6: Job Tenure for First Measure of Recruiting Source[1]

SOURCE	Research		Internet		Referral from Current CCO		Advert.		Walk In		Job Fair		Past Employee	
	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover
N	4	2	216	164	22	91	183	131	22	16	22	16	12	15
Minimum	18	138	0	12	0	12	0	19	0	96	0	96	9	47
Maximum	106	138	529	579	350	551	524	558	350	537	350	537	158	411
Median	75.5	128	78.0	313	93.5	320	85.0	250	93.5	316.5	93.5	316.5	58.5	229
Mean	68.8	138	114.6	294.5	113.0	304.0	113.5	247.3	113.0	302.3	113.0	302.3	62.7	204.7
SD	41.9	0	101.2	126.5	100.8	133.9	02.3	134.2	100.8	103.2	100.8	103.2	40.9	124.3

SOURCE	Arizona Republic		Yahoo		American on Line		Miami Herald		College Campus		Monster	
	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover
N	39	26	12	13	11	11	16	7	12	8	61	40
Minimum	0	19	29	12	26	103	16	47	12	103	2	26
Maximum	310	523	314	397	347	425	413	495	227	411	529	537
Median	102	295	127	264	65	341	96	320	96.5	337.5	67	358.5
Mean	117.6	288.7	150.9	228.8	139.9	310.0	117.5	265	97.1	296.4	101.0	340.8
SD	83.9	106.3	107.3	141.1	112.8	103.4	95.6	167.4	59.8	115.7	108.2	121.9

SOURCE	Employment Guide		Career Builder		Other	
	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover	Turned Over	Yet to Turnover
N	35	34	55	30	94	75
Minimum	0	26	4	47	0	12
Maximum	367	523	412	523	393	570
Median	78	152	84	288	78	278
Mean	96.1	191.9	112.5	286.0	105.2	260.7
SD	79.9	121.6	93.5	136.5	94.2	130.0

1. Some of these categories are subsequently broken down into smaller subcategories (e.g. Advertising contains figures reported separately for the Arizona Republic, Miami herald, and Employment Guide). Further, only sources with N $\geq$ 10 were reported.

Case II: Johnson Granite and Quarry, Inc.

Johnson Granite and Quarry, Inc., or JGQ, is a family owned and operated granite, sand, and gravel quarrying business in a large Midwestern city. At the time of this analysis, JGQ employed 142 unskilled, semi-skilled, and skilled quarry workers and 18 exempt employees.[13] Then and now it supplies residential and commercial construction contractors throughout 20 Midwest states with sand and gravel aggregate for use in concrete driveways, foundations, retaining walls, and fence footings. It also provides custom cut and polished granite counter tops, flooring, and trim to residential and commercial builders nationwide. Midwestern homeowners made up 90% of JGQ sales until around 1970, when demand started to increase and shift from residential and commercial builders. By 1990 residential and commercial builders constituted close to 90% of sales.

The current JGQ pay system reflects the following policies:

1. All incumbents received the same, flat hourly wage in each job – no performance-based or seniority-based pay caused people in the same job to be earning different hourly wages.
2. Walk-ins and print-media ads attracted applicants from outside the company for almost all openings.
3. The average cost to recruit, hire, train, and process employment paperwork was ~ $800 for each nonexempt employee hired.
4. Some turnover was acceptable because the Johnson brothers believed a slightly unstable work force kept out unions.
5. Each employee received a "standard" benefit package that was almost identical in cost and composition across all granite and quarry companies nationwide. Benefit cost averages $1000 per employee, or $142,000 total annual cost for 142 nonexempt employees.

[13] Johnson Granite and Quarry is an amalgam of three or four real quarrying operations. The late Dr. Frederick Hills was kind enough to ask me to help him address turnover problems among these firms many years ago. I cobbled together information from this effort to create the data presented here.

Salaries at JGQ were competitive in the labor market when the founder retired from operational responsibilities in 2000, leaving ownership and management responsibility to his three children. Unfortunately, as wages and prices slowly rose over the next eight years, JGQ did not adjust its salaries as fast. In fact, JGQ was currently paying just above the federally mandated minimum wage for its entry-level unskilled quarry worker positions. Voluntary turnover increased quickly, though the Johnsons were not concerned because the labor market was loose and they could always find replacements willing to work for the lower wages JGQ paid. After all, as one of the Johnsons said after a monthly management team meetings, "somebody has to be the 'low wage employer' in the market, so it might as well be us!" Unfortunately, as the labor market tightened, JGQ's HR manager found it increasingly difficult to maintain enough workers to meet customer demand – voluntary turnover was too high and JGQ often couldn't attract enough applicants to fill available openings, leading to delays in filling customer orders, in receiving payment for those orders, and possible loss of business. Further, JGQ's total cost of replacing someone who voluntarily turns over, including recruiting, interviewing, training, and administrative overhead costs, was conservatively estimated at \$800. JGQ incurred 126 x \$800 = \$100,800 in extra HR costs due to voluntary turnover last year.

Don't Jump to Conclusions. This case is set up to show a pay system's relationship with voluntary turnover. The real JGQ HR manager would gather information from a number of sources and possibly do one or more pilot studies to be sure changes in the pay system are likely to have the biggest effect on voluntary turnover. I rarely encounter situations in one and only one HR system could address an HR problem. Usually a combination of changes in recruiting, personnel selection testing, compensation systems, job redesign, and/or training will address the business metric problem. To keep things relatively simple for purposes of the Johnson Granite and Quarry case, we only examine the pay system → voluntary turnover relationship here. In the real world, HR professionals make sure any increase in voluntary turnover was due to employees' feeling unfairly paid before tinkering with wages.

JGQ's HR manager and his team carefully examined past voluntary turnover levels, the cost of that turnover, and JGQ's ability to find applicants to fill openings caused by voluntary turnover. Even in the worst of times, the JGQ HR team had been able to attract applicants to fill open positions and meet customer demand for gravel and granite when annual voluntary turnover was 45% or less. The HR team presented its analyses and preliminary conclusion at the next monthly management meeting. After asking a few questions of clarification, the management team asked the HR team to generate one or more recommendations to change JGQ pay levels that both 1) reduced turnover to the 'acceptable" target level of ~ 45% and 2) JGQ could afford. With 142 employees, 45% turnover would lead to .45 x 142 ≅ 60 quits and incur 60 x \$800 = \$48,000 in HR-related turnover costs.

Within the next 4 weeks the HR team had assembled information contained in Table 7-Table 9. Table 7 contains descriptive information about the 142 unskilled, semi-skilled, and skilled JGQ exempt employees across 10 unskilled, 10 semi-skilled, and 10 skilled job titles.

