Temporal Patterns of Functional and Dysfunctional Employee Turnover

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Abstract

This study examined temporal patterns in collective employee turnover over a 75 month interval. Time series models were fit to subgroups of functional and dysfunctional turnover. Dysfunctional turnover was defined as voluntary separation among high and average performers and functional turnover was defined as voluntary separation of low performers. Results provided support for the hypothesis that temporal patterns of functional and dysfunctional turnover differ. Patterns among high and average performers were similar, such that employee turnover across several global regions increased during or near July. In contrast, employee turnover among low performers tended to spike during or soon after October. Forecast (prediction) accuracy of turnover differed across groups based on individual performance level. Specifically, turnover among low and average performers was forecast with greater accuracy than overall aggregated turnover or turnover among high performers, the latter being the most difficult to forecast. After time-dependent variation (autocorrelation) was removed from global turnover among high, average, and low performers, these series were cross-correlated with similarly cleaned organizational performance outcomes (i.e., net sales, operating income, diluted net earnings per share). Results from these analyses indicated that organizational performance had a lagged negative relationship with turnover among high performers. The dynamic nature of the turnover and performance variables examined underscores the importance of considering employee turnover as a continuous process. As such, employee turnover should be proactively managed over time.

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Chapter 1

Introduction

Employee turnover has been studied from a variety of perspectives across several disciplines, including Organizational Behavior, Industrial-Organizational (I-O) Psychology, Human Resource Management (HRM), Economics, Sociology, Accounting, and Industrial Relations (Mobley, 1982). This is not surprising, given the well-documented negative consequences of excessive employee turnover (Hausknecht, Trevor, & Howard, 2009; Hinkin & Tracey, 2000; Price, 1989; Morrow & McElroy, 2007; Simons & Hinkin, 2001; Tracey & Hinkin, 2008).

One method of categorizing turnover is to label it as either functional or dysfunctional to the organization (Campion, 1991). Functional turnover improves organizational functioning, whereas dysfunctional turnover is disruptive and costly to organizations (Dalton, Todor, & Krackhardt, 1982). The present study builds upon previous research on functional and dysfunctional turnover and literature examining turnover from a longitudinal perspective. Specifically, the aim of this study is to examine patterns of functional and dysfunctional turnover within a time series framework. Previous research has demonstrated that the antecedents of functional and dysfunctional turnover differ and that turnover antecedents change over time. Based upon these findings, it is hypothesized that functional and dysfunctional turnover exhibit different patterns over time. This hypothesis is tested using time series analysis of several years of monthly turnover data from a large consumer products company. As stated, previous research supports the present research in two ways: (1) functional and dysfunctional turnover often have different antecedents (e.g., Hart, 1990; Hollenbeck & Williams, 1986; Johnson, Griffeth, & Griffin, 2000; Johnston & Futrell, 1989; Miller, 1987; Park, Ofori-Dankwa, & Bishop, 1994; Williams, 1999); and (2) the antecedents of turnover at the individual-level have been shown to change over time (e.g., Dickter, Roznowski, & Harrison, 1996; Johnston, Griffeth, Burton, & Carson, 1993; Kammeyer-Mueller, Wanberg, Glomb, & Ahlburg, 2005; Sturman & Trevor, 2001; Youngblood, Mobley, & Meghno, 1983).

In the following section, relevant turnover literature is reviewed. First, turnover is defined. Then, performance as an antecedent of turnover is discussed. Next, studies examining turnover functionality are summarized. Then, the relationship between turnover and time is discussed, and hypotheses based on previous research are offered.

Chapter 2

Literature Review

Turnover Defined

Turnover is defined as "the cessation of membership in an organization by an individual who received monetary compensation from the organization" (Mobley, 1982; p. 10). At the individual level, turnover has often been viewed as a dichotomy between staying with an organization and leaving the organization (Campion, 1991). At the collective level, turnover can also be viewed as the number or percentage of employees who leave a group, unit, or organization during a specified time period (Hausknecht & Trevor, 2011).

The amount of published research on collective turnover has increased in recent years across several academic disciplines. This interest in a more macro-level perspective of turnover is understandable given findings of collective turnover predicting organizational productivity, performance, and customer service (Hausknecht & Trevor, 2011). Although individual-level turnover is very important for explaining why employees stay with or leave an organization, collective-level turnover is also very important to organizations for human resources (HR) planning. For example, strategic HR planning could benefit from an awareness of patterns of different groups of employees separating at different rates or at different times of the year. Turnover in the present study is examined at the collective level as the number of employees leaving an organization each month over several years.

Many types of turnover can be found in organizations (Campion, 1991). For example, turnover can be classified as voluntary or involuntary, avoidable or unavoidable, and functional or dysfunctional. Voluntary vs. involuntary turnover pertains to whether or not the termination of employment was initiated by the employee or the organization, avoidable vs. unavoidable pertains to the feasibility of preventing the turnover by the organization, and functional vs. dysfunctional refers to turnover that is desirable (e.g., when poor performers leave; functional) as opposed to turnover that is undesirable (e.g., when average or strong performers leave; dysfunctional). Dysfunctional turnover has received attention from HR practitioners and researchers who note the utility of turnover functionality as opposed to overall frequency (e.g., Beadles, Lowery, Petty, & Ezell, 2000; Campion, 1991; Hollenbeck & Williams, 1986; Park et al., 1994).

Performance as an Antecedent of Turnover

Individual employee performance has been put forth as an important antecedent of turnover both theoretically and empirically (Bycio, Hackett, & Alvares, 1990; McEvoy & Cascio, 1987; Williams & Livingstone, 1994; Zimmerman & Darnold, 2009). Several meta-analyses have demonstrated a moderate negative relationship between performance and turnover. McEvoy and Cascio reported a ρ of -.28 between performance and turnover, suggesting that turnover is lower among good performers. This meta-analytic finding has been replicated by Bycio et al. (ρ = -.25), Williams and Livingstone (ρ = -.31), and Zimmerman and Darnold (ρ = -.17). A meta-analysis conducted by Williams and Livingstone replicated and extended earlier meta-analytic findings. Williams and Livingstone reported that (1) the negative relationship between performance and turnover is unaffected by unemployment rates and the length of time between measurements of the two variables (a more recent meta-analysis by Griffeth, Hom, and Gaertner [2000] found that lag time was a significant moderator of this relationship); (2) this relationship was stronger in organizations using performance-contingent rewards; and (3) there was support for a U-shaped relationship between performance and turnover such that in some cases the relationship between turnover and performance is negative, and in others it is positive (e.g., when high performers leave an organization to take a better job). Several primary studies have found a positive relationship between performance and turnover (Jackofsky, 1984; Jackofsky, Ferris, & Breckenridge, 1986; Johns, 1989; Mossholder, Bedeian, Norris, Giles, & Feild, 1988; Trevor, Gerhart, & Boudreau, 1997).

In the most recent meta-analysis of the performance–turnover relationship, Zimmerman and Darnold (2009) added to existing knowledge regarding this relationship by testing a process model via meta-analytic structural equations modeling (SEM). They found that the performance–turnover relationship is partially mediated through job satisfaction and intentions to quit. Specifically, higher job performance leads to increased job satisfaction, which then leads to lower intention to quit, which finally leads to reduced voluntary turnover. Job performance also has a direct negative effect on voluntary turnover. The authors interpret the direct path from performance to turnover based on Lee and Mitchell's (1994) unfolding model of turnover. Specifically, employees may react to shocks in the work environment, such as a low performance evaluation, that may lead to quitting without initiating job satisfaction or withdrawal cognitions.

From a theoretical standpoint, the relationship between performance and turnover is quite complex. Allen and Griffeth (1999) noted that "…performance may have simultaneous and sometimes conflicting influences on turnover through both the perceived ease and the perceived desirability of movement, as well as sometimes leading directly to turnover" (p. 535). Allen and Griffeth put forth an integrative process model involving several mediators and moderators of the performance–turnover relationship. The model posits three mediators of the performance–withdrawal relationship: desirability of movement (e.g., job satisfaction, organizational commitment, opportunity to transfer), performance-related shocks (e.g., salient performance feedback, unsolicited job offers), and ease of movement (e.g., number and quality of alternatives). The performance–desirability of movement relationship was proposed to be moderated by reward contingency, such that weaker reward contingency would lead to a stronger relationship between performance and desirability of movement. Further, the performance–ease of movement relationship was proposed to be moderated by external visibility of performance, such that increased external visibility would lead to a stronger relationship between performance and ease of movement. Finally, desirability of movement, performance-related shocks, and ease of movement lead to withdrawal processes (e.g., withdrawal cognitions, job search behavior, and turnover intentions) which then lead to actual turnover. Most of these propositions were directly or indirectly supported by previous empirical research. For example, Harrison, Virick, and William (1996) examined the performance–turnover relationship among 189 sales representatives from a U.S. telecommunications company under both moderate and maximal reward contingency over time. They found that the performance–turnover relationship was much stronger under maximally contingent rewards.

More recent primary studies have shed additional light on the performance–turnover relationship. In a follow-up empirical test of their theoretical model, Allen and Griffeth (2001) supported many of the proposed mediators and moderators discussed above. Specifically, with a sample of 130 medical services employees, the authors found that the performance–turnover relationship was mediated through perceived alternatives and turnover intentions such that higher job performance led to increased perceived alternatives, which led to increased turnover intentions and finally, increased actual turnover. Further, they found that the performance–alternatives relationship was moderated by visibility such that high visibility of performance was associated with a moderate, positive relationship between performance and perceived alternatives, with no relationship between these two variables for those with low visibility of performance. Additionally, a hypothesized performance–satisfaction relationship was moderated by contingent rewards such that highly contingent rewards were associated with a moderate, positive relationship between performance and job satisfaction, with no relationship between these two variables when rewards were not contingent upon performance.

Jackofsky (1984) proposed that job performance and employee turnover should be related in a curvilinear manner. Specifically, the relationship should be U-shaped such that low performers and high performers turnover more often than average performers. This is due to factors that push low performers away from the organization (either involuntary turnover or pressure by the organization for these employees to voluntarily exit) and factors that pull high performers to other organizations (e.g., ease of movement). Jackofsky et al. (1986) found support for this hypothesis among 169 male accountants and 107 truck drivers.

Trevor et al. (1997) examined relationships among voluntary turnover, job performance, salary growth, and promotions in a sample of 5,143 exempt employees across a broad spectrum of job types, divisions, and locations from a single organization in the petroleum industry. The authors found support for Jackofsky's (1984) hypothesis in that turnover was higher among low and high performers than average performers. However, this relationship was moderated by salary growth and promotions such that low salary growth and high promotions each produced a more pronounced curvilinear performance–turnover relationship.

Salamin and Hom (2005) examined curvilinear and moderating effects on the performance–turnover relationship among 11,098 Swiss bank employees. Using survival analysis, they found that performance was curvilinearly related to turnover such that low and high performers were more likely to quit than average performers, and that bonus pay deterred high performers from quitting more so than pay increases. They also found that the average number of job levels advanced per promotion increased turnover risk to a greater extent than did promotion rate. In sum, although performance and turnover are related, this relationship is not always negative or linear.

Turnover Functionality

Although the negative consequences of turnover have been emphasized more often, employee turnover can have both positive and negative consequences for individuals and organizations (Dalton, Krackhardt, & Porter, 1981; Dalton & Todor, 1979; 1982; Dalton et al., 1982; Tziner & Birati, 1996). Table 1 in the Appendix lists many of the known costs and benefits of voluntary employee turnover. Negative financial and non-financial consequences of turnover are well documented and can be substantial (Hausknecht et al., 2009; Hinkin & Tracey, 2000; Price, 1989; Morrow & McElroy, 2007; Simons & Hinkin, 2001; Tracey & Hinkin, 2008). However, refinements to utility analysis have indicated that it is important to consider the functional aspects of employee turnover when assessing its impact on organizations (Tziner & Birati, 1996; Sturman, Trevor, Boudreau, & Gerhart, 2003).

As discussed previously, performance and turnover are clearly related. Individual employee performance acts as an antecedent to turnover and turnover affects organizational performance. Also, individual performance impacts the organizational consequences of turnover in another way. Specifically, while turnover among average and above average performers is detrimental to organizations, turnover among poor performers can be beneficial. Turnover that is detrimental to organizations is known as dysfunctional, and turnover that is beneficial is known as functional. Dalton and colleagues (Dalton et al., 1981; Dalton & Todor, 1979; 1982; Dalton et al., 1982) were among the first to make this distinction, and found a substantial amount of functional turnover in organizations. For example, Dalton et al. (1981) found that up to 71% of voluntary turnover among 1,389 employees from 190 U.S. bank branches was functional. Specifically, among voluntary turnovers, 71% of these employees were easy to replace and for 42% of these employees their supervisor indicated that they would not rehire the employee or rated the employee's performance as low.

Jackofsky (1984) posited that individual job performance, when incorporated with turnover, would refine the turnover criterion. Jackofsky warned against testing theories regarding determinants of voluntary turnover with samples containing low performers, stating, "The turnover among low performing employees may not strongly reflect the same factors that influence turnover among their higher performing counterparts. The development of a relevant sample based on performance scores, therefore, allows for a concomitant development of a 'clean' criterion measure against which hypothesized voluntary turnover factors can be tested" (p. 81).

Numerous studies have documented the prevalence of functional and dysfunctional turnover in organizations, and several have examined the antecedents of functional and dysfunctional turnover (e.g., Hart, 1990; Hollenbeck & Williams, 1986; Johnson, Griffeth, & Griffin, 2000; Johnston & Futrell, 1989; Miller, 1987; Park et al., 1994; Williams, 1999). For example, Hollenbeck and Williams found that 53% of turnover among 112 retail salespersons was functional to the organization. They also reported that turnover functionality was unrelated to work attitudes (i.e., various dimensions of job satisfaction, motivation to turnover, job involvement, and organizational commitment). As a group, these work attitudes explained 4% of the variance in turnover functionality, which was non-significant. Individually, none of the work attitudes was significantly related to turnover functionality at the conservative cut-off set by the authors, that is, $p < .01$. However, at a slightly less conservative but wellaccepted cutoff ($p < .05$) two dimensions of job satisfaction were significantly correlated with turnover functionality: satisfaction with the work itself ($r = .21$) and satisfaction with coworkers ($r = .19$). Also, the authors demonstrated that the antecedents of turnover frequency and turnover functionality were dissimilar. The same work attitudes that were unsuccessful in predicting turnover functionality explained 11% of the variance in turnover frequency, which was statistically significant. Also, three individual variables were significant predictors of turnover frequency: satisfaction with pay ($r = .32$), motivation to turnover ($r = -.29$), and organizational commitment ($r = .27$). The authors concluded that the antecedents of traditional turnover (frequency) and turnover functionality likely differ. In discussing their findings, the authors suggested that variables associated with both turnover frequency and performance are likely to impact turnover functionality. Thus, antecedents of work motivation, such as contingent reward structures, goal setting and feedback, and/or training, may be likely antecedents of functional turnover.

Miller (1987) examined attitudinal differences between functional and dysfunctional leavers. Miller defined turnover functionality along three dimensions: quality of the leaver, ease of replacing the leaver, and criticality of the vacated position. Following the work of Dalton et al. (1981), the quality dimension was a combination of two items: supervisor-rated employee performance and whether the supervisor would rehire the employee. In a sample of 2,706 employees who had voluntarily resigned from a U.S. utility company, Miller found that functional turnover accounted for 23.3% of leavers on the quality dimension, 43.5% of leavers on the ease of replacement dimension, and 21.7% of leavers on the criticality of position dimension. It was also found that percentages of functional turnover varied widely across nine occupational groups.

Miller (1987) examined employee attitudes and reasons for leaving as potential antecedents of functional and dysfunctional turnover. These included attitudes about upper management, the work itself, merit pay and promotion, the employee’s immediate supervisor, advancement opportunities and salary, job stress, job security, and overall job satisfaction. All of these attitude dimensions were assessed in three contexts: reasons for leaving, pre-turnover attitudes, and post-turnover attitudes. Canonical discriminant analysis was used to test for differences between the attitudes of functional and dysfunctional leavers. Negative attitudes regarding the employee’s immediate supervisor demonstrated the highest discrimination between functional and dysfunctional turnover for the quality and ease of replacement dimensions. Specifically, high quality employees (high performers who the supervisor would rehire) and employees who were not easy to replace demonstrated less negative attitudes toward their former immediate supervisor than low quality employees and employees who were easy to replace. Low quality and easy to replace employees were less satisfied with their immediate supervisor than high quality and difficult to replace employees across three contexts: pre-turnover, at the time of departure, and post-turnover. Results regarding the criticality of position dimension were less clear. Combining attitudes into a group, pre-turnover and post-turnover attitudes respectively explained 26% and 21% of the variance in quality of leavers, 11% and 5% of the variance in ease of replacement, and 5% and 3% of the variance in criticality of position. In sum, it was found that: (1) functional turnover exists in non-trivial amounts; (2) percentages of functional turnover differ across occupations; (3) functional and dysfunctional turnover have different attitudinal antecedents; and (4) attitudes explain a sizeable amount of the variance in turnover functionality. This last finding disputes the findings of Hollenbeck and Williams (1986); however, it should be noted that Miller's sample was much larger than the 112 retail salespersons surveyed by Hollenbeck and Williams, and also included participants from multiple occupations.

Johnston and Futrell (1989) also found evidence that that the antecedents of turnover frequency and turnover functionality are dissimilar. In a sample of 103 sales personnel of a national consumer goods manufacturer, turnover functionality was related most strongly to salary (r = .34), while turnover frequency (stay = 1; leave = -1) was related to propensity to leave (r = -.33), leadership role clarification (r = .24), leadership consideration (r = .23), role conflict (r = -.22), role ambiguity (r = -.19), and overall job satisfaction (r = .31). It should be noted that a regression of turnover functionality on the predictors revealed that both salary and leadership role clarification were related to functionality, while a discriminant analysis revealed that propensity to leave was the only significant predictor of turnover frequency. For turnover functionality, results indicated that higher salary and greater clarification of role expectations by supervisors led to greater likelihood that high performers would remain with the organization. However, for turnover frequency, results indicated only that as propensity to leave increased, the likelihood of an individual leaving the organization also increased.

Phillips, Griffeth, Griffin, Johnston, Hom, and Steel (1989) examined factors differentiating high and low performing quitters and stayers in a sample of hospital nurses. They found that high performing leavers were most dissatisfied with promotion and growth opportunities while low performing stayers were most satisfied in general. In a follow-up study, Griffeth, Phillips, Hom, and Steel (1990) found that low performing leavers were the least satisfied and that good performing stayers had satisfaction levels similar to good performing leavers and poor performing stayers (Williams, 1999).

Hart (1990) examined turnover functionality in a sample of 468 U.S. mental health workers. In accordance with the organization's philosophy, turnover was defined as functional among poor and average performers and as dysfunctional among above average performers. According to this operationalization, 72% of the organization's turnover was functional. Further, Hart examined not only the functionality of actual turnover but also the functionality of turnover intentions (e.g., poor and average performers with high intentions to quit were labeled as functional and above average performers with high intentions to quit were considered dysfunctional). Due in part to a low base rate of actual turnover, discriminant analyses examining differential antecedents of turnover functionality were not statistically significant. However, discriminant analyses of turnover intentions were statistically significant and informative. Specifically, job satisfaction, recognition, pay for performance perceptions, and labor market perceptions discriminated among groups of high vs. low/average performers with high vs. low turnover intentions. Thus, partial support was found for the hypothesis that functional and dysfunctional turnover have different antecedents.

Bailey (1991) examined functional and dysfunctional turnover and store performance among 4,972 full-time sales employees from 16 stores of a major U.S.

department store chain. Also, the effects of age, race, and gender on turnover were examined. It was found that age, race, and an interaction between age and gender all significantly influenced turnover functionality. Specifically, turnover was more functional among minorities, and whereas turnover functionality generally increased with age among females, it increased with age among males from ages 25 to 64, but sharply decreased in functionality (became more dysfunctional) among men aged 65 and over. Further, store-level employee turnover functionality correlated .46 with store sales growth. These findings indicate that turnover functionality may differ across age groups, minority vs. majority groups, and gender; and that functional turnover can benefit organizations.

Park et al. (1994) examined organizational and environmental determinants of functional and dysfunctional voluntary turnover. The authors collected data at the organization-level with a survey completed by a personnel director from each of 100 small U.S. manufacturing organizations. Park et al. found that functional turnover was negatively related to unemployment level and pay, and was positively related to organizational focus on individual incentive programs. In contrast, dysfunctional turnover was not significantly related to any of these variables. Dysfunctional turnover was found to be negatively related to presence of unions, and was positively related to organizational focus on group incentive programs. In contrast, functional turnover was not significantly related to any of these variables. The authors offered several potential explanations for these findings. For instance, the finding that functional turnover decreases as unemployment level increases (and vice versa) may occur because poorly performing employees are less likely to quit when unemployment levels are high and more likely to quit when unemployment levels are low due to the availability of alternative jobs. Additionally, the finding that functional turnover decreases as pay increases may occur because if pay is high for poor performers relative to other organizations (as was the operationalization in this study) then they will be less likely to leave the organization. Further, the finding that functional turnover was positively related to individual incentive programs likely occurs because poor performers receive lower pay than average and high performers and thus leave the company. In contrast, the finding that dysfunctional turnover was positively related to group incentive programs most likely occurs because average and high performers would likely receive lower pay than they would with individual incentive programs and thus leave the company for higher paying jobs.

Williams (1999) examined antecedents of turnover among four groups of U.S. sales representatives: poor performing leavers, good performing leavers, poor performing stayers, and good performing stayers. Overall, objective reward contingency ($R^2 = .34$), state unemployment rate ($R^2 = .11$), state sales unemployment rate ($R^2 = .08$), education ($R^2 = .09$), and tenure ($R^2 = .08$) accounted for most of the variance in turnover functionality. Perceived reward contingency, pay satisfaction, job satisfaction, age, and gender were unrelated to functionality. More specifically, poor performing leavers received 100% of their pay from commissions, good performing leavers received 91% of their pay from commissions, good performing stayers received 77% of their pay from commissions, and finally, poor performing stayers received 39% of their pay from commissions. With respect to unemployment rates, poor performing leavers quit when unemployment was high and job opportunities were low. This was explained by the fact that poor performing leavers, who received 100% commission, earned considerably less total pay than good performers or poor performers who stayed. This study replicated the findings of others (e.g., Hollenbeck & Williams, 1986) indicating that job satisfaction, which is traditionally an acceptable predictor of turnover frequency, is not a very good predictor of turnover functionality.

Johnson et al. (2000) examined antecedents of turnover functionality among 217 business-to-business sales personnel of a U.S. consumer goods manufacturer. They found that high-performing leavers had the lowest promotion satisfaction, satisfaction with supervision, and overall job satisfaction. High-performing stayers had the highest and low-performing leavers had the lowest level of satisfaction with the work itself. Low-performing leavers also had the highest and high-performing stayers had the lowest amount of role ambiguity. Functional and dysfunctional turnover was also differentially influenced by anxiety about work, intentions to quit, role conflict, and perceived alternative job opportunities. Thus, unlike previous research, Johnson et al. demonstrated that traditional antecedents of turnover frequency may also predict turnover functionality.

Shaw and Gupta (2007) examined relationships between pay dispersion and the quits patterns of good, average, and poor performers among 226 truck drivers. They found a three-way interaction such that under high pay system communication, pay dispersion was negatively related to good performer quits when performance-based pay increases were emphasized, and positively related when they were not. Also, under high pay system communication, pay dispersion was negatively related to average performer quits when seniority-based pay increases were emphasized, but this relationship was attenuated when they were not. However, pay dispersion was not consistently related to quit patterns when pay system communication was low.

Shaw, Dineen, Fang, and Vellella (2009) examined relationships between employee-organization exchange relationships, HRM practices, and quit rates of good and poor performers in two studies involving 209 truck drivers (Study 1) and the full-time employee population of 93 single-unit supermarkets (Study 2). They found that HRM inducements and investments related negatively to good- and poor-performer quit rates, whereas expectation-enhancing practices related negatively to good-performer quit rates and positively to poor-performer quit rates. They also found that expectation-enhancing practices attenuated the negative relationship between inducements and investments and good-performer quit rates in Study 1, and exacerbated the negative relationship with poor-performer quit rates in Study 2.

In sum, several empirical studies have demonstrated differential antecedents of functional and dysfunctional turnover. Also, to be discussed in the following section, several studies have demonstrated that the antecedents of turnover change and unfold over time. The present study builds upon these two general findings by empirically examining the temporal patterns of functional and dysfunctional turnover.

Turnover and Time

Within the past decade, a growing number of researchers have argued for an explicit consideration of time in organizational research in general (e.g., George & Jones, 2000; Mitchell & James, 2001) and in turnover processes in particular (e.g., Holtom, Mitchell, Lee, & Eberly, 2008; Kammeyer-Mueller et al., 2005; Steel, 2002; Weller, Holtom, Matiaske, & Mellewigt 2009). In a large-scale review of turnover and retention research, Holtom et al. emphatically called for an increased awareness of time in turnover research, stating "Our review of the turnover research, especially of the past 10 years, has shown that it is essential to consider time in the turnover process" (p. 258). Further, in a model depicting turnover research findings from 1995 to 2008, Holtom et al. noted several areas of study where researchers have integrated temporal elements into turnover theory. These included work attitudes such as job satisfaction (Trevor, 2001) and organizational commitment (Bentein, Vandenberg, Vandenberghe, & Stinglhamber, 2005), withdrawal cognitions (Lee & Rwigema, 2005), withdrawal behaviors (Mossholder, Settoon, & Henagan, 2005), alternative employment opportunities (Kammeyer-Mueller et al., 2005), and individual performance (Sturman & Trevor, 2001).

One of the most interesting findings from this growing body of research is that the antecedents of turnover may change over time (Holtom et al., 2008; Lee & Rwigema, 2005, Steel, 2002). Some antecedents may decrease in importance and some may increase in importance over time for individuals depending on environmental or psychological factors (e.g., unemployment rates; job satisfaction; organizational commitment). For instance, Dickter et al. (1996) examined the influence of time on predictors of voluntary turnover among 1,026 employees from a diverse array of occupations across the U.S. The authors found that time moderated relationships between job satisfaction and cognitive ability with turnover, such that the relationships of these two predictors with turnover decreased over time. More specifically, as time progressed, the strength of the relationship between job satisfaction and turnover became less negative (moving closer to zero). The same relationship was found for cognitive ability.

In one of the first large-scale, longitudinal examinations of the turnover process, Youngblood et al. (1983) found different relationships among predictors and turnover over time in a sample of 1,445 U.S Marine Corps enlistees. For example, behavioral intentions to quit were found to be lowest and to decline in the time period immediately prior to turnover. Further, changes in job satisfaction over time, in addition to level, were related to turnover.

In another relatively early examination of the effects of time on turnover antecedents, Farkas and Tetrick (1989) found that relationships among job satisfaction, organizational commitment, and reenlistment intentions among 440 U.S. Navy personnel changed as tenure increased. The authors posited that commitment and satisfaction may be either cyclically or reciprocally related over time. Hom and Griffeth (1991) also found that relationships among antecedents of turnover (e.g., job satisfaction; withdrawal cognitions and behaviors) changed over time with tenure among 129 nurses.

Johnston et al. (1993) investigated relationships among organizational commitment, propensity to leave, promotion satisfaction, promotions, and turnover in a sample of 157 salespersons. Relationships among the variables of interest as well as salary were found to vary over time. Further, time had a significant main effect on intrinsic motivation, job involvement, and job satisfaction, which all decreased over time.

Somers (1996) applied survival analysis along with traditional Ordinary Least Squares (OLS) and logistic regression analyses to withdrawal/turnover data from 244 nurses. The results from survival techniques were quite different from those from the traditional techniques and differed from previous research. Specifically, job satisfaction predicted turnover while job search behavior did not. One of the key distinctions of survival analysis that may have contributed to these disparate findings is an explicit incorporation of time (tenure) into the modeling of employee withdrawal and turnover processes.

Somers (1999) applied neural network-based statistical analyses to the prediction of turnover among 577 nurses. Not only did two neural network paradigms (multilayer perceptron and learning vector quantization) outperform logistic regression in the prediction of turnover, but uncovered interesting relationships among turnover antecedents over time. Specifically, relationships between antecedent variables (e.g., job satisfaction, job withdrawal intentions, affective commitment) demonstrated non-linear changes over time in the form of floor and ceiling effects which had little effect on turnover at first and then very large effects on turnover once a threshold was reached. This study highlights both the dynamic nature of turnover antecedents and the importance in applying innovative statistical techniques to capture previously unknown relationships among variables.

Utilizing event history (survival) analyses, Harrison et al. (1996) demonstrated that time-dependent performance is a better predictor of turnover than time-stationary performance. Further, performance change over time improved the prediction of turnover by capturing significant incremental variance in turnover risk. Sturman and Trevor (2001) replicated Harrison et al.'s findings among 1,413 loan originators from a U.S. financial services organization. The authors also extended Harrison et al.'s findings by demonstrating that performance trends interacted with current performance in the prediction of voluntary turnover. More specifically, they found that the negative relationship between performance trend and voluntary turnover was very strong when current performance was low but was negligible when current performance was high. These studies highlight the dynamic nature of an important antecedent of turnover behavior, that is, employee performance.

Trevor (2001) performed survival analysis on data from 5,506 employees across hundreds of occupations in the U.S., examining the effects of job satisfaction on voluntary turnover. Findings indicated that this relationship was moderated by unemployment rate, education, cognitive ability, and occupation-specific training. More specifically, when unemployment was low, job satisfaction was more strongly negatively related to turnover. Also, the negative relationship between job satisfaction and turnover was stronger when each of three indicators of 'movement capital' (i.e., education, cognitive ability, and occupation-specific training) were high. Further, a negative relationship between unemployment rate and turnover was stronger when the three indicators of movement capital were low. Trevor notes that these findings have implications for dysfunctional turnover of high performers. Specifically, the interaction between job satisfaction and movement capital indicates that more mobile employees are more likely to turnover than less mobile employees due to job dissatisfaction. Further, these more mobile employees are likely to be high performers due to higher education, cognitive ability and occupation-specific training. Thus, the loss of these employees is likely to be quite dysfunctional to the organization.

Bentein et al. (2005) used latent growth modeling (LGM) to examine relationships between changes in commitment over time, intentions to quit, and actual turnover among 330 alumni of a university in Belgium employed across a variety of occupations. The authors found that a steeper decline over time in an individual's affective and normative commitment was associated with a greater rate of increase in both intentions to quit and actual turnover.

Kammeyer-Mueller et al. (2005) examined time-dependent relationships between job satisfaction, organizational commitment, critical events, unemployment, perceived costs of turnover, search for alternative jobs, and turnover behavior among 932 full-time, exempt employees from 7 U.S. organizations involved in manufacturing, food distribution, health care, and education. Survival analysis and hierarchical linear modeling (HLM) revealed that all of the antecedents predicted turnover when examined over time. Also, critical events predicted turnover directly (not through attitudes) which is consistent with the unfolding model of voluntary turnover (Lee & Mitchell, 1994). Further, changes in antecedents over time (e.g., decreases in commitment and increases in job search behavior) played an important role in predicting turnover.

Boswell, Boudreau, & Tichy (2005) examined changes in within-individual job satisfaction over time in relation to job change (voluntary turnover) among 538 high-level managers identified through an executive search firm. Using dynamic panel analysis, they found that low job satisfaction preceded a voluntary job change, with an increase in job satisfaction immediately following a job change, followed by a decline in job satisfaction. Their findings indicate that job satisfaction as an antecedent to turnover is a dynamic process.

In a study of the dynamism of job satisfaction, organizational commitment, and withdrawal intentions in relation to turnover decisions, Lee and Rwigema (2005) asked 108 white collar or professional workers from manufacturing, service, and retail firms in South Africa to recall levels of the predictor variables at different points in time leading up to a decision to stay or quit their job. Results revealed that changes in the predictor variables were found to be significantly more predictive of final turnover decisions than static measurements of these variables. Further, different antecedents were more important in the turnover process at different times.

Chang, Choi, and Kim (2008) studied turnover antecedents, i.e., cognitive style, work values and career orientation, among 132 R&D professionals in a Korean electronics firm. Survival analysis of data from a 7-year period revealed that the positive effect of intrinsic work values on turnover was strongest in the 3rd and 4th year of employee tenure. Also, the positive effect of cosmopolitan orientation – commitment to a profession more so than a particular organization – on turnover increased over time as tenure increased.

Weller et al. (2009) examined a turnover model incorporating dynamic predictors via survival analysis among 2,706 German employees from multiple occupations. The authors found that turnover risk for individuals recruited through personal recruitment sources was lower early in an employee's tenure than for individuals recruited through formal sources. Also, this risk peaked significantly later for those recruited through personal sources. However, this relationship was moderated by tenure such that the turnover rate differential due to the use of personal recruitment sources diminished as tenure increased. Finally, the recruitment source effect on turnover risk was partially mediated by job satisfaction.

In summary, it is clear that turnover is a dynamic process in which antecedents change over time. Also, several studies have demonstrated that functional and dysfunctional turnover have different antecedents. Although findings have been mixed, some studies have also found different antecedents for turnover functionality and traditional turnover frequency. Based upon these findings, it is hypothesized that functional and dysfunctional turnover demonstrate different patterns over time from one another. It is also hypothesized that functional and dysfunctional turnover demonstrate different patterns over time from overall turnover. These hypotheses are tested by examining time series patterns of monthly quit rates for good, average, and poor performers from a large consumer products company over a six year period.

