Pertanika J. Soc. Sci. & Hum. 24 (S): 1 - 18 (2016)

SOCIAL SCIENCES & HUMANITIES

Journal homepage: http://www.pertanika.upm.edu.my/

A Comparative Study on the Forecast of Labour Turnover Rate

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ABSTRACT

Despite the voluminous research on turnover, most studies tend to focus on individual-level predictors of turnover and have not been able to offer sufficient predictive power for managers to forecast their labour turnover projections. In this study, the popular forecasting methods of Random Walk, Historical Average, Moving Average, Exponentially Weighted Moving Average (EWMA), and Autoregressive (AR) were compared for their forecast performance on labour turnover rate. Data for this study was obtained from the Job Openings and Labour Turnover Survey (JOLTS) compiled by the US Bureau of Labor. This study also evaluated the existence of monthly seasonal effects in the labour turnover rate. The results showed that the best forecasting model for the labour turnover rate is the Autoregressive (AR) model with order 3, within-sample and post-sample. The study also found that monthly seasonal effects exist in the labour turnover rate.

Keywords: Autoregressive, forecast, labour turnover rate, seasonal effect

INTRODUCTION

Human resources and staffing are important in ensuring the success of an organisation. Companies increasingly recognise the role human capital plays in driving competitive advantage in today's globalised economy. There is mounting evidence that the most important source of long-term competitive advantage is human and social capital (Pfeffer, 1995; Becker, Huselid, & Ulrich, 2001). Therefore, retaining a high-performing work-force is vital for companies to survive in a highly competitive market.

The human capital theory can be extended explain the effects of employee

ARTICLE INFO

Article history:
Received: 14 April 2016
Accepted: 28 October 2016

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ISSN: 0128-7702

turnover in terms of intellectual capital drain from the organisation (Stovel & Bontis, 2002). Reducing employee turnover can have a significant effect on company performance. Companies in Fortune's 2002 "100 Best Organizations to Work For" that reported much lower annual employee turnover rates (12.6% to 26%) than comparable companies in their industry are shown to have significantly "higher average stock returns, higher operating performance, higher return on assets and higher returns on capital employed" (Cascio, 2005).

Employee or labour turnover is the subject of much interest in organisational sciences and economics. Studies devoted to labour turnover have surpassed 2,500 (Griffeth, Hom, & Gaertner, 2000) in the past 40 years. Clearly, the phenomenon is critical from individual, organisational, and industry perspectives. The study of forecasting employee turnover is important for two reasons. First, labour turnover is costly and disruptive to organisations. The cost of turnover is often difficult to ascertain in full but estimates show that the financial impact of employee turnover ranges from 100% to 300% of the departing employee's annual salary (Moody, 2000). It usually involves many tangible and intangible costs, and is reflected in recruitment, selection, induction, temporary staffing, training of new employees, cost of being short-staffed and product and/or service quality (Cheng & Brown, 1998; Holtom, Mitchell, Lee, & Eberly, 2008). In a difficult labour market situation, these costs can be very high. Therefore, companies are keen to minimise labour turnover as much as possible, and where possible, to have the ability to predict such figures in advance for strategic reasons.

Second, there is theoretical justification for further academic research. Majority of studies in organisational sciences (psychology and sociology) on employee turnover tend to focus on individual-level predictors of turnover (Muchinsky & Morrow, 1980). Most of the studies have been criticised for failing to offer either predictive or explanatory power (Maertz & Campion, 1998; Hom, Mitchell, Lee, & Griffeth, 2012). Studies are far from complete, and there is still no reliable predictive method for turnover. How good are the existing forecasting methods in modelling the US labour turnover rate? With this research question in mind, this study aims to evaluate the performance of several popular forecasting methods and the existence of monthly seasonal effects in the labour turnover rate.

Section 2 reviews relevant literature in labour turnover and forecasting in order to support the framework of this study. Section 3 describes data source and methodology employed in the analysis, i.e. the *ad hoc* forecasting methods of Random Walk, Moving Average and Autoregressive models. Section 4 presents and discusses empirical results of the research while Section 5 summarises the findings and significance of the study as well as provides recommendations for future study.