Table 7: Job Evaluation, Current Pay, and Voluntary Turnover Rate

Job[1]	Job Evaluation Points	Current Hourly Rate	Number of Positions	Annual Quits	% Voluntary Turnover
1_{us}	245	$5.85	10	7	70.00%
2_{us}	250	$5.85	10	5	50.00%
3_{us}	250	$5.95	5	3	60.00%
4_{us}	255	$6.15	5	2	40.00%
5_{us}	255	$5.95	6	5	83.33%
6_{us}	260	$5.75	6	6	100.00%
7_{us}	260	$6.05	6	4	66.67%
8_{us}	260	$6.15	6	3	50.00%
9_{us}	265	$6.55	6	2	33.33%
10_{ss}	265	$6.90	6	0	0.00%
11_{ss}	265	$7.00	5	1	20.00%
12_{ss}	270	$6.70	5	3	60.00%
13_{ss}	270	$6.70	5	3	60.00%
14_{ss}	270	$7.10	5	0	0.00%
15_{ss}	280	$7.20	5	1	20.00%
16_{ss}	285	$7.20	5	0	0.00%
17_{ss}	290	$7.30	5	2	40.00%
18_{ss}	290	$7.50	5	0	0.00%
19_{ss}	300	$7.40	4	3	75.00%
20_{s}	300	$7.60	4	7	175.00%
21_{s}	300	$7.70	3	5	166.67%
22_{s}	305	$7.60	3	7	233.33%
23_{s}	305	$7.50	3	12	400.00%
24_{s}	310	$8.00	3	5	166.67%
25_{s}	310	$7.70	3	6	200.00%
26_{s}	320	$7.80	3	12	400.00%
27_{s}	320	$8.05	3	5	166.67%
28_{s}	330	$8.25	3	5	166.67%
29_{s}	330	$8.35	2	5	250.00%
30_{s}	340	$8.55	2	7	350.00%

1. US = unskilled, SS = semi-skilled, & S = skilled.

The HR team had created and implemented a point-factor job evaluation system in the early 1990's and taken steps to keep it current as jobs changed over time. A standing job evaluation committee consisted of a compensation specialist from the HR team, 9 exempt employees (3 unskilled, 3 semi-skilled, and 3 skilled), and two first level supervisors who were deemed "subject matter experts" due to their extensive knowledge, experience, and skill in these 30 jobs. The point factor job evaluation system first identified "compensable factors," or tasks, duties, responsibilities, working conditions, knowledge, skill, or ability requirements deemed worthy of compensation in a job. The job evaluation committee then identified and assigned points to compensable factors within each job. The sum total of all points assigned compensable factors in each of the 30 jobs is found Table 7's second column. The third column contains the current hourly wage each job receives, while columns 4, 5, and 6 contain the number of positions, voluntary quits, and percentage voluntary turnover rate (column 5 ÷ column 4 = column 6).

Table 8: Wage and Salary Surveys

Job	Labor Market W & S Survey			Product Market W & S Survey
	25th Percentile	50th Percentile	75th Percentile	
1	$5.75	$5.95	$6.15	$6.20
3	$6.05	$6.25	$6.45	$6.45
7	$6.35	$6.45	$6.55	$6.55
13	$6.45	$6.80	$7.10	$6.95
15	$7.00	$7.40	$7.85	$7.05
17	$7.20	$7.50	$7.85	$7.25
20	$7.40	$7.70	$8.05	$7.60
24	$7.85	$8.25	$8.65	$7.70
26	$8.25	$8.65	$9.05	$8.05
29	$8.55	$9.05	$9.55	$8.15

Finally, Table 8 identifies 10 key or benchmark jobs that 1) have large number of employees flowing back and forth between the external labor market and JGQ and 2) occur in a large number of employers with nearly identical task, duties, and responsibility profiles. The "labor market" consists of all firms hiring unskilled, semi-skilled, and skilled labor from the same applicant pool as JGQ for applicants for these 10 key jobs. N = 200 labor market competitors responded to the Table 8's wage and salary survey. JGQ also fills vacancies in the other 20 jobs primarily from the external labor market (i.e., promotion from one of the 10 benchmark jobs), though the 20 non-key jobs are fairly unique to JGQ. Table 8 reports recent results from both Labor Market and Product Market wage and salary surveys for these 10 jobs. Table 8 reports the 25th, 50th, and 75th percentile wages paid for these jobs by over 200 employers of the 10 key jobs in the regional labor market. Product Market wage and salary survey results were obtained from 15 firms that directly compete with JGQ in selling sand, gravel, and granite products to residential and commercial builders nationwide. These 15 product market competitors are geographically diverse and may or may not obtain their workers from JGQ's labor market. So, while the "going" or typical wage paid for Job 1 in JGQ's labor market is $5.95 (i.e., the median), JGQ's product market competitors pay an average of $6.20. If JGQ's paid a wage equal to the $5.95 median wage available from other employers in the area, JGQ would still enjoy a $.25 cost advantage relative to its product market competitors. In fact, JGQ is currently paying $5.85 an hour, somewhere below the 50th percentile but above the 25th percentile wage applicants could get elsewhere in the area, yielding a $.35 cost advantage to its gravel and granite competition. In contrast, product market competitors are paying $8.15 an hour for job 29, while the JGQ is paying $8.55 an hour. As $8.55 is also the 25th percentile wage paid in the labor market, JGQ is already at a $.50 cost disadvantage while paying very close to the lowest wage in the area.

Ok, now what do we do? Well, let's revisit our goal. Analysis by JGQ's HR team, confirmed at their last monthly management meeting, suggested enough applicants could be generated through existing recruiting sources to fill positions left open by a 45% voluntary turnover rate. Our charge is to identify one or more pay plans expected to cause voluntary turnover to be less than or equal to 45% and that JGQ can afford. We will first estimate what JGQ can afford, then determine the cost of alternative pay systems predicted to reduce turnover to ~ 45%.[14] The current voluntary turnover rate is 88.7%, as Table 7 shows 126 individuals voluntarily turned over out of 142 employees working in these 30 jobs, and 126 ÷ 142 = 88.7%.

How Much Can JGQ Afford?

Current total hourly wage bill for all 142 employees will equal the number of employees in each job times the job's hourly wage, added up over all 30 jobs, or

$$2000\sum_{i=1}^{k} n_i y_{current\ \$} + C_T + C_B$$

Equation 5

where 2000 = number of annual work hours (50 weeks at 40 hours per week), k = 30 jobs, n_i = number of employees in job i, $y_{current\ \$}$ = current wage for job i, C_T = \$800 x total number turned over = total cost of voluntary turnover, and C_B = \$142,000 = total cost of benefits. Using n_i from column 4, and $y_{current\ \$}$ from column 3 in Table 7, $\sum_{i=1}^{30} n_i y_{current\ \$} = \$966.70$. C_T = \$100,800, so JGQ's total annual labor cost (excluding benefits) is \$966.70 x 2000_{hours} + \$100,800 + \$142,000 = \$2,075,400.[15]

It is probably safe to assume JGQ cannot afford to pay more for labor then competitors in the sand, gravel, and granite quarrying business pay. As economists say, in a perfectly competitive economy, JGQ and its competitors will not be able to charge meaningfully different prices for the sand, gravel, and granite they produce. Assuming other variable and fixed costs

[14] The order here is not important. I simply prefer to know what budgetary limits might exist before I start crafting HR solutions to a problem.
[15] Fifty annual work weeks x 40 hours per week = 2000 hours annually.

are comparable (e.g., cost of raw materials, capital, utilities, etc.), JGQ and its product market competitors should have about the same monies left over to pay labor.[16] So, from Table 8 we can determine how JGQ compares on labor costs for 10 key jobs relative to its product market competitors. How do JGQ's wages compare for the other 20 jobs?

The bad news is that these 20 "nonkey" jobs contain unique configurations of tasks, duties, responsibilities, skill requirements, and other "compensable factors" that are not comparable to job content in other organizations. The good news is that the point factor job evaluation system broke all 30 jobs down into basic compensable factors before assigning points based on the relative value of each factor. Two jobs with the same total compensable factor points were viewed by the job evaluation committee as delivering equal value to the firm, even though the jobs may consistent of very different profiles of compensable factors. JGQ's jobs 2 and 3 received 250 points from the job evaluation process, and hence judged by JGQ's job evaluation committee as making contributions of equal value to the firm. Recall, Job 3 was a key job, while Job 2 was not.