Chapter 3

The Present Study

The literature review in the previous chapter reported that substantial functional and dysfunctional turnover can be found in organizations (e.g., Dalton et al., 1981; Hart, 1990; Hollenbeck & Williams, 1986; Miller, 1987). Also, the antecedents of turnover frequency and functionality often differ (e.g., Hollenbeck & Williams, 1986; Johnston & Futrell, 1989; Williams, 1999). Further, the antecedents of functional and dysfunctional turnover differ (e.g., Hart, 1990; Hollenbeck & Williams, 1986; Johnson et al., 2000; Johnston & Futrell, 1989; Miller, 1987; Park et al., 1994; Williams, 1999). Additionally, while the role of time has been examined among antecedents of turnover, turnover as an outcome has traditionally been operationalized as a dichotomous variable occurring at one point in time (e.g., Holtom et al., 2008). More specifically, the bulk of turnover research has focused on the occurrence when individual employees voluntarily transition from being employed with an organization to no longer being employed with that organization. Although turnover research has shifted away from stationary antecedents towards dynamic antecedents, the majority of turnover research has focused on turnover as a dichotomous, stationary outcome (e.g., stay or leave). One argument of the present research is that turnover as an outcome variable should be examined as a continuous process over time.

Several studies have demonstrated that functional and dysfunctional turnover have different antecedents. To summarize a few examples, unemployment level, pay, and individual incentive programs have been found to predict functional turnover (Park et al.,

1994) and dissatisfaction with promotion and growth opportunities, union presence, and group incentive programs have been found to predict dysfunctional turnover (Park et al., 1994; Phillips et al., 1989). Further, although job satisfaction and organizational commitment are antecedents of both functional and dysfunctional turnover, facets of these constructs have demonstrated differential relationships with functional and dysfunctional turnover (Griffeth et al., 1990; Johnson et al., 2000; McNeilly & Russ, 1992; Miller, 1987; Phillips et al., 1989). Further, many of these antecedents of turnover have been found to be dynamic (e.g., Trevor, 2001; Bentein et al., 2005). Based upon these findings, it is hypothesized that functional and dysfunctional turnover exhibit different temporal patterns.

Based on the research summarized in the previous chapter, the present study is guided by four primary research questions:

1) *Do functional turnover and dysfunctional turnover demonstrate different temporal patterns?*
2) *Does overall level of turnover have a different temporal pattern than functional or dysfunctional turnover?*
3) *Does forecast (prediction) accuracy differ for functional and dysfunctional turnover?*
4) *Does forecast accuracy of functional and dysfunctional turnover differ from that of overall turnover?*

Traditional turnover research has focused on predicting and explaining employee turnover in an effort to reduce or eliminate it (Staw, 1980). However, decades of research has shown us that we are never going to completely eliminate turnover, nor should we

(Dalton et al., 1982; Holtom et al. 2008). Instead, organizations should proactively manage turnover. The better researchers and practitioners can understand and predict turnover, the better we can manage it. One step in this direction is to understand the temporal nature of turnover. Although the temporal patterns of turnover antecedents have been explained through a growing body of research, the temporal pattern of turnover itself remains largely unexplored. The present study addresses this gap by examining the temporal nature of functional and dysfunctional turnover at a large consumer products company. In doing so, the importance of considering employee turnover as a continuous process to be proactively managed is emphasized.

Dalton and Todor (1979) noted that turnover should be seasonal for at least some industries and that, in the presence of seasonal variation, turnover frequency at a particular point in time would not be meaningful. Further, dynamic trends in turnover antecedents have been found when these variables are examined longitudinally. Fortunately, there is a well-established method for estimating linear (and nonlinear) trends and seasonality over time that has a long tradition in the fields of statistics and economics, that is, time series analysis (Chatfield, 2000). Due to the likelihood of seasonal variation and temporal trends in employee turnover, time series analysis was used in the present study to examine temporal patterns of functional and dysfunctional employee turnover from a multinational consumer products company. Based upon empirical research mentioned previously, it is hypothesized that functional and dysfunctional turnover exhibit different temporal patterns and also hypothesized that these patterns differ from that of overall turnover frequency. In examining these hypotheses, this study extends the findings of previous longitudinal turnover research by examining seasonality in turnover.

In order to examine the research questions and test the hypotheses, 75 months of continuous turnover data was obtained from a large consumer products company. Time series analysis was used to examine the primary research questions. The following chapter describes the sample data, statistical analyses, and specific methods for testing hypotheses.

Chapter 4

Methods

Participants and Procedure

Just over 6 years (75 months) of turnover data was obtained from a large U.S.-based multinational consumer products company. Turnover was defined as the number of employees who left the organization each month from January 2003 through March 2009. The analysis sample consisted of voluntary turnover only (*N* = 14,970 employees). Among these employees 47.6% were female and 52.4% male. Age at time of turnover was available for 11,772 employees (*M* = 32.48, *SD* = 7.18). Employees came from one of six levels in the organizational hierarchy: Administrative and Technical (A&T; *N* = 6,962; 46.5%), Management level 1 (*N* = 3,000; 20.0%), level 2 (*N* = 3,314; 22.1%), level 3 (*N* = 1,395; 9.3%), level 4 (*N* = 221; 1.5%), and level 5 (*N* = 77; 0.5%). Finally, most employees were single (*N* = 7,178; 47.9%), followed by married (*N* = 4,840; 32.3%), divorced (*N* = 179; 1.2%), widowed (*N* = 61; 0.4%), and separated (*N* = 33; 0.2%); however, a large percentage of employees were categorized as not being assigned a marital status (*N* = 2,679; 17.9%). Although often related to turnover, data regarding number of children was only available for 2,886 employees (*M* = 1.70, *SD* = 0.90). Finally, employee tenure is very often related to turnover, however, this data was only available for 2,582 employees (*M* = 7.25 years, *SD* = 5.50), most of these in the U.S. Due to large amounts of missing data among several demographic variables, and because they were not of concern to the research questions of this study, relationships between demographics and turnover were not examined.

Data were first separated into functional and dysfunctional turnover. In accordance with organizational policy, functional turnover was defined as turnover among poor performers (3-rated employees) and dysfunctional turnover was defined as turnover among average and strong performers (2- and 1-rated employees). According to the organization, the loss of average and strong performers would be dysfunctional while the loss of poor performers would be functional to the organization. In the sample under study in the current research, performance ratings were distributed as follows: 1-rated = 1,455 (9.7%), 2-rated = 11,891 (79.4%), and 3-rated = 1,624 (10.8%).

Due to the possibility of regional differences in turnover, data were also split into global and regional turnover. Employees were located in one of seven global geographic regions. These were Western Europe (WE; N = 3,337; 22.3%), North America (NA; N = 2,943; 19.7%), Central & Eastern Europe, Middle East, & Africa (CEEMEA; N = 2,761; 18.4%), Greater China, including mainland China and its markets (GC; N =1,714; 11.4%), Latin America (LA; N = 1,610; 10.8%), all of Asia except China, Korea and Japan and including Australia and India (AAI; N =1,316; 8.8%), and Northeast Asia, including Japan and Korea (NEA; N = 1,289; 8.6%).

Additionally, data were split based upon employee-reported reasons for separation. Employees offered four main reasons for voluntarily leaving the organization. These were career change (N = 4,974; 33.2%), alternative job opportunity (N = 3,799; 25.4%), family reasons (N = 2,684; 17.9%), and dissatisfaction with the company (N = 1,281; 8.6%); however, for 2,232 (14.9%) employees, although the employee voluntarily left the organization, they did not disclose their reason for leaving.

Data were examined at each of the three different employee performance rating levels within each geographic region and among each group of employees reporting the same reason for separation. Due to concerns regarding low base rate of turnover, which can affect the accuracy of statistical models applied to the data, turnover by rating by region by separation reason was not examined. In sum, data sets were nested in two ways: (1) monthly turnover by rating by region, and (2) monthly turnover by rating by separation reason.

The three different methods of cutting the data (rating, region, reason) resulted in a total of 37 data sets: global overall (1 data set), global one-, two-, and three-rated (3 data sets), one-, two-, and three-rated for each of the seven regions (21 data sets), and one-, two-, and three-rated for each of the four separation reasons (12 data sets). Once these 37 data sets were created, cross-validation (holdout) data was removed from each data set in the form of a 12-month ‘holdout’ sample and a 6-month ‘holdout’ sample (the former subsumed the latter). This resulted in a total of 74 “training” data sets (these are used to create time series models based on features of the data) and 74 holdout data sets to cross-validate the models fit to the training data. In other words, models were tested on 63 months of data for 37 data sets (with 12 months removed from the total 75 months of data as a holdout), and on 69 months of data for 37 data sets (with 6 months removed from the total 75 months of data as a holdout).

Study Variables

All of the variables described below with the exception of organizational performance were obtained from electronic personnel records kept on each employee by the organization.

Termination Date. The date that each employee left the organization was used to determine the amount of monthly employee turnover.

Termination Reason. This variable was used to categorize separations as voluntary, company-initiated, or retirement. Voluntary employee turnover was of primary interest in the present study. Reasons for voluntary turnover (collected at exit) included career change (such as change field/career or return to school), family reasons, alternative job opportunity, or dissatisfaction with the company. Among employees leaving due to career-related reasons 14% stated that they were returning to school, 28% moved directly into a new field/career, and 58% noted their career-related reason for separation as "other". Company-initiated turnover and turnover due to retirement were excluded from all analyses.

Performance Rating. The performance ratings utilized by the organization were supervisor-rated evaluations of subordinate performance. An overall performance rating was assigned to each employee by their immediate supervisor as part of the organization's regular performance evaluation system. This rating process occurs on an annual basis and is a forced-distribution rating system such that a predetermined percentage of employees from a work group are assigned to one of three performance levels: 1 – top rated, 2 – mid rated, or 3 – bottom rated. These percentages are set by the organization in a top-down manner and are based on historical employee performance data. As stated previously, in the present research, performance ratings were distributed as: 1-rated, 10%, 2-rated, 79%, and 3-rated, 11%. New employees who have not been with the organization long enough to receive a formal performance evaluation are assigned an N (new or not rated); and for some employees performance ratings are restricted, which are designated R (restricted information). Because the present study focused on functional and dysfunctional turnover, which is determined by employee performance, employees in these latter two categories were excluded from all analyses.

The ratings used were each employee's last performance evaluation rating. The performance evaluation system leading to the numerical ratings assigned by supervisors was carefully developed by HR managers, several of them I-O Psychologists, with input from top management, and has been refined over time. The evaluation process begins with a goal setting session involving the employee and manager at the beginning of the year. At the end of the year the employee and manager review these goals and the manager determines if the goals were satisfactorily met by the subordinate. Further, the manager rates the employee on several carefully developed dimensions of performance using behaviorally-anchored rating scales (BARS) provided by global HR and provides feedback to the subordinate regarding strengths and areas in need of improvement. These performance ratings, along with a written description of the employee's successes and failures regarding their major work assignments throughout the year are utilized by the manager and upper management in determining the employee's final performance rating (1, 2, or 3). Finally, if a work group is too small to reflect the performance distribution imposed by the organization, then work groups are combined until a minimum group size is obtained. In such situations, managers from each work group and also upper managers discuss the performance of each employee until all employees are assigned a rating that meets the distributional requirements of the performance appraisal system. Because the rating process is annual, all ratings used in the present study were obtained at most one year prior to the exit date of each employee.

Organizational Performance. Data on several metrics of organizational effectiveness were pulled from quarterly reports posted on the organization's website. Reports were obtained for the same period as turnover data (2003-2009). Metrics common to all quarters were net sales, operating income, net earnings, and diluted net earnings per common share. However, net earnings was redundant with operating income (r = .99), and more redundant with the other outcomes than operating income, so net earnings was not used in further analyses. A problem with the remaining outcomes was that they were reported quarterly and the turnover data was reported monthly. Thus, the quarterly data was expanded into monthly series using the SAS PROC EXPAND routine. This procedure extrapolates series such as quarterly data into monthly data. This extrapolated monthly data was examined in conjunction with employee turnover. Correlations among these outcomes before and after the quarterly data (N = 25) were expanded into monthly data (N = 75) were net sales—operating income (r = .94 before, r = .92 after), net sales—diluted net earnings p/share (r = .61 before, r = .59 after), and operating income—diluted net earnings p/share (r = .70 before, r = .71 after).

Data Analysis

Time series analysis was used to examine temporal patterns in turnover. A time series is a sequence of observations, measured at successive times, spaced at (often uniform) time intervals. Time series analysis involves fitting statistical models to time series data, and is a subfield of the more general field of longitudinal data analysis (Singer & Willett, 2003). Time series models typically require at least ten observations in time to model a phenomenon, but may often require many more (e.g., 50+) depending upon the complexity of the model. The time series examined in the present study consisted of 75 monthly observations. Time series forecasting utilizes statistical models to forecast future events based on past observations. Such models capitalize on autoregressive, seasonal, and sometimes cyclical patterns in the data to predict future values (Chatfield, 2000; Delurgio, 1998).

Time Series Models Tested

Several models were fit to each sample in an effort to determine the best model for a particular dataset (Delurgio, 1998). The models examined on the present data were: (1) Additive Time Series Regression, (2a) Holt-Winters Exponential Smoothing (HWES) with Additive Seasonality, (2b) HWES with Multiplicative Seasonality, (3) Decomposition Modeling, and (4) Autoregressive-Integrated-Moving-Average (ARIMA) modeling. All modeling was conducted with NCSS 2007 (Hintze, 2007). Each of these modeling techniques is now described in more detail.

Additive Time Series Regression. In time series regression the dependent variable (DV) is the variable you wish to forecast (i.e., turnover), observations are the observed values at each interval (i.e., the number of employees who left the company each month), and independent variables (IVs) are trend (e.g., Jan. 2003 = 1, Feb. 2003 = 2 …Feb. 2008 = 62) and month (e.g., Jan. = 1, Feb. = 2 …Dec. = 12). Trend is a continuous predictor and month is a categorical predictor. Because month is categorical, one of the months is treated as a reference variable against which the means within each other month are compared. It is recommended that the reference variable chosen have the within-month mean closest to the grand mean (i.e., the average across all months; January in this example). The equation for the example model is:

$$\hat{Y} = \text{Intercept} + \beta_2^{Feb} + \beta_3^{Mar} + \beta_4^{Apr} + \beta_5^{May} + \beta_6^{Jun} + \beta_7^{Jul} + \beta_8^{Aug} + \beta_9^{Sep} + \beta_{10}^{Oct} + \beta_{11}^{Nov} + \beta_{12}^{Dec} + \beta_{13}^{Trend}$$

Each β is a separate regression coefficient and β for the reference variable (Jan.) is not estimated.

Holt-Winters Exponential Smoothing with Additive Seasonality. Exponential smoothing assigns exponentially decreasing weights to observations further back in a time series. Thus, recent observations are given more weight. This smoothing attempts to account for overall, trend, and seasonal patterns in the data. Whereas time series regression of monthly data requires 12 parameters to account for trend and seasonality, HWES only requires 3 parameters to account for trend and seasonality, i.e., alpha (a leveling factor), gamma (slope), and delta (seasonality). The leveling factor accounts for error though differencing and a moving average (to be discussed in more detail below), slope is trend, and seasonality is variation due to month of the year in this case. HWES is fairly simple and often very accurate. This type of HWES models seasonality additively.

Holt-Winters Exponential Smoothing with Multiplicative Seasonality. This approach is essentially the same approach as above except that seasonality is modeled multiplicatively rather than additively through the use of logarithms. HWES can also have an additive or multiplicative trend. However, long horizon forecasts (e.g., 12 months or more) with multiplicative trends tend to over- or under-forecast. Thus, only HWES with an additive trend is considered here.

Decomposition Modeling. Decomposition modeling is the only approach discussed here that directly assesses cyclical patterns in the data. Decomposition modeling decomposes patterns in the data into trend, seasonality, a cyclical pattern, and error. Cyclical patterns generally span beyond day-to-day, week-to-week, or month-to-month seasonal patterns and may even span several years in some cases. They are typically difficult to detect without large data sets (e.g., a decade of monthly data; possibly more for quarterly data) but can account for important variance in the DV over time. A thorough examination of decomposition algorithms is beyond the scope of this manuscript, thus, interested readers should consult Brocklebank and Dickey (2003) and Delurgio (1998).

Autoregressive-Integrated-Moving-Average (ARIMA) Modeling. ARIMA modeling, also called the Box-Jenkins approach (Box & Jenkins, 1970; Box, Jenkins, & Reinsel, 2008), can be much more statistically complex than the approaches listed above and thus has fewer concrete guidelines and rules of thumb. ARIMA modeling is generally a black box procedure; that is, estimated parameter values may not be interpretable, although the algorithms provide forecast values and indices of model fit. Also, model selection requires a number of judgment calls. As an example of possible complexity, Bianchi, Jarrett, and Hanumara (1998) reported an ARIMA model for predicting calls to AT&T telemarketing centers with 17 model parameters. ARIMA essentially models three types of parameters. The first is autoregression (AR). A first-order AR model is essentially a regression model. The second type of parameter is the amount of differencing. First-order differencing means that the DV is essentially transformed such that an observation in time becomes that value minus the preceding value. Second-order differencing subtracts the value before the preceding value, and so on. Differencing attempts to control for serial dependencies in the data (e.g., autocorrelations). The third type of parameter is called a moving average (MA). In ARIMA, the moving average component models error terms. Furthermore, all three of these types of parameters can vary in magnitude (e.g., 1, 2, 3…) and also can model non-seasonal and/or seasonal patterns in the data, thus yielding 6 types of parameters of varying orders: *p, d, q, P, D,* and *Q*. An example is an ARIMA (3,0,2,5,1,4) model. This model is of the following orders for the non-seasonal components: AR(3), no differencing, and MA(2); and of the following orders for the seasonal components: AR(5), first differencing, and MA(4). This model is fairly complex in that it has 15 parameters (3+0+2+5+1+4). Often, ARIMA models with more than 10 parameters will over-fit the initial data and perform poorly in cross-validation samples. This problem can be even more serious when the differencing parameters exceed 1 or 2. No ARIMA model with more than 10 parameters was examined in the present data (most had 4 to 8 parameters total).

Model Identification Procedures

Most of the models described in the present research require seasonality to be present in the data in order to perform adequately. This requires the application of some basic model identification procedures. Step 1 involves visually examining scatter plots of the data. This will often reveal basic trends and may also show seasonality if the pattern is strong enough. Next, in each full dataset a one-way Analysis of Variance (ANOVA) is performed with month as a fixed factor. If the F-test is significant, then seasonality is present. The Kruskal-Wallis test is utilized if the data is not normally distributed. A significant χ^2 on this test will also indicate that seasonality is present. Finally, the autocorrelation and partial autocorrelation functions (ACF and PACF) are examined. Patterns in plots and values will indicate if the data contains autoregressive patterns, moving average patterns, or both (Delurgio, 1998).

Preliminary Data Analyses

Outliers

The impact of outliers is an important concern in times series analysis, as with any type of data analysis. Outliers can severely reduce predictive validity but *cannot* be thrown out in time series data. If an outlier is removed, then all data subsequent to the outlier must also be removed. Also, what one might consider to be an outlier may explain important variance in the data. Because outliers cannot be thrown out in time series data, a number of techniques have been developed to deal with them. Some of these methods are briefly described here. Two methods of outlier detection are the examination of statistics from multiple regression methods (e.g., Studentized Residual; Cook's D), and a method developed specifically for time series data by Alwan and Roberts (1988) based on statistical process control (SPC). Once outliers are detected, they can be (a) cut out of the data by throwing out all data up to and including that data point (not always the best option unless the observation occurs very early in the series), (b) integrated into the model (for some time series techniques such as Dynamic Regression), (c) smoothed, or (d) down-weighted with Robust Regression procedures. The last two options were utilized in the present study.

Outliers can be ‘smoothed’ via linear smoothing (e.g., running means) or nonlinear smoothing procedures (e.g., running medians). In these procedures, the mean or median of a band of a few data points ordered in time within those months (or days, or weeks, depending upon the presence and type of seasonality) containing outliers is calculated and used to replace those few values. Only months (or weeks, depending upon the time interval under study) with outliers are smoothed and a mean or median of 3-5 data points is typically recommended. Note that cross-validation samples are *never* smoothed. If there happens to be an outlier in the cross-validation data then it is typically recommended that more data be collected until the outlier is no longer in the holdout sample. Outlier smoothing procedures are very commonly applied in the time series forecasting literature. In contrast to data smoothing, rather than manipulating the data directly Robust Regression reduces the impact of outliers by down-weighting the impact of outliers on regression weights.

In present study, outliers in the “training” samples were detected using methods described by Alwan and Roberts (1988) and were dealt with using running medians smoothing on bands of three data points (referred to hereafter as RMD3) and also Robust Regression. For the sake of brevity, outlier analysis results for all 37 data sets are omitted from this manuscript. What follows is a brief overview of how outliers affected data analysis and what was done to address this.

The Alwan and Roberts (1988) method detected outliers in 14 of the 37 data sets. Among these 14 data sets, RMD3 was applied to the data within months for any data set exhibiting seasonality (how this was detected is described later) and RMD3 was applied to the data points immediately preceding and following each outlier in the series for all data sets exhibiting no seasonality. For example, for a series with seasonality, an outlier occurring in March 2006 would be smoothed using the median of the values for March 2005, March 2006, and March 2007. For a series without seasonality, an outlier occurring in March 2006 would be smoothed using the median of the values for February 2006, March 2006, and April 2006.

In addition to smoothing outliers, Robust Regression was applied to all data sets. Obviously, so outliers were not adjusted twice in the same data set, Robust Regression was applied only to raw monthly data, including outliers, and not to smoothed data. As a check that data manipulation (RMD3 smoothing) was not adversely affecting the validity of the data, holdout R^2 values for models fit to the data smoothed with RMD3 were compared with R^2 values for models fit to raw data including outliers.

Model Fitting and Cross-Validation

Time series models were first fit to each data set with cross-validation data removed. In order to examine model-data fit, several criteria were utilized. These included the assessment of model assumptions (e.g., collinearity), model interpretation (e.g., magnitude, direction, and significance of coefficients), R^2 in model-fitting sample, R^2 in holdout (cross-validation) sample, an examination of residuals (e.g., normality, homogeneity of variance, and white noise), prediction intervals, model parameter parsimony, and finally a scatter plot of forecast values on holdout values. All of these should be familiar to most readers experienced with non-time series statistics with the exception of white noise. A time series demonstrates white noise if there is no autocorrelation among residuals. If the actual observations (raw data) demonstrate white noise then time series modeling is not feasible (there is no pattern to explain). However, if applying a model to data with a time-dependent pattern causes there to be a white noise pattern in the residuals (examined via the Portmanteau Test), this indicates that the selected model has accounted for all temporal patterns in the data and the only remaining variation is white noise (Delurgio, 1998).

Holdout (cross-validation) pseudo R^2 was calculated for each model using the formula below.

$$R^2_{\text{pseudo}} = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - y_{\text{mean}})^2}$$

Pseudo R^2 is the sum of the squared residuals divided by the total sum of squares. Specifically, n is the holdout sample size, y is the actual value of turnover for each month, $\hat{y}$ is the predicted (forecast) value of turnover, and y_{mean} is the mean turnover for the holdout time period. Prediction error was calculated using mean absolute percentage error (MAPE) and root mean squared error (RMSE). MAPE is the sum of the absolute percentage error divided by *n* with percentage error being the residual divided by the observed value multiplied by 100, and RMSE is the square root of the sum of the squared residuals divided by *n* - 1. Final diagnostics examining forecast accuracy involved correlating and plotting the predicted values (forecasts) from the models with the cross-validation (holdout) data.

Qualitative (e.g., plots of temporal patterns) and quantitative aspects (e.g., best fitting models for each data set; parameter estimates for trend and seasonality) of time series models fit to functional and dysfunctional turnover were compared to assess the primary hypothesis that functional and dysfunctional turnover demonstrate different temporal patterns. Also, temporal patterns of global functional and dysfunctional turnover were compared with that of total global turnover. More stringent tests of the differences between these time series, involving statistical tests of their independence (Haugh, 1976), are described next.

Cross-Correlations among Turnover Rates and with Organizational Performance

A more stringent test of research question 1 (do functional and dysfunctional turnover demonstrate different temporal patterns) was conducted using guidelines outlined by Haugh (1976). Haugh introduced a simple procedure for testing the independence of time series. The first step in this procedure is to pre-whiten each univariate series by fitting models which remove autocorrelation from the residuals. The residuals of these models form white noise series. Each of these white noise series is then cross-correlated. Significant correlations at various lags represent deviations from independence. Haugh then provided two statistics, S_M and S_M*, both involving summed cross-correlations, which can be compared to a chi-square distribution to examine their statistical significance (testing the null hypothesis of independence). Haugh only provided approximate guidance regarding the appropriate number of lags to include in these formulas (e.g., ±*N*/10), so Haugh's statistics were calculated in the present study at all lags around zero up to ±8 (75/10 rounded up). Statistical independence was examined for global turnover among high, average, and low performers. In all, 54 test statistics were calculated. This is because there were three comparisons among series (Rate 1–Rate 2, Rate 1–Rate 3, Rate 2–Rate 3), two test statistics (S_M and S_M*), and each test statistic was calculated at nine intervals (0 lags to ±8 lags). ARIMA models were fit to the full data set (N = 75 months) for turnover among high, average, and low performers to obtain white noise series.

Similar procedures were followed to examine relationships between turnover and organizational performance. Specifically, the white noise residual series of high, average, and low performer turnover were cross-correlated with white noise residual series of net sales, operating income, and diluted net earnings per share. ARIMA models were fit to the full dataset (N = 75 months) for each of these organizational effectiveness outcomes to obtain white noise series.

Chapter 5

Results

As described in the previous section, several time series models were applied to a total of 74 data sets (37 cuts of the data with either 6- or 12-month holdout samples removed). Specifically, all of the following models were tested in all 74 data sets: (1) Additive Time Series Regression, (2) Robust Regression (discussed in the section regarding outliers), (3) Holt-Winters Exponential Smoothing (HWES) with Additive Seasonality, (4) HWES with Multiplicative Seasonality, (5) Decomposition Modeling, and (6) Autoregressive-Integrated-Moving-Average (ARIMA) modeling. This resulted in model information (e.g., parameter estimates, variance accounted for by the model, estimates of model error) and cross-validity information (e.g., holdout R^2, forecast error) for 444 models (6 time series models x 74 data sets). Obviously, results for all of these models cannot be presented here. Thus, results from a sample of regions (North America, AAI, and Northeast Asia) and one voluntary separation reason (Career-related turnover) are reported here. These regions and this separation reason was chosen because, in general, holdout R^2 (cross-validity) values were higher for these data sets. Before these specific values are discussed, descriptive information for each of the selected data sets is presented.

Descriptive Turnover Information

Descriptive statistics of monthly turnover for the selected data sets mentioned above are presented in Table 2. Also, Figures 1 – 16 in the Appendix show the full 75-month trend of monthly turnover for each. Table 3 presents correlations of monthly turnover rates among high (1-rated), average (2-rated), and low (3-rated) performers. As discussed previously, the organization regards 1- and 2-rated performance as dysfunctional and 3-rated performance as functional. Correlations among these variables confirm this distinction. The average correlation among 1- and 2-rated turnover is .35 and the average correlation between 1- and 2-rated turnover with 3-rated turnover is .04. The average correlation among different cuts of 3-rated turnover is .45. This shows that 1- and 2-rated (dysfunctional) turnover are more strongly related to each other than either are related to 3-rated (functional) turnover. In fact, at the global level, monthly turnover among 1- and 2-rated employees is correlated at .73. This finding resulted in the creation of one additional data set, that is, global dysfunctional turnover (monthly turnover among both 1- and 2-rated employees). However, within specific data cuts correlations among 1- and 2-rated turnover were lower (ranging from .21 in North America to .64 among employees leaving for career-related reasons). Thus, 1- and 2-rated turnover were not combined within regional data cuts or for career-related separation data, i.e., low, average, and high performers were examined separately.

Detecting Seasonality

To detect the presence of seasonality, first plots of each time series (Figures 1 – 16) were visually examined. Oscillation throughout each series provided a first indication that seasonality might be present. The next step taken to identify seasonality was to conduct a one-way ANOVA in each full 75-month dataset with month as a fixed factor. The results of these ANOVAs are presented in Table 4. F-tests were significant, indicating that seasonality is present, for turnover among 3-rated employees globally, in

North America and AAI, and among employees leaving for career-related reasons. F-tests were significant for turnover among 2-rated employees in North America and Northeast Asia, and among employees leaving for career-related reasons. Seasonality was not detected by this method for any 1-rated employees, or for global overall or dysfunctional turnover. Kruskal-Wallis tests revealed the same pattern of results[1]. Plots of average turnover by month are presented in Figures 17 – 21. These figures reveal that dysfunctional (1- and 2-rated) turnover tends to peak during the summer months (e.g., during or near July)[2] while functional (3-rated) turnover tends to peak during the late fall/early winter months (e.g., October through December). Although there is some variation across cuts of the data, these general trends provide initial support for the hypothesis that functional and dysfunctional turnover have different temporal patterns (research question 1).

Time Series Model Estimation and Cross-Validation

Six types of statistical models were fit to each time series. These were Additive Time Series Regression, Robust Regression, HWES with Additive and Multiplicative Seasonality, Decomposition Modeling, and ARIMA modeling. For all of these methods except ARIMA, the number of model parameters is typically fixed once it is decided to account for seasonality (and cyclical variation for Decomposition Modeling). The regression models each have 12 parameters (11 months plus trend), HWES has 3 parameters (a leveling factor, slope, & seasonality), and Decomposition Modeling has 4

[1] It should be noted that methods of detecting seasonality using ANOVA are not error free. Thus, autocorrelation and partial autocorrelation functions were also examined for each series. Plots and values revealed that seasonality was likely present for some series, but these patterns were not clear.
[2] Seasons here pertain to the northern hemisphere.

parameters (trend, seasonal, cyclical, & error components). However, the number and form of parameters modeled with ARIMA can vary widely across data sets, especially if they exhibit seasonal patterns. Specifically, as discussed in the methods section, ARIMA models can vary along six dimensions (*p, d, q, P, D,* and *Q*). Due to this variability, the specific ARIMA models fit to the data presented here are shown in Table 5. Notice that even though ANOVA tests did not indicate that all series contained statistically significant seasonal variation, all ARIMA models required seasonal parameters to adequately model the data. This indicates that at least some seasonal variation was present in all of these data sets. It may be that this seasonal variation is not very strong for some series or that ANOVA has less power to detect seasonal variation than ARIMA. Note that ARIMA controls for other patterns in the data in addition to seasonal variation.

Table 6 presents a wealth of information about the time series models fit to the data. Primarily, it provides several model fit statistics for each time series model, such as model-fit pseudo R^2, holdout pseudo R^2, the squared correlation[3] between predicted and actual forecast values (denoted $\hat{y}$—y r^2), holdout mean absolute percentage error (MAPE), and holdout root mean squared error (RMSE). Note that two very important statistics, model-fit pseudo R^2 and holdout pseudo R^2, are provided for models fit to 63 months of data with a 12 month holdout and models fit to 69 months of data with a 6 month holdout[4]. It may appear that values for only one type of HWES model are

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[3] If r was negative r^2 was reported as zero.

[4] Remember that outliers were detected in several data sets, and that RMD3 smoothing was applied to the data affected by outliers. Also, as a check that this smoothing did not adversely affect the validity of the data, holdout pseudo R^2 values for models fit to the data smoothed with RMD3 were compared with pseudo R^2 values for models fit to raw data including outliers. It should be noted that 2-rated employees in North America were the only data presented here in which RMD3 smoothing increased the cross-validity of the

provided in Table 6. However, the estimates in this column include both additive and multiplicative seasonal models. The estimates in the table are for the HWES model with higher holdout R^2 values (additive or multiplicative) for each series. Additionally, for the regression models reported in Table 6, there is notation indicating if the linear trend was statistically significant, if seasonality was significant (i.e., parameters for specific moths were significant), and if both trend and seasonality were significant. An examination of these regression parameters compliments the ANOVA results to increase our understanding of seasonality present in each series. Also, unlike ANOVA, time series regression models both seasonality and linear trend over time simultaneously. White noise tests of residuals were also examined and used in model building, but are not presented here.

Overall, the time series models fit the data moderately well in data-fitting samples but many did not maintain predictive validity in cross-validation samples. For example, the average variance explained (R^2) in training samples reported in Table 6 across all models was .41 while the average cross-validation R^2 across all models was only .08. Regarding specific time series techniques, in model-fitting samples R^2 values were generally about average for regression and ARIMA models, below average for HWES and above average for Decomposition Modeling. However, in cross-validation samples R^2 values were on average the lowest for regression models, followed by Decomposition Models which typically performed poorly in 12-month holdouts and about average compared to other models in 6-month holdouts. HWES models performed above average

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time series models fit to the data. Thus, only results from smoothed data for 2-rated employees in North America are presented here.

compared to other models in 12-month and 6-month holdouts. Finally, ARIMA models outperformed all other models on average in both 12- and 6-month holdouts (average R^2 = .13 and .21, respectively). Despite this, even 21% variance explained is not especially noteworthy in time series analysis. There was also considerable variation in R^2 values across all samples. For example, holdout R^2 values were notably higher for career-related turnover (as high as .75) than for regional turnover series.

Figures 22 – 44 plot forecast (predicted) monthly turnover rates against actual holdout turnover rates for those models explaining at least 3% of the variance in a particular holdout sample (6- or 12-month). Not surprisingly due to the wide variation in holdout R^2 values, several of these figures demonstrate relatively accurate forecast values, especially with respect to capturing the pattern of a series (e.g., Figures 28, 34, 40, and 41) and many demonstrate relatively inaccurate forecasts. It can be seen from these figures that in general, ARIMA models outperformed other modeling techniques. ARIMA models also demonstrated the lowest MAPE and RMSE values on average (Table 6).

Research Question 3: Does forecast accuracy differ for functional and dysfunctional turnover?