LITERATURE REVIEW

Definition of Turnover

Turnover is defined as the ratio of the number of employees who have left an organisation during the period being considered divided by the average number of employees in that organisation during the period (Price, 1977).

$$\frac{\textit{Number of employees who leave during a given period}}{\textit{Average number of employees in a given period} \times 100\%}$$

Turnover is viewed as both the entrance of new employees into the organisation and the departure of existing employees from the organisation (Price, 1989). Managers refer to turnover as the entire process associated with filling a vacancy. Woods (1995) describes this replacement cycle as turnover.

Classification of Turnover

Turnover can be classified as voluntary or involuntary, referring to employee initiated or company initiated termination respectively. Most studies on turnover view it as either voluntary or involuntary, with the bulk of research devoted to voluntary turnover (Abelson, 1987).

Researchers have refined the concept of voluntary turnover into avoidable and unavoidable turnover whereby the former refers to employee-initiated leaving often related to job dissatisfaction and lack of organisational commitment (Carsten & Spector, 1987; Chonko, 1986; Dam, 2005; Egan, Yang, & Bartlett, 2004; Firth, Mellor, Moore, & Loquet, 2004). Unavoidable voluntary turnover on the other hand, refers to employee-initiated terminations due to spousal relocation, personal health issues, family matters, retirement, death, or educational pursuit (Joinson, 2000).

Some scholars view turnover in terms of either positive or negative consequences of employee leaving the organisation (Dalton, Todor, & Krackhardt, 1982; Hom & Griffeth, 1995). Positive consequences of turnover result when poor performing employees leave the organisation (Hollenbeck & Williams, 1986) and are replaced by new employees who bring in new skills and knowledge to the workplace (Levin & Kleiner, 1992).

Importance of Measuring Turnover

Organisational Effectiveness. There is a need for organisations to measure employee turnover (Campion, 1991). For most organisations, turnover is an index of organisational effectiveness (Vandenberg & Nelson, 1999). At the most basic level, turnover measurements are base rates with some context sensitivity (e.g. national labour market) for organisations to monitor and be aware of its human resource situation. Campion (1991) points out that a high labour turnover may indicate weak human resource policies and recruitment policies, poor supervisory practices and grievance procedures, and lack of motivation. Glebbeek and Bax (2002) find that excessive labour turnover affects a firm's economic performance. Turnover measures can also include greater context sensitivity and used as planning, prediction and control tools for improving efficiency (Marchington & Wilkinson, 1996; Morrell, Loan-Clarke, & Wilkinson, 2001).

Strategic Management of Human Resource. Human resource management is often viewed in the broader context of strategic management in its application. There is value in conducting periodic audits of an organisation's human resource to ensure that the organisation's human resource needs are met (Devanna, Fombrun, Tichy, & Warren, 1981). A critical aspect of any human resource management audit would include forecasting the firm's demand for and supply of labour (Walker, 1980). Turnover rates are one of the major factors that affect the supply of labour.

From a managerial perspective, it is important to monitor turnover rates and to take corrective action when the costs of turnover become excessive. Accurate forecasting and planning of an organisation's human resource requirements includes both an awareness of turnover rates and a strategy for keeping turnover rates at a desired level (Terborg & Lee, 1984). As such, reliable prediction of turnover can be used to develop strategies for managing turnover alongside broader human resource management or business strategy. Although organisations are unlikely ever to control resourcing completely, improvements in management of turnover may have a generative effect.