Does this mean JGQ can afford to pay Job 2 as much as Job 3? The answer is "yes, if the job evaluation system accurately captured and assigned points to all compensable factors contributing to JGQ's jobs." A quick examination of Table 8 suggests JGQ's job evaluation system yielded point totals consistent with what JGQ's labor market and product market competitors were paying for these jobs – as job evaluation points go up, hourly wage goes up in both the labor market and product market. A poor job evaluation system would assign points in

[16] See Mahoney (1979) for a discussion of marginal revenue product theory and how it justifies use of Product Market wage and salary survey data when estimating ability to pay.

a way that did not reflect a job's true value to the firm, causing point totals to be inconsistent with the 10 key job market wages.

Great! If the job evaluation points are a good measure of job worth, then all we need is some way to turn the points into an estimate of how much each of JGQ's 20 unique jobs would have been worth to JGQ's product market competition! Recall Table 7 & Table 8 give us point values and Product Market wage and salary survey results for 10 key jobs, respectively. If we regress Product Market wage and salary survey wages ($y_{pm\$}$) onto job evaluation points (x_{points}), we could estimate the correlation $r_{x_{points}y_{pm\$}}$ and Equation 6 below:

$$\hat{y}_{pm\$} = b_0 + b_1 x_{points}$$

Equation 6

Plugging the points and $y_{pm\$}$ values from Table 7 and Table 8 into Excel yields . . .

$$\hat{y}_{pm\$} = \$.688447 + \$.02279 x_{points}$$

Equation 7

. . . and $r_{x_{points}y_{pm\$}} = .99$. Wow, $r_{x_{points}y_{pm\$}} = .99$ suggests JGQ's point factor job evaluation system is strongly related to wages paid by JGQ's product market competitors, giving us even more confidence in the quality of JGQ's job evaluation system. Equation 7 estimates a job evaluated to be worth 0 points is worth ~ 69¢ an hour,[17] and each point added by a job's compensable factors increases its hourly value to sand, gravel, and granite quarry firms by 2¼¢.

Let's assume the relationship between product market value and job evaluation points is true for points assigned to all compensable factors <u>regardless</u> of whether the compensable factors

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[17] While Equation 7 suggests a job with 0 points is worth 69¢ an hour, 0 points is outside the range of the 10 job point totals used in the analysis that generated Equation 7. I would never rely on estimates of jobs' product market wages when their points that fall meaningfully outside the range of point values used to produce Equation 7.

are in one of the 10 key jobs or one of the 20 nonkey jobs. This assumption is not too extreme, especially since $r_{x_{points}y_{pm\$}} = .99$ suggests the point factor system accurately portrays economic value of compensable factors found in the 10 key jobs. Replacing x_{points} in Equation 7 with job evaluation points from each of the 20 nonkey jobs lets us estimate what wages would have been paid <u>if</u> JGQ's gravel and granite competitors also employed people in jobs with these unique combinations of tasks, duties, responsibilities, etc. Once we have an estimate of what each of the 30 jobs would be paid in the product market from Equation 7 (i.e., $\hat{y}_{pm\$}$), we can insert these values into Equation 5. Doing so results in $\sum_{i=1}^{30} n_i \hat{y}_{pm\$}$=\$991.24.

So, now we know JGQ's current total hourly wage bill is \$966.70 while JGQ can afford to pay up to \$991.24 while still remaining in line with its product market competition. Further, we know current voluntary turnover incurs \$100,800 in turnover-related HR costs, while 45% annual voluntary turnover would incur \$48,000 in turnover-related HR costs. With ~\$25 an hour to play with, or \$25 x 2000 = \$50,000 in extra annual wage budget, <u>and</u> the \$100,800 - \$48,000 = \$52,800 in expected savings due to reduced turnover-related HR costs, a pay system that achieves a 45% voluntary turnover rate should give us a little over \$100,000 annually available to use in creating that pay system. To figure out how spend the \$100,000 in a way that decreases turnover, we have to explore how pay and turnover are related.

<u>How is Pay Related to Voluntary Turnover?</u>

Firms typically design compensation systems to pay an affordable, fair wage. Three classic ways employees can feel unfairly paid involve external, internal, and individual equity perceptions. External equity perceptions occur when employees feel fairly paid relative to what other labor market employers pay for the same job. Internal equity perceptions occur when individual employees feel fairly paid relative to other employees in the jobs immediately above and below them at JGQ. Finally, individual equity perceptions occur when an employee feels fairly paid relative to what other employees doing exactly the same job at JGQ are paid.

However, all JGQ employees holding positions within the same job are paid equally. Exceptionally high performing employees may still feel individual pay inequity because they are paid at the same level as their lesser performing peers. Unfortunately, without some measure of actual or perceived job performance, we cannot investigate how individual equity perceptions might predict voluntary turnover.

What if it is individual equity? If efforts described below did not yield a new pay system forecasted to reduce voluntary turnover, I would interview first level supervisors and select incumbents in the 30 jobs to determine whether individual inequity perceptions were a possible cause. If incumbents expressed frustration with their pay relative to others "who didn't work as hard," I would suggest JGQ management consider a performance management system that both evaluating individual worker performance and adjusted pay levels accordingly.

Do we have measures of external or internal equity perceptions? Well, no, not without actually asking both the 142 current employees and 126 employees who voluntarily turned over during the last year about their perceptions of pay fairness. Unfortunately, even if we asked employees about their perceptions of pay fairness, we might not get accurate answers. Self-serving bias would surely have some unknown influence on employee responses. We could, however, obtain indirect measures of external and internal pay equity "potential" for each job. Equation 8 & Equation 9 show how we might determine if indirect measures of external and internal equity predict turnover (T),

$$\hat{T} = b_0 + b_1 E_{external}$$

Equation 8

$$\hat{T} = b_0 + b_1 E_{internal}$$

Equation 9

where $\hat{T}$ = predicted turnover, $E_{external}$ = a measure of how close employees' current salaries are to what is paid in the external labor market, and $E_{internal}$ = a measure of how close employees' current wages are to what an internally equitable wage would be. Since we have a measure of percent voluntary turnover T for each job in Table 7, all we need are measures of $E_{external}$ and $E_{internal}$ to estimate Equation 8 & Equation 9.

How do we come up with $E_{external}$ and $E_{internal}$? Internal and external "fairness" perceptions involve employees comparing their current wage $y_{\$_i}$ to some internally or externally "equitable" wage, or $y_{\$internal}$ and $y_{\$external}$. This usually happens during informal conversations with other employees, friends, family, or acquaintances that go something like "did you hear that Craig Smith, the guy that used to work the loader here at JGQ last spring, got on at the Williams Quarry? I heard he is making $X.XX an hour!" In this instance, the JGQ employee hearing this statement immediately compares her/his hourly wage to $X.XX an hour in an external equity comparison. Similar conversations in which wage information about other JGQ employees is exchanged result in internal equity comparisons. Note, information accuracy is usually irrelevant and not considered in these conversations, as are any notions of sampling theory, i.e., whether Craig Smith's $X.XX wage is "typical," extremely high, or extremely low when compared to similar jobs elsewhere.