In training samples, the times series models fit the data best among average performers (average R^2 = .56), then among low performers (average R^2 = .35), and worst among high performers (average R^2 = .26). However, in holdout samples, times series models fit the data best among low performers (average R^2 = .14), then among average performers (average R^2 = .11), and again, worst among high performers (average R^2 =

.01). Squared correlations between predicted and actual forecast values, which essentially capture pattern as opposed to deviation (error), also followed this pattern (average r^2 = .32, .27, and .12 for low, average, and high performer turnover, respectively). Following the same pattern as the variance accounted for in training samples, holdout MAPE was on average lowest among average performers (25.92), higher among low performers (42.74), and highest (indicating poor fit) among high performers (50.11).

Research Question 4: Does forecast accuracy of functional and dysfunctional turnover differ from that of overall turnover?

Comparisons of forecast accuracy between global overall turnover and global turnover among high, average, and low performers produced mixed results. Holdout pseudo R^2 values were higher on average when turnover was examined separately by performance level rather than aggregated. In contrast, MAPE was slightly lower, squared correlations between predicted and actual forecast values slightly higher, and training sample pseudo R^2 values were higher on average for global overall turnover. However, the averages of forecast accuracy statistics across models fit to specific performance levels included turnover among high performers, which were consistently poor. A comparison of overall global models to models forecasting turnover among just average and low performers revealed that holdout pseudo R^2 values were highest among low performers (average R^2 = .19), squared correlations between predicted and actual forecast values were also highest among low performers (average r^2 = .48), training sample pseudo R^2 values were highest among average performers (average R^2 = .64), and MAPE was lowest among average performers (average = 22.93). Note that all of these averages are at the global level. Results from regional and career-related turnover models mirror the results summarized above, and further demonstrate that models fit to turnover among average and low performers were more accurate in general than models fit to aggregated overall turnover. However, even overall turnover was modeled more accurately than turnover among high performers.

Research Question 1: Do functional and dysfunctional turnover demonstrate different temporal patterns?

In addition to initial evidence provided by ANOVA and plots of average turnover by month that functional and dysfunctional turnover demonstrate different temporal patterns, another method of examining differences involved an examination of the estimated parameters of the time series regression models. Results of these models are quite easy to interpret, as opposed to ARIMA models which have been described as a 'black box' method. Thus, for regression models fit to turnover data among high, average, and low performers explaining at least 5% of the variance in a particular holdout sample (6- or 12-month), an additional regression analysis was performed on the full sample of 75 months of data. This was done so that parameter estimates used for the explanation of seasonal variation and trend would benefit from maximum statistical power. Tables 7 – 14 present the results of these time series regressions. As discussed in the methods section, month is a categorical predictor, so one of the months is treated as a reference variable against which the means of the other months are compared. Typically, to provide conservative estimates of seasonal parameters, the reference month chosen for each model is closest to the grand mean. This was the case for all regression models fit to training data presented in Table 6. However, for the eight regressions presented in Tables 7 – 14, the month demonstrating the highest average turnover in each series was used as the reference variable specifically to test the significance of the peak of each series against all other months. This was done because here the primary interest was to see if peak turnover months differed among high, average, and low performers. Also, remember that a regression coefficient is not estimated for the reference variable, but the magnitude of the coefficients of all other months estimate the deviation from the referant.

Three of these regressions involved turnover among average performers (global, Table 7; Northeast Asian, Table 12; career-related, Table 13). In general, turnover for these groups was highest during the summer months. Also, controlling for seasonal variation, there was a significant positive trend in global turnover among average performers and career-related turnover among average performers, but the trend was not significant for Northeast Asian turnover among average performers. Only one regression is shown for turnover among high performers (North American, Table 9). Similar to turnover among average performers, turnover among high performers in North America spiked during the summer (July). However, trend was not significant. The remaining four regressions display turnover among low performers (global, Table 8; North American, Table 10; AAI, Table 11; career-related, Table 14). In contrast with turnover among average and high performers, turnover among low performers typically spiked in the late fall/early winter (e.g., October through December). The trend in turnover among low performers was significant and positive for three of the four groups, i.e., global, North American, and AAI, but not for career-related turnover.

A more stringent test of research question 1 (do functional and dysfunctional turnover demonstrate different temporal patterns) was conducted using guidelines outlined by Haugh (1976) to test the independence of time series among high, average, and low performer turnover. As mentioned in the methods section, the first step in this procedure is to pre-whiten each univariate series. To do so, ARIMA models were fit to the full data set (N = 75 months) for turnover among high, average, and low performers. These models had to be somewhat “overfit” to the data to obtain white noise in the residuals. The final white noise series resulted from the following ARIMA models: rate 1 (3,0,3) (0,0,2), rate 2 (1,0,2) (1,0,1), and rate 3 (1,0,3) (0,0,1). These models fit the data to an acceptable degree, i.e., R^2 = 45.08, 64.38, and 50.84, respectively. Unlike previous model-fitting procedures, the primary concern here was to obtain white noise series. Thus, although appropriate model-building procedures were followed (e.g., all parameters significant, high R^2, low error statistics), holdout statistics were not calculated because white noise residuals had to be obtained for the entire series. In short, here the focus is on explanation, not necessarily prediction, as was the focus with previous time series models.

Cross-correlations of the white noise (residual) series for turnover among high, average, and low performers are presented in Table 15. There were no statistically significant cross-correlations between high performer and low performer turnover or between average performer and low performer turnover. Further, Haugh’s (1976) test statistics for the independence of time series (S_M and S_M*) were not significant for these comparisons at any lags. These findings provide evidence to support the statistical independence of functional and dysfunctional turnover in these data. Confirming expectations, there were significant cross-correlations between high performer and average performer turnover. Specifically, at lags -6 (r_{12} = -.25) and 0 (r_{12} = .30). The cross-correlation at lag -6 is interpreted such that as voluntary turnover among average performers increases, voluntary turnover among high performers decreases 6 months later. Further, Haugh's test statistics were significant at up to ±1 lags (S_M = 9.56, S_M^* = 9.60, df = 3, critical χ^2 = 7.82). Thus, turnover among high and average performers is not statistically independent.

Research Question 2: Does overall level of turnover have a different temporal pattern than functional or dysfunctional turnover?

Haugh's (1976) method was not deemed appropriate to test the statistical independence of overall turnover from functional or dysfunctional turnover. This is because overall turnover is made up of functional and dysfunctional turnover, thus guaranteeing dependence. In fact, most models examining overall turnover in the present study were similar to models examining turnover among average performers, which comprised nearly 80% of overall turnover. However, overall turnover models were nowhere near a perfect match to the variety of models fit to high, average, and low performer turnover. Thus, it could be said that partial support was found for the differentiation of overall turnover patterns from its component parts, especially when compared with turnover among low performers.

Supplementary Analyses: Turnover and Organizational Performance

Similar procedures as above were followed to examine relationships between turnover and organizational performance. Specifically, the white noise residual series of high, average, and low performer turnover discussed above were cross-correlated with white noise residual series of net sales, operating income, and diluted net earnings per share. ARIMA models for these series fit the data exceptionally well, i.e., net sales (3,1,0) (1,1,0) R^2 = 99.20, operating income (3,1,0) (1,1,0) R^2 = 98.87, and diluted net earnings per share (3,1,0) (1,2,0) R^2 = 95.70. Table 16 presents cross-correlations of white noise series for turnover among high, average, and low performers with white noise series of net sales, operating income, and diluted net earnings per share.

The pattern of significant cross-correlations reveals several interesting findings. First, as net sales increase, voluntary turnover among high performers decreases one month later. Additionally, the relationship between operating income and voluntary turnover among high performers appears to be reciprocal. Specifically, as operating income increases, voluntary turnover among high performers decreases one month later. Also, as voluntary turnover among high performers decreases, operating income increases two months later. As diluted net earnings per share increase, voluntary turnover among high performers decreases one month later. Strangely, as voluntary turnover among high performers decreases, diluted net earnings per share decrease seven months later. However, this finding is less reliable due to the large lag time. Other variables would have more of an opportunity to influence the outcome over a period of seven months.

As net sales increase, voluntary turnover among average performers decreases one month later. No significant cross-correlations were found between voluntary turnover among average performers and operating income. Similar to high performers, as voluntary turnover among average performers decreases, diluted net earnings per share decrease seven months later. However, this finding is less reliable due to the large lag time. No significant cross-correlations were found between voluntary turnover among low performers and net sales. Also, no significant cross-correlations were found between voluntary turnover among low performers and operating income. Unexpectedly, as voluntary turnover among low performers decreases, diluted net earnings per share increase two months later. However, conversely, as voluntary turnover among low performers decreases, diluted net earnings per share decrease six months later.

Summary of Results

This study sought to answer four basic research questions: (1) Do functional turnover and dysfunctional turnover demonstrate different temporal patterns? (2) Does overall level of turnover have a different temporal pattern than functional or dysfunctional turnover? (3) Does forecast (prediction) accuracy differ for functional and dysfunctional turnover? (4) Does forecast accuracy of functional and dysfunctional turnover differ from that of overall turnover?

In response to research question 1, plots of average turnover by month and results of ANOVA and time series regression provided evidence that functional turnover and dysfunctional turnover demonstrate different temporal patterns. Specifically, dysfunctional turnover tends to peak during the summer months (e.g., during or near

July) while functional turnover tends to peak during the late fall/early winter (e.g., October through December) for the organization studied here.

A more stringent test of research question 1 was conducted using Haugh's (1976) test statistics for the independence of time series. Findings provided evidence to support the statistical independence of functional and dysfunctional turnover, thus supporting the primary hypothesis that temporal patterns of functional and dysfunctional turnover differ. Additionally, empirically validating the practice of the organization of treating turnover among both average and high performers as dysfunctional, turnover among high and average performers was statistically dependent.

Unfortunately, research question 2 – comparing the temporal pattern of overall turnover with patterns of functional and dysfunctional turnover – could not be adequately tested with the present data due to guaranteed dependence because overall turnover is made up of functional and dysfunctional turnover.

Regarding research question 3, which involved the forecast accuracy of functional and dysfunctional turnover, findings provided evidence to support the proposition that forecast accuracy differs for turnover among employees at different performance levels. The clearest finding was that forecast accuracy was lowest for predicting turnover among high performers. This finding is unfortunate as these forecasts would be the most valuable to the organization.

Results from the examination of research question 4, which compared the forecast accuracy of functional and dysfunctional turnover with that of overall turnover, were not clear. Essentially, if forecast accuracy for overall turnover models was compared with average forecast accuracy statistics across models fit to turnover among high, average, and low performers, several of these statistics favored overall turnover models. However, poor prediction among models fit to high performer turnover attenuated these averages. Thus, when forecast accuracy statistics for overall turnover models were compared with the same statistics for average and low performers, accuracy was higher on average when turnover was modeled at these two performance levels rather than modeled in aggregate. In sum, although turnover among high performers could not be modeled very accurately, models fit to turnover among average and low performers generally fit the data better than models fit to aggregated overall turnover.

Although not part of the formal research questions, supplementary analyses examined relationships between turnover and organizational performance (i.e., net sales, operating income, diluted net earnings per share). Significant cross-correlations revealed several interesting findings, such as reciprocal relationships between employee turnover and organizational effectiveness. All significant lagged correlations at less than six lags revealed negative relationships between turnover and organizational performance, most of these among high performers. Lagged correlations were also strongest between high performer turnover and organizational performance.

Chapter 6

Discussion

The importance of examining collective turnover has been argued in a recent large-scale review (Hausknecht & Trevor, 2011). Also, the importance of considering time in organizational research and in turnover research specifically has been emphasized (Mitchell & James, 2001; Ployhart & Vandenberg, 2010). Turnover functionality has also increased our understanding of the turnover process and its antecedents and outcomes (Park et al., 1994; Williams, 1999). This study examined collective employee turnover with a specific emphasis on predicting and explaining change over time and describing differences in turnover among employees at different performance levels.

Broadly, results provided support for dynamic patterns in employee turnover and differences in these patterns for dysfunctional turnover among high and average performers and functional turnover among low performers. Thus, the primary hypothesis that functional and dysfunctional turnover demonstrate different temporal patterns was supported. The dynamic nature of these data underscores the importance of considering employee turnover as a continuous process. As such, employee turnover should be proactively managed over time. For example, results revealed that average and high performers were more likely to separate from the organization during the summer and low performers were more likely to separate during the late fall/early winter. Awareness of these patterns could be integrated into HR planning and strategy formation. For example, the organization studied here could time interventions aimed at reducing voluntary turnover to occur just before and/or during the summer in order to have the greatest impact on turnover among high and average performers. Additionally, different linear trends, controlling for seasonality, were found at different performance levels and in different regions. Knowledge of which groups of employees are separating at the highest rates after controlling for other sources of variation would also be very useful information to organizations.

Remember that all turnover examined in the present study was volunatry, so lay-offs do not directly account for seasonal differences. One possible seasonal influence on turnover among average and high performers is that the fiscal year for the company under study always ended on June 30, so if performance feedback at that time was positive, but not coupled with a raise or promotion, this may have influenced average and high performers to leave in July. Additionally, poor performers may have separated later in the year due to a probationary period that is imposed in between a first-time low performance evaluation and involuntary separation after continued underperformance. Another potential explanation for the gap in time between high/average performer turnover and low performer turnover is that it likely took low performers longer to find alternate employment than higher performers if the annual performance evaluation triggered job search behavior. These explanations are consistent with Lee and Mitchell's (1994) unfolding model of turnover and the turnover model proposed by Allen and Griffeth (1999).

Overall, the highest forecast accuracy was found for models of turnover due to career-related reasons. These models explained up to 28% of the variance in career-related turnover among high performers, 64% of the variance in career-related turnover among average performers, and 75% of the variance in career-related turnover among poor performers. Remember that these estimates are from cross-validation samples. Seasonality was clearly present in these data. Average and high performer separations in July and August due to career-related reasons may have coincided with school enrollment, which typically occurs in August. Most employees had a Bachelor's degree, so if cognitive ability is related to performance, and considerable research demonstrates that it is, then average and high performers with higher cognitive ability would be more likely to enter graduate school.

The fact that seasonality was clearly present for turnover due to career-related reasons highlights the need to consider this seasonal variation in turnover theory and research. A sizable amount of time-dependent variance in career-related turnover was captured with time series models. In fact, the variance explained by time alone was much greater than that explained by many multivariate predictive models of employee turnover. Therefore, an important implication of the present research is that time-related variation in turnover, especially career-related turnover, should be integrated into theoretical models of turnover and empirical turnover research.

Aside from turnover due to career-related reasons, time series models explained nearly a third or more of the variance in cross-validation samples of average and low performers in the three global regions. For example, in North America average performer R^2 = .32 and poor performer R^2 = .41, in Asia except China, Korea and Japan and including Australia and India average performer R^2 = .53 and poor performer R^2 = .41, and in Northeast Asia, including Japan and Korea average performer R^2 = .32 and poor performer R^2 = .32. Thus, univariate time series models, which capitalize on systematic variation over time such as seasonal and cyclical patterns and linear trends, have the potential to explain a sizable proportion of the variance in employee turnover which has been unexplored in previous research. Specifically, although previous turnover research has examined linear change in turnover (simple increases and decreases over time), seasonality and cyclicality have been ignored.

This study provided evidence that seasonality was present in turnover across a number of global regions and among employees at different performance levels. This finding has clear implications for organizational research and practice. Theoretical models of employee turnover are limited at present in that they do not take into account seasonal variation in turnover. Further, practitioners do not currently integrate seasonal variation into statistical models of turnover. The presence of seasonality may play an important role in the results of a turnover study, but if trends and seasonality are effectively modeled then they can be parsed out and/or controlled for when assessing the effectiveness of an intervention, providing less biased estimates of effect size of that intervention. This supports the importance of well-maintained human capital record-keeping and tracking by organizations, such as tracking monthly turnover.

Turnover models such as the unfolding model (Lee & Mitchell, 1994) and constructs such as job embeddedness (Felps et al., 2009) have emerged as important explanations of employee turnover. Accordingly, interventions have been developed by practitioners to bolster job attitudes and other factors that pull employees to remain with an organization, and to mitigate the effects of negative events or ‘push factors’. However, the effectiveness of interventions is sometimes assessed through simple pre/post designs (e.g., Austin & Harkins, 2008; DeWeese, 2006; Gallagher & Nadarajah 2004; Latona, 1981; Sommer & Merritt, 1994) which do not typically control for the potentiality of seasonality in the data. These designs measure baseline turnover at time 1, then introduce an intervention in an effort to decrease turnover, and then measure turnover at time 2 once the effects of the intervention are thought to have been given enough time to take effect. However, such designs do not take into account the fact that turnover may or may not change from one time to another for a variety of reasons that are outside of the influence of the intervention. For example, economic and market conditions may cause turnover to increase or decrease for many months or even years. Also, there may be seasonal and/or cyclical variation in turnover such that individuals may be less likely to quit at certain times of the year (e.g., just before and after the winter holidays when personal expenses are likely to be high) and more likely to quit at other times of the year (e.g., during a particular industry's hiring cycle; during an academic enrollment period). Such variations in turnover could easily bias the results of a pre/post design. For example, if there is seasonal variation in turnover then the presumed impact of the intervention could be either inflated or deflated depending upon the nature of the seasonality and the particular months in which pre- and post-intervention turnover are assessed.

The present research calls for an integration of time series concepts into turnover theory and models. The findings presented here clearly indicate that attention should be given to previously ignored seasonal and/or cyclical variation in employee turnover over time. Theory and research failing to consider these sources of variation may leave a large proportion of the variance in change in turnover unexplained. In turn, this unexplained source of variance could influence the results of a turnover study such that findings indicating a change or a lack of change could be incorrectly attributed to other study variables such as an organizational intervention. Although not utilized in the present research, multivariate time series models can be used to control for time-dependent variance such as seasonality and cyclicality while simultaneously modeling the effects of an intervention and/or other variables of interest (e.g., employee attitudes, market conditions, etc.). Future research should therefore combine the strengths and findings of traditional turnover research with time series concepts by utilizing multivariate time series modeling techniques. Although some of these techniques can be quite complex, as demonstrated in the present study they can be as simple as adding month of the year into a multiple regression equation as a categorical predictor to control for seasonality.

Results also indicated that as voluntary turnover among average performers increased, voluntary turnover among high performers decreased six months later. One possible explanation for this is that as the performance gap from the loss of average performers was felt, pressure was put on high performers to stay. Also, the loss of average performers could have freed up capital to offer high performers larger bonuses and pay raises.

Regarding relationships between collective turnover and organizational performance outcomes, organizational performance had stronger and more pervasive negative effects on high performer turnover than high performer turnover had on organizational performance. Organizational performance may have influenced turnover among high performers because they ‘jumped ship’ following a substantial drop in organizational performance and/or because bonuses and raises were diminished following low organizational performance. The finding that organizational performance influenced turnover mirrors previous meta-analytic findings of the relationship between individual employee performance and turnover (Bycio et al., 1990; McEvoy & Cascio, 1987; Williams & Livingstone, 1994; Zimmerman & Darnold, 2009), but at a higher level of analysis. Additionally, similar to the findings reported here, a meta-analysis by Griffeth et al. (2000) found that lag time was a significant moderator of this relationship. This study extends previous research by examining the impact of aggregate (company) performance on collective turnover. Further, turnover and organizational performance demonstrated univariate autocorrelation. Thus, it was essential to account for this time-dependent variation in each series before examining relationships between turnover and performance. This necessary precaution is not typical in published turnover research.

Time series analysis was used in the present study to demonstrate the presence of non-trivial temporal variation in employee turnover. Future research should consider such variation in study design and attempt to measure and control for it in analysis. Further, the finding that functional and dysfunctional turnover exhibit different temporal patterns underscores the need to disentangle turnover among employees at various performance levels from overall aggregate turnover. The finding that dysfunctional turnover is independent from functional turnover suggests that they should not be aggregated into overall turnover, especially in longitudinal research designs. Doing so would mask important differences in the temporal patterns of turnover among employees at different performance levels.

Limitations and Directions for Future Research

One of the primary limitations of the present research was that the variance explained in cross-validation samples was low for many models. A potential explanation for this is that all of the cross-validation samples occurred after the start of the global economic crisis, and the majority of the data used to create the models occurred before the start of the crisis. Market conditions are related to turnover such that sustained poor conditions typically coincide with increased involuntary turnover and decreased voluntary turnover. The economic downturn would have been very difficult to predict. However, if data throughout the economic downturn were integrated with previous data and used to fit new time series models, it is likely that cyclical variation could be better modeled which would in turn explain more variance in holdout samples, i.e., forecast accuracy would improve.

An additional limitation was that no attitudinal antecedents of turnover were included. Decades of research has demonstrated that attitudes such as job satisfaction and organizational commitment are important predictors of turnover. However, some research has provided evidence that these variables are not very good predictors of turnover functionality (e.g., Johnston & Futrell, 1989). Hollenbeck and Williams (1986) reported that turnover functionality was unrelated to work attitudes and thus concluded that the antecedents of turnover frequency and turnover functionality likely differ. The authors suggested that variables associated with both turnover frequency and performance, such as work motivation, are likely to impact turnover functionality. Maertz and Griffeth (2004) propose eight motives relating to voluntary turnover. Future research could examine relationships between these motivational variables and turnover functionality. Following the findings of this study, future research should also integrate attitudes/motives into multivariate time series models with turnover functionality.

Also, individuals still remaining with the organization were not included in the present study. However, survival analysis dictates that everyone has an eventual turnover date, and stayers in a specific time frame simply have not yet reached their turnover date. Thus, the present study excluded potential bias due to right-censored data, or data from individuals for whom the date of turnover is unknown (Dickter et al., 1996).

Popular methods in the organizational sciences such as latent growth modeling (LGM; Chan, 1998; Meredith & Tisak, 1990) and random coefficient modeling (RCM; Bliese & Ployhart, 2002) were not used here. LGM was not used in the present research for two reasons: (1) the variable of interest in the present study (turnover) was observed (not unobserved, or latent); and (2) within-person change over time could not be examined with the present data (no variable was observed more than once for the same individual). RCM was not used for the second reason.

Finally, selecting employees to optimize functional turnover may also lower employee performance (e.g., antecedents negatively related to employee performance should be positively related to turnover functionality). Thus, future research should examine those antecedents of dysfunctional turnover that are not strongly tied to employee performance.

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Appendix

Table 1. Costs and Benefits of Voluntary Turnover

Costs of Turnover	Possible Benefits of Turnover
Exit costs Exit interviews Farewell parties on work time Administrative time to process final pay, close retirement accounts, etc.	Poor performers may choose to leave and can be replaced with better employees Leavers are replaced with more junior employees who cost less
Replacement costs Recruitment advertising Selection testing, interviewing, reference checking, medical exams, etc. Hiring bonuses, relocation costs New employee orientation Administrative costs to add to payroll, enroll in benefits, etc. Formal training Informal mentoring and coaching of new employees by supervisors and peers	Morale improves following departure of problematic employees Leavers are replaced with people having more up-to-date technical skill Vacancies are created to allow for internal promotions of other employees, thus increasing their career satisfaction and motivation Receptiveness to innovation and change may increase Voluntary turnover is less painful than retrenchments
Other costs Lost business due to client loyalty to departing employees Lost business or poor quality due to short staffing before replacement, or lower skills before new hires are up to speed Expenses of hiring temporaries or paying overtime while awaiting replacements Reduced morale of those remaining, increased stress on those remaining while short staffed or breaking in replacements Reduction in company's reputation as an employer when staff may choose to leave, reduced ability to recruit in the labor market Inability to pursue growth of other business opportunities due to lack of staff Loss of training dollars invested in departing employee Loss of explicit and tacit organization-specific knowledge held by departing employee	

Note. Reprinted with permission from Fisher, Schoenfeldt, and Shaw (2006), Table 16.3.

Table 2. Descriptive Statistics of Monthly Turnover Rates

Turnover	*Min*	*Max*	*M*	*SD*
Global Overall	112	368	199.60	64.14
1 Rated	6	42	19.40	7.33
2 Rated	84	325	158.55	54.48
3 Rated	5	79	21.65	12.73
North America	7	82	39.24	11.42
1 Rated	0	10	3.64	2.29
2 Rated	6	68	32.03	10.11
3 Rated	0	13	3.57	2.60
AAI	4	33	17.55	6.46
1 Rated	0	6	1.60	1.27
2 Rated	3	27	14.20	5.54
3 Rated	0	7	1.75	1.56
Northeast Asia	2	36	17.19	6.37
1 Rated	0	5	1.67	1.18
2 Rated	0	27	13.04	5.47
3 Rated	0	8	2.48	1.98
Career-related	36	132	66.32	21.34
1 Rated	1	15	5.99	3.01
2 Rated	28	109	52.53	17.96
3 Rated	1	28	7.80	5.06

Note. N = 75 months. AAI is all of Asia except China, Korea and Japan and including Australia and India.

Table 3. Correlations of Monthly Turnover Rates among High, Average, and Low Performers

	Turnover	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Rate 1															
2	Rate 2	.73*														
3	Rate 3	.15	.23*													
4	NA Rate1	.39*	.09	-.22												
5	NA Rate2	.52*	.66*	-.13	.21											
6	NA Rate3	.23*	.32*	.65*	-.02	.13										
7	AAI Rate1	.44*	.35*	.27*	.06	.17	.34*									
8	AAI Rate2	.59*	.72*	.22	.17	.42*	.30*	.29*								
9	AAI Rate3	-.04	.03	.59*	-.10	-.20	.32*	.08	.15							
10	NEA Rate1	.28*	.28*	-.14	.03	.35*	-.16	-.13	.05	-.21						
11	NEA Rate2	.23	.48*	.00	-.02	.30*	-.14	-.01	.10	-.10	.26*					
12	NEA Rate3	-.01	.07	.46*	-.08	-.08	.05	.12	.05	.32*	-.17	.13				
13	Career Rate 1	.74*	.60*	.22	.31*	.42*	.36*	.42*	.53*	.03	.05	.08	-.06			
14	Career Rate 2	.68*	.86*	.17	.16	.67*	.21	.40*	.64*	-.01	.16	.41*	.02	.64*		
15	Career Rate 3	.06	.10	.85*	-.17	-.17	.59*	.20	.03	.45*	-.18	.00	.23*	.16	.14	

Note. $N = 75$. * $p < .05$. Rate 1, 2, and 3 are global monthly turnover for 1-, 2-, and 3-rated employees. NA is North America. AAI is all of Asia except China, Korea and Japan and including Australia and India. NEA is Northeast Asia. Career is career-related turnover.

Table 4. Seasonal Analysis of Variance Results

Turnover	*DF*	Sum of Squares	Mean Square	*F*
Global Overall	11	37125.12	3375.01	0.80
Dysfunctional	11	45696.91	4154.264	1.18
1 Rated	11	479.93	43.63	0.79
2 Rated	11	39324.63	3574.97	1.25
3 Rated	11	3347.61	304.33	2.22*
North America				
1 Rated	11	63.49	5.77	1.12
2 Rated	11	2890.78	262.80	3.54*
3 Rated	11	151.4181	13.765	2.49*
AAI				
1 Rated	11	10.38	0.94	0.54
2 Rated	11	303.71	27.61	0.88
3 Rated	11	54.50	4.95	2.48*
Northeast Asia				
1 Rated	11	21.76	1.98	1.54
2 Rated	11	1127.09	102.46	5.93*
3 Rated	11	73.15	6.65	1.94
Career-related				
1 Rated	11	117.49	10.68	1.22
2 Rated	11	8155.38	741.40	2.97*
3 Rated	11	608.71	55.34	2.71*

Note. * $p < .05$.

Table 5. Final ARIMA Model Parameters

Turnover	Holdout	ARIMA (*p, d, q, P, D, Q*)*		
Global Overall	12 month	(0,0,0) (5,0,0)		
	6 month	(1,0,0) (3,0,0)		
Dysfunctional	12 month	(0,0,0) (0,0,5)		
	6 month	(1,0,0) (0,1,1)		
		Employee Performance		
		1 Rated**	2 Rated**	3 Rated***
Global	12 month	(0,0,1) (0,1,3)	(0,0,0) (5,0,0)	(3,0,2) (0,1,1)
	6 month	(0,0,1) (0,1,3)	(1,0,0) (1,0,1)	(3,0,2) (0,1,1)
North America	12 month	(0,0,0) (0,1,3)	(0,0,0) (1,1,3)	(0,0,0) (2,1,0)
	6 month	(0,0,7) (0,0,0)	(0,0,0) (1,1,3)	(0,0,0) (2,0,2)
AAI	12 month	(0,0,0) (4,0,0)	(1,0,1) (3,0,0)	(0,0,1) (4,1,2)
	6 month	(0,0,0) (4,0,0)	(1,0,1) (3,0,0)	(0,0,1) (4,1,2)
Northeast Asia	12 month	(0,0,0) (0,0,9)	(0,0,0) (3,1,0)	(0,0,0) (3,1,3)
	6 month	(0,0,0) (2,1,6)	(0,0,0) (0,0,5)	(0,0,0) (4,0,3)
Career-related	12 month	(0,0,0) (2,0,1)	(0,0,0) (6,1,0)	(0,0,0) (2,0,6)
	6 month	(0,0,0) (2,0,2)	(1,0,0) (4,0,0)	(0,0,2) (0,1,5)

Note. * *p* = non-seasonal autocorrelation (AR), *d* = non-seasonal differencing, *q* = non-seasonal moving average (MA), *P* = seasonal AR, *D* = seasonal differencing, *Q* = seasonal MA. ** Dysfunctional turnover; *** Functional turnover.

Table 6. Summary of Models Forecasting Monthly Turnover

Monthly Turnover	Model Fit Statistics	Additive Regression	Robust Regression	H-W Exp Smoothing	Decomposition	ARIMA
Rate 1 (High Performance)	63 mo. Model-Fit R^2	.32*	.33*	.35	.58	.39
	12 mo. Holdout R^2	.00	.00	.00	.00	.00
	12 mo. $\hat{y}$—y r^2	.03	.00	.21	.02	.32
	12 mo. MAPE	27.67	28.96	69.79	30.45	27.26
	12 mo. RMSE	7.54	7.75	18.37	8.08	9.40
	69 mo. Model-Fit R^2	.39*	.39*	.40	.63	.38
	6 mo. Holdout R^2	.00	.00	.00	.00	.00
Rate 2 (Average Performance)	63 mo. Model-Fit R^2	.55*	.59***	.73	.73	.39
	12 mo. Holdout R^2	.00	.12	.00	.00	.05
	12 mo. $\hat{y}$—y r^2	.20	.22	.33	.30	.47
	12 mo. MAPE	20.95	18.65	37.66	21.91	15.46
	12 mo. RMSE	45.04	40.67	88.44	46.37	42.30
	69 mo. Model-Fit R^2	.61*	.68*	.67	.83	.64
	6 mo. Holdout R^2	.00	.00	.00	.00	.12
Rate 3 (Low Performance; Functional)	63 mo. Model-Fit R^2	.34**	.26^	.32	.54	.40
	12 mo. Holdout R^2	.00	.00	.44	.00	.00
	12 mo. $\hat{y}$—y r^2	.56	.36	.61	.47	.38
	12 mo. MAPE	29.28	40.32	25.98	32.39	41.72
	12 mo. RMSE	14.04	19.08	9.74	15.12	17.99
	69 mo. Model-Fit R^2	.33***	.24*	.29	.53	.36
	6 mo. Holdout R^2	.15	.00	.41	.47	.45

Note. $\hat{y}$—y r^2 is the squared correlation between predicted and actual forecast values (if r is negative r^2 is reported as zero). * Regression trend significant, $p > .05$. ** Regression seasonality significant, $p > .05$. *** Regression trend and seasonality significant, $p > .05$. ^ No statistically significant regression coefficients. MAPE is mean absolute percentage error. RMSE is root mean squared error.

Table 6. Continued

Monthly Turnover	Model Fit Statistics	Additive Regression	Robust Regression	H-W Exp Smoothing	Decomposition	ARIMA
NA Rate 1	63 mo. Model-Fit R^2	.16^	.18^	.00	.21	.12
	12 mo. Holdout R^2	.03	.00	--	.00	.00
	12 mo. $\hat{y}$—y r^2	.07	.06	--	.03	.02
	12 mo. MAPE	57.99	57.62	--	58.65	69.83
	12 mo. RMSE	2.20	2.24	--	2.28	2.72
	69 mo. Model-Fit R^2	.15^	.18**	.00	.06	.14
	6 mo. Holdout R^2	.05	.00	--	.04	.00
NA Rate 2 $_{RMD3}$	63 mo. Model-Fit R^2	.55***	--	.39	.61	.37
	12 mo. Holdout R^2	.00	--	.21	.00	.32
	12 mo. $\hat{y}$—y r^2	.21	--	.24	.23	.33
	12 mo. MAPE	50.30	--	33.58	51.44	29.43
	12 mo. RMSE	13.94	--	11.15	14.64	10.31
	69 mo. Model-Fit R^2	.48***	--	.28	.58	.33
	6 mo. Holdout R^2	.00	--	.00	.00	.00
NA Rate 3	63 mo. Model-Fit R^2	.49***	.49***	.32	.53	.32
	12 mo. Holdout R^2	.00	.00	.00	.00	.00
	12 mo. $\hat{y}$—y r^2	.00	.01	.00	.00	.00
	12 mo. MAPE	59.23	55.73	62.45	66.54	50.82
	12 mo. RMSE	3.44	3.54	3.55	3.75	4.06
	69 mo. Model-Fit R^2	.44***	.46***	.31	.49	.31
	6 mo. Holdout R^2	.00	.18	.00	.00	.41

Note. $\hat{y}$—y r^2 is the squared correlation between predicted and actual forecast values (if r is negative r^2 is reported as zero). * Regression trend significant, $p > .05$. ** Regression seasonality significant, $p > .05$. *** Regression trend and seasonality significant, $p > .05$. ^ No statistically significant regression coefficients. MAPE is mean absolute percentage error. RMSE is root mean squared error.