Research on Predicting Turnover. Over the years, many theories have been conceived and constructs proposed to better understand and predict turnover. Beginning with March and Simon (1958), theorists put forth comprehensive models (Lee & Mitchell, 1994; Mobley, Griffeth, Hand, & Meglino, 1979; Price & Mueller, 1981; Steers, Mowday, & Porter, 1979) or new explanatory constructs (Mitchell, Holtom, Lee, Sablynski, & Erez, 2001; Trevor, 2001). Other researchers pioneered methodological solutions to improve predictors' measurement (Griffeth, Steel, Allen, & Bryan, 2005) or forecasting power with advanced panel analytical techniques (Bentein, Vandenberghe, Vandenberg, & Stinglhamber, 2005; Kammeyer-Mueller, Wanberg, Glomb, & Ahlburg, 2005), excepting developments in statistical adjustments of turnover (Bass & Ager, 1991; Huselid, 1995; Morita, Lee, & Mowday, 1993) or its substitution by a broader withdrawal construct (Hanisch, Hulin, & Roznowski, 1998).

The bulk of turnover models rely on assessing the predictive role of any of a vast number of competing variables (Hom et al., 2012). However, the contextual, relational and epistemological complexities surrounding the phenomenon of turnover makes modelling a challenge (Checkland, 1981; Morrell et al., 2001). Research studies on turnover suffer from the tendency of being an either/or phenomenon i.e. either psychological or economic in nature, as dictated by the dominant perspectives of turnover research. Studies that have focused on the psychological aspect, have for the most part, failed to capture the significance of economic factors in predicting and understanding the turnover process, although economic factors may add appreciably to the understanding of turnover (Griffeth et al., 2000).

Justification for Further Study. Current studies that focus on employee turnover have been criticised for failing to offer findings that are either predictive or explanatory. Many employees leave for reasons other than dissatisfaction with the current job or for opportunities elsewhere (Hom et al., 2012; Maertz & Campion, 1998). The inability for any current model to 'fit' empirical data implies that no comprehensive or universal account of turnover has been found. As such, there is still no reliable prediction of turnover both at the individual level as well as at the aggregate level. This has inspired us to carry out this study.

DATA AND METHODOLOGY

Data of Labour Turnover Rate

This study uses data gleaned from the United States monthly labour turnover rates sourced from the Job Openings and Labor Turnover Survey (JOLTS), obtained from US Bureau of Labor Statistics (BLS). The reason for choosing US as the focal point of this study is the availability and reliability of aggregate labour turnover data, which is neither easily

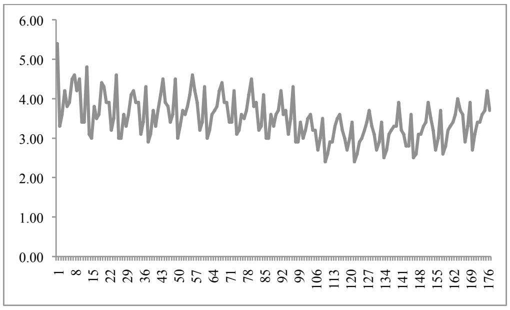

Figure 1. Time series graph for US labour turnover rate from January 2001 to September 2015

accessible nor reliable in many countries including Malaysia. Figure 1 shows the time series graph for US labour turnover rate for the period spanning more than 14 years from January 2001 to September 2015.

A total of 176 observations were utilised in this study. The first 126 observations were used for parameter estimation and the last 50 were reserved for forecasting evaluation. The JOLTS provides the most comprehensive data series available on labour statistics. Figure 2 presents the time series graph for US labour turnover growth

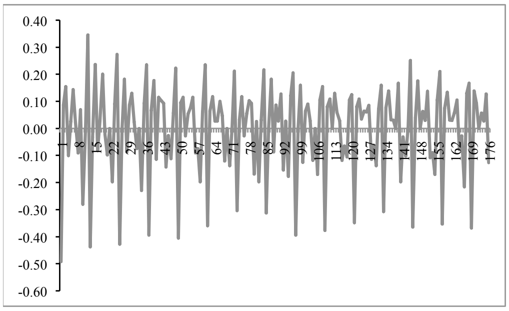

Figure 2. Time series graph for US labour turnover growth rate (log difference) from January 2001 to September 2015

rates (log difference), T, from January 2001 to September 2015. Summary statistics of the log difference for US labour turnover rates are displayed in Figure 3.