Clearly JGQ will not be privy to such conversations and hence cannot know with certainty what $X.XX figures might be influencing employees' pay equity perceptions. However, if we could somehow predict or estimate what these $X.XX values, i.e., estimate the kind of comparison wages we might expect employees to hear about ($\hat{y}_{\$internal_i}$ and $\hat{y}_{\$external_i}$) if/when they have wage-related conversations for each of the 30 jobs, we could subtract each job's current wage $y_{\$_i}$ from its internally equitable wages $\hat{y}_{\$internal_i}$ and externally equitable wages $\hat{y}_{\$external_i}$ as follows:

$$E_{external_i} = (\hat{y}_{\$external_i} - y_{\$_i})$$

Equation 10

$$E_{internal_i} = (\hat{y}_{\$internal_i} - y_{\$_i})$$

Equation 11

The farther away employees' current wages are from our estimates of internally ($\hat{y}_{\$internal}$) and externally ($\hat{y}_{\$external}$) equitable wages, the larger $E_{internal}$ and $E_{external}$ become, and the more JGQ employees are expected to feel unfairly paid. The more they feel unfairly paid, the more JGQ employees are expected to voluntarily turnover. If external and internal equity perceptions are causing voluntary turnover, we expect $E_{external}$ and $E_{internal}$ to have strong positive correlations with T <u>and</u> we could predict how much voluntary turnover T decreases if JGQ's wages were brought closer to $\hat{y}_{\$external}$ & $\hat{y}_{\$internal}$ using Equation 10 & 11. So, let's do that.

<u>Estimating</u> $\hat{y}_{\$external}$ & $\hat{y}_{\$internal}$. How do we come up with estimates of what equitable wages might be in the external labor market, or $\hat{y}_{\$external_i}$? Similarly, how do we come up with estimates of what might be considered internally equitable wages, or $\hat{y}_{\$internal_i}$? Recall we already estimated what the equitable product market wages ($\hat{y}_{pm\$}$) were for each of the jobs in Equation 6 & Equation 7 above. Modifying Equation 6 slightly, we can do the same thing to estimate what the equitable external labor market wage $\hat{y}_{\$external}$ might be:

Which Way do We Subtract? Equation 10 & Equation 11 could have been subtracted in either direction (e.g., $E_{external_i} = (y_{\$_i} - \hat{y}_{\$external_i})$ for Equation 10). However, because voluntary turnover problems led to our analyses, I assumed JGQ employees are most likely to feel under paid. Subtracting $y_{\$_i}$ from $\hat{y}_{\$internal_i}$ and $\hat{y}_{\$external_i}$ in Equation 10 & Equation 11 generally insures $E_{external}$ and $E_{internal}$ are both positive. Subtracting this way leads to the expectation that JGQ employees will perceive greater external and internal inequity as $E_{external}$ and $E_{internal}$ get bigger <u>and</u>, consequently, be more likely to voluntarily turnover.

$$\hat{y}_{\$external} = b_0 + b_1 x_{points}$$

Equation 12

Table 8 contains three different Labor Market wage and salary survey estimates of $y_{\$external}$ for 10 key jobs. As before, plugging the key jobs' 50th percentile Labor Market wage and salary survey data from Table 8 and job evaluation points from Table 7 into Excel permits us to estimate slopes and intercepts, yielding:

$$\hat{y}_{\$50} = -2.65 + .035x_{points}$$

Equation 13

where a job with 0 points is estimated to be worth -$2.65 if paid at the 50th percentile labor market level, and each additional point is worth 35¢ an hour. Equation 14 and 15 below show how points relate to wages paid at the 25th and 75th percentile levels in the labor market:

$$\hat{y}_{\$25} = -2.01 + .032x_{points}$$

Equation 14

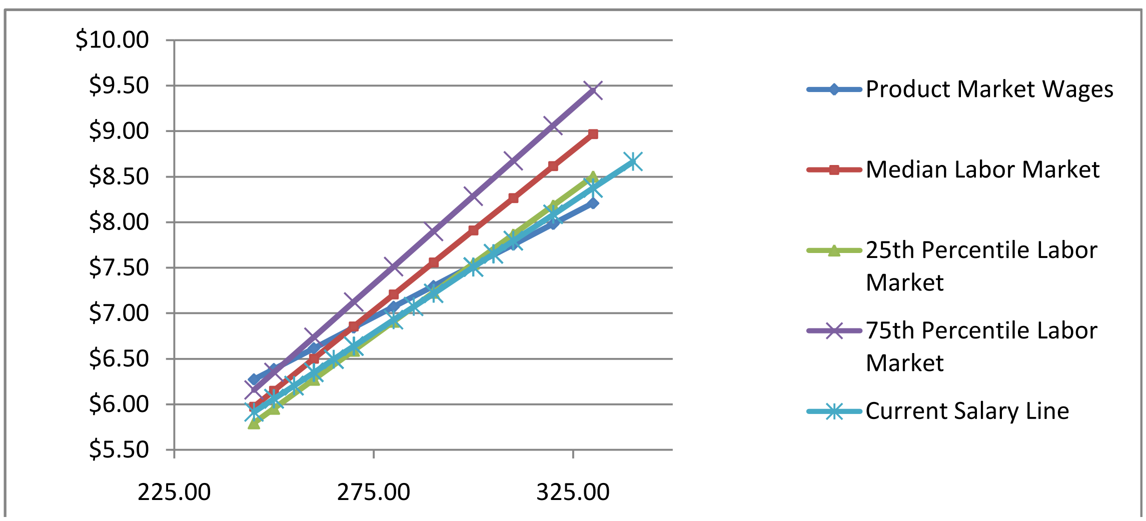
$$\hat{y}_{\$75} = -3.33 + .039x_{points}$$

Equation 15

Correlations r_{xy} for Equation 13, Equation 14, & Equation 15 are all > .99, which again suggest the point factor job evaluation system provides credible estimates of job worth. Equation 14, Equation 13, and Equation 15 indicate each point is worth 3.2¢, 3.5¢, and 3.9¢ when predicting the 25th, 50th, and 75th percentile labor market salaries, respectively. Importantly, Equation 13-Equation 15 give us three different ways of estimating $\hat{y}_{\$external} = \hat{y}_{\$25},\ \hat{y}_{\$50},\ \&\ \hat{y}_{\$75}$ for JGQ's 30 jobs. While experience tells me information about high wage jobs (e.g., 75th percentile jobs) tends to spread by word-of-mouth more often than about low wages jobs, we will nonetheless calculate $E_{external} = (\hat{y}_{\$external} - y_{\$_i})$ three different ways for $\hat{y}_{\$external} = \hat{y}_{\$25},\ \hat{y}_{\$50},\ \&\ \hat{y}_{\$75}$.

The first four lines in Figure 2 help us visually interpret Equation 7, Equation 13, Equation 14, & Equation 15 by plotting predicted values of $\hat{y}_\$$ against the 10 key jobs' point values. The last plotted turquoise line is for the values corresponding to $\hat{y}_{\$current} = b_0 + b_1 x_{points}$ (Equation 7) which was computed using all 30 values of $\hat{y}_{\$current}$ and x_{points} (the last key job in the first four plots, job #29, contains 330 points, while job #30 contains 340 points and causes the last turquoise line to extend a little further to the right). Importantly, the Current Salary Line plots wages each job would be paid if $y_{\$current_i} = -1.17 + .029x_{points_i}$ (i.e., <u>not</u> each job's current wage).