Table 6. Continued

Monthly Turnover	Model Fit Statistics	Additive Regression	Robust Regression	H-W Exp Smoothing	Decomposition	ARIMA
AAI Rate 1	63 mo. Model-Fit R^2	.20^	.27^	.00	.25	.14
	12 mo. Holdout R^2	.00	.00	--	.00	.00
	12 mo. $\hat{y}$—y r^2	.00	.00	--	.00	.23
	12 mo. MAPE	42.21	37.90	--	41.05	45.84
	12 mo. RMSE	1.32	1.31	--	1.45	1.00
	69 mo. Model-Fit R^2	.21*	.28*	.00	.22	.17
	6 mo. Holdout R^2	.00	.00	--	.00	.00
AAI Rate 2	63 mo. Model-Fit R^2	.53***	.57***	.49	.65	.50
	12 mo. Holdout R^2	.00	.00	.00	.00	.00
	12 mo. $\hat{y}$—y r^2	.05	.03	.10	.07	.21
	12 mo. MAPE	16.33	17.19	26.15	18.75	18.53
	12 mo. RMSE	4.59	4.70	6.91	4.88	5.44
	69 mo. Model-Fit R^2	.58*	.62***	.47	.66	.53
	6 mo. Holdout R^2	.00	.00	.53	.00	.33
AAI Rate 3	63 mo. Model-Fit R^2	.30^	.31^	.09	.30	.39
	12 mo. Holdout R^2	.06	.00	.00	.21	.34
	12 mo. $\hat{y}$—y r^2	.61	.57	.55	.53	.75
	12 mo. MAPE	36.37	40.13	41.35	36.69	50.11
	12 mo. RMSE	1.82	2.00	1.89	1.67	1.52
	69 mo. Model-Fit R^2	.31***	.34***	.10	.31	.34
	6 mo. Holdout R^2	.03	.00	.00	.30	.41

Note. $\hat{y}$—y r^2 is the squared correlation between predicted and actual forecast values (if r is negative r^2 is reported as zero).
* Regression trend significant, $p > .05$. ** Regression seasonality significant, $p > .05$. *** Regression trend and seasonality significant, $p > .05$. ^ No statistically significant regression coefficients. MAPE is mean absolute percentage error. RMSE is root mean squared error.

Table 6. Continued

Monthly Turnover	Model Fit Statistics	Additive Regression	Robust Regression	H-W Exp Smoothing	Decomposition	ARIMA
NEA Rate 1	63 mo. Model-Fit R^2	.27***	.34***	.04	.32	.41
	12 mo. Holdout R^2	.00	.00	.00	.00	.00
	12 mo. $\hat{y}$—y r^2	.17	.18	.16	.23	.04
	12 mo. MAPE	57.36	50.78	60.18	67.59	40.80
	12 mo. RMSE	1.48	1.38	1.49	1.68	1.10
	69 mo. Model-Fit R^2	.23^	.26^	.02	.35	.32
	6 mo. Holdout R^2	.00	.00	.00	.00	.00
NEA Rate 2	63 mo. Model-Fit R^2	.56***	.65***	.42	.59	.45
	12 mo. Holdout R^2	.00	.00	.00	.00	.00
	12 mo. $\hat{y}$—y r^2	.22	.20	.12	.22	.14
	12 mo. MAPE	25.79	26.17	39.45	26.73	28.00
	12 mo. RMSE	4.61	4.72	6.33	4.95	5.11
	69 mo. Model-Fit R^2	.53**	.62**	.37	.56	.41
	6 mo. Holdout R^2	.15	.23	.12	.32	.13
NEA Rate 3	63 mo. Model-Fit R^2	.27^	.34**	.09	.37	.50
	12 mo. Holdout R^2	.00	.00	.00	.00	.03
	12 mo. $\hat{y}$—y r^2	.12	.13	.07	.06	.27
	12 mo. MAPE	42.73	37.83	56.37	43.70	32.63
	12 mo. RMSE	2.67	2.50	3.59	2.75	2.42
	69 mo. Model-Fit R^2	.30**	.35**	.11	.38	.50
	6 mo. Holdout R^2	.00	.00	.00	.00	.32

Note. $\hat{y}$—y r^2 is the squared correlation between predicted and actual forecast values (if r is negative r^2 is reported as zero).
* Regression trend significant, $p > .05$. ** Regression seasonality significant, $p > .05$. *** Regression trend and seasonality significant, $p > .05$. ^ No statistically significant regression coefficients. MAPE is mean absolute percentage error. RMSE is root mean squared error.

Table 6. Continued

Monthly Turnover	Model Fit Statistics	Additive Regression	Robust Regression	H-W Exp Smoothing	Decomposition	ARIMA
Career Rate 1	63 mo. Model-Fit R^2	.32*	.35*	.11	.39	.26
	12 mo. Holdout R^2	.01	.00	.01	.00	.28
	12 mo. $\hat{y}$—y r^2	.06	.00	.44	.07	.44
	12 mo. MAPE	68.10	69.56	39.75	67.83	35.47
	12 mo. RMSE	3.64	3.85	3.63	3.68	3.09
	69 mo. Model-Fit R^2	.40*	.43***	.07	.48	.39
	6 mo. Holdout R^2	.00	.00	.00	.00	.00
Career Rate 2	63 mo. Model-Fit R^2	.52***	.58***	.59	.68	.52
	12 mo. Holdout R^2	.30	.30	.30	.41	.64
	12 mo. $\hat{y}$—y r^2	.47	.46	.45	.59	.68
	12 mo. MAPE	23.45	23.31	17.75	21.23	13.88
	12 mo. RMSE	14.71	14.80	14.76	13.57	10.56
	69 mo. Model-Fit R^2	.59***	.67***	.50	.76	.60
	6 mo. Holdout R^2	.00	.00	.00	.00	.53
Career Rate 3	63 mo. Model-Fit R^2	.34**	.39**	.29	.50	.24
	12 mo. Holdout R^2	.00	.00	.17	.00	.39
	12 mo. $\hat{y}$—y r^2	.33	.24	.51	.27	.61
	12 mo. MAPE	36.81	48.20	29.79	44.70	26.53
	12 mo. RMSE	6.54	7.71	4.75	7.38	4.08
	69 mo. Model-Fit R^2	.27**	.30**	.18	.46	.53
	6 mo. Holdout R^2	.32	.00	.75	.41	.65

Note. $\hat{y}$—y r^2 is the squared correlation between predicted and actual forecast values (if r is negative r^2 is reported as zero).
* Regression trend significant, $p > .05$. ** Regression seasonality significant, $p > .05$. *** Regression trend and seasonality significant, $p > .05$. ^ No statistically significant regression coefficients. MAPE is mean absolute percentage error. RMSE is root mean squared error.

Table 6. Continued

Monthly Turnover	Model Fit Statistics	Additive Regression	Robust Regression	H-W Exp Smoothing	Decomposition	ARIMA
Dysfunctional (Rates 1 & 2)	63 mo. Model-Fit R^2	.53*	.56*	.73	.73	.28
	12 mo. Holdout R^2	.00	.08	.00	.00	.15
	12 mo. $\hat{y}$—y r^2	.24	.23	.85	.34	.56
	12 mo. MAPE	20.06	18.38	70.73	21.22	15.22
	12 mo. RMSE	47.91	45.15	160.61	49.37	43.42
	69 mo. Model-Fit R^2	.61*	.66*	.68	.83	.67
	6 mo. Holdout R^2	.00	.00	.00	.00	.14
Global Overall	63 mo. Model-Fit R^2	.51*	.53*	.73	.73	.37
	12 mo. Holdout R^2	.04	.10	.00	.06	.00
	12 mo. $\hat{y}$—y r^2	.14	.15	.82	.26	.54
	12 mo. MAPE	15.54	14.95	69.13	14.90	16.22
	12 mo. RMSE	44.48	42.92	182.08	43.99	53.50
	69 mo. Model-Fit R^2	.59*	.66*	.67	.83	.70
	6 mo. Holdout R^2	.00	.00	.13	.00	.00

Note. $\hat{y}$—y r^2 is the squared correlation between predicted and actual forecast values (if r is negative r^2 is reported as zero).
* Regression trend significant, $p > .05$. ** Regression seasonality significant, $p > .05$. *** Regression trend and seasonality significant, $p > .05$. ^ No statistically significant regression coefficients. MAPE is mean absolute percentage error. RMSE is root mean squared error.

Table 7. Time Series Regression Results for Global Turnover among Average Performers

Independent Variable	Dependent Variable – Global 2-Rated Turnover			
	Regression Coefficient	Standard Error	*t*	*p* < .05
Intercept	135.07	14.87	9.09	Yes
January	-37.12	18.25	-2.03	Yes
February	-64.93	18.39	-3.53	Yes
March	-47.70	19.10	-2.50	Yes
April	-37.96	18.93	-2.01	Yes
May	-32.71	18.80	-1.74	No
June	2.48	18.73	0.13	No
July*				
August	-9.16	19.10	-0.48	No
September	-27.07	19.28	-1.40	No
October	-58.60	18.70	-3.13	Yes
November	-72.60	18.71	-3.88	Yes
December	-37.95	18.87	-2.01	Yes
Trend	1.50	0.18	8.52	Yes

Note. * Reference month. $N = 75$. Method is Huber's Robust Multiple Regression. $R^2 = .63$, Adjusted $R^2 = .56$, R^2-Press = .24, Root Mean Squared Error = 31.86, Mean Absolute Percent Error = 17.49.

Table 8. Time Series Regression Results for Global Turnover among Low Performers

	Dependent Variable – Global 3-Rated Turnover			
Independent Variable	Regression Coefficient	Standard Error	*t*	*p* < .05
Intercept	29.51	4.74	6.23	Yes
January	-18.31	5.72	-3.20	Yes
February	-18.70	5.72	-3.27	Yes
March	-20.37	5.72	-3.56	Yes
April	-20.03	5.94	-3.37	Yes
May	-22.94	5.94	-3.86	Yes
June	-16.02	5.94	-2.70	Yes
July	-23.26	5.94	-3.92	Yes
August	-22.18	5.93	-3.74	Yes
September	-21.09	5.93	-3.55	Yes
October*				
November	-11.91	5.93	-2.01	Yes
December	-10.49	5.93	-1.77	No
Trend	0.25	0.06	4.46	Yes

Note. * Reference month. $N = 75$. Method is Additive Multiple Regression. $R^2 = .45$, Adjusted $R^2 = .35$, R^2-Press = .20, Root Mean Squared Error = 10.28, Mean Absolute Percent Error = 41.13.

Table 9. Time Series Regression Results for North American Turnover among High Performers

Independent Variable	Dependent Variable –N. American 1-Rated Turnover			
	Regression Coefficient	Standard Error	*t*	*p* < .05
Intercept	6.31	1.04	6.09	Yes
January	-2.00	1.27	-1.57	No
February	-3.28	1.27	-2.58	Yes
March	-2.13	1.27	-1.67	No
April	-2.03	1.32	-1.54	No
May	-2.18	1.32	-1.66	No
June	-3.01	1.32	-2.28	Yes
July*				
August	-1.49	1.32	-1.13	No
September	-3.32	1.32	-2.52	Yes
October	-2.47	1.32	-1.88	No
November	-2.80	1.32	-2.12	Yes
December	-3.46	1.32	-2.62	Yes
Trend	-0.01	0.01	-0.69	No

Note. * Reference month. N = 75. Method is Additive Multiple Regression. R^2 = .17, Adjusted R^2 = .01, R^2-Press = .00, Root Mean Squared Error = 2.28, Mean Absolute Percent Error = 60.16.

Table 10. Time Series Regression Results for North American Turnover among Low Performers

	Dependent Variable –N. American 3-Rated Turnover			
Independent Variable	Regression Coefficient	Standard Error	t	$p < .05$
Intercept	4.96	0.85	5.81	Yes
January	-2.88	1.03	-2.79	Yes
February	-3.72	1.03	-3.62	Yes
March	-4.30	1.03	-4.19	Yes
April	-3.75	1.08	-3.46	Yes
May	-2.36	1.07	-2.20	Yes
June	-3.54	1.09	-3.25	Yes
July	-3.46	1.06	-3.28	Yes
August	-3.04	1.08	-2.81	Yes
September	-3.96	1.08	-3.67	Yes
October*				
November	-0.32	1.06	-0.30	No
December	-3.47	1.06	-3.28	Yes
Trend	0.04	0.01	3.60	Yes

Note. * Reference month. N = 75. Method is Huber's Robust Multiple Regression. R^2 = .46, Adjusted R^2 = .36, R^2-Press = .00, Root Mean Squared Error = 1.78, Mean Absolute Percent Error = 52.70.

Table 11. Time Series Regression Results for AAI Turnover among Low Performers

	Dependent Variable –AAI 3-Rated Turnover			
Independent Variable	Regression Coefficient	Standard Error	*t*	*p* < .05
Intercept	2.39	0.60	3.96	Yes
January	-2.55	0.73	-3.50	Yes
February	-1.71	0.73	-2.35	Yes
March	-1.88	0.73	-2.58	Yes
April	-1.02	0.76	-1.35	No
May	-2.05	0.76	-2.71	Yes
June	-2.41	0.76	-3.18	Yes
July	-2.26	0.76	-2.99	Yes
August	-1.45	0.76	-1.92	No
September	-1.98	0.76	-2.62	Yes
October*				
November	-0.86	0.76	-1.13	No
December	-0.05	0.76	-0.06	No
Trend	0.02	0.01	3.37	Yes

Note. * Reference month. $N = 75$. Method is Additive Multiple Regression. $R^2 = .41$, Adjusted $R^2 = .30$, R^2-Press = .13, Root Mean Squared Error = 1.31, Mean Absolute Percent Error = 52.93.

Table 12. Time Series Regression Results for Northeast Asian Turnover among Average Performers

	Dependent Variable –NEA 2-Rated Turnover			
Independent Variable	Regression Coefficient	Standard Error	*t*	*p* < .05
Intercept	15.19	1.50	10.10	Yes
January	-4.95	1.86	-2.66	Yes
February	-3.46	1.84	-1.88	No
March	-2.27	1.81	-1.25	No
April	-4.76	1.98	-2.41	Yes
May	-7.81	1.88	-4.15	Yes
June	2.24	1.94	1.16	No
July*				
August	3.86	1.98	1.95	No
September	-2.63	2.03	-1.30	No
October	-8.53	1.91	-4.47	Yes
November	-10.07	1.95	-5.17	Yes
December	-2.17	1.95	-1.11	No
Trend	0.03	0.02	1.70	No

Note. * Reference month. $N = 75$. Method is Huber's Robust Multiple Regression. $R^2 = .62$, Adjusted $R^2 = .55$, R^2-Press = .16, Root Mean Squared Error = 3.23, Mean Absolute Percent Error = 27.44.

Table 13. Time Series Regression Results for Career-related Turnover among Average Performers

	Dependent Variable –Career-related 2-Rated Turnover			
Independent Variable	Regression Coefficient	Standard Error	*t*	*p* < .05
Intercept	60.47	6.06	9.97	Yes
January	-26.29	7.43	-3.54	Yes
February	-31.37	7.43	-4.22	Yes
March	-32.59	7.43	-4.38	Yes
April	-24.74	7.72	-3.21	Yes
May	-20.77	7.71	-2.69	Yes
June	-11.63	7.71	-1.51	No
July*				
August	-3.87	7.71	-0.50	No
September	-18.06	7.71	-2.34	Yes
October	-29.26	7.72	-3.79	Yes
November	-34.96	7.72	-4.53	Yes
December	-24.33	7.72	-3.15	Yes
Trend	0.37	0.07	5.11	Yes

Note. * Reference month. $N = 75$. Method is Additive Multiple Regression. $R^2 = .54$, Adjusted $R^2 = .45$, R^2-Press = .32, Root Mean Squared Error = 13.36, Mean Absolute Percent Error = 18.20.

Table 14. Time Series Regression Results for Career-related Turnover among Low Performers

	Dependent Variable –Career-related 3-Rated Turnover			
Independent Variable	Regression Coefficient	Standard Error	*t*	*p* < .05
Intercept	13.94	2.06	6.75	Yes
January	-8.09	2.49	-3.25	Yes
February	-8.84	2.49	-3.55	Yes
March	-9.87	2.49	-3.96	Yes
April	-9.46	2.59	-3.65	Yes
May	-10.49	2.59	-4.05	Yes
June	-8.36	2.59	-3.23	Yes
July	-8.56	2.59	-3.31	Yes
August	-8.60	2.59	-3.33	Yes
September	-7.30	2.59	-2.82	Yes
October*				
November	-4.87	2.59	-1.88	No
December	-4.40	2.59	-1.70	No
Trend	0.03	0.02	1.45	No

Note. * Reference month. N = 75. Method is Additive Multiple Regression. R^2 = .34, Adjusted R^2 = .22, R^2-Press = .03, Root Mean Squared Error = 4.48, Mean Absolute Percent Error = 77.90.

Table 15. Cross-correlations of Pre-whitened (Residual) Series for Turnover among High, Average, and Low Performers

	Cross-correlation		
Lag	Rate 1—Rate 2	Rate 1—Rate 3	Rate 2—Rate 3
-8	-.03	.13	.23
-7	.05	.19	-.09
-6	-.25*	-.23	.24
-5	.07	-.02	-.22
-4	.04	.08	-.10
-3	.01	.02	-.07
-2	.04	-.01	-.03
-1	.18	-.07	-.04
0	.30*	-.06	.00
1	.08	.14	.16
2	.13	-.15	.00
3	.02	.07	.06
4	.00	.15	-.02
5	-.01	-.05	-.06
6	.10	.09	.07
7	-.05	-.09	.12
8	-.15	.14	.06

* $p < .05$. N = 67-75.

Table 16. Cross-correlations of Pre-whitened (Residual) Series for Turnover among High, Average, and Low Performers with Organizational Performance

	Cross-correlation								
	Rate 1 (High Performance)			Rate 2 (Average Performance)			Rate 3 (Low Performance)		
Lag	Net sales	Operating income	Diluted net earnings p/share	Net sales	Operating income	Diluted net earnings p/share	Net sales	Operating income	Diluted net earnings p/share
-8	-.12	-.13	-.16	.03	.04	-.11	.00	-.01	.10
-7	.09	.10	-.13	-.14	-.15	-.15	.09	.04	-.03
-6	-.05	-.04	.06	.05	.05	.00	-.07	-.16	-.07
-5	-.11	-.20	-.02	-.01	-.06	-.04	.05	.01	-.13
-4	.17	.03	.22	.02	.07	.16	.02	.03	-.03
-3	-.03	-.10	-.11	.04	.02	.06	.06	.04	.11
-2	.14	.09	.06	.09	.04	.12	-.06	-.14	.13
-1	-.27*	-.27*	-.32*	-.24*	-.17	-.19	-.15	-.13	.16
0	.00	.08	.00	.22	.21	.10	.13	.09	-.06
1	.08	-.07	-.04	.07	-.05	.02	-.02	-.06	-.16
2	-.18	-.25*	-.08	-.06	-.15	-.03	-.02	-.05	-.24*
3	-.12	-.09	-.01	-.08	-.15	-.01	-.07	-.15	-.07
4	.05	.13	.16	-.14	-.07	-.09	.03	.00	.09
5	-.20	-.11	-.18	.09	.11	.15	-.10	-.10	.11
6	-.11	-.03	.00	-.10	-.15	.04	.05	.00	.25*
7	.02	.05	.26*	.07	.02	.27*	.02	-.01	.10
8	-.02	-.04	.17	.03	-.06	.14	-.09	-.09	-.23

* $p < .05$. $N = 67\text{-}75$.

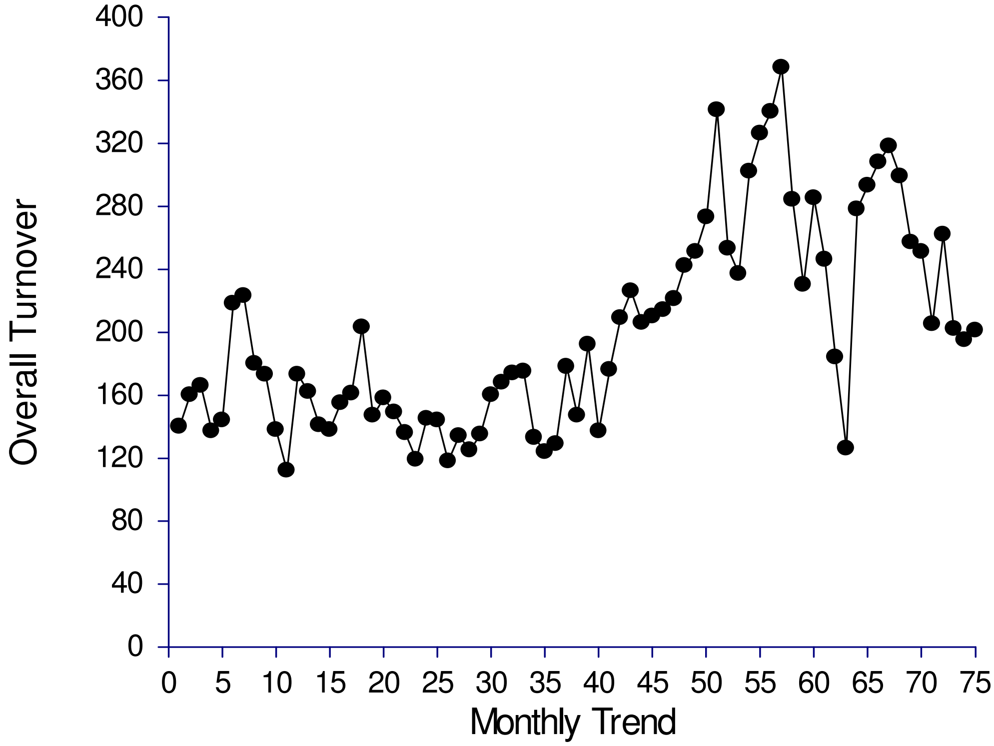

Figure 1. Overall Global Monthly Turnover from Jan 2003 through Mar 2009

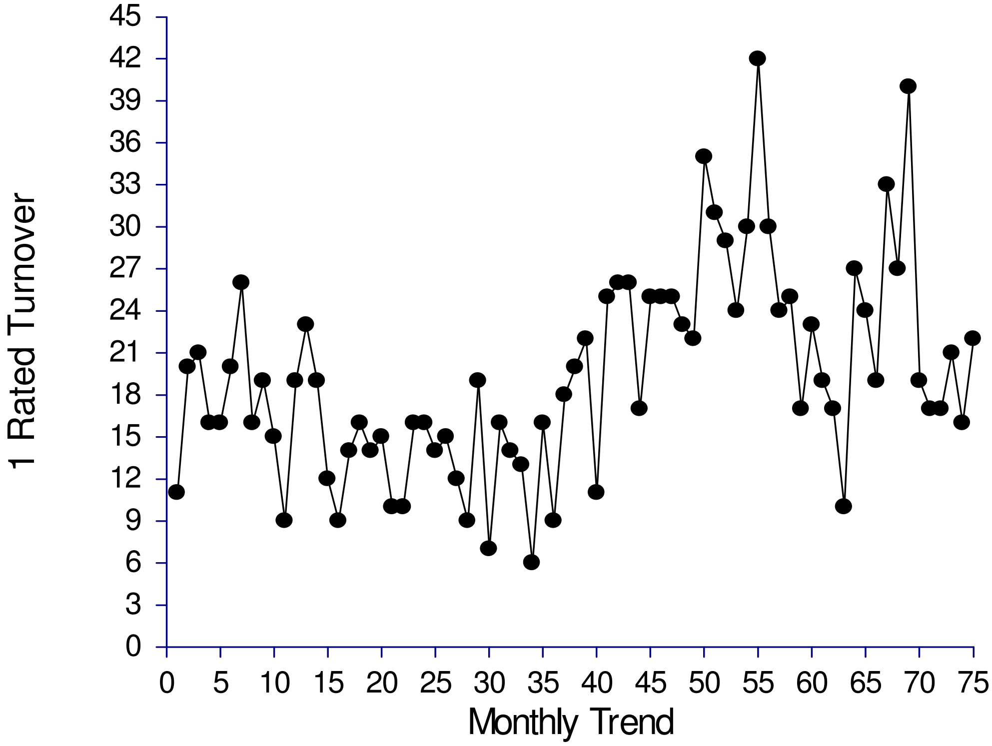

Figure 2. Global Monthly Turnover from Jan 2003 through Mar 2009 among High Performers

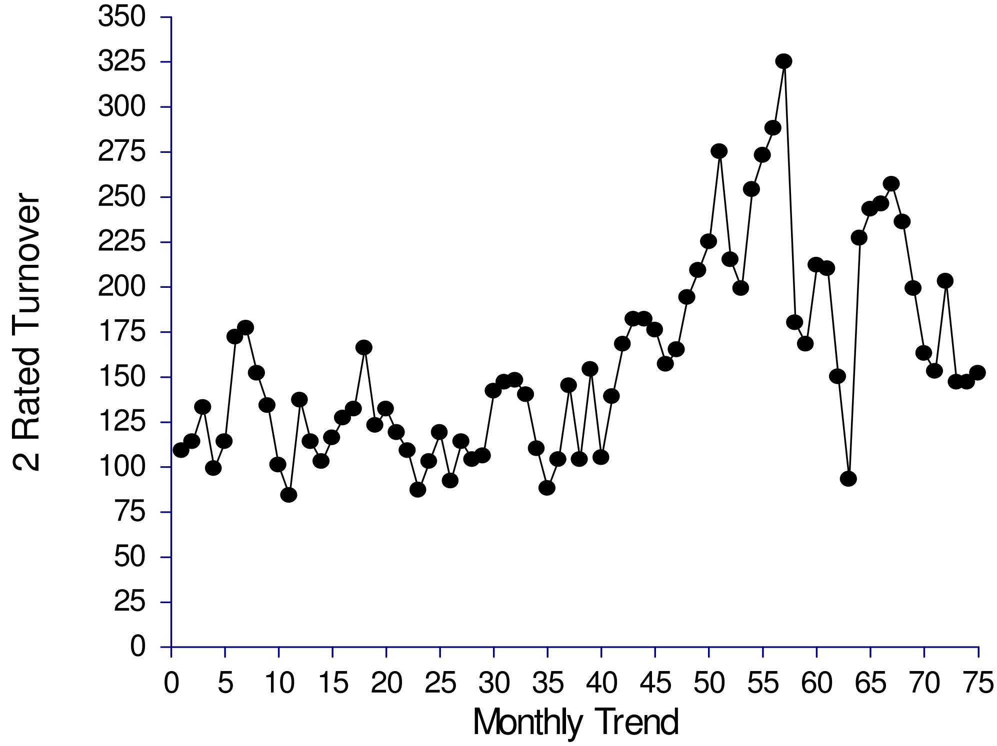

Figure 3. Global Monthly Turnover from Jan 2003 through Mar 2009 among Average Performers

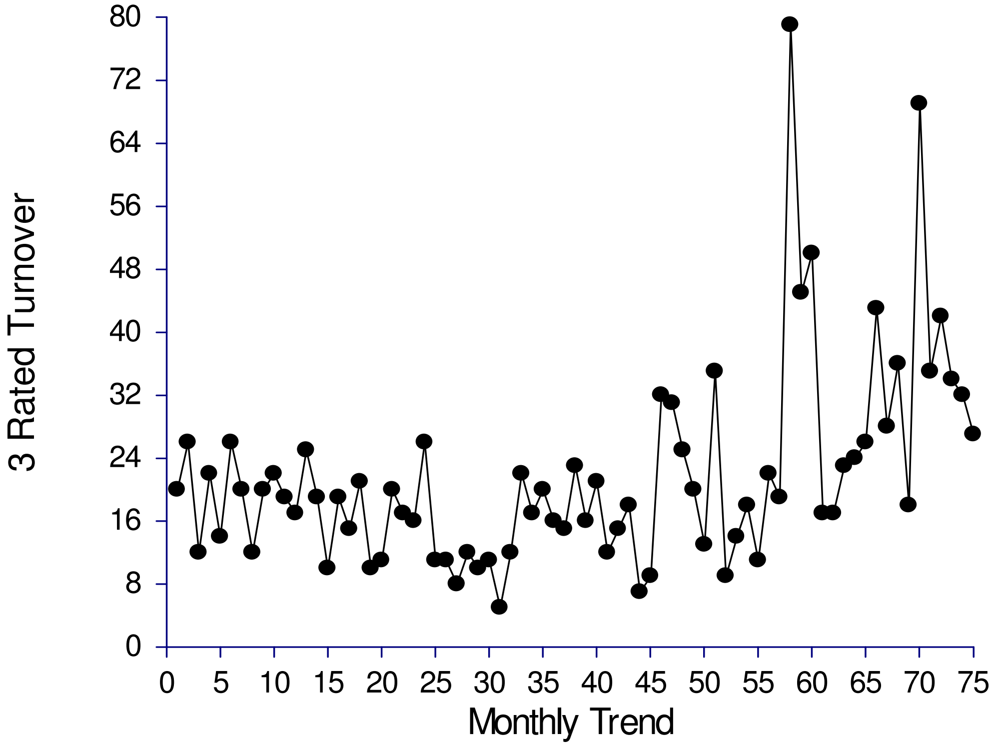

Figure 4. Global Monthly Turnover from Jan 2003 through Mar 2009 among Low Performers

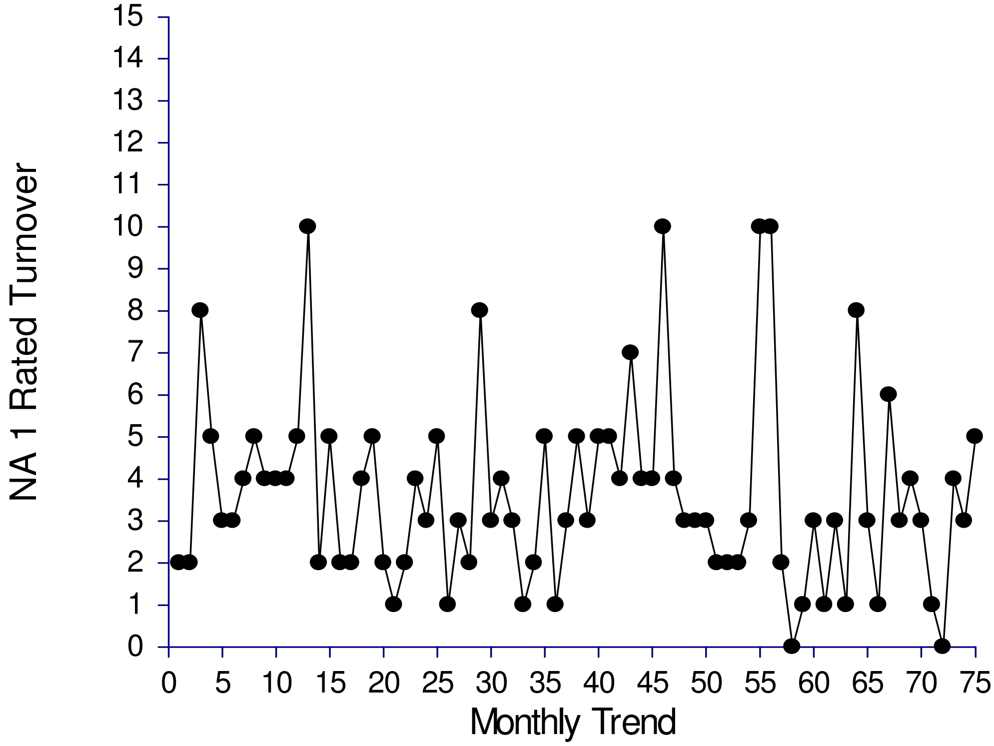

Figure 5. Monthly Turnover from Jan 2003 through Mar 2009 among High Performers in North America

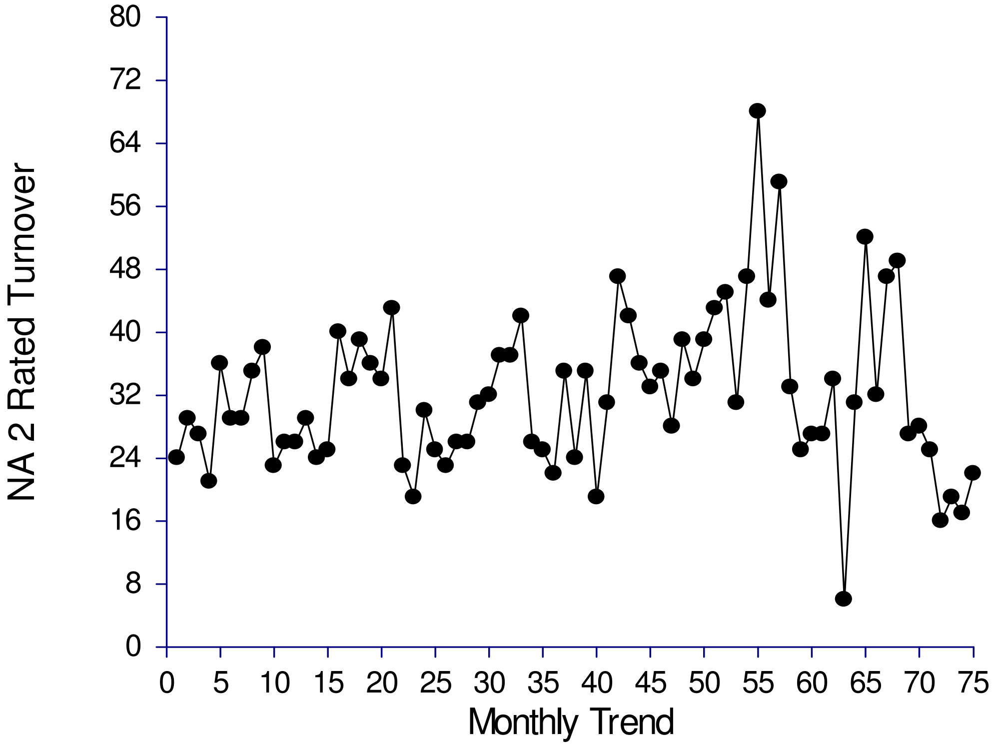

Figure 6. Monthly Turnover from Jan 2003 through Mar 2009 among Average Performers in North America