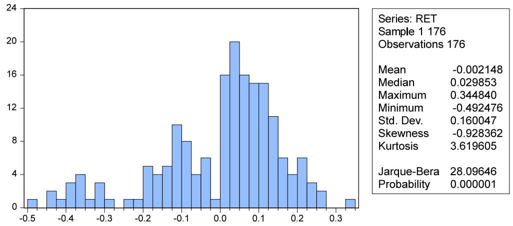

Figure 3. Summary statistics of the log difference for US labour turnover rate

Methodology: Forecasting methods used in this study

Random Walk Model. Random Walk (RW) is a mathematical formalisation of a trajectory that consists of taking successive random steps. The random-walk model was suggested by Meese and Rogoff (1983), who find that no estimated renowned theoretical model outperforms the random-walk model. The driftless random-walk model for log difference of labour turnover rate (growth rate), *T*, is specified as:

$$\hat{T}_{t+1} = T_t \ .$$

Random Walk model assumes that the best forecast of next month's turnover rate is this month's turnover rate.

Historical Average Method. The historical average method (Montgomery, 1976) or 'naïve' method equates all the future forecasts with the same forecast, $\hat{T}_{t+1}$ i.e. and can be written as

$$\hat{T}_{t+1} = (T_t + T_{t-1} + \ldots + T_1)/N$$

where N is the total number of observations.

Simple Moving Average Method. The simple moving average method (Montgomery, 1976) is a popular approach to turnover rate forecasting, which can be written as

$$\hat{T}_{t+1} = (T_t + T_{t-1} + \ldots + T_{t-\tau})/\tau \ .$$

where τ is the size of moving frame. Simple moving average method is always set as a benchmark. Any sensible forecasting procedure should do at least as well as a simple moving average.

Exponentially Weighted Moving Average (EWMA). The exponentially weighted moving average (EWMA) (Montgomery, 1976) is essentially an extension of the aforementioned simple moving average turnover rate measure, which allows more recent observations to have a stronger impact on the forecast of turnover rate than older data points, i.e.

$$T_{t+1} = \frac{\sum_{i=1}^{\tau} \beta^i T_{t+1-i}}{\sum_{i=1}^{\tau} \beta^i} \ .$$

Exponential Smoothing (ES) Method. The exponential smoothing method (Gardner, 1985) can be formulated as

$$\hat{T}_{t+1} = \alpha T_t + (1-\alpha)\hat{T}_t \quad \text{and} \quad 0 \le \alpha \le 1$$

where α = (1 - *β*) Parameter (1 - α) is also seen as a 'decay' factor, which determines how much weight is given to recent versus older observations. In this study, the value of α is chosen to produce the best fit by minimising the root mean squared in-sample forecast errors.

In fact, EWMA is a truncated version of exponential smoothing with a finite τ. Under an EWMA specification, the latest observation carries the largest weight, and weights associated with previous observations decline exponentially over time.

Autoregressive (AR) Model. One way to solve the serial correlation problem is to take advantage of the correlation between adjacent observations. An autoregressive model can be used to accomplish this task (Akaike, 1969). An autoregressive model expresses a forecast as a function of previous values of that time series. One way to do this is to use the dependent variable lagged one or more periods as an independent variable. This model is expressed as:

$$\hat{T}_{t+1} = \phi_0 + \phi_1 T_t$$

Table 1 presents a summary of the forecasting methods adopted in the empirical analysis.