Figure 2: Plots of Labor and Product Market Wage Lines



Importantly, we can consider the current salary line $\hat{y}_{\$current}$ to be an "internally equitable" pay line since it predicts wages would be if the relationship between points and current pay were "fair," or the same, for all jobs. For example, jobs #5 and #6 received 255 and 260 points even though their current hourly wages are $5.95 and $5.75, respectively. Incumbents in job #6 might feel inequitably under paid when considering wages paid to incumbents in job #5 immediately below their job that, according to the job evaluation system, is supposedly not as valuable to

JGQ. Based on the "internally equitable" pay line $\hat{y}_{\$current}$ = -1.17 + .029x_{points} , job #5 should be paid \$6.21 while job #6 should be paid \$6.35 an hour if each job evaluation point was valued the same way for all jobs. So, if we can consider $\hat{y}_{\$internal} = \hat{y}_{\$current}$, and substituting $\hat{y}_{\$current}$ into Equation 11 creates $E_{internal_i} = (\hat{y}_{\$current_i} - y_{\$_i})$.

Now we can see whether paying to internally or externally equitable pay lines is likely to reduce voluntary turnover by computing r_{xy} for Equation 8 & Equation 9 (recall the correlation r_{xy} tells us how strong the x→y, or in this instance, the E→T, relationship is). Before we do that, let's first take a moment to consider a number of things about Figure 2 (some people like algebra and equations while others like geometry and pictures, so we will look at the pictures first!). For example, $\hat{y}_{\$current}$ (light blue X's) is above the product market wage line (blue diamonds) until about job #20 and is above the 25th percentile wage line (light green triangles) until about job #15. Hence, JGQ is currently paying below what it is able to pay for the first 20 jobs, and more than it is able to pay for jobs 21-30. As JGQ's total wage bill is currently ~ \$25 an hour less than it is able to pay while staying competitive in the product market, one could also say JGQ is underpaying jobs 1-20 by about \$25 more than it is overpaying jobs 21-30.[18]

This highlights an interesting fact. If there were equal numbers of employees in each of the 30 jobs, JGQ could afford any pay line that crosses the center of the $\hat{y}_{pm\$}$ product market pay line between jobs #15 & #16. Any pay line passing between jobs #15 & #16 from below the $\hat{y}_{pm\$}$ line will underpay jobs 1-15 by the same amount it overpays jobs 16-30. Similarly, any line

[18] We will ignore for the moment any cost savings that might become available for wages if turnover is reduced.

passing through jobs #15 & 16 from above the $\hat{y}_{pm\$}$ line will overpay jobs 1-15 by the same amount it underpays jobs 16-30. As JGQ has higher staffing levels in jobs 1-15, the cross over point for all affordable pay lines will actually be somewhere between jobs 10-14.

Can We Predict Turnover? If JGQ were to pay to one of these wage lines, which one is likely to reduce voluntary turnover the most? Table 9 contains current actual wage $y_{\$current}$, predicted internally equitable wage $\hat{y}_{\$internal}$, the different between current wage and internally equitable $E_{internal} = (y_{current} - \hat{y}_{\$internal})$, and percent voluntary turnover T. Table 10 describes how well voluntary turnover T is predicted by estimates of external equity (i.e., Equation 7 applied to 25th, 50th, and 75th percentile-based external equity comparisons) and an estimate of internal equity. A simple interpretation of Table 10's prediction equations is that if JGQ paid an internally equitable wage, $E_{internal} = 0$ and the predicted turnover rate for each of the 30 jobs would be 117%. If JGQ paid wages equal to the median external labor market wage, $E_{median} = 0$ and predicted voluntary turnover would be 28% for each job.

Table 9: Job Evaluation, Current Pay, and Voluntary Turnover Rate

Job #	$y_{current}$	$\hat{y}_{\$internal}$	$E_{internal}$	T = % Voluntary Turnover
1	$5.85	$5.92	$0.07	70.00%
2	$5.85	$6.06	$0.21	50.00%
3	$5.95	$6.06	$0.11	60.00%
4	$6.15	$6.21	$0.06	40.00%
5	$5.95	$6.21	$0.26	83.33%
6	$5.75	$6.35	$0.60	100.00%
7	$6.05	$6.35	$0.30	66.67%
8	$6.15	$6.35	$0.20	50.00%
9	$6.55	$6.49	($0.06)	33.33%
10	$6.90	$6.49	($0.41)	0.00%
11	$7.00	$6.49	($0.51)	20.00%
12	$6.70	$6.64	($0.06)	60.00%
13	$6.70	$6.64	($0.06)	60.00%
14	$7.10	$6.64	($0.46)	0.00%
15	$7.20	$6.93	($0.27)	20.00%
16	$7.20	$7.07	($0.13)	0.00%
17	$7.30	$7.22	($0.08)	40.00%
18	$7.50	$7.22	($0.28)	0.00%
19	$7.40	$7.51	$0.11	75.00%
20	$7.60	$7.51	($0.09)	175.00%
21	$7.70	$7.51	($0.19)	166.67%
22	$7.60	$7.65	$0.05	233.33%
23	$7.50	$7.65	$0.15	400.00%
24	$8.00	$7.80	($0.20)	166.67%
25	$7.70	$7.80	$0.10	200.00%
26	$7.80	$8.09	$0.29	400.00%
27	$8.05	$8.09	$0.04	166.67%
28	$8.25	$8.38	$0.13	166.67%
29	$8.35	$8.38	$0.03	250.00%
30	$8.55	$8.66	$0.11	350.00%

Note, red numbers in parentheses are negative.

Table 10: External & Internal Pay Equity and Turnover Prediction

Predictor	Prediction Equation	r_{TE}
$E_{internal_i} = (\hat{y}_{\$internal_i} - y_{\$_i})$	$\hat{T}_i = 1.17 + 1.86E_{internal_i}$	.39*
$E_{25\%tile_i} = (\hat{y}_{25\%tile_i} - y_{\$_i})$	$\hat{T}_i = 1.18 + 2.72E_{25\%tile_i}$	.60**
$E_{median_i} = (\hat{y}_{median_i} - y_{\$_i})$	$\hat{T}_i = 0.28 + 2.89E_{median_i}$	.74**
$E_{75\%tile_i} = (\hat{y}_{75\%tile_i} - y_{\$_i})$	$\hat{T}_i = -.45 + 2.56E_{75\%tile_i}$	.80**

* = p < .05, ** = p < .01

Interestingly, difference between current wage and 75th percentile labor market wage ($E_{75\%tile}$) predicted voluntary turnover most accurately at $r_{TE_{75\%tile}} = .80$. Further, if JGQ were to pay a 75th percentile labor market wage, predicted levels of voluntary turnover would be -45% for each job! One explanation for this might be that most workers probably don't see Labor Market wage and salary survey results and instead get most of their information about local available wage rates through word of mouth. My personal experience suggests news of an acquaintance who was just hired somewhere else at a low wage (e.g., 25th percentile) does not travel quickly. In contrast, news that someone doing a comparable job receiving a very high wage (e.g., 75th percentile) travels very fast, often inflated as it' is passed along, and consequently often has a strongest effect on fairness perceptions. However, one can never know with certainty exactly what wage information is available to employees from what sources. I have seen wage and turnover pattern where $E_{25\%}$ is the best predictor of voluntary turnover.