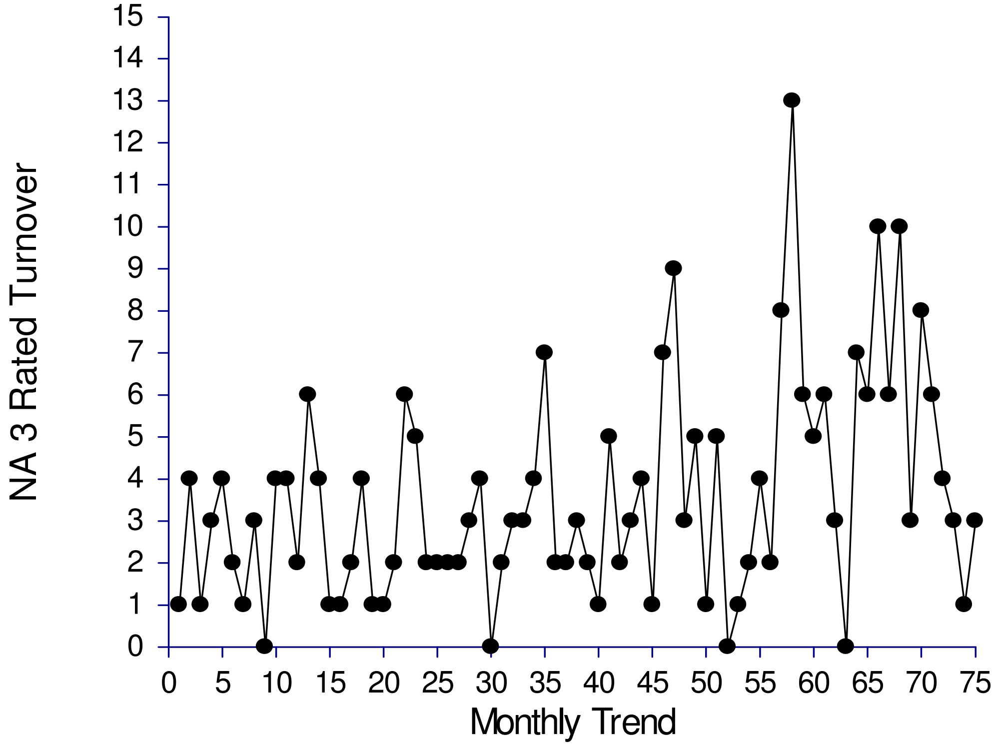

Figure 7. Monthly Turnover from Jan 2003 through Mar 2009 among Low Performers in North America

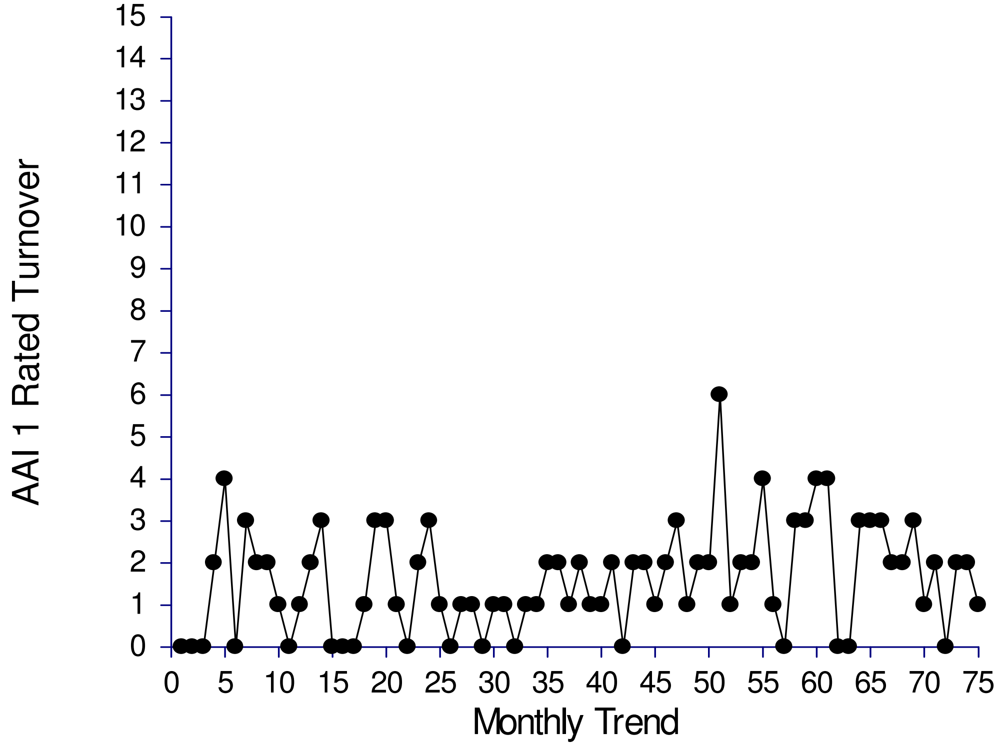

Figure 8. Monthly Turnover from Jan 2003 through Mar 2009 among High Performers in all of Asia except China, Korea and Japan and including Australia and India

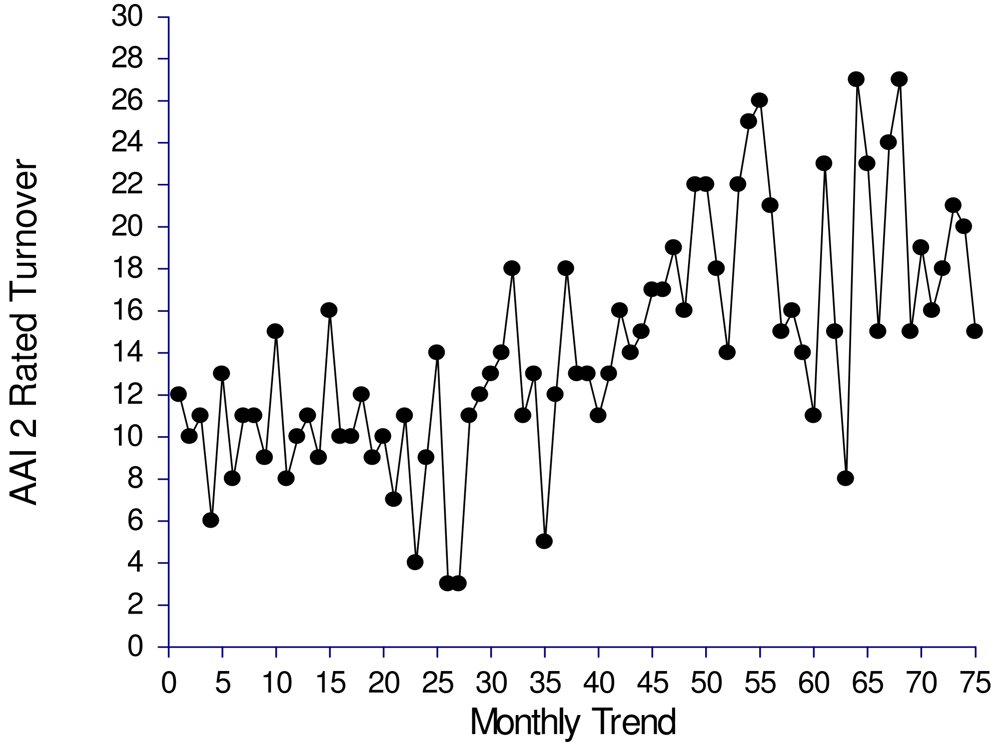

Figure 9. Monthly Turnover from Jan 2003 through Mar 2009 among Average Performers in all of Asia except China, Korea and Japan and including Australia and India

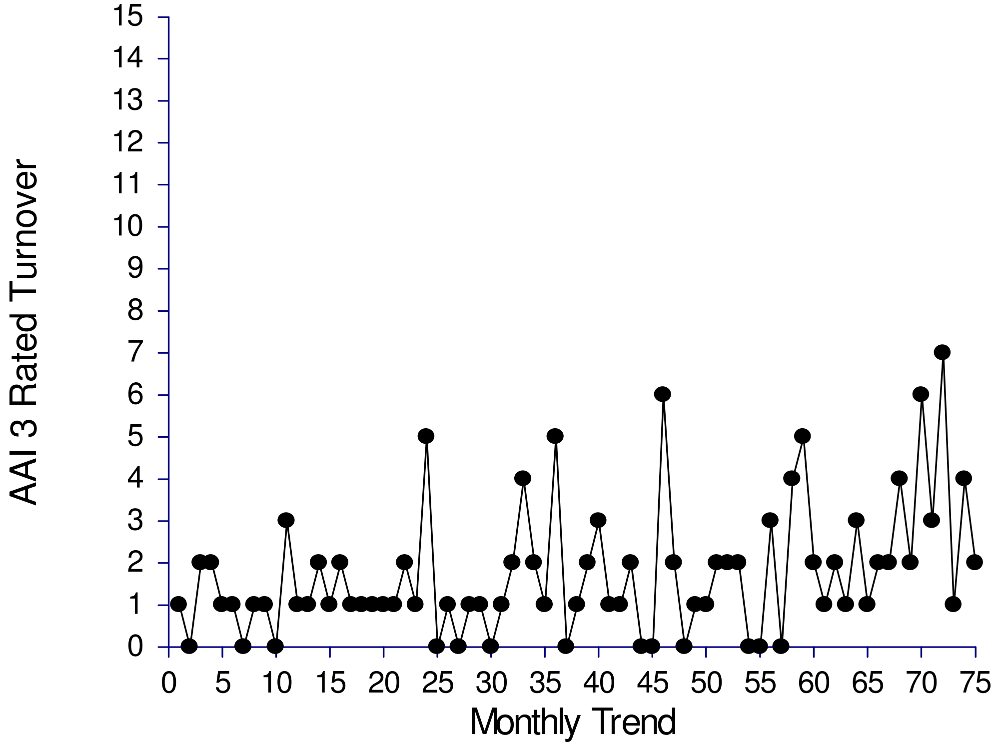

Figure 10. Monthly Turnover from Jan 2003 through Mar 2009 among Low Performers in all of Asia except China, Korea and Japan and including Australia and India

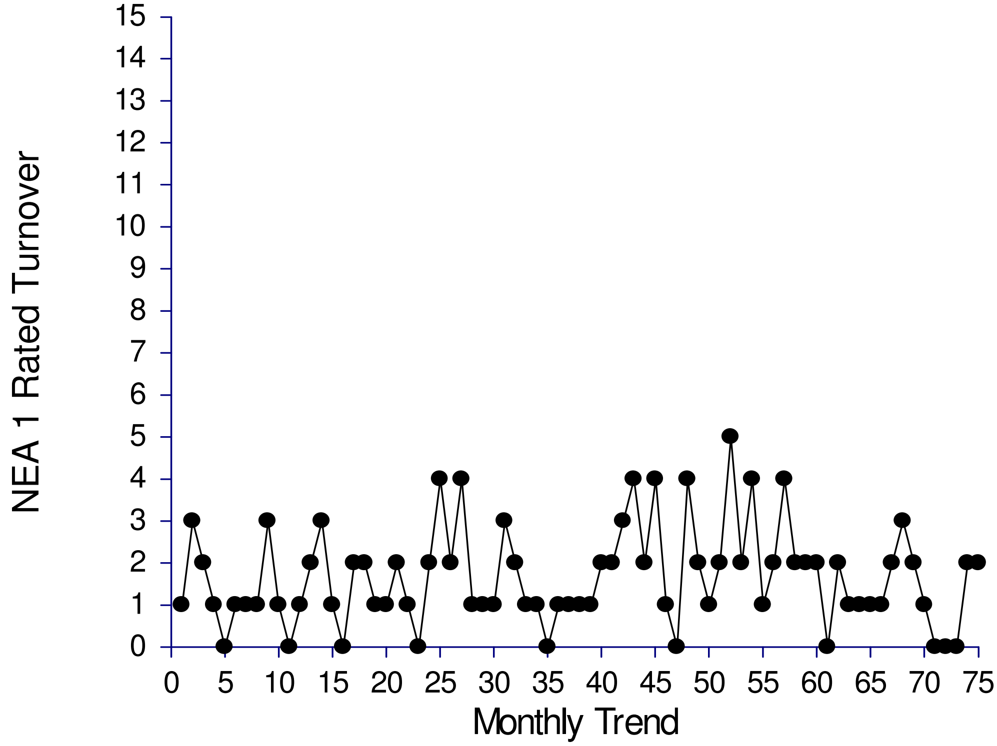

Figure 11. Monthly Turnover from Jan 2003 through Mar 2009 among High Performers in Northeast Asia

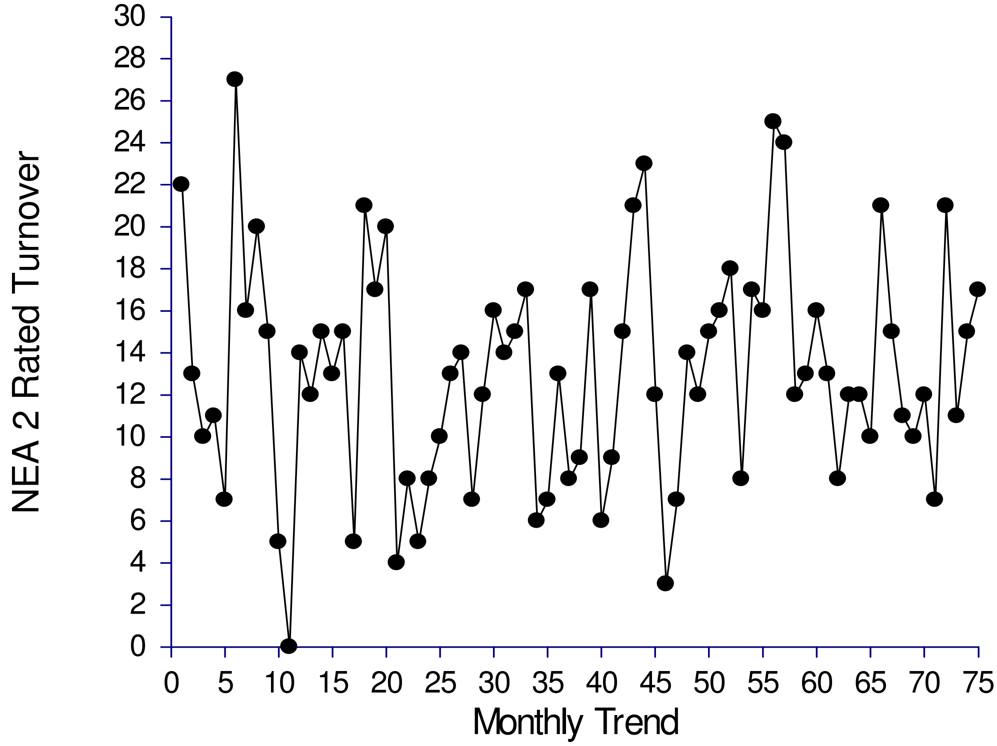

Figure 12. Monthly Turnover from Jan 2003 through Mar 2009 among Average Performers in Northeast Asia

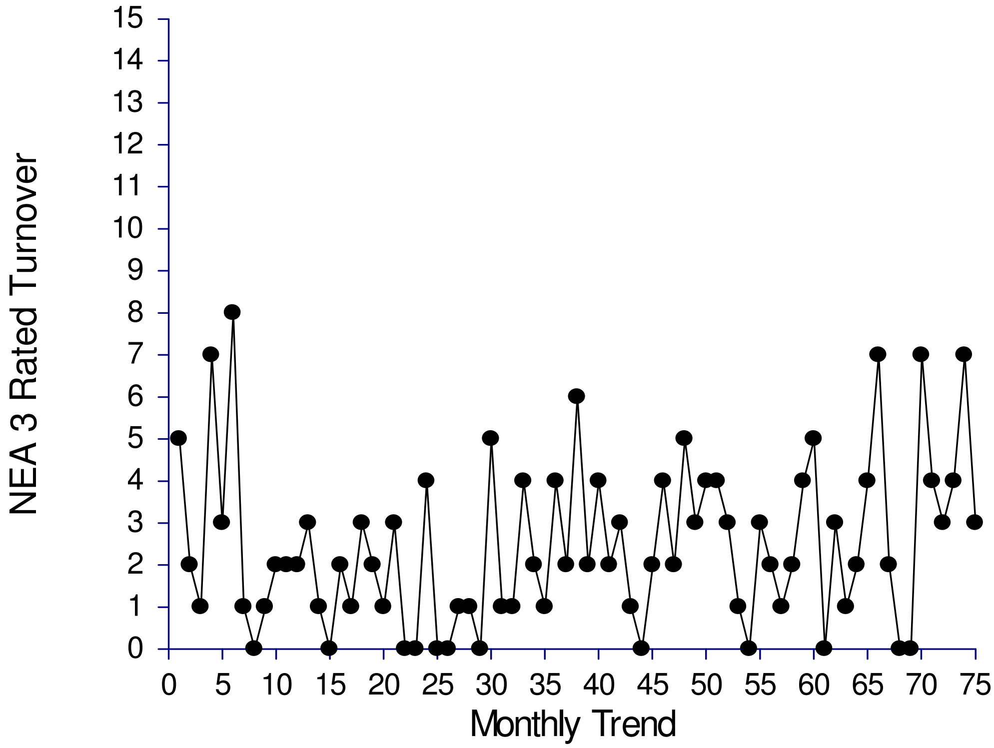

Figure 13. Monthly Turnover from Jan 2003 through Mar 2009 among Low Performers in Northeast Asia

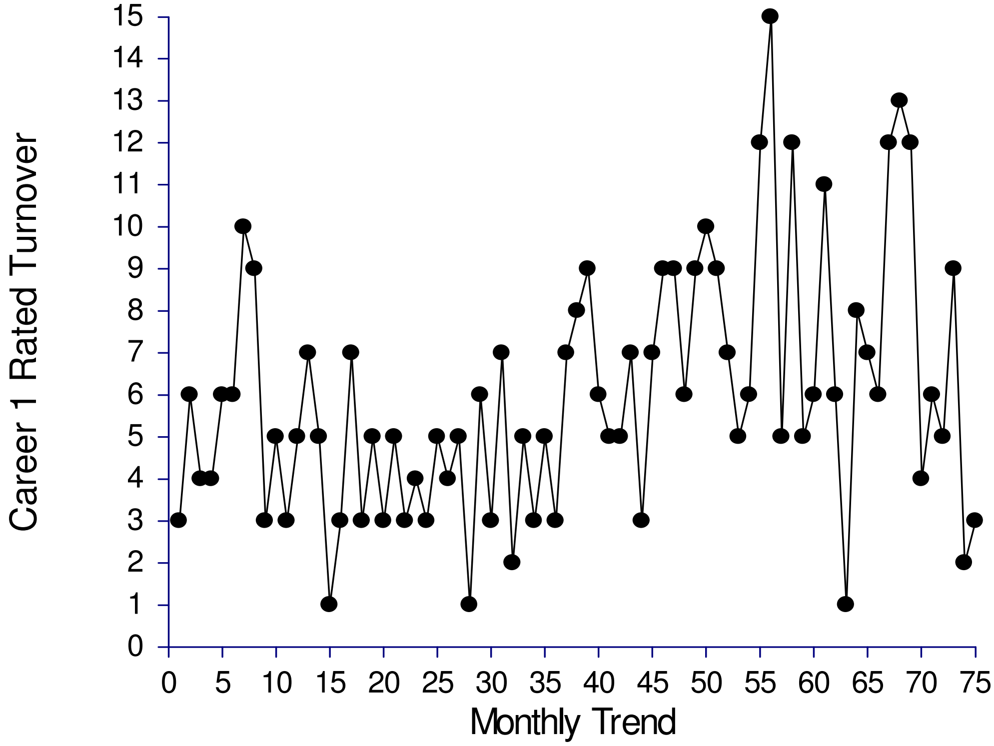

Figure 14. *Monthly Turnover from Jan 2003 through Mar 2009 among High Performers Leaving for Career-related Reasons*

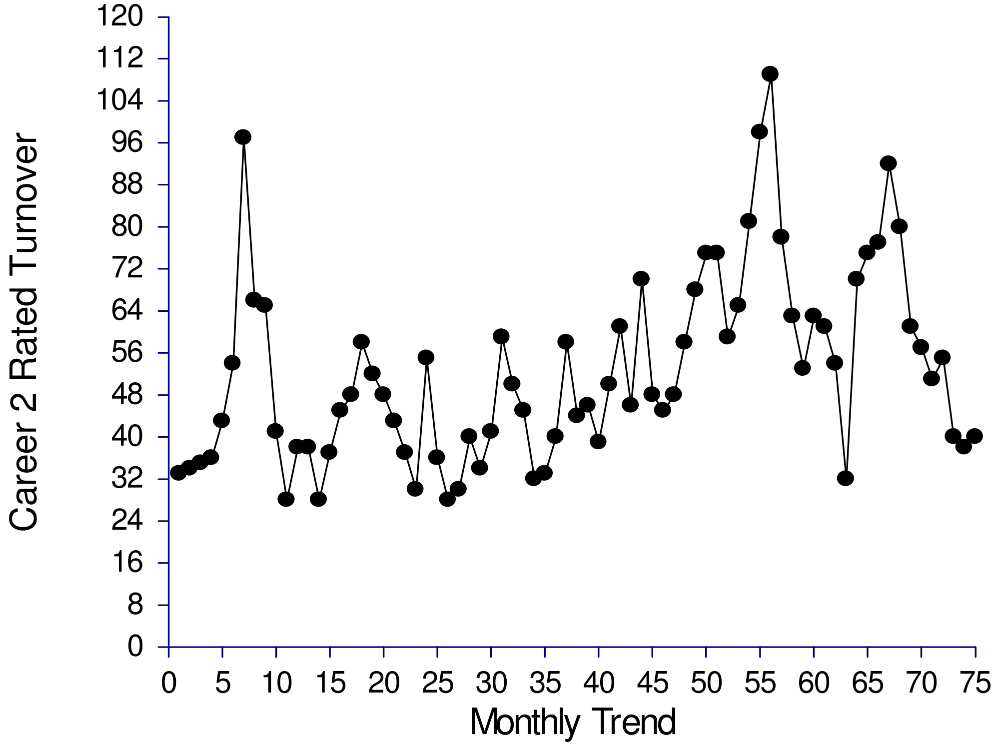

Figure 15. Monthly Turnover from Jan 2003 through Mar 2009 among Average Performers Leaving for Career-related Reasons

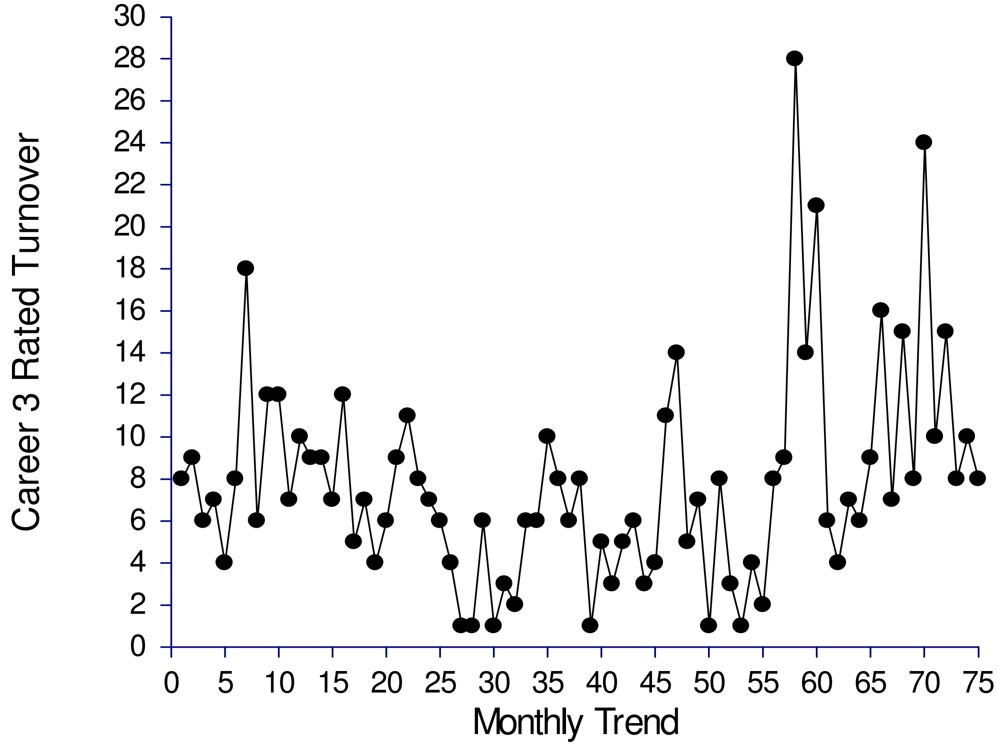

Figure 16. Monthly Turnover from Jan 2003 through Mar 2009 among Low Performers Leaving for Career-related Reasons

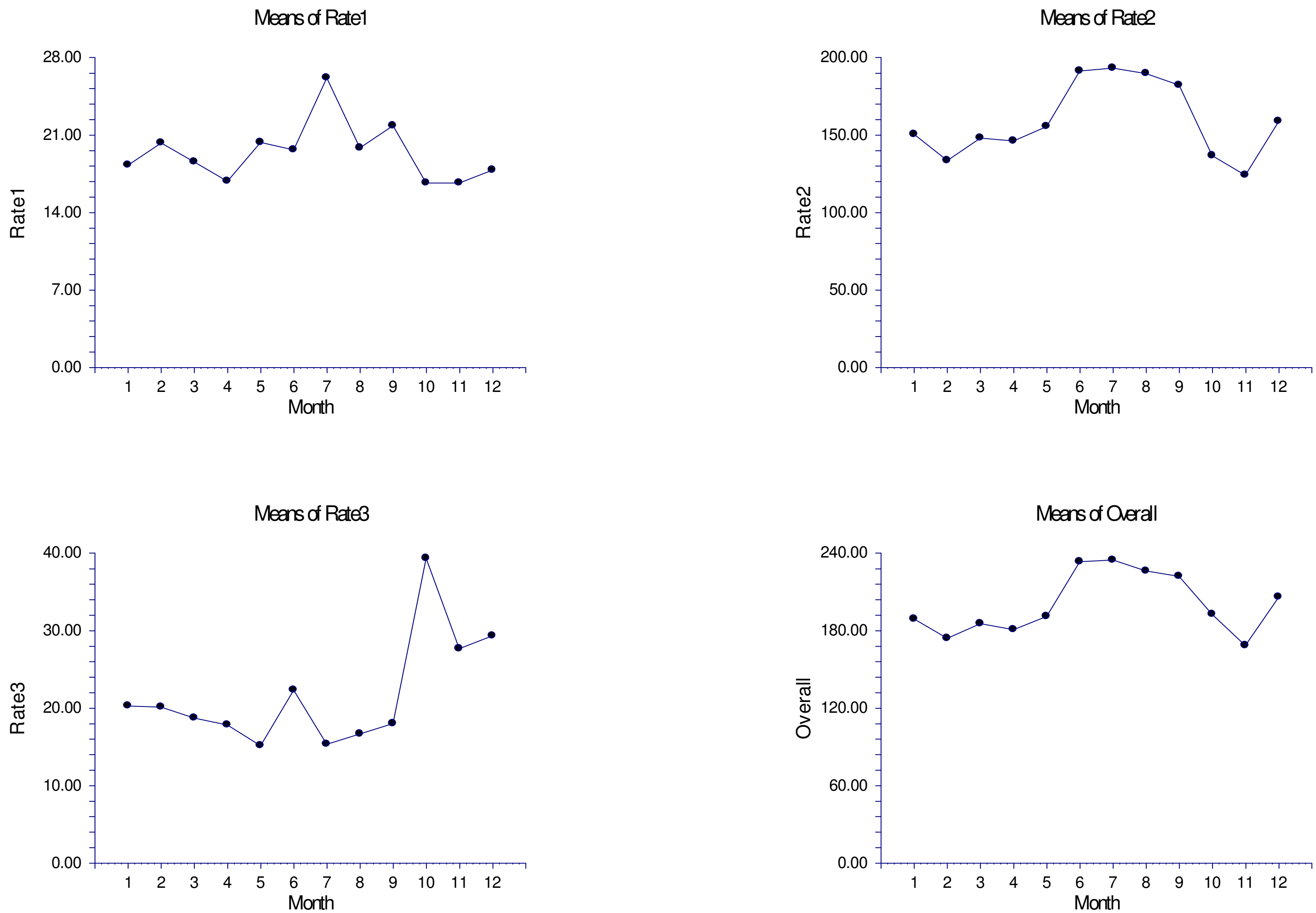

Figure 17. Average Monthly Global Turnover by Performance Rating and Overall

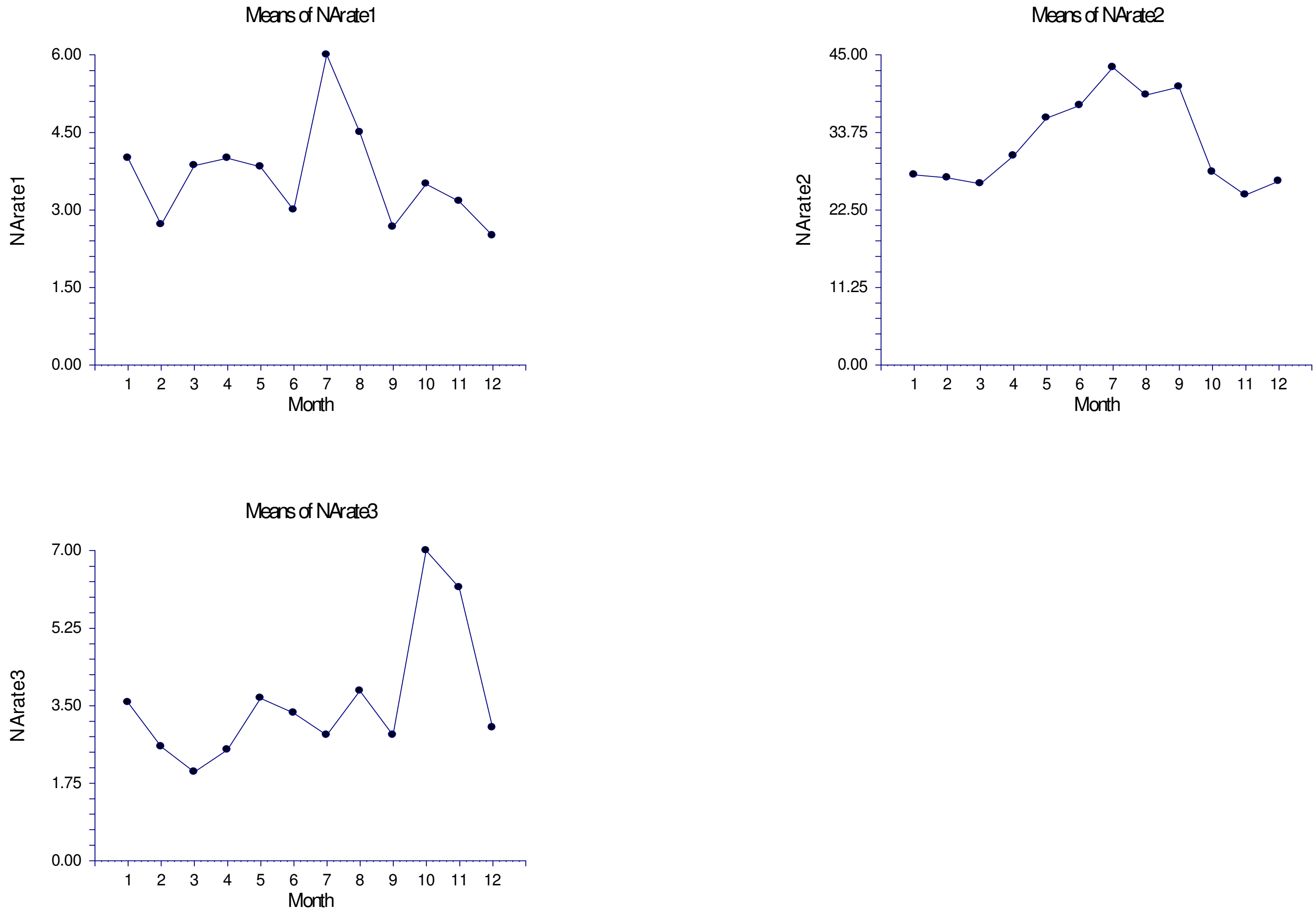

Figure 18. Average Monthly Turnover by Performance Rating in North America

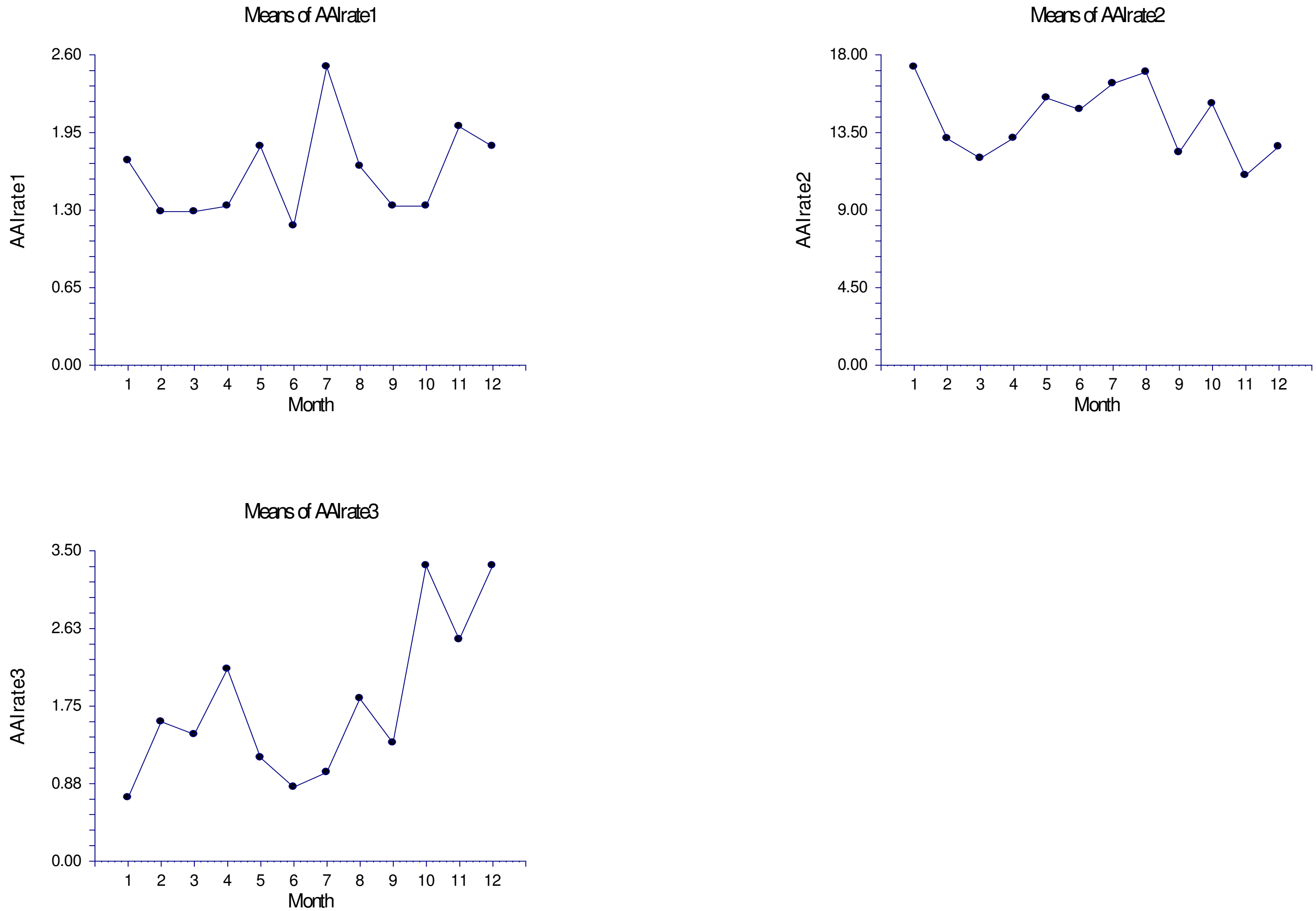

Figure 19. Average Monthly Turnover by Performance Rating in all of Asia except China, Korea and Japan and including Australia and India