Table 1
Forecasting methods used in this study

Methods	Description
Random Walk	Best forecast of a future value is the present value
Naïve Variance Forecast	This month's turnover rate is based on the average historical turnover rate
Moving Average 1, 3, 12	Simple moving average, moving window = 1, 3, 12
EWMA	EWMA with α = 0.06.
EWMA-RMSE	EWMA with optimized parameter using:
Autoregressive (AR) Method	AR(1): $\hat{T}_{t+1} = \phi_0 + \phi_1 T_t$ AR(3): $\hat{T}_{t+1} = \phi_0 + \phi_1 T_t + \phi_2 T_{t-1} + \phi_3 T_{t-2}$ AR(5): $\hat{T}_{t+1} = \phi_0 + \phi_1 T_t + \phi_2 T_{t-1} + \phi_3 T_{t-2} + \phi_4 T_{t-3} + \phi_5 T_{t-4}$ AR(11): $\hat{T}_{t+1} = \phi_0 + \phi_1 T_t + \phi_2 T_{t-1} + \phi_3 T_{t-2} + \phi_4 T_{t-3} + \ldots + \phi_{11} T_{t-10}$

Post-Sample Forecasting Evaluation Criteria

Earlier studies have used the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) as evaluation criterion respectively to compare forecast errors. Both of these evaluation criterions are perceived to be easier for interpretation (Akgiray, 1989; Brailsford & Faff, 1996; Brooks, 1998; Romprasert, 2010)

Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are chosen as our evaluation criterion in this study to determine the best forecasting method used in our analysis. The MAE and RMSE are computed using the following formulae:

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |(T_t - \hat{T}_t)|$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(T_t - \hat{T}_t)^2}$$

The RMSE criterion is more sensitive to occasional large error since squaring the error disproportionately weighs forecast errors more heavily relative to MAE (Brooks, 1998).

RESULTS AND DISCUSSION

In-sample forecasting performance

The parameter estimate of exponential smoothing (ES) method obtained through the optimisation of RMSE for in-sample one-step-ahead predictions is presented in Table 2.

Table 2
Estimation results for the EWMA method through the minimisation of RMSE for in-sample predictions

Method	α
EWMA	0.088

The results for within-sample estimation and diagnostic tests of AR(1), AR(3), AR(5) and AR(11) are presented in Tables 3 and 4 respectively. The parameter estimates of AR models are given below. The figures in parentheses are the t-statistics.

AR(1): $\hat{T}_{t+1} = -0.001 - 0.317T_t$
(-0.08) (-3.86)

AR(3): $\hat{T}_{t+1} = -0.002 - 0.456T_t - 0.454T_{t-1} + 0.072T_{t-2}$
(-0.18) (-4.98) (-4.98) (0.82)

AR(5): $\hat{T}_{t+1} = -0.004 - 0.452T_t - 0.556T_{t-1} - 0.050T_{t-2} - 0.233T_{t-3} - 0.052T_{t-4}$
(-0.35) (-4.84) (-5.52) (-0.44) (-2.30) (-0.57)

AR(11):

$$\hat{T}_{t+1} = -0.024 - 0.780T_t - 0.904T_{t-1} - 0.730T_{t-2} - 0.868T_{t-3} - 0.724T_{t-4} - 0.873T_{t-5} - 0.742T_{t-6}$$

(-4.44) (-12.34) (-17.75) (-9.82) (-14.87) (-9.90) (-15.09) (-10.12)

$$- 0.878T_{t-7} - 0.735T_{t-8} - 0.903T_{t-9} - 0.734T_{t-10}$$

(-15.14) (-9.86) (-17.58) (-11.80)

The Durbin–Watson statistic is a test statistic used to detect the presence of autocorrelation (a relationship between values separated from each other by a given time lag) in the residuals (prediction errors) from a regression analysis. The Durbin-Watson statistic is always between 0 and 4. A value of 2 means that there is no autocorrelation in the sample. Values approaching 0 indicate positive autocorrelation and values toward 4 indicate negative autocorrelation.

By comparing the values of Durbin-Watson Statistics, we found that AR(3) and AR(5) have the values of 1.96 and 2.0, respectively. This indicates that AR(3) and AR(5) have no autocorrelation in the residuals of the models.

By looking at the values of Akaike information criterion (AIC) and Schwarz information criterion (SIC), we found that the higher the order of AR, the better (more negative) the model. In this case, AR(11) is the best model according to the goodness-of-fit criteria of AIC and SIC.