Predicting Voluntary Turnover. Those of you familiar with ordinary least squares multiple regression might guess that an even better prediction of voluntary turnover might come from the following equation:

$$\hat{T} = b_0 + b_1E_{internal} + b_2E_{25\%tile} + b_3E_{50\%tile} + b_4E_{75\%tile}$$

If this equation predicted voluntary turnover T much better than any of the simple regression equations in Table 10, it would mean the wage line that reduced voluntary turnover the most would be a weighted combination (where b_1 to b_4 would be the weights) of differences between current wages and an internally equitable wage line ($\hat{y}_{\$internal}$) and current wages and the 25th, 50th, & 75th percentile wage lines.

Curiously, internal equity was the weakest predictor of voluntary turnover, as elimination of internal inequity should yield 118% turnover in each job. This weak prediction is understandable once you realize that if JGQ paid wages equal to $\hat{y}_{\$25\%tile}$, $\hat{y}_{\$median}$, & $\hat{y}_{\$75\%tile}$, the new wage structure would also be just as internally equitable. Specifically, recall that $E_{internal_i} = (\hat{y}_{\$current_i} - y_{\$_i})$. We thought $\hat{y}_{\$current}$ captured a wage that might viewed as internally equitable because $\hat{y}_{\$current}$ results from taking current wages and redistributing them in direct proportion to job evaluation point totals. Unlike JGQ's current wage structure, jobs with equal point totals would receive the same $\hat{y}_{current\ \$}$ and jobs with different point totals would receive different $\hat{y}_{\$current}$. However, each of the three $E_{external}$ prediction equations involving $\hat{y}_{\$25\%tile}$, $\hat{y}_{\$median}$, & $\hat{y}_{\$75\%tile}$ could be viewed as both externally and internally equitable since $\hat{y}_{\$25\%tile}$, $\hat{y}_{\$median}$, & $\hat{y}_{\$75\%tile}$ also distribute wages in direct proportion to job evaluation point totals. Hence, it is not surprising that $E_{75\%tile}$ predicted voluntary turnover twice as well as $E_{internal}$. $E_{75\%tile}$ may have been the strongest predictor of voluntary turnover simply because it reflected how different current salaries were from a salary that would be both internally equitable and on the high side of "fair" in the external labor market.

Alternative Pay Structures, Expected Turnover, and Cost. Of the four possible solutions examined above, paying to the median (50th percentile) external labor market wage rate is expected to yield 28% voluntary turnover and comes closest to our target 45% level. Table 11 compares current labor costs, "affordable" labor costs, and labor costs expected if JGQ's wage level was at the labor market median.

Table 11: Current vs. Affordable Labor Costs

	Current Wages & Turnover	Affordable Wages & Turnover	Median Labor Market Wage
Total Wage Bill	$1,933,400	$1,982,480	$1,991,750
Total HR-related Voluntary Turnover Costs	$100,800	$48,000	$32,000
Benefits Costs	$142,000	$142,000	$142,000
Total Labor Bill	$2,176,200	$2,172,480	$2,165,750

Paying to the median Labor Market wage line to obtain 28% annual expected voluntary turnover may not be "optimal" if only because JGQ can live with 45% annual voluntary turnover. Alternate solutions could permit some combination of lower wages and higher turnover costs as long as total costs remained affordable.

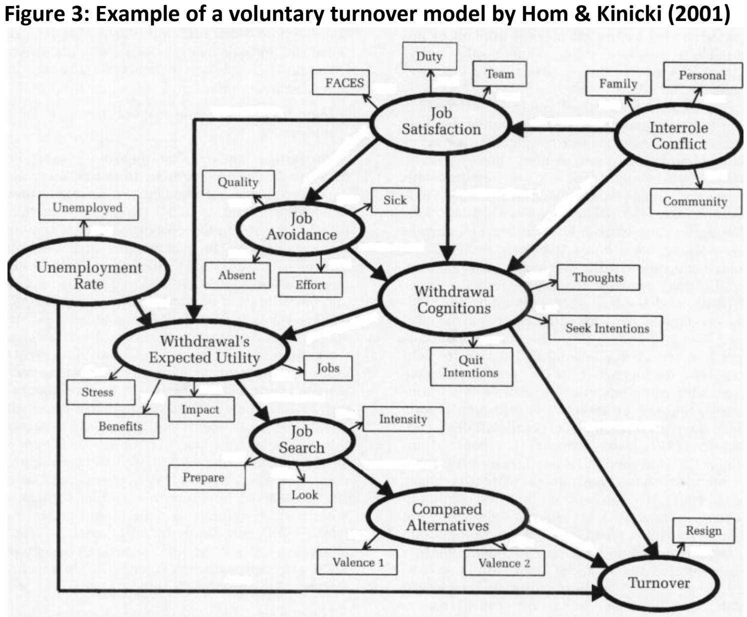
Trends and patterns in Table 7 might suggest alternative wage lines. For example, skilled jobs (#21-30) exhibit the highest voluntary turnover rates. In fact, 69 individuals had voluntarily turned from 28 skilled positions last year, while 31individuals had voluntarily turned over from 68 unskilled positions in jobs #1-10. JGQ might want to consider adopting a wage structure characterized by a relatively flat line for jobs #1-20 that then "bends" upward for jobs 21-30. A wage line that "kinked" between jobs #20 &#21 would result in a steeper slope, or larger number of pennies per job evaluation point, for the skilled jobs where voluntary turnover was highest. Essentially, JGQ would be robbing a little from Peter (i.e., employees in unskilled and semi-skilled jobs) to pay Paul (i.e., employees in skilled jobs).

One might even consider a "double kinked" wage line with a relatively steep slope for unskilled Jobs #1-10, a relatively flat slope for semi-skilled Jobs #11-20, followed by a steeper slope for skilled Jobs #21-30. In both the single and double kinked wage lines, extra monies diverted to jobs where 69 incumbents voluntarily turned over last year (i.e., Jobs #21-30) might reduce voluntary turnover further. If I were part of the JGQ HR team, I would recommend presenting two alternative wage lines to the JGQ management committee. The first would simply involve paying to the predicted median labor market wage line ($\hat{y}_{\$median}$ in Figure 2). The second wage line considered would have a single "kink," bending upward to pay more per point for Jobs #21-30. I would recommend adopting the $\hat{y}_{\$median}$ wage line for the coming year paired with re-analysis of the wage ↔ voluntary turnover relationship in 12 months. If skilled Jobs #21-30 still exhibited high voluntary turnover, I would then recommend slightly modifying the pay line to reflect a steeper slope and more money per point for skill jobs. Importantly, analyses conducted up to this point in time help us understand what pay system changes are expected to lower voluntary turnover rates. The key word in the last sentence is <u>expected</u>. We won't know whether voluntary turnover costs are actually reduced until we perform follow-up analyses 12 months after a new pay system is implemented. Forecasts are very helpful, but documentation of actual reductions in voluntary turnover-related costs combined with the absence of any production deadlines missed due to labor shortages is essential. JGQ's management committee should only value HR efforts if actual turnover rates and costs change in the expected directions 12 months from now.

Discussion

It is with some sadness that I have to say we have barely scratched the surface of issues related to employee turnover. It is with even more sadness that I realize the chapter is devoid of any theory or explanation of why employees voluntarily resign their positions. Theories or models of voluntary employee turnover do exist (Griffeth, Hom, & Gaertner, 2000; Hom & Kinicki, 2001; Mobley, Griffeth, Hand, & Meglino, 1979; Price & Mueller, 1981). Figure 3 portrays possibly the best summary of the various models available.