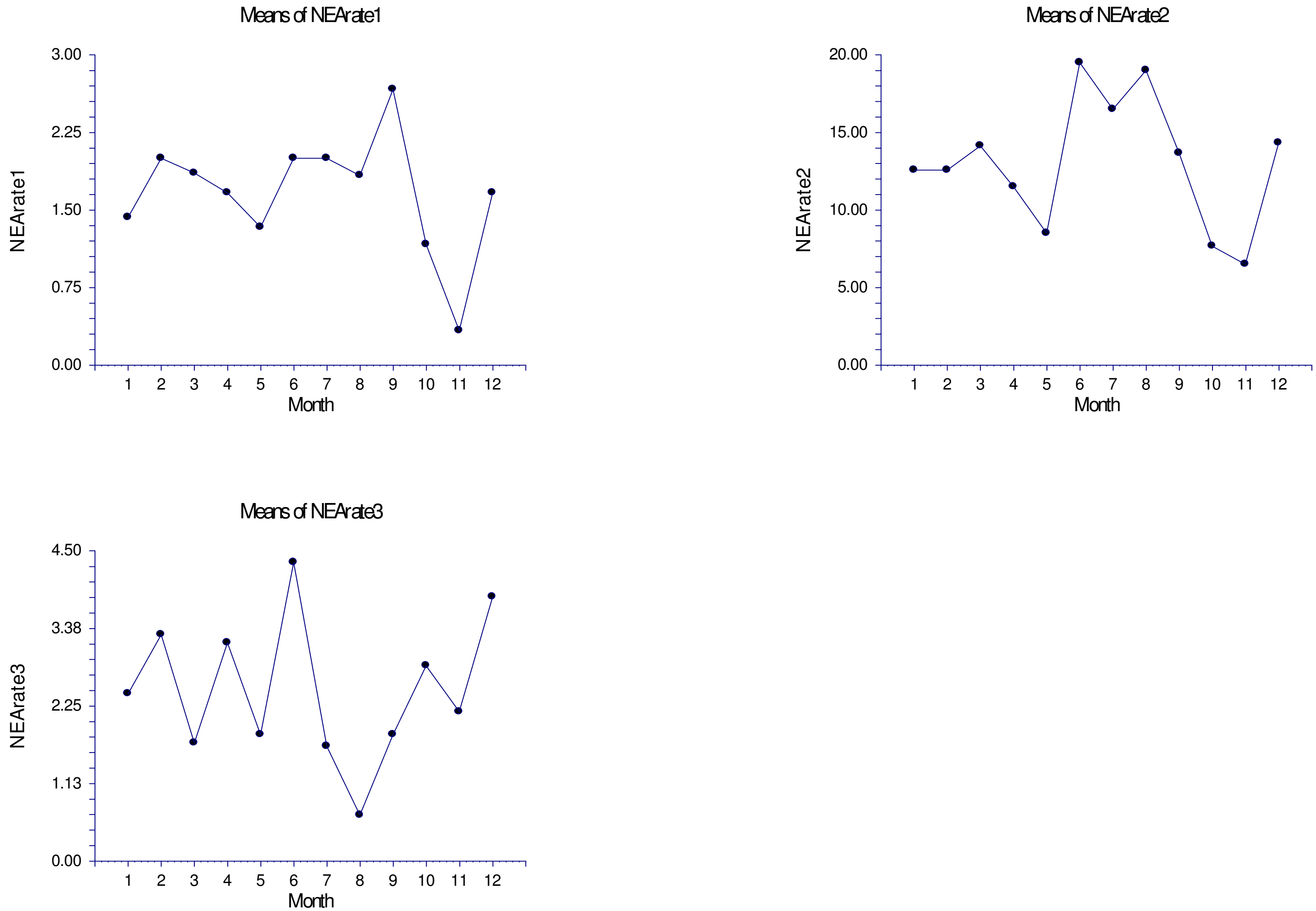

Figure 20. Average Monthly Turnover by Performance Rating in Northeast Asia

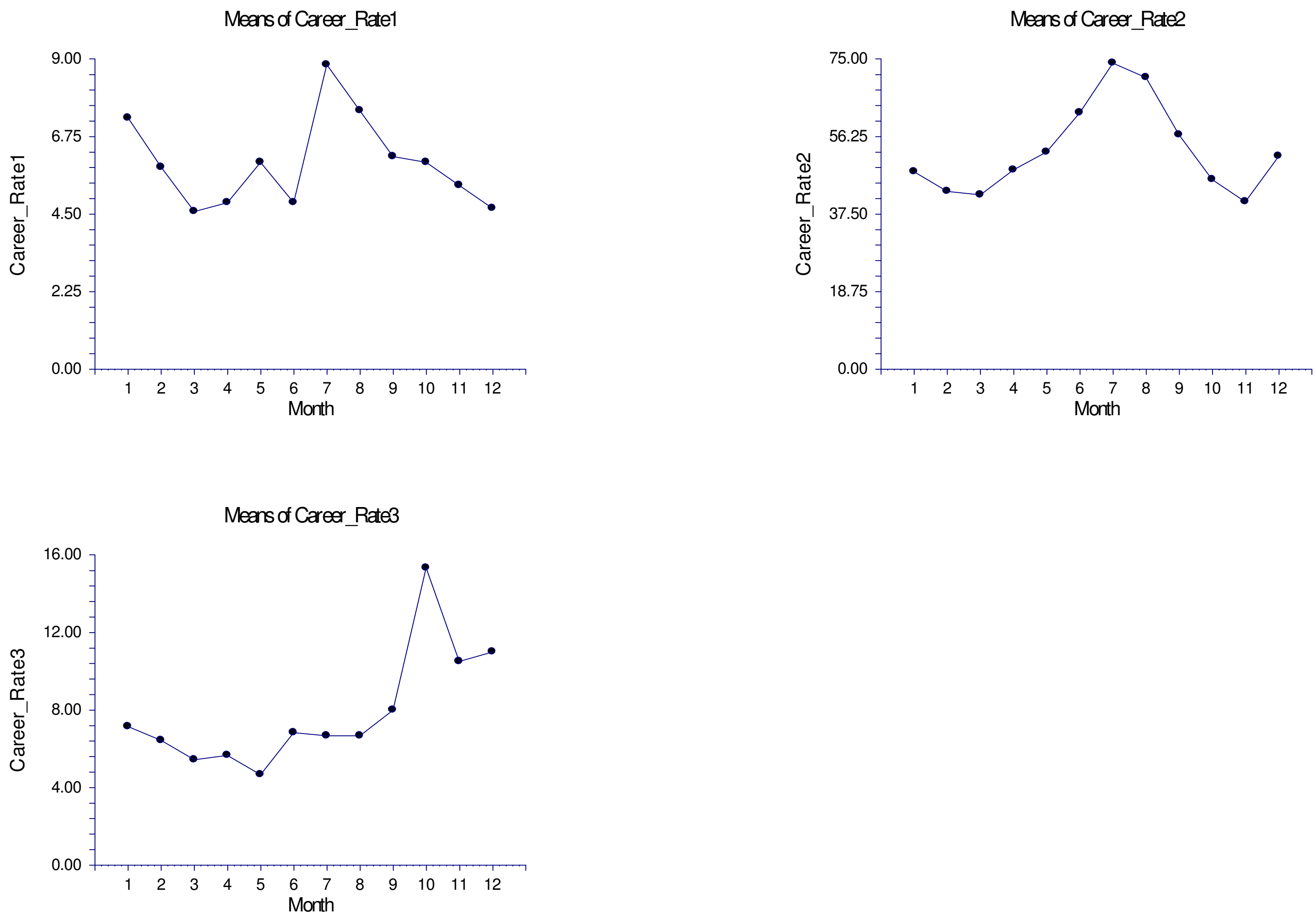

Figure 21. Average Monthly Turnover by Performance Rating among Employees Leaving for Career-related Reasons

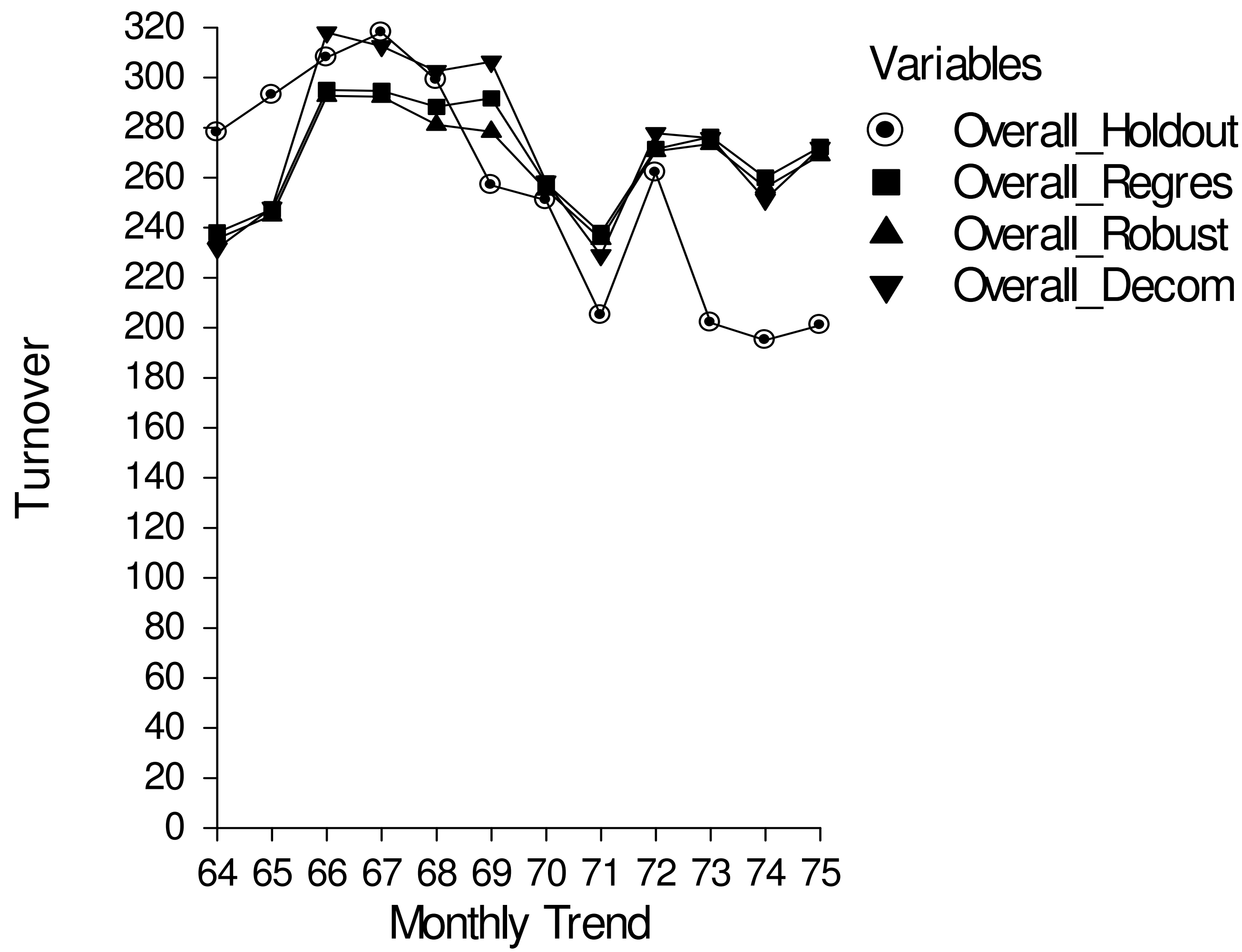

Figure 22. Predicted Monthly Turnover from Additive Regression, Robust Regression, and Decomposition Modeling Plotted against Overall Global Turnover Holdout Values from April 2008 through March 2009

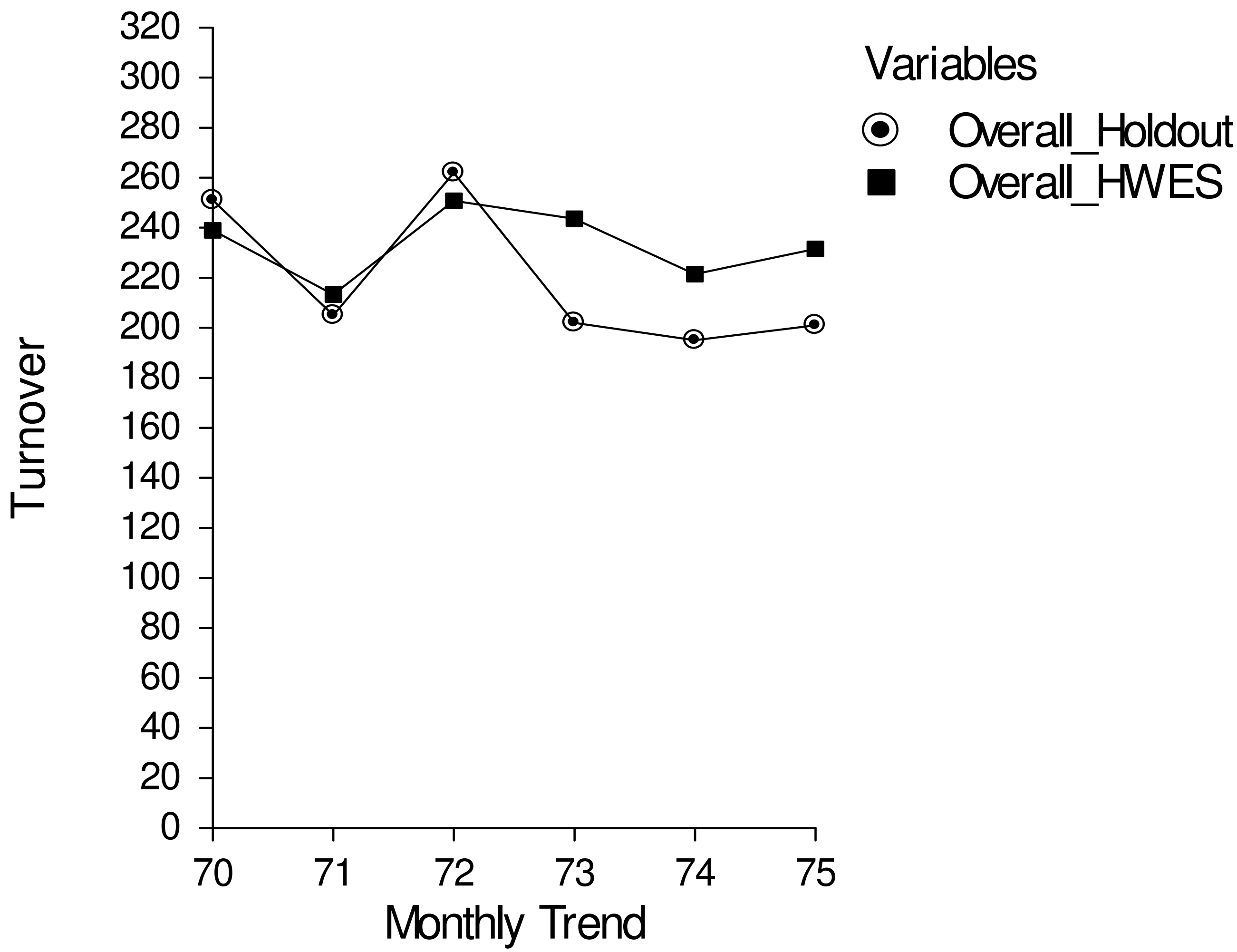

Figure 23. Predicted Monthly Turnover from HWES Plotted against Overall Global Turnover Holdout Values from October 2008 through March 2009

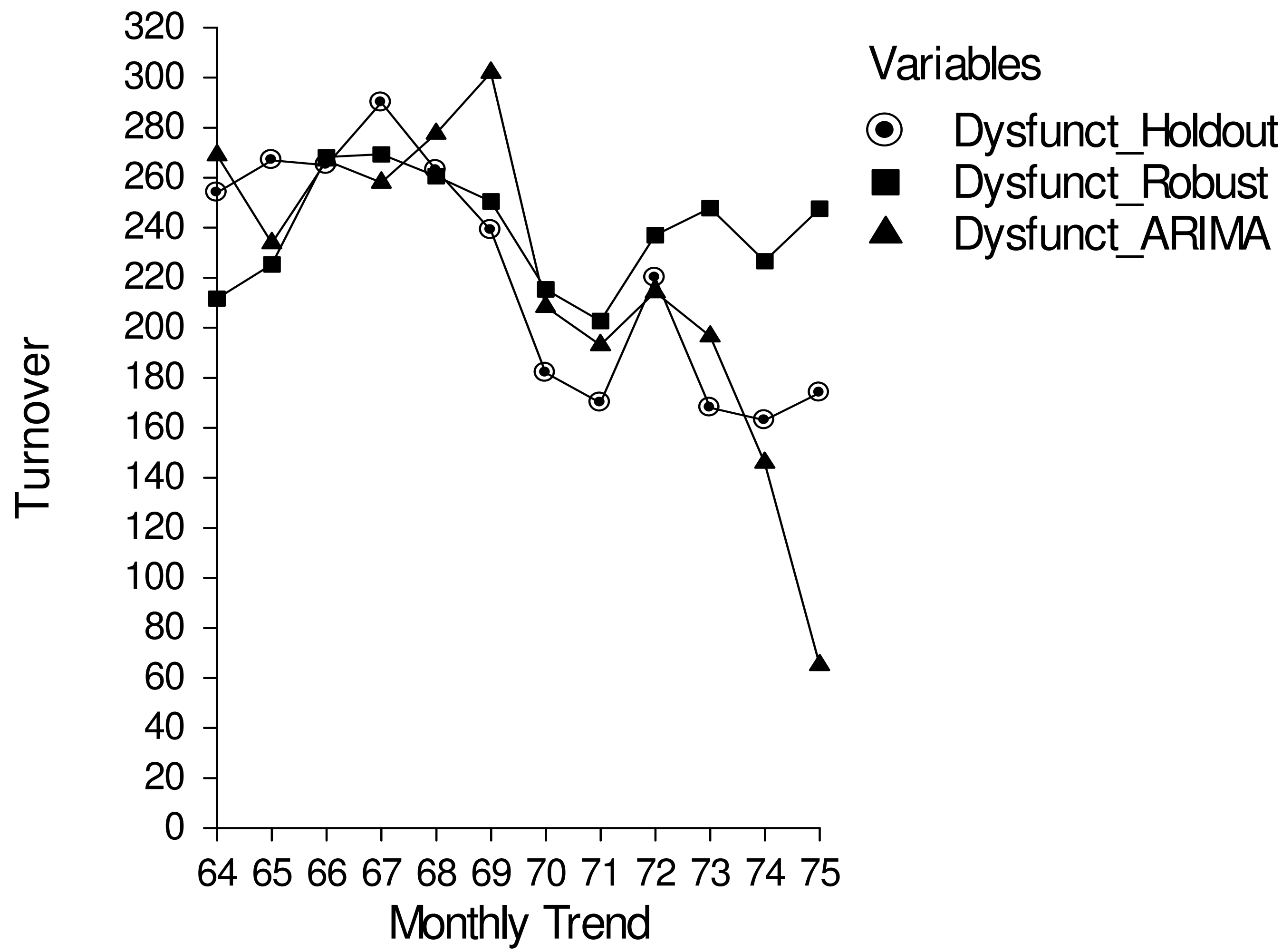

Figure 24. Predicted Monthly Turnover from Robust Regression and ARIMA Plotted against Dysfunctional Global Turnover Holdout Values from April 2008 through March 2009

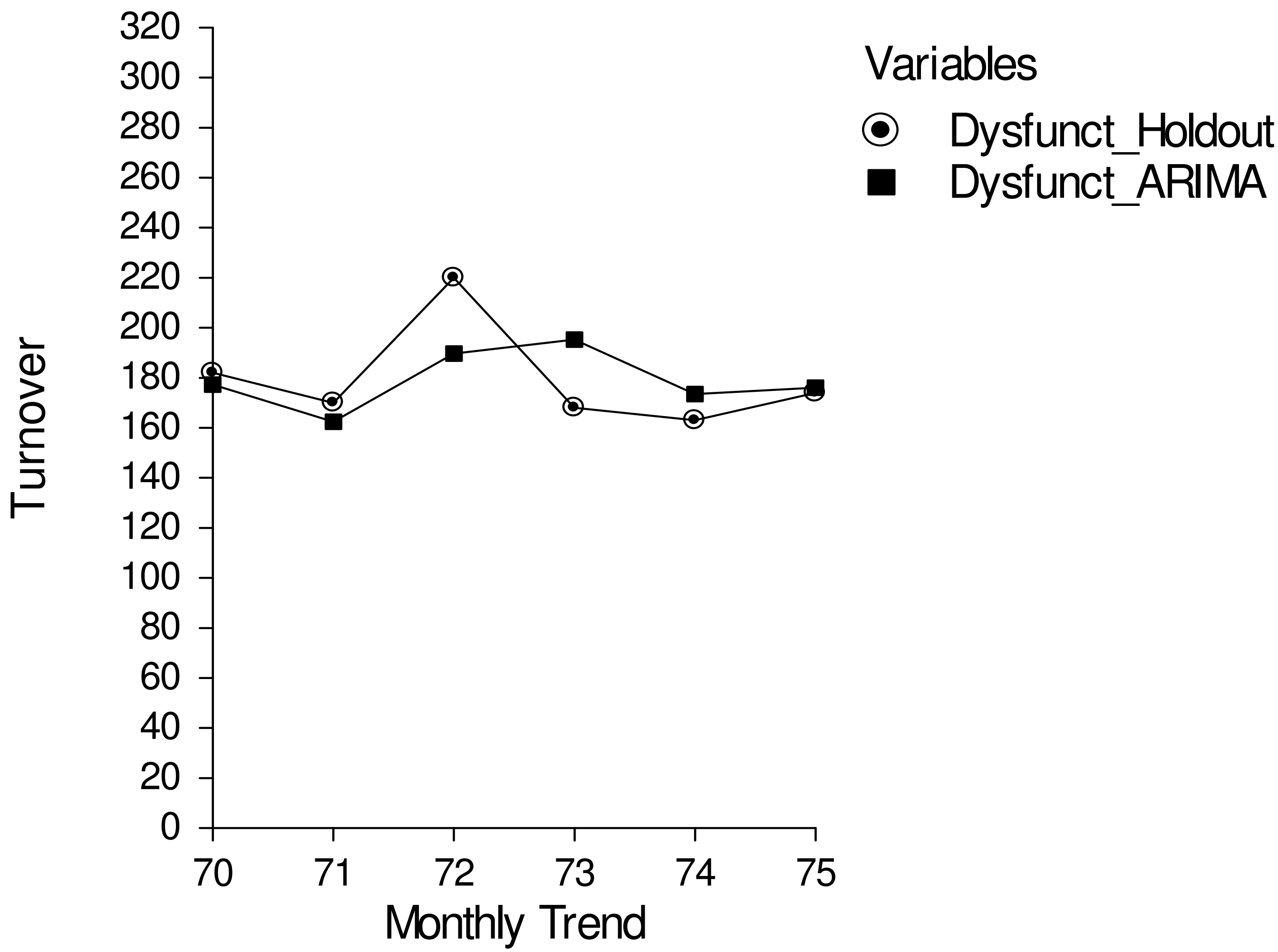

Figure 25. Predicted Monthly Turnover from ARIMA Plotted against Dysfunctional Global Turnover Holdout Values from October 2008 through March 2009

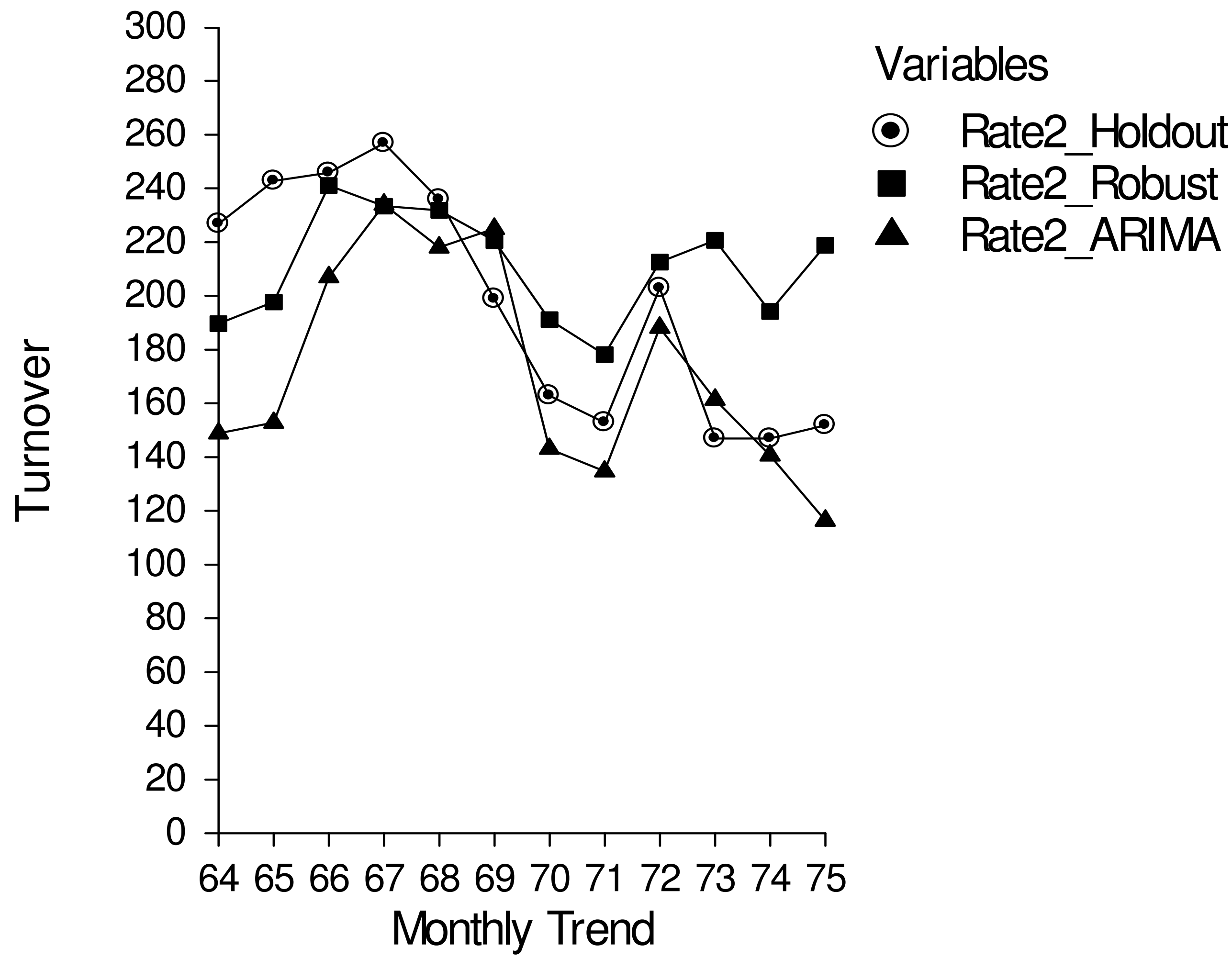

Figure 26. Predicted Monthly Turnover from Robust Regression and ARIMA Plotted against 2-Rated Global Turnover Holdout Values from April 2008 through March 2009

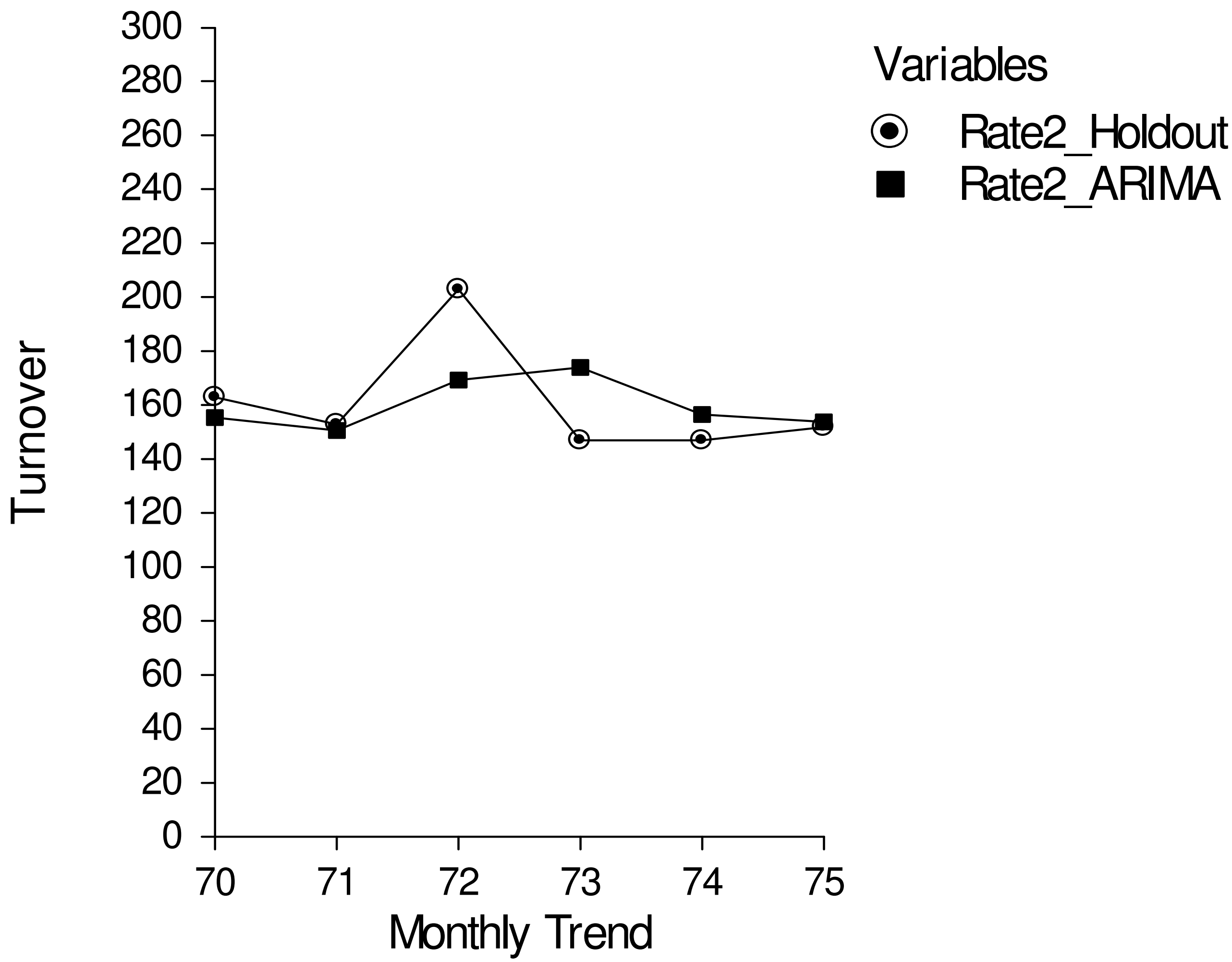

Figure 27. *Predicted Monthly Turnover from ARIMA Plotted against 2-Rated Global Turnover Holdout Values from October 2008 through March 2009*