Similarly, for Log Likelihood (Log L) criterion, we found that the higher the order or AR, the better (more positive) the model. In this case, AR(11) is the best model according to the goodness-of-fit criteria of Log L.

The in-sample forecast results for all the turnover rate forecasting methods used in this study are displayed in Table 5. Using the MAE as the evaluation criterion, the AR(3) method is ranked first, followed by AR(5) and AR(1). Similarly, using the RMSE as the evaluation criterion, the best forecasting methods is still AR(3), followed by AR(5) and AR(1).

Post-sample forecasting performance

Good performance in terms of within-sample diagnostics and goodness-of-fit statistics do not guarantee good performance in forecasting. A good forecasting method should withstand the robustness of the post-sample test; a test design that is closer to reality (Choo, Muhammad Idrees, & Mat Yusoff, 1999). In this section, forecasting evaluation criteria such as MAE and RMSE are employed to evaluate 50 one-step-ahead post-sample forecasts generated by different methods.

Table 3
Parameter estimation results of the autoregressive models

Parameter	Model			
	AR(1)	AR(3)	AR(5)	AR(11)
ϕ_0	-0.001	-0.002	-0.004	-0.024
Std. Error	0.014	0.012	0.012	0.005
p-value	0.936	0.858	0.725	0.000
ϕ_1	-0.317	-0.457	-0.453	-0.780
Std. Error	0.082	0.092	0.094	0.063
p-value	0.000	0.000	0.000	0.000
ϕ_2		-0.454	-0.556	-0.904
Std. Error		0.091	0.101	0.051
p-value		0.000	0.000	0.000
ϕ_3		0.072	-0.050	-0.730
Std. Error		0.088	0.114	0.074
p-value		0.416	0.660	0.000
ϕ_4			-0.233	-0.868
Std. Error			0.101	0.058
p-value			0.023	0.000
ϕ_5			-0.052	-0.724
Std. Error			0.091	0.073
p-value			0.571	0.000
ϕ_6				-0.873
Std. Error				0.058
8p-value				0.000
ϕ_7				-0.742
Std. Error				0.073
p-value				0.000
ϕ_8				-0.878
Std. Error				0.058
p-value				0.000
ϕ_9				-0.735
Std. Error				0.074
p-value				0.000
ϕ_{10}				-0.903
Std. Error				0.051
p-value				0.000
ϕ_{11}				-0.734
Std. Error				0.062
p-value				0.000

Table 4
Diagnostics for autoregressive models

	AR(1)	AR(3)	AR(5)	AR(11)
R-squared	0.108	0.332	0.362	0.891
Adjusted R-squared	0.101	0.315	0.334	0.879
S.E. of regression	0.151	0.132	0.131	0.056
Sum squared resid	2.811	2.083	1.983	0.327
Log likelihood	59.814	76.299	77.046	173.950
F-statistic	14.861	19.728	13.056	76.448
Prob(F-statistic)	0.000	0.000	0.000	0.000
Mean dependent var	0.000	-0.002	-0.001	0.000
S.D. dependent var	0.159	0.160	0.161	0.162
Akaike info criterion	-0.925	-1.176	-1.174	-2.817
Schwarz criterion	-0.880	-1.084	-1.036	-2.530
Hannan-Quinn criter.	-0.907	-1.138	-1.118	-2.700
Durbin-Watson stat	2.347	1.961	2.002	1.054

Table 5
Rankings of the turnover rate forecasting methods based on MAE and RMSE for in-sample one-step-ahead predictions

Model	MAE	Rank	RMSE	Rank
RW	206.5	11	266.1	11
naïve var fcst	126.1	5	164.1	5
MA3	138.7	8	169.1	7
MA6	141.0	9	177.3	10
MA12	125.7	4	163.8	4
EWMA	130.6	6	168.9	6
EWMA-RMSE	132.7	7	171.2	9
AR1	123.8	3	155.6	3
AR3	107.4	1	136.7	1
AR5	107.6	2	138.6	2
AR11	146.0	10	170.3	8

-The post-sample forecast results for all the turnover rate forecasting methods used in this study are given in Table 6. Using the MAE as the evaluation criterion, the AR(3) method is ranked first, followed by AR(5) and AR(1). Similarly, using the RMSE as the evaluation criterion, the best forecasting method is still AR(3), followed by AR(5) and AR(1) methods. Interestingly, we find that the in-sample forecasting results are similar to the post-sample results.