Figure 3: Example of a voluntary turnover model by Hom & Kinicki (2001)



A quick look at Figure 3 tells us the unemployment rate, alternative jobs the employee might be considering, and "withdrawal cognitions" (a fancy way of saying "intention to quit") cause voluntary turnover. No fooling. Believe it or not, "scholars" have been arduously working to test and expand models like this since the mid-1970s. There is some evidence that measures of things like job satisfaction, organizational commitment, and intention to turnover from large scale employee attitude surveys weakly predict voluntary turnover. Unfortunately, I am not aware of any results showing voluntary turnover decreased after the firm tried to increase job satisfaction, organizational commitment, and/or reduce intention to turnover. Perhaps most troubling is the fact that all of these models assume every employee arrives at "withdrawal cognitions" the same way. I have to conclude models like these are of little use (they are of absolutely no use in managing involuntary turnover). They are of absolutely no use to managers trying to select applicants likely to have long job tenures (e.g., Case I above).

Kurt Lewin, a famous social psychologist, is widely quoted as having said "there is nothing as useful as a good theory." I agree completely. In fact, I would take it a step further in applied arenas like business administration and say "if a theory is not useful it is not very good."[19] Applied to theories of voluntary employee turnover, one has to conclude such theories are not very good. I consider the two cases described above as examples of "best practices" when managing turnover. Unfortunately, the absence of good theory in the presence of useful tools and "best practices" characterizes much of HR policies and practices.

[19] Clearly this is not true in basic sciences, where a theory has served a useful purpose if it motivates research that leads to better theory. Unfortunately for many of my more scholarly colleagues, business administration is not a basic science. I am constantly amazed at the amount of "scholarly" time and energy spent on topics that never come close to explaining anything of interest to line managers (e.g., organizational citizenship).

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Appendix

Cross Validation

I frequently describe situations in this text where we want to know how well some business metric (y) is predicted by some predictor (x). Predictors might include the financial services firms' personnel selection test scores in Chapter 4's Case I. Alternatively, they might involve measures of internal or external equity ($E_{internal}$ or $E_{external}$ from Equation 8 & Equation 9 above. In each instance I am estimating some prediction model $\hat{y} = b_0 + b_1x_1$ from some information gathered from a sample of current employees/applicants. However, I wish to use the prediction equation $\hat{y} = b_0 + b_1x_1$ to forecast values of $\hat{y}$ attained by some sample of future applicants or employees. Equation 4, reprinted below, attempts to predict job tenure from a personality test score, a biodata scale score, and season of the year an employee was hired.

$$\hat{y}_{job\ tenur\ e} = b_0 + b_1x_{personality} + b_2x_{biodata} + b_3X_{season}$$

Equation 4

"Ordinary least squares regression analysis" (OLS) is the method Excel uses to general an estimate of this equation. OLS regression generates estimates of b_0, b_1, b_2, & b_3 in C that "optimally" predict $y_{job\ tenure}$. Unfortunately, sometimes relationships exist between x and y in a sample that occur solely by chance. These relationships are not found in the population and appear in the sample by random chance. OLS regression analysis optimizes prediction so well that the resulting model reflects these chance relationships (if the chance x→y relationship had not existed in the sample, different values of b_0, b_1, b_2, & b_3 in Equation 4 would have resulted). Worse, when we use Equation 4 to predict future CCO applicants' job tenure, the same "chance" x→y relationships will not exist, causing poorer prediction of job tenure by Equation 4 relative to how well it did in the original sample. Put another way, sources of random error decrease

Equation 4's ability to predict future applicants' job tenure. Random sampling error in the original sample used to estimate Equation 4 and random sampling error among future applicant samples both lower predictive power (r_{xy} or $R_{y-x_1x_2x_3}$). Estimates of r_{xy} or $R_{y-x_1x_2x_3}$ obtained when Equation 4 was generated from the original sample will not accurately describe how predictive Equation 4 will be in future samples, as initial r_{xy} or $R_{y-x_1x_2x_3}$ estimates cannot reflect sampling error contributed by that future sample.

So, how do we estimate $R_{y-x_1x_2x_3}$ for Equation 4's predictions in that future sample? Cross validation. Simply stated, cross validation involves generating a prediction model from one portion of a sample, then seeing how well it predicts in a different portion of the sample. The simplest form of cross validation involves the following steps:

1. Start with a large initial sample, then randomly split the sample into two subsamples. The "calibration" sample is typically larger than the "cross validation" sample, though the cross validation sample must be large enough to detect (i.e., find statistically significant) the r_{xy} or $R_{y-x_1x_2x_3}$ you expect to find. For the moment, assume we have N = 800 in the calibration sample and N = 200 in the cross validation sample.
2. Estimate your prediction equation (e.g., Equation 4) in the calibration sample as well as its multiple correlation $R_{y-x_1x_2x_3}$.
3. Apply Equation 4 to the N = 200 cross validation sample. You will now have 200 values of actual job tenure y_i paired with 200 values of $\hat{y}_i$ created by combining each cross validation CCO's x_1, x_2, and x_3 with values of b_0, b_1, b_2, & b_3 from the calibration sample's Equation 4.
4. Use Excel to compute the simple correlation between the actual y_i value and predicted $\hat{y}_i$ value in the cross validation sample (i.e., $r_{\hat{y}y}$). This $r_{\hat{y}y}$ is the best estimate of what $R_{y-x_1x_2x_3}$ should be when taking into both sources of sampling error. Stated another way, $r_{\hat{y}y}$ is the best estimate of how well Equation 4 will actually predict job tenure in some future sample.

Of course, no two cross validities $r_{\hat{y}y}$ will be the same unless each one happened to create identical calibration and cross validity samples is Step 1. This suggests that some cross validities might be inappropriately high or low depending the random composition of the calibration and cross validation samples. There are a number of ways to get better estimates of $r_{\hat{y}y}$, though one has been shown to be much better than the others. I will first touch on why cross validities are especially important for empirically keyed biodata scores, then describe the ".632 bootstrap" method of estimating cross validity.

Cross Validities & Empirical Keys. The empirical keying procedure used in Case I captured all linear and nonlinear relationships between each biodata question and job tenure. "Linear" relationships are captured by a "straight line" prediction equation like $\hat{y} = b_0 + b_1 x_{item}$. "Nonlinear" relationships can look like any line with curves in it. Nonlinear relationships with one bend in the curve are captured by $\hat{y} = b_0 + b_1 x_1 + b_2 x_1^2$, with two bends are captured by $\hat{y} = b_0 + b_1 x_1 + b_2 x_1^2 + b_3 x_1^3$, etc.[20] The good news is that creating an empirical key based on the strength of simple straight line relationships between each response option and job tenure y_i (or any criterion), the key ends up capturing the strength of all linear and nonlinear relationships between biodata items and the criterion.[21] An empirical key developed to score Case I's 45 item biodata inventory containing 225 response options "optimizes" 225 different x→y relationships. This constitutes 225 opportunities to take advantage of chance x→y relationships caused by random sampling error. It is not uncommon for a biodata inventory's empirical key to exhibit criterion validities of $r_{xy} > .75$ in the calibration sample, only to see it drop to $r_{xy} \approx .25$ in the cross validation sample. Believe it or not, this was called "shrinkage" long before an episode of "Seinfeld" made the term famous. Regardless, severely inappropriate conclusions would be drawn using the Taylor-Russell or BCG utility models from Chapter 3 and

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[20] The empirical key described here does not capture interactive item→job tenure relationships that look like $\hat{y} = b_0 + b_1 x_{item\,1} + b_2 x_{item\,2} + b_3 x_{item\,1} + b_4 x_1 x_2$.