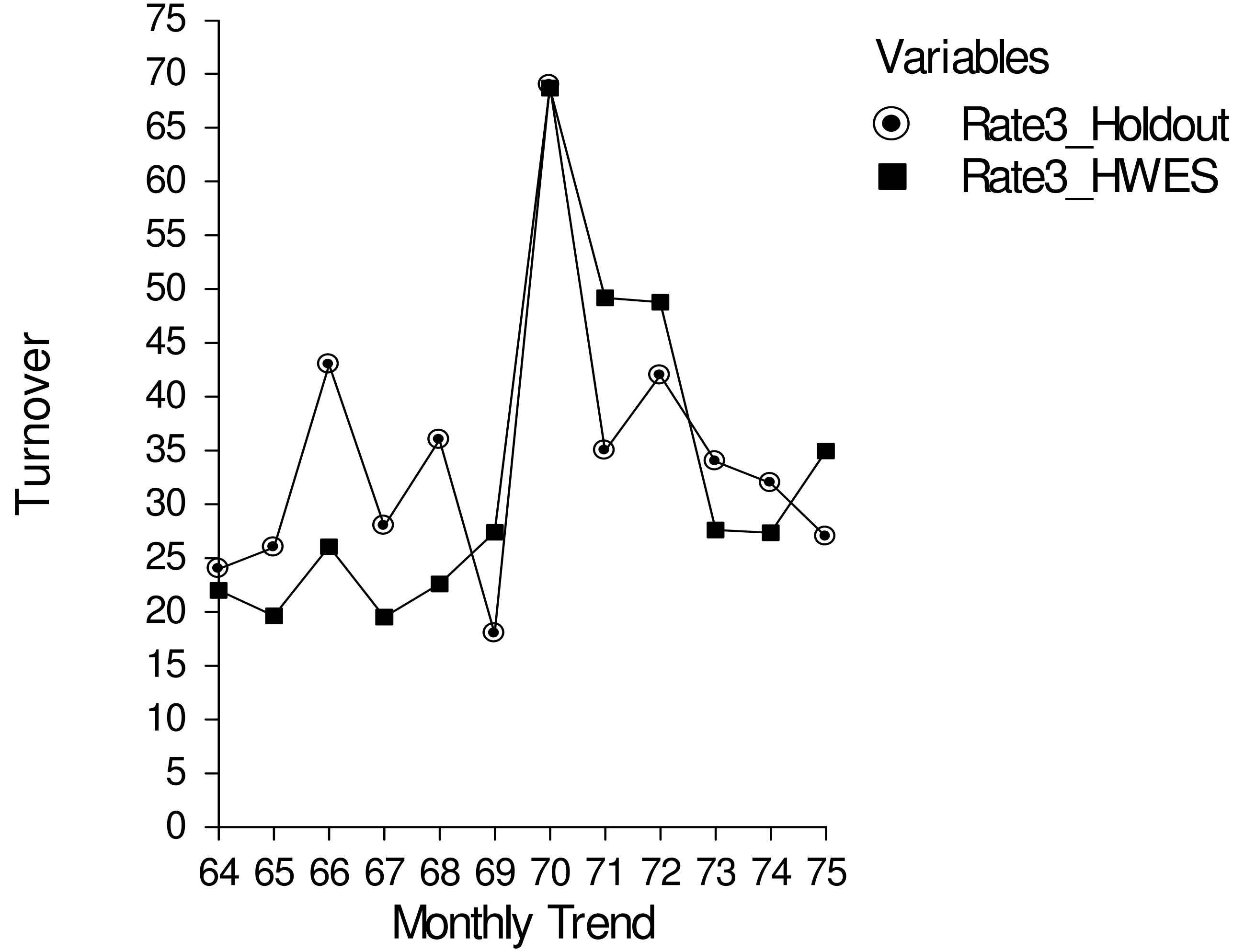

Figure 28. Predicted Monthly Turnover from HWES Plotted against 3-Rated Global Turnover Holdout Values from April 2008 through March 2009

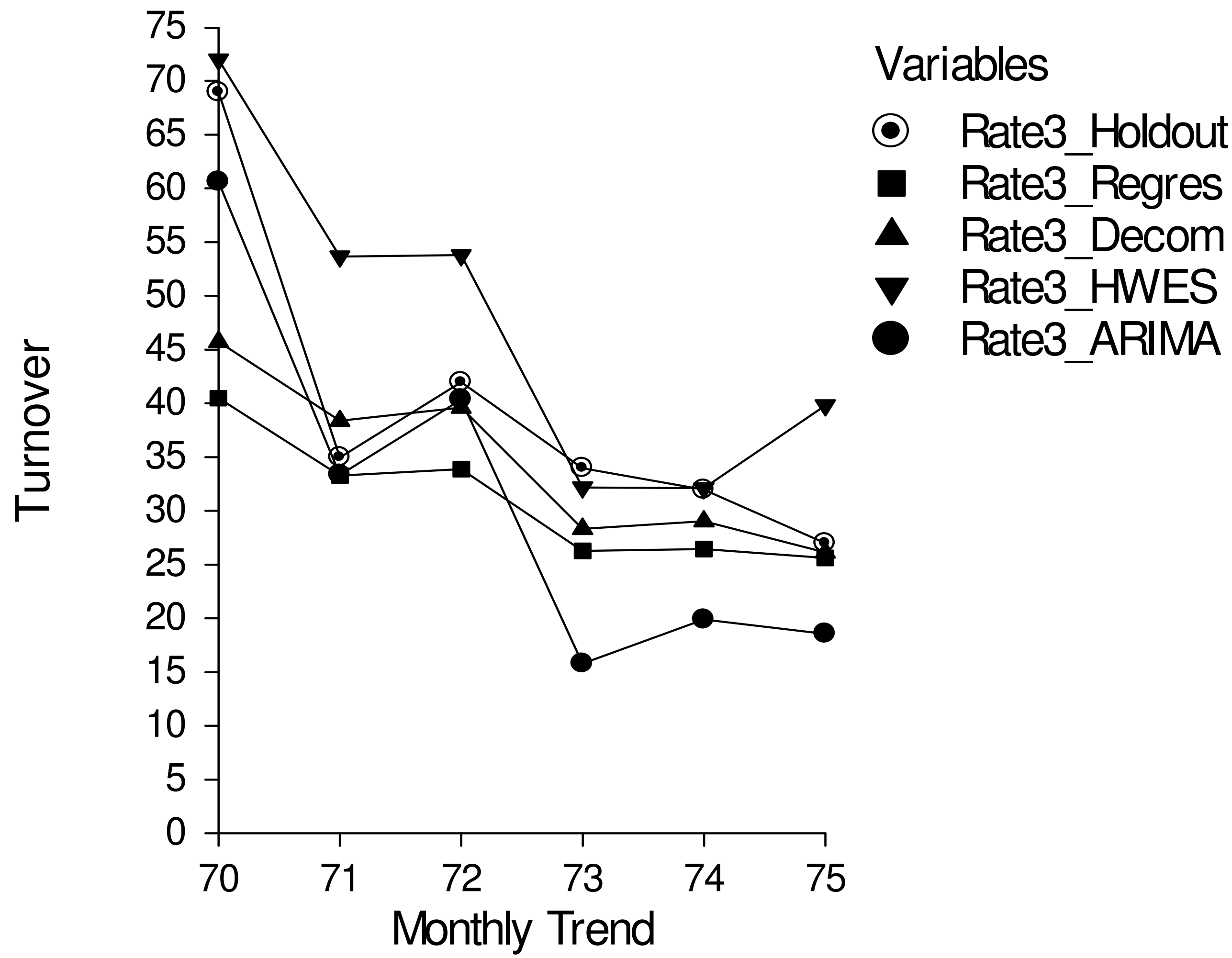

Figure 29. Predicted Monthly Turnover from Additive Regression, Decomposition Modeling, HWES, and ARIMA Plotted against 3-Rated Global Turnover Holdout Values from October 2008 through March 2009

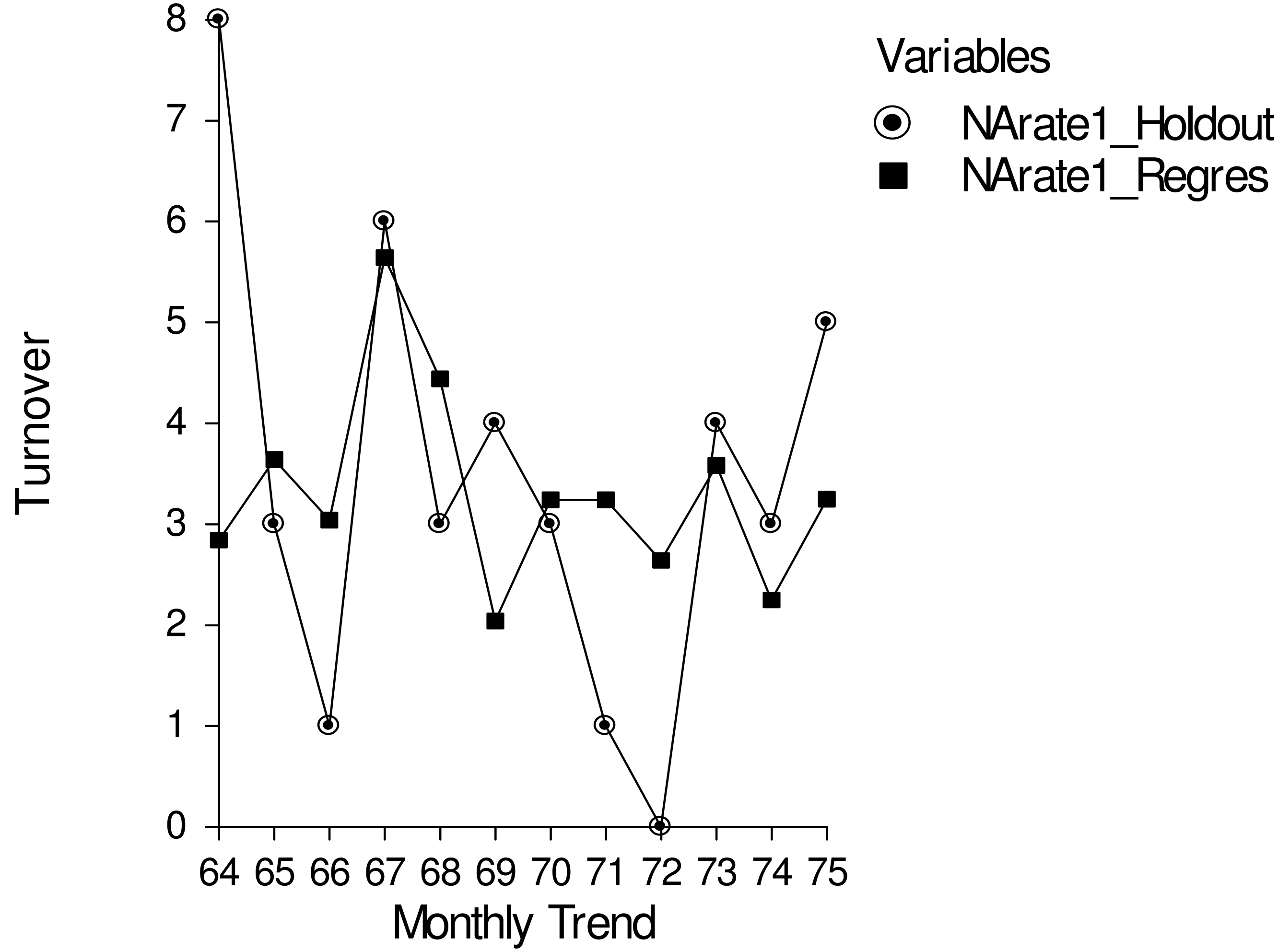

Figure 30. Predicted Monthly Turnover from Additive Regression Plotted against 1-Rated North American Turnover Holdout Values from April 2008 through March 2009

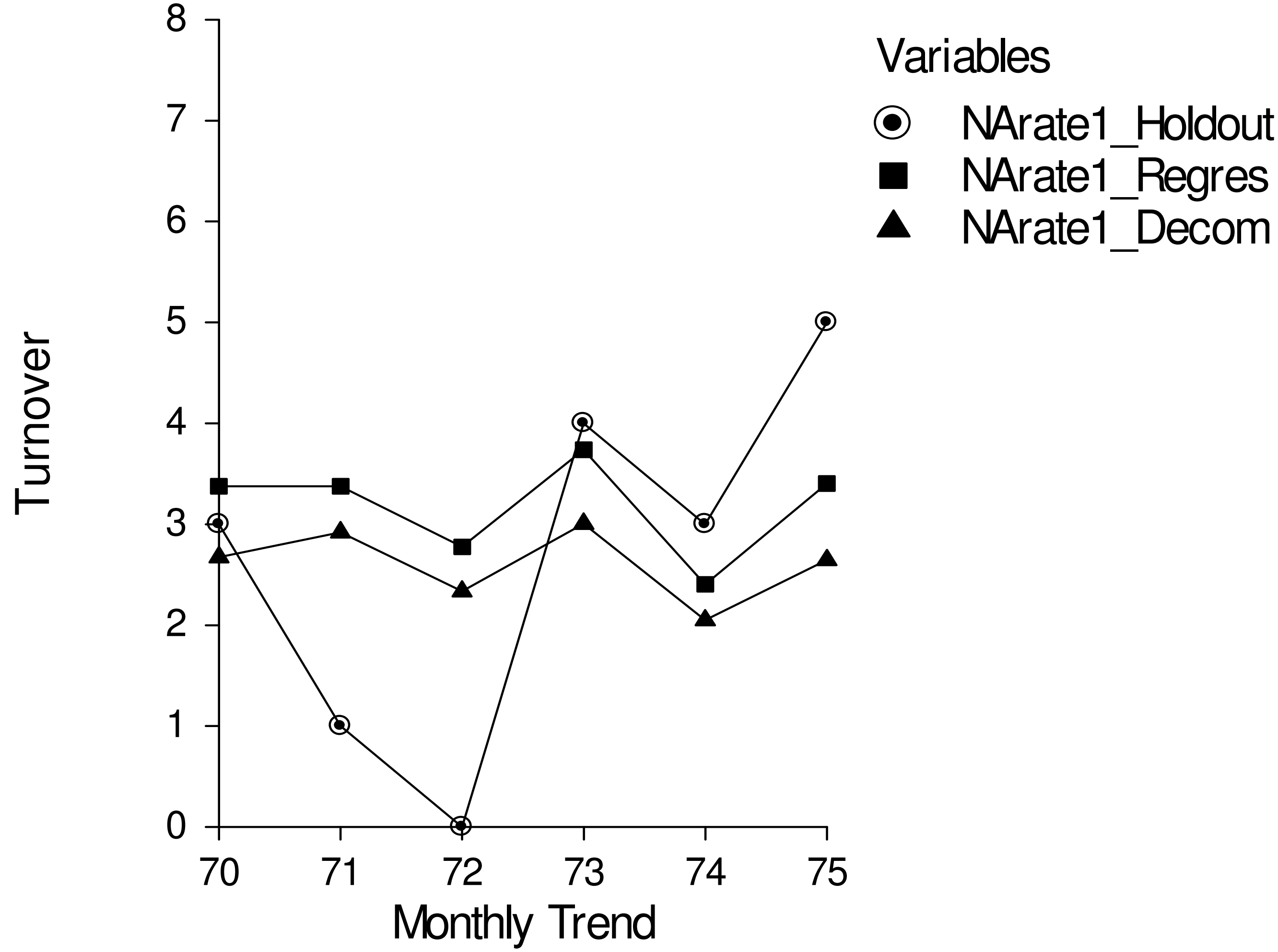

Figure 31. *Predicted Monthly Turnover from Additive Regression and Decomposition Modeling Plotted against 1-Rated North American Turnover Holdout Values from October 2008 through March 2009*

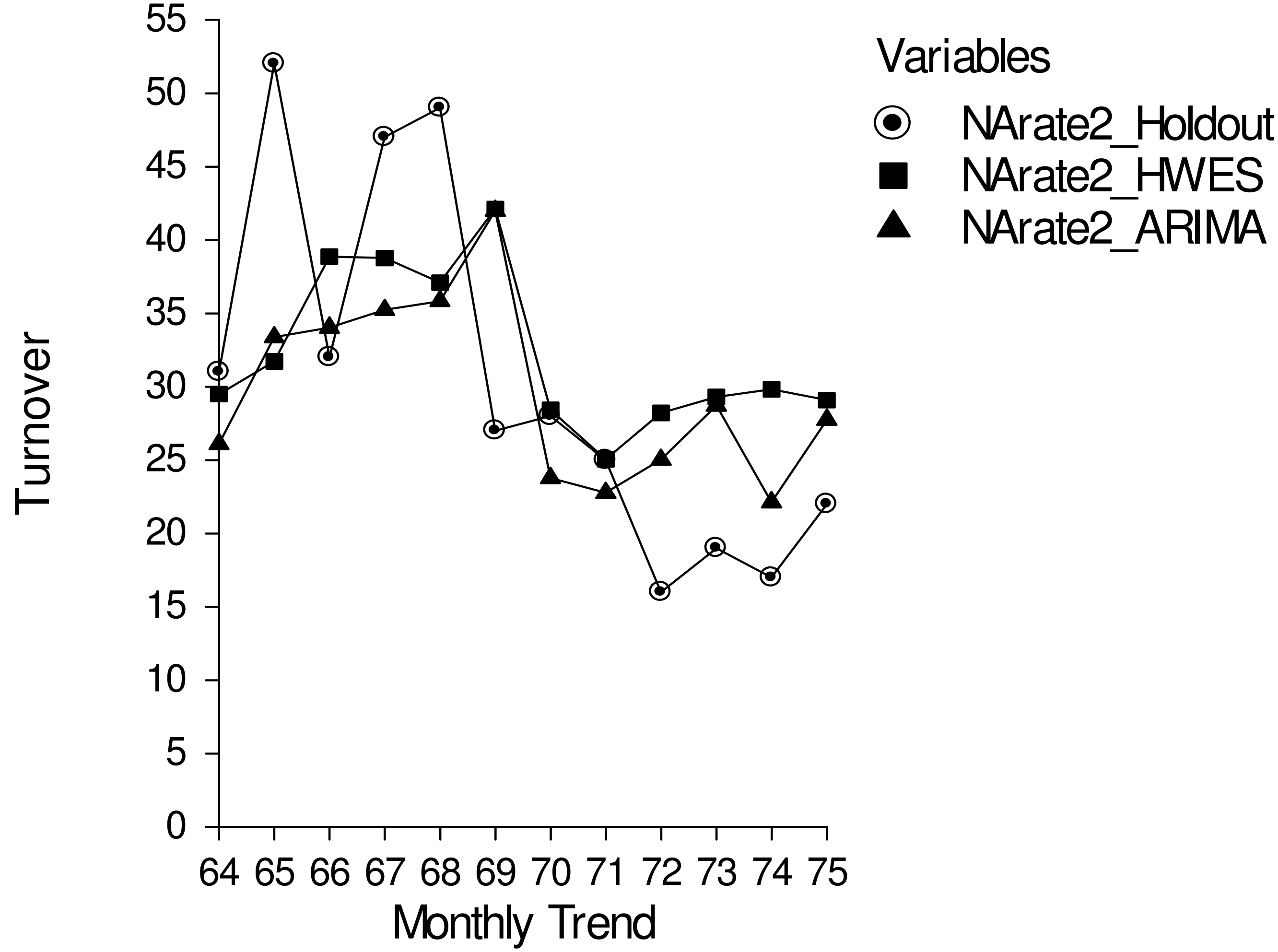

Figure 32. Predicted Monthly Turnover from HWES and ARIMA Plotted against 2-Rated North American Turnover Holdout Values from April 2008 through March 2009

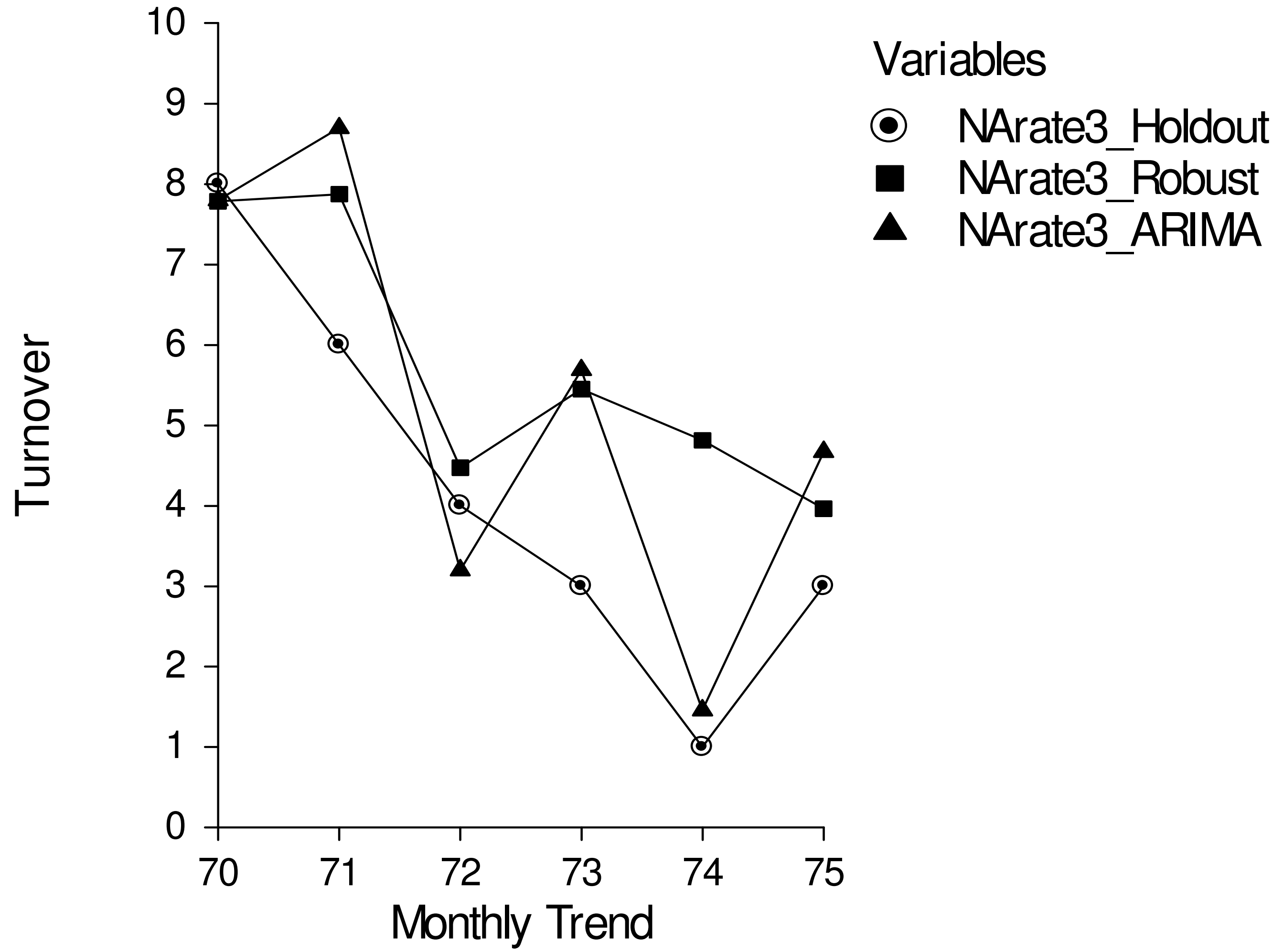

Figure 33. Predicted Monthly Turnover from Robust Regression and ARIMA Plotted against 3-Rated North American Turnover Holdout Values from October 2008 through March 2009

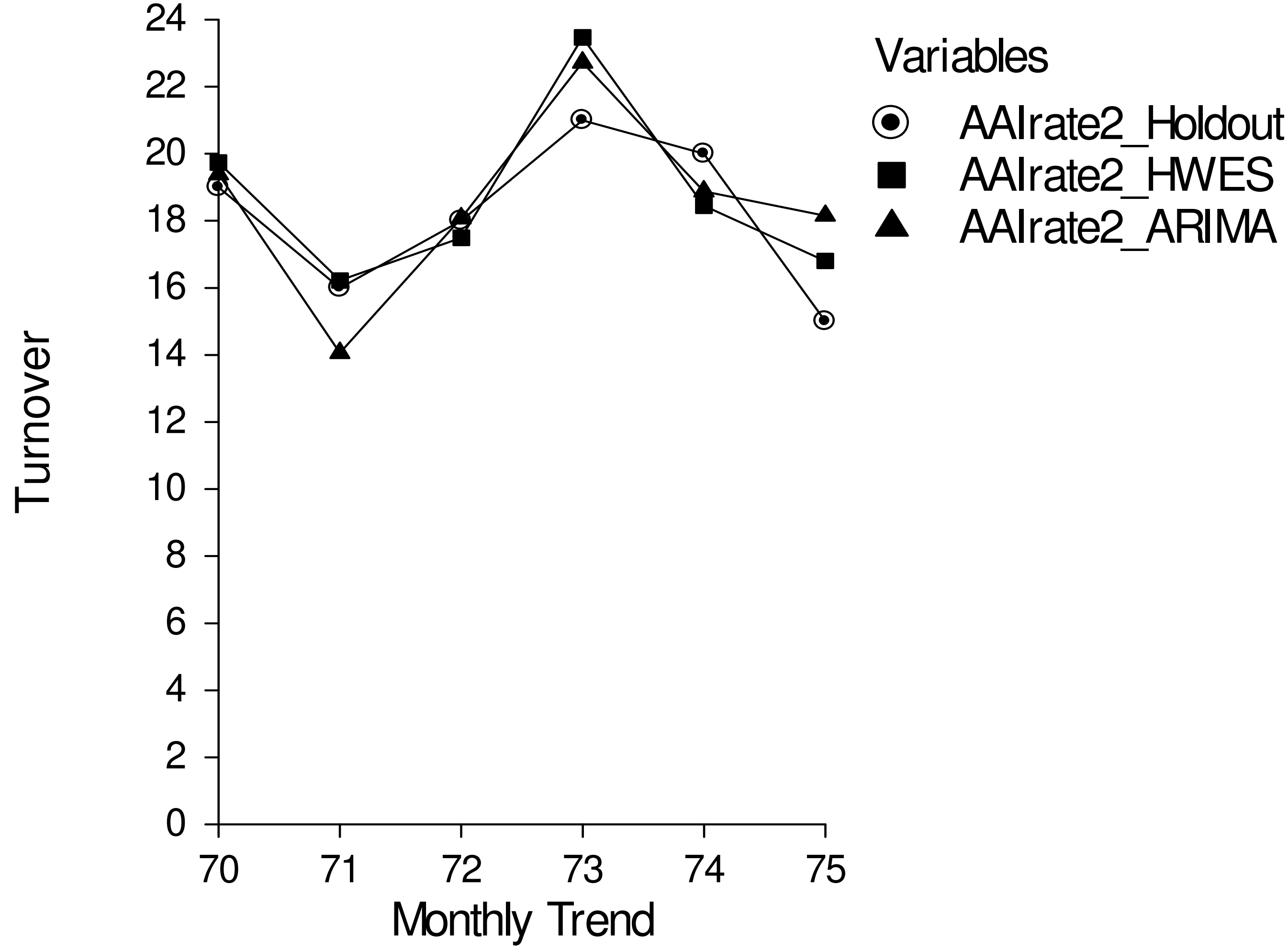

Figure 34. Predicted Monthly Turnover from HWES and ARIMA Plotted against 2-Rated AAI Turnover Holdout Values from October 2008 through March 2009

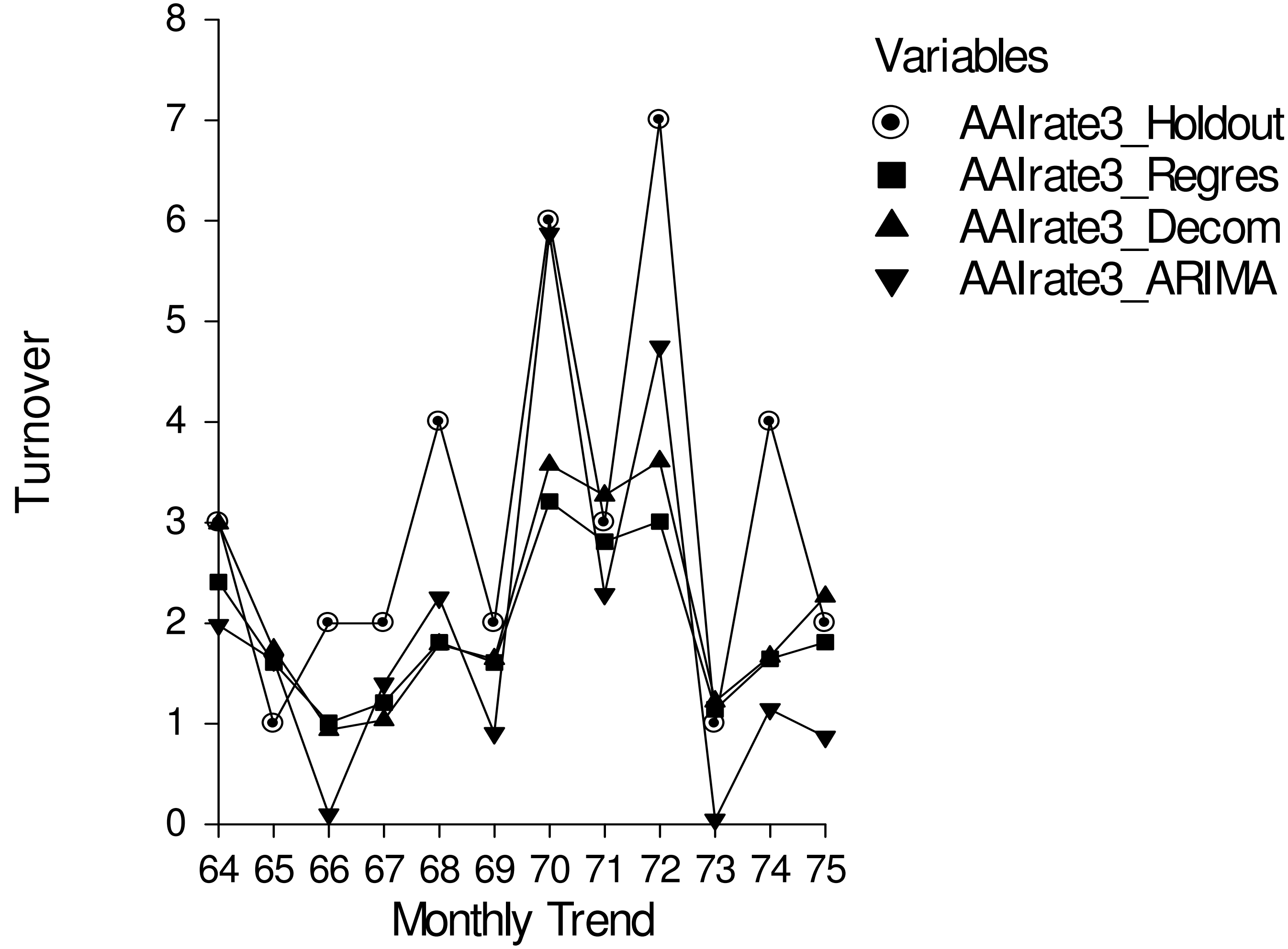

Figure 35. Predicted Monthly Turnover from Additive Regression, Decomposition Modeling, and ARIMA Plotted against 3-Rated AAI Turnover Holdout Values from April 2008 through March 2009

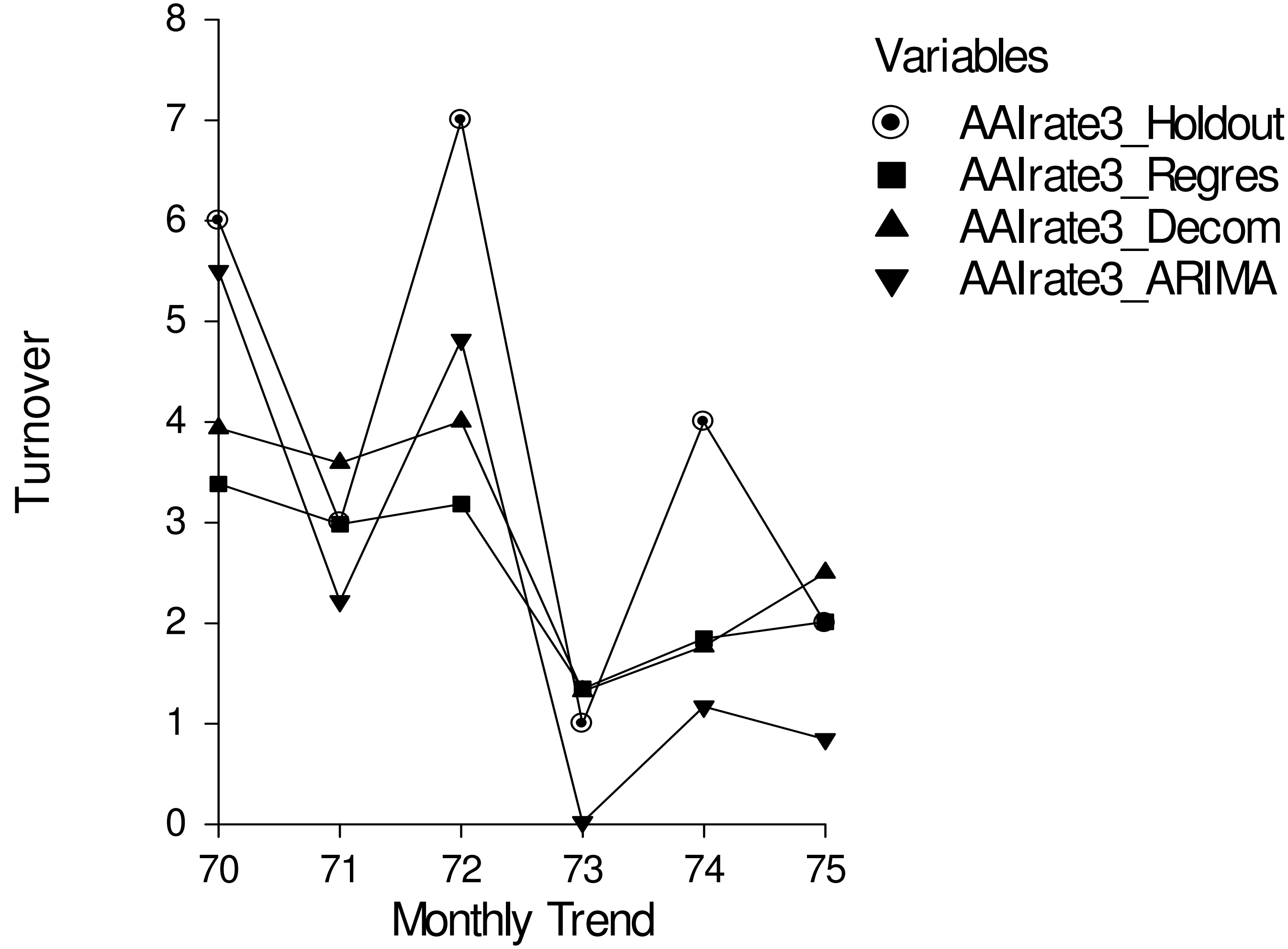

Figure 36. Predicted Monthly Turnover from Additive Regression, Decomposition Modeling, and ARIMA Plotted against 3-Rated AAI Turnover Holdout Values from October 2008 through March 2009