These results are also consistent with Taylor's (2004) where he applied STES methods to forecast the volatility of stock market and found that STES and AR methods are always better than GARCH family models in post-sample forecasting.

Table 6
Rankings of the turnover rate forecasting methods based on MAE and RMSE for post-sample one-step-ahead predictions

Model	MAE	Rank	RMSE	Rank
RW	238.8	11	174.6	11
naïve var fcst	147.8	4	117.1	5
MA3	154.5	8	131.0	8
MA6	168.8	9	137.1	9
MA12	148.3	5	115.8	4
EWMA	152.1	6	119.8	6
EWMA-RMSE	154.3	7	121.6	7
AR1	140.2	3	115.6	3
AR3	130.6	1	103.8	1
AR5	133.4	2	106.7	2
AR11	174.5	10	153.5	10

In conclusion, based on MAE and RMSE forecasting evaluation criteria, AR(3) method is better than other *ad hoc* methods in forecasting the turnover rate in US. To our knowledge, this is the first empirical evidence for the application of AR methods in forecasting turnover rate in US.

Existence of monthly seasonal effects in turnover rate

In this study, we also examined the existence of monthly seasonal effects in the US labour turnover rate. Dummy variables were measured from JAN (January) through NOV (November) in relation to the reference month, December. We found that AR(3) is the best model in terms of in-sample and post-sample forecasting performance, hence, only this model is considered for investigating monthly seasonal effects.

Table 7 presents the within-sample estimation of AR(3) with Monthly Seasonal Effect (AR-Season). Seven out of 11 monthly seasonal dummy variables in the mean equation are statistically significant at 5% level indicating monthly seasonality effects in the US labour turnover rate. To our knowledge, this is the first empirical evidence of monthly seasonal effects of turnover rate in the US. The figures in parentheses are t-statistics.

The results of diagnostics and goodness-of-fit tests, such as adjusted R^2 and log-likelihood, for AR-Season model are also presented in Table 7. The higher values of the coefficient of determination, R^2, indicate more informational content of in-sample forecasts. The adjusted R^2 displayed Table 7is 0.942 with the presence of seasonal effects compared with a lower value of adjusted R^2 of the AR(3), which is 0.315 shown Table 4, in the previous section. This indicates that the AR-Season model in this study has the most predictive power to explain the turnover rate in US. In other words, the seasonal effects do improve the value of adjusted R^2.

$$
\begin{aligned}
T_t = & \underset{(-1.11)}{-0.031} \underset{(-5.88)}{-0.564\,T_{t-1}} \underset{(-4.12)}{-0.424T_{t-2}} \underset{(0.59\,)}{+0.057T_{t-3}} \underset{(7.39)}{+0.214JAN} \underset{(-4.14)}{-0.182FEB} \underset{(-1.52)}{-0.052MAR} \underset{(0.77)}{+0.031APR} \\
& \underset{(2.87)}{+0.102MAY} \underset{(3.25)}{+0.129JUN} \underset{(3.21)}{+0.136JUL} \underset{(4.53)}{+0.176AUG} \underset{(-0.35)}{-0.016SEP} \underset{(-0.67)}{-0.022OCT} \underset{(-7.22)}{-0.205NOV} +\varepsilon_t
\end{aligned}
$$

Table 7
Within-sample estimation results and diagnostics for the Autoregressive model, AR(3), with monthly seasonal effects