[21] As response options are dichotomous (0 = not selected, 1 = selected), all response option→criterion relationships must be linear. Prove this for yourself by drawing an XY plot on a piece of paper. When X can take on only two possible values, there is no way to draw anything other than a straight line relationship between X and Y.

calibration sample's estimate of $r_{xy} = .75$. In this instance, the "shrunk" estimate of $r_{xy} = .25$ is a more accurate representation of a biodata score's predictive power in future samples.

In contrast, Case I's personality test score summed points awarded to response options based on how well each response option reflected the personality construct of interest. Importantly, unlike the empirically keyed biodata score, personality scoring procedures did not "optimize" prediction of job tenure. OLS optimization only had a chance to operate once when Equation 4 estimated the regression coefficient b_1 associated with $x_{personality}$.

Estimating cross validities is generally a good thing to do whenever we want to generalize results from current samples to future samples. The more opportunities a prediction process has to take capture chance relationships, the greater shrinkage will be and the more important cross validation becomes.

.632 Bootstrap Cross-Validation. Efron and Tibshurani (1993, 1997) described and proved the ".632 cross-validation bootstrap" yields the best estimates of predictive power in future samples. The major assumption required by the procedure is that the sample you have in hand (i.e., the sample you would normally randomly split into calibration and cross validity samples) is representative of the population of interest. This is more restrictive than assuming a sample was randomly drawn from a population. However, even when randomly draw a sample from some population, we act as if the sample was representative of the population in drawing inferences from that sample. For example, in Chapter 2 we wanted to know whether business metrics differed depending on whether we trained new realtors under a new versus old training system. We gathered business metric information on 50 and 150 new realtors hired and trained under the new and old training systems, respectively. Importantly, the z statistic used assumed these were random sample drawn from some "population" of possible newly hired realtors.

Once we concluded the new training system yielded higher business metrics than the old training system, we effectively acted as if the population was exactly like the sample and recommended use of the new realtor training system with all future newly hired realtors. While using the z statistic required random sampling, we effectively acted as if the sample was representative of the population when it came time to implement policy. While "representative sampling" is not a stumbling block to use of bootstrapping procedures, we should nonetheless take every precaution to make sure the CCO sample in Chapter 4's Case I does not deviate in some extreme way from future CCO applicant populations.

Now, how do we do it? "Bootstrapping" involves taking a sample from our sample with replacement. What? While somewhat confusing when described in a single sentence, "bootstrapping" involves the following steps:

1. Draw a representative sample from the population of interest. Let's assume N = 1000 for this example.
2. Draw a sample of N = 1000 with replacement from the original sample of N = 1000. "With replacement" means . . .
    a. Select one CCO from the N = 1000, record all of that CCO's data (i.e., 225 biodata inventory response options and $y_{job\ tenure}$) in "line 1" of some Excel file, then put that CCO back into the original N = 1000 sample. Let's assume CCO #562 was the one chosen at random and recorded on line 1.
    b. Select one CCO from the N = 1000, record all of that CCO's data (i.e., 225 biodata inventory response options and $y_{job\ tenure}$) in "line 2" of the Excel file, then put that CCO back into the original N = 1000 sample. While not likely, there is a 1/1000 chance that this 2nd CCO is also CCO #562. There is a 999/1000 chance it will be one of the other original 1000 CCOs.
    c. Repeat sampling one CCO, recording her/his data in the Excel file, and putting the CCO back a total of 1000 times. The Excel file now contains a single "bootstrap" sample of N = 1000 CCOs drawn from the original N = 1000. By random chance, this process selects some CCOs more than once. In fact, if you will trust me on this, the Excel file is expected to contain data from ~ 632 different CCOs out of the original N = 1000. This is where the ".632" part of the ".632 cross-validation bootstrap" label comes from.
    d. We then identify which CCOs had not been randomly selected for inclusion in the n_b=1000 bootstrap sample. We expect 1000 – 632 = 368 CCOs not to have been selected as part of the n_b =1000 bootstrap sample. We then save the data (i.e., 225

biodata inventory response options and $y_{job\ tenure}$) for those ~ 368 CCOs into a separate Excel file.

3. Step 2 created a single bootstrap sample paired with a second file containing data on the ~ 368 CCOs not included in n_b = 1000 bootstrap sample. We next repeat Step 2 1000 times, creating b = 1000 bootstrap samples of n_b = 1000 CCOs paired with 1000 samples of the ~ 368 CCOs who did not appear in each bootstrap sample.
4. Develop empirical keys to predict job tenure from the 225 response options in each of the b = 1000 bootstrap samples.
5. Use the keys to create biodata scores $x_{biodata}$ in the second sample of ~ 368 CCOs paired with each of the b = 1000 bootstrap samples.
6. Calculate $r_{x_{bio\ data}\ y_{job\ \ tenure}}$ in each of the b = 1000 samples of ~ 368 CCOs. Average $\bar{r}_{x_{biodata}\ \ y_{job\ \ tenure}}$.

Steps 1-3 create b =1000 bootstrap "calibration" samples of n_b =1000 and b = 1000 "cross validation" samples with n_{cv} ~ 368. Steps 4-6 develop b = 1000 empirical keys, calculate the cross validities of those empirical keys $r_{x_{biodata}\ \ y_{job\ \ tenure}}$ in b= 1000 independent samples of ~ 368 CCOs <u>not</u> used to create the empirical key, before averaging those 1000 cross validities. Efron and Tibshirani (1997) showed that average cross validity $\bar{r}_{x_{biodata}\ \ y_{job\ \ tenure}}$ derived this way is a better estimate of predictive power in future samples than estimates derived any other way. Effectively, it averages 1000 cross validity estimates, so this should not be surprising. Case I's simple correlation between the biodata score and job tenure reported to the client was $\bar{r}_{x_{biodata}\ \ y_{job\ \ tenure}}$. Further, the multiple correlation $R_{y-x_1x_2x_3}$ reported for Equation 4 can be estimated from the original CCO data in Excel <u>or</u> using a more advanced statistical analysis software package (e.g., SPSS, Systat, or SAS) with only simple correlations between $y_{job\ tenure}$, $x_{personality}$, $x_{biodata}$, x_{season} and sample size as input. $R_{y-x_1x_2x_3}$ = .13 and .15 in Case I were computed using the latter procedure, with the cross validity estimate $\bar{r}_{x_{biodata}\ \ y_{job\ \ tenure}}$ as the biodata-job tenure correlation.

Unfortunately, no commercially available software computes .632 bootstrap cross validities. I wrote a custom program in a package called Resample Stats (www.resample.com) for this purpose. My purpose here is to make HR professionals more informed consumers of tools needed to assess HR practice → business metric relationships. I want HR professionals to conceptually understand what cross validation involves and why it is useful. HR professionals need more advanced graduate-level training than I provide here before attempting advanced techniques (e.g., .632 bootstrap cross validation or ANCOVA mentioned earlier in Chapter 4).