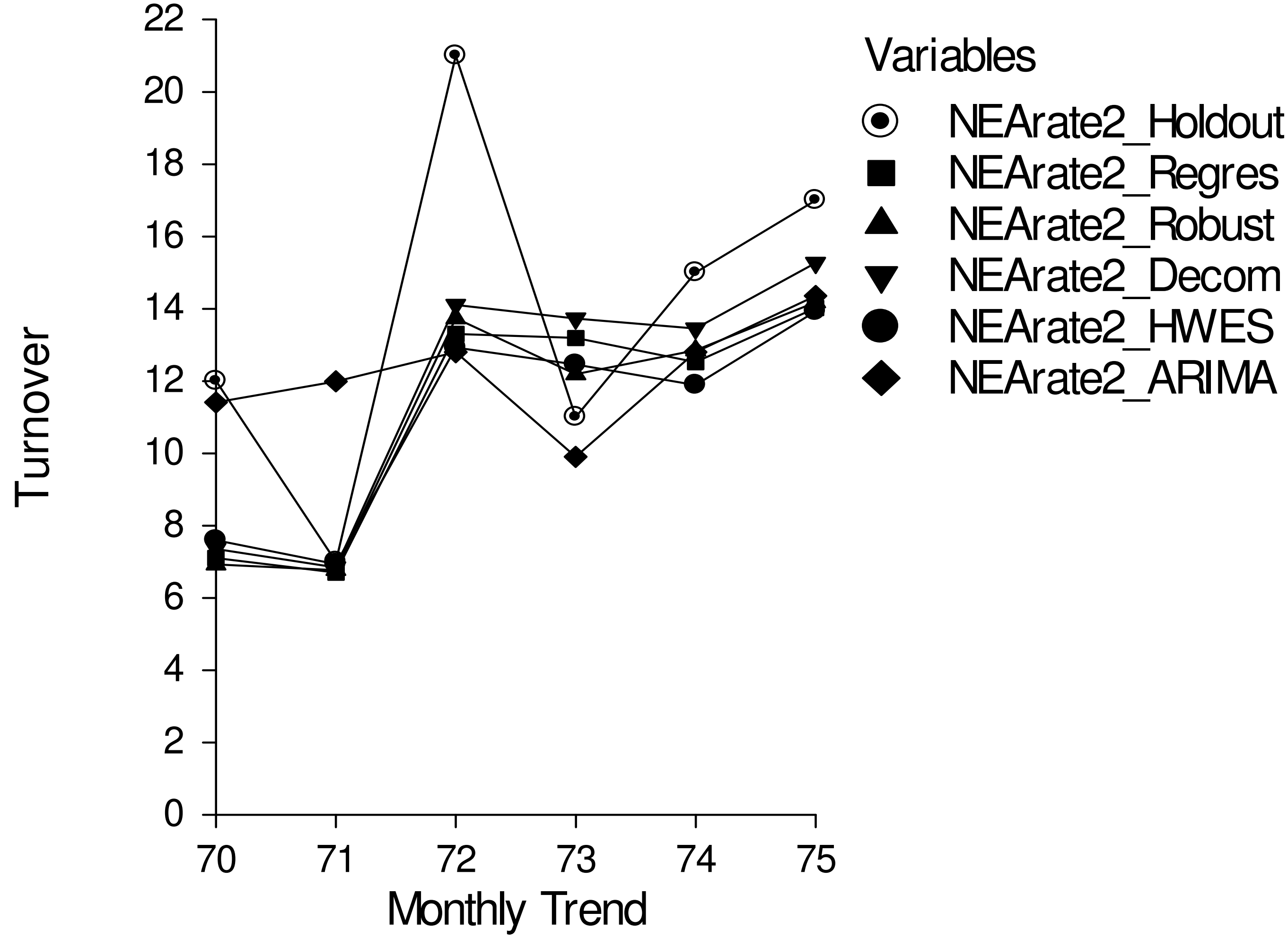

Figure 37. Predicted Monthly Turnover from Additive Regression, Robust Regression, Decomposition Modeling, HWES, and ARIMA Plotted against 2-Rated Northeast Asian Turnover Holdout Values from October 2008 through March 2009

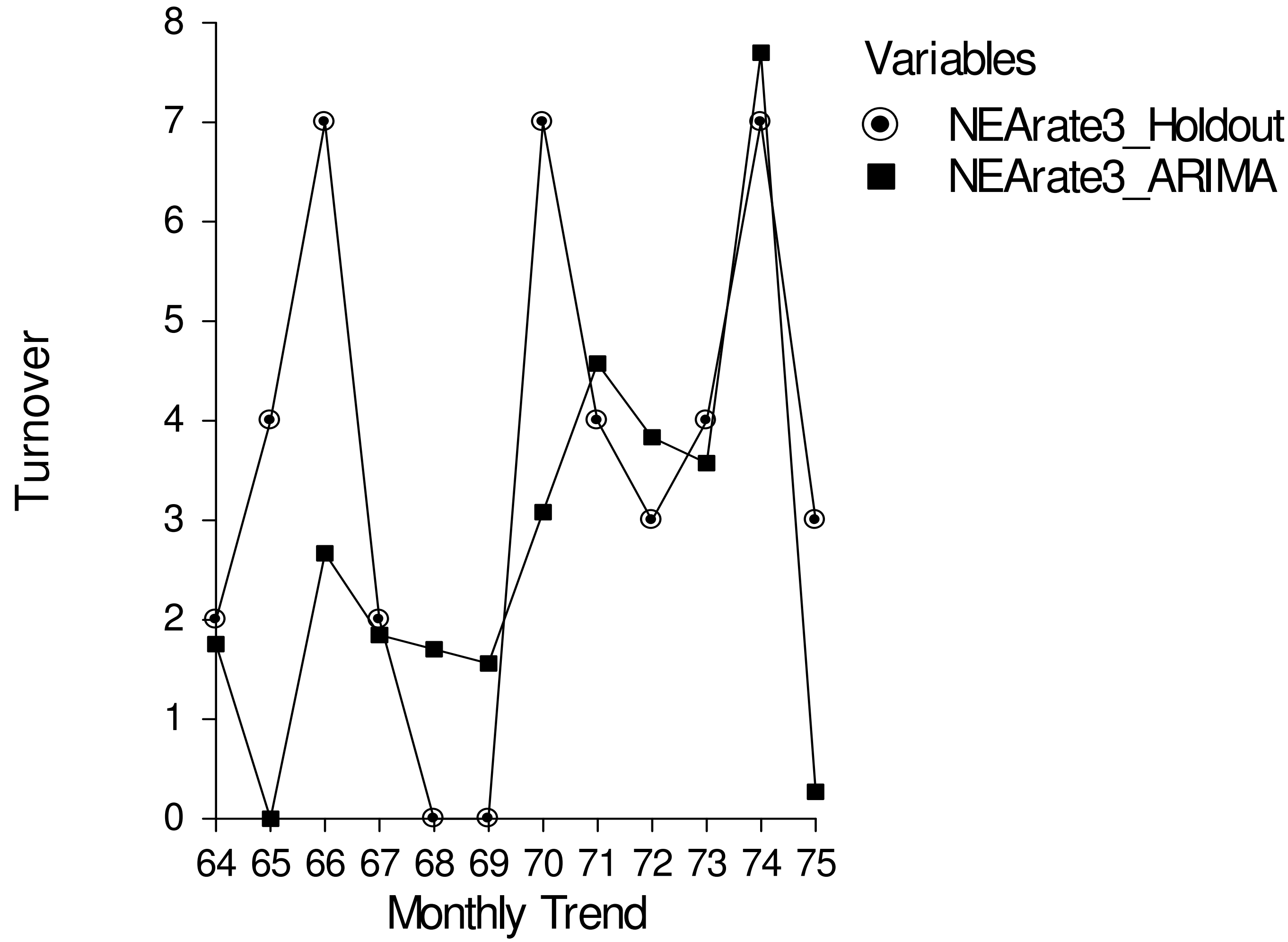

Figure 38. Predicted Monthly Turnover from ARIMA Plotted against 3-Rated Northeast Asian Turnover Holdout Values from April 2008 through March 2009

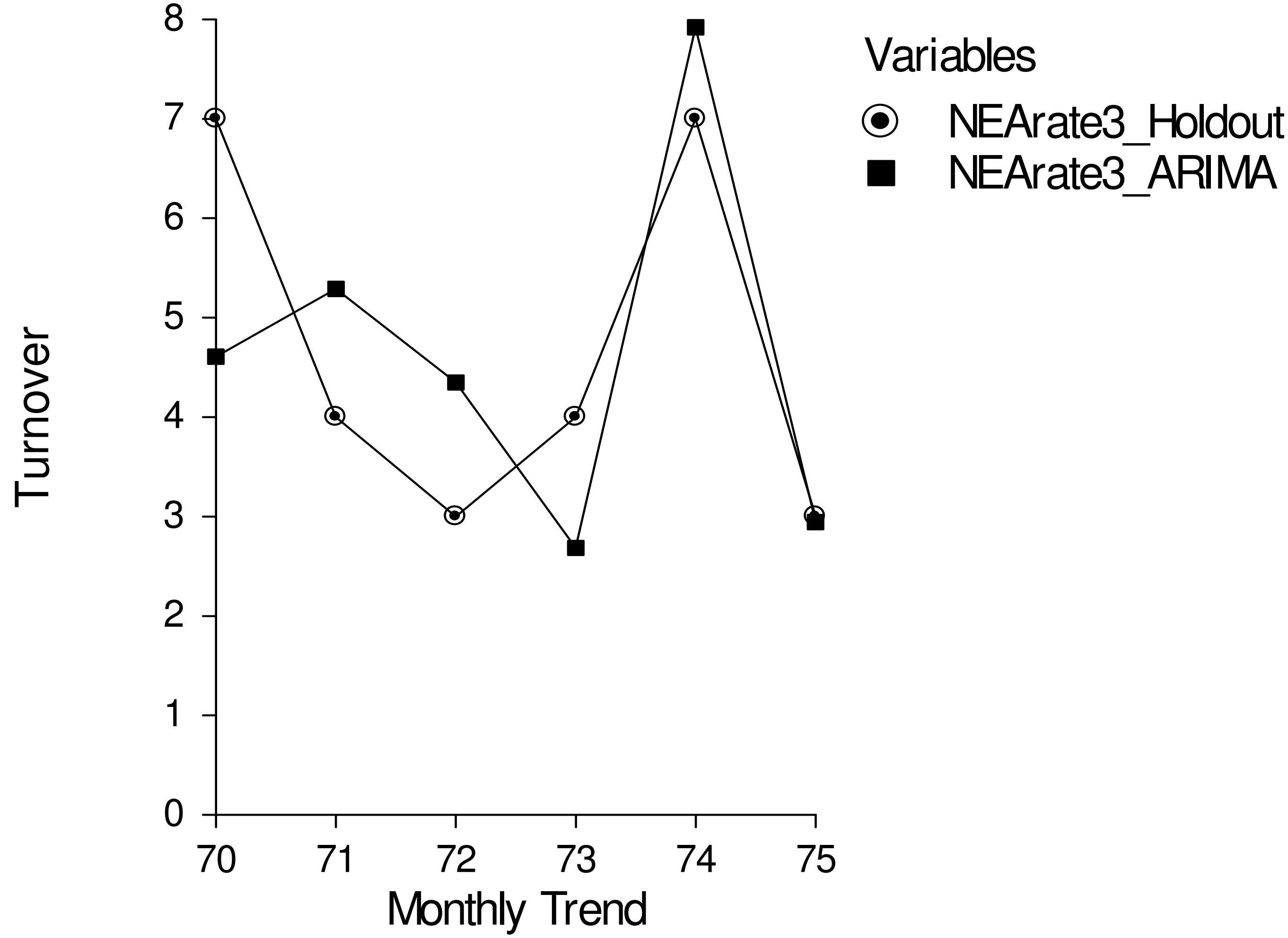

Figure 39. Predicted Monthly Turnover from ARIMA Plotted against 3-Rated Northeast Asian Turnover Holdout Values from October 2008 through March 2009

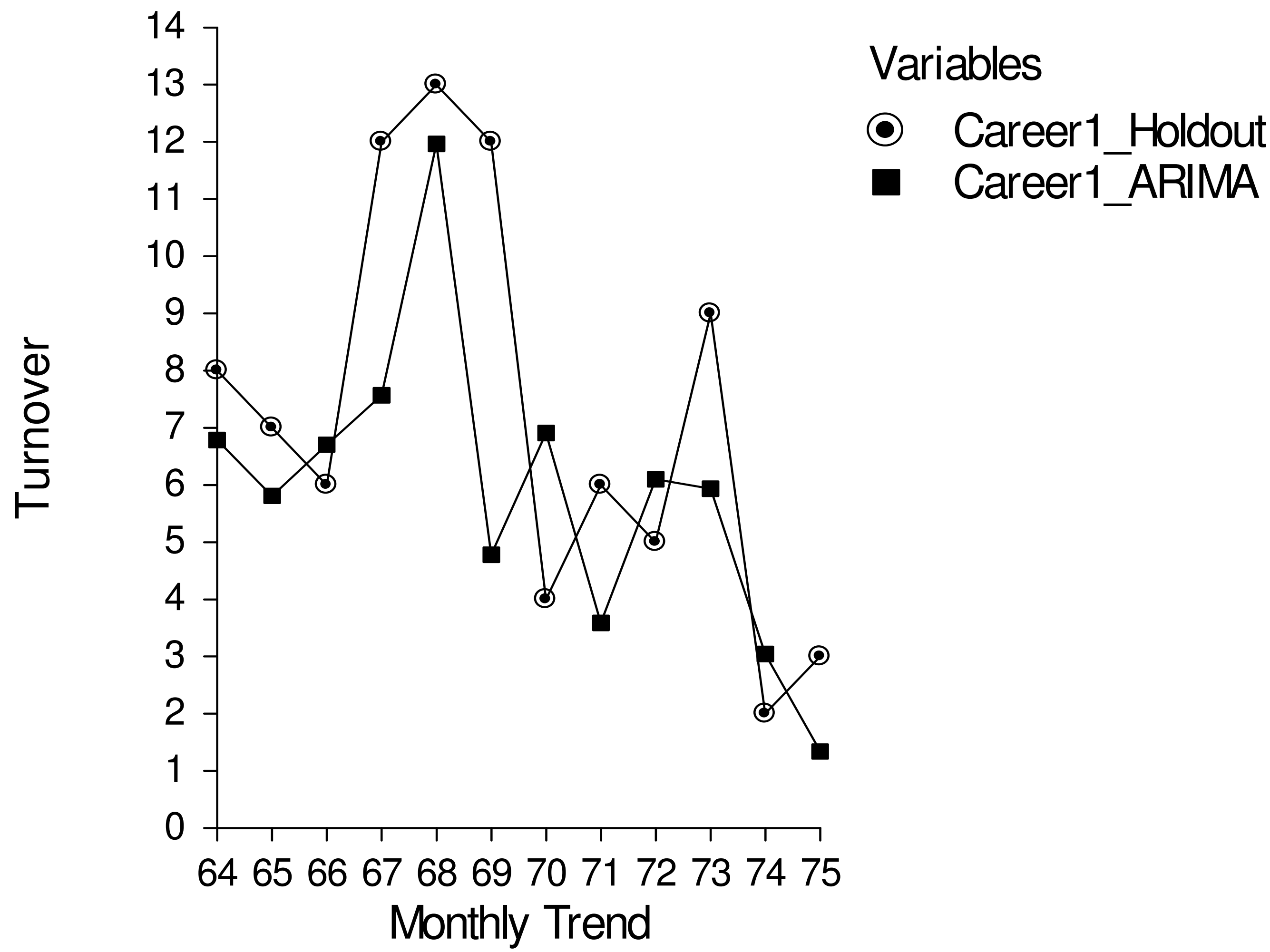

Figure 40. Predicted Monthly Turnover from ARIMA Plotted against 1-Rated Global Career-related Turnover Holdout Values from April 2008 through March 2009

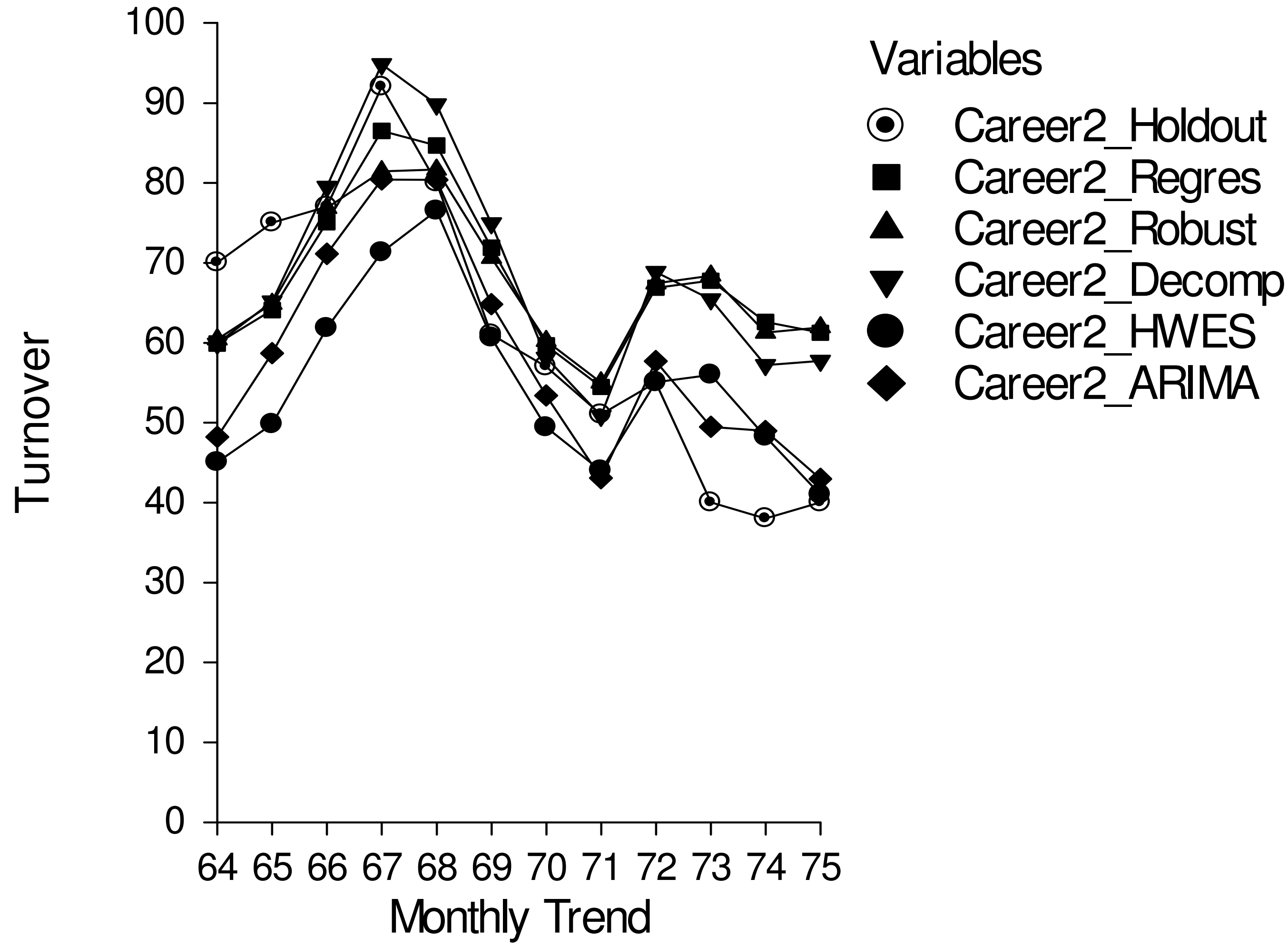

Figure 41. Predicted Monthly Turnover from Additive Regression, Robust Regression, Decomposition Modeling, HWES, and ARIMA Plotted against 2-Rated Global Career-related Holdout Values from April 2008 through March 2009

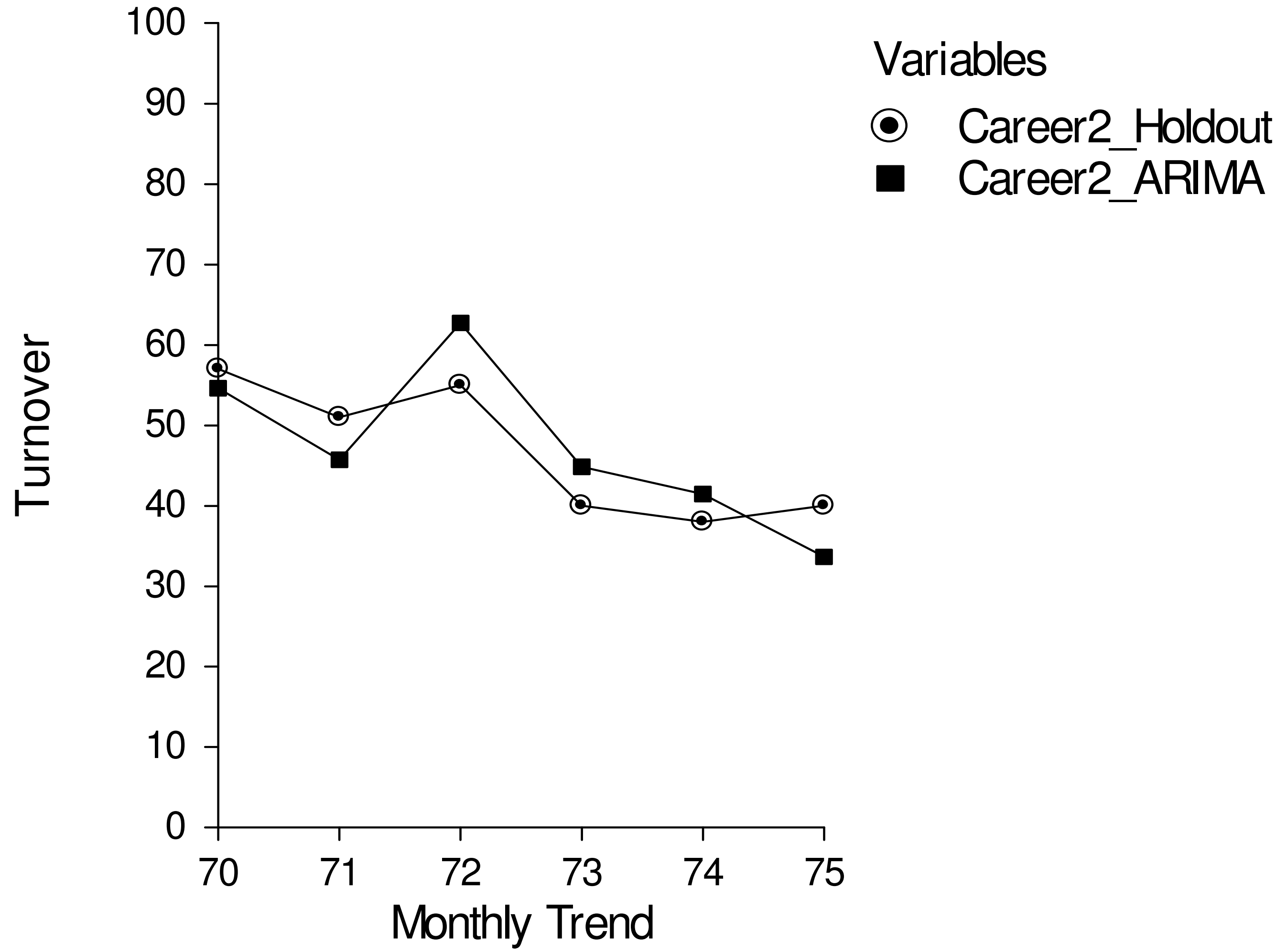

Figure 42. *Predicted Monthly Turnover from ARIMA Plotted against 2-Rated Global Career-related Holdout Values from October 2008 through March 2009*

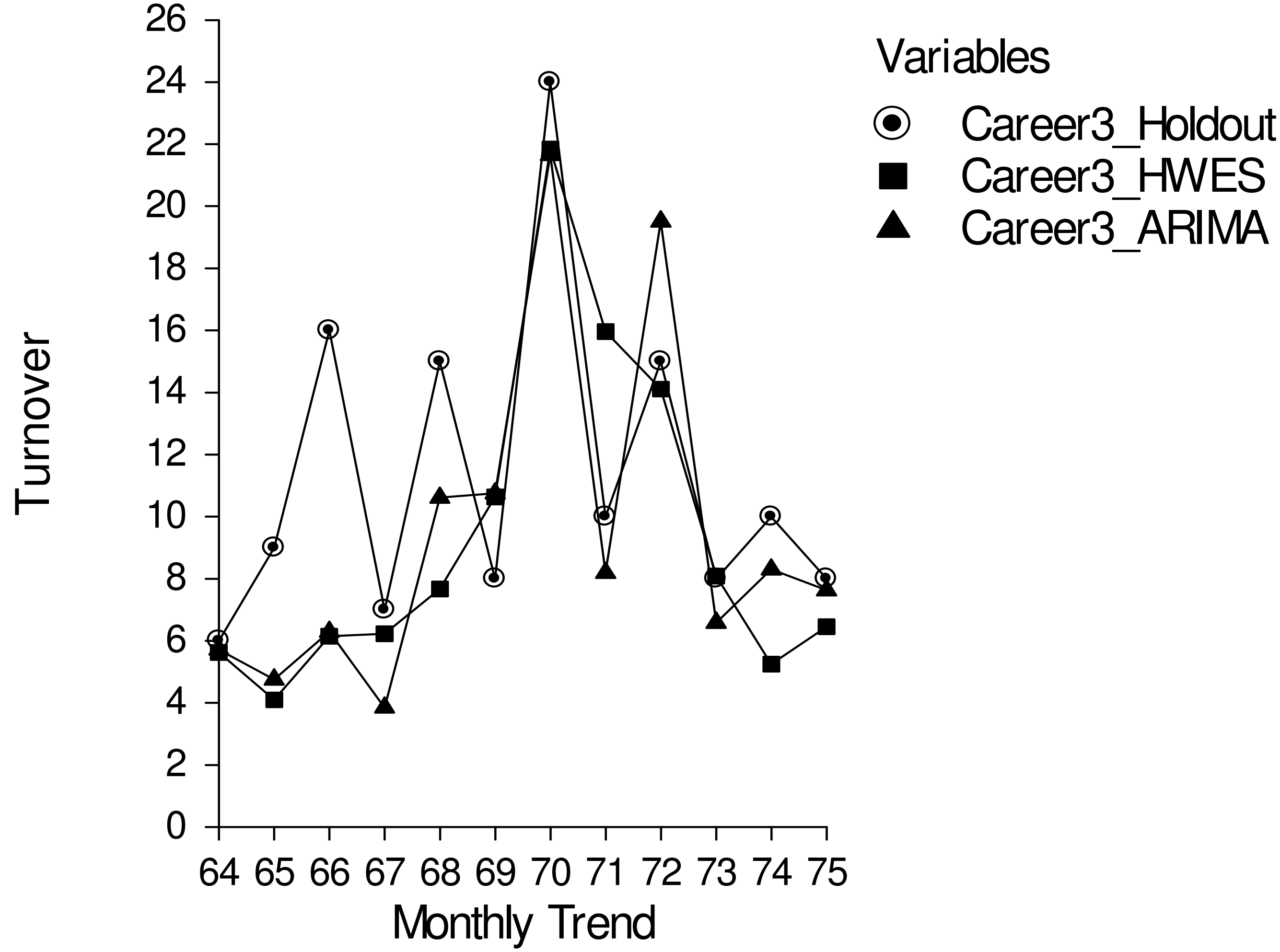

Figure 43. Predicted Monthly Turnover from HWES and ARIMA Plotted against 3-Rated Global Career-related Holdout Values from April 2008 through March 2009

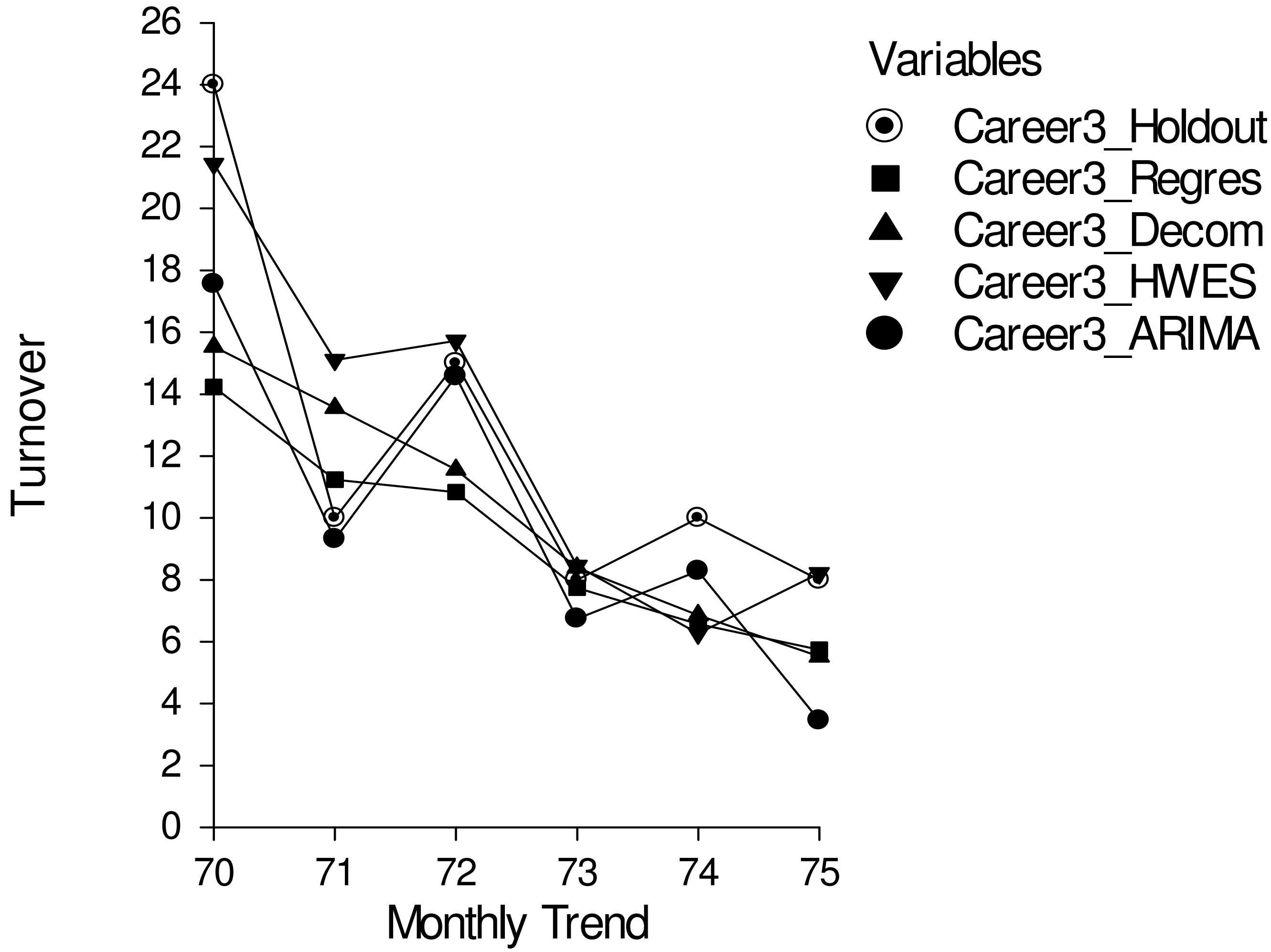

Figure 44. Predicted Monthly Turnover from Additive Regression, Decomposition Modeling, HWES, and ARIMA Plotted against 3-Rated Global Career-related Holdout Values from October 2008 through March 2009

Bio

Matthew Scott Fleisher was born in Tampa, FL on May 6, 1982. He graduated from the University of South Florida in 2005 with a B.A. in Psychology. He graduated from the University of Tennessee in 2011 with a Doctorate in Industrial and Organizational Psychology and a minor in Statistics. He is currently a Research Scientist in the Personnel Selection & Development Program at the Human Resources Research Organization (HumRRO). His applied work has involved test design and validation for employee selection, survey design and analysis, performance appraisal, job analysis, leadership assessment, and training program evaluation. In addition to his applied experience, he has published research in the areas of personality, work ethic, assessment centers, and graduate training.