	Estimates	Std. Error	t-Statistic	p-value
ϕ_0	-0.031	0.028	-1.107	0.271
ϕ_1	-0.564	0.096	-5.876	0.000
ϕ_2	-0.424	0.103	-4.122	0.000
ϕ_3	0.057	0.095	0.594	0.554
M1	0.214	0.029	7.389	0.000
M2	-0.182	0.044	-4.137	0.000
M3	-0.052	0.034	-1.524	0.130
M4	0.031	0.040	0.773	0.441
M5	0.102	0.036	2.868	0.005
M6	0.129	0.040	3.248	0.002
M7	0.136	0.042	3.214	0.002
M8	0.176	0.039	4.535	0.000
M9	-0.016	0.046	-0.348	0.728
M10	-0.022	0.033	-0.670	0.504
M11	-0.205	0.028	-7.216	0.000
R-squared	0.949	Mean dependent var		-0.002
Adjusted R-squared	0.942	S.D. dependent var		0.160
S.E. of regression	0.038	Akaike info criterion		-3.569
Sum squared resid	0.159	Schwarz criterion		-3.226
Log likelihood	234.517	Hannan-Quinn criter.		-3.430
F-statistic	143.609	Durbin-Watson stat		2.000
Prob(F-statistic)	0.000			

CONCLUSIONS

Retaining a high-performing workforce is vital for a company's success and survival in today's highly competitive market and globalised economy. However, many organisations face the challenge of labour turnover, which is both costly and disruptive to them. Companies are keen to minimise labour turnover as much as possible as reducing turnover causes significant improvement in their performance. One way organisations can manage turnover more strategically is to have the ability to forecast turnover rates.

Despite the voluminous research on turnover, most studies tend to focus on individual-level predictors of turnover and have not been able to offer predictive power for managers to forecast their labour turnover projections.

Using the United States (US) labour turnover data, this study evaluated the best forecasting model for the US labour turnover rate from a range of forecasting methods: Random Walk, Naïve Variance Forecasting, Moving Average, Exponentially Weighted Moving Average (EWMA), and Autoregressive (AR) model. This study also evaluated the existence of monthly seasonal effects in the labour turnover rate.

From the results of the study, the conclusions are: (i) The best forecasting method for the US labour turnover rate is the Autoregressive (AR) model with order 3, within-sample and post-sample; (ii) Monthly seasonal effects do exist in the US labour turnover rate.

SIGNIFICANCE OF STUDY

Findings of this study will be of interest and valuable to the following groups:

1. **Business and Industry:**
   a. A more precise forecast of aggregate labour turnover can be an important variable in modelling of labour turnover at industry and organisational levels. From the perspective of strategic Human Resources management, having a more precise forecast of labour turnover can help companies to plan more strategically, manage the valuable human resources more efficiently and prevent adverse financial consequences associated with high turnover rates.
   b. Statistical methods such as forecasting can become a valuable strategic tool for Human Resource departments in their reporting and decision making.

2. **Policy makers:**
   a. The insights gained from this study will be of interest to policy makers, economic planning agencies, labour and human resources development agencies. With the availability of better and more precise methods of forecasting labour turnover rates, the relevant agencies can better assess the economic situation and the labour market situation. Such forecast can provide vital strategic

inputs into the development of effective policies and economic development plans for the future.

RECOMMENDATIONS FOR FURTHER STUDY

Economists typically examine turnover from an industry perspective, using predictors such as unemployment levels and labour force composition (Campbell III, 1993; Hom, Katerberg, & Hulin, 1979). There is evidence that rates of employee turnover in businesses correlate with aggregate data such as underlying labour market trends and cyclical and structural developments in the macro-economic environment (D'Arcy, Gustafsson, Lewis, & Wiltshire, 2012; Terborg & Lee, 1984). However, research in this area suffers from the tendency of being an "either or phenomenon" i.e. either psychological or economic in nature, as dictated by the dominant research perspectives on turnover. Psychological literature has for the most part, failed to capture the significance of economic factors in predicting and understanding the turnover process although economic factors may add appreciably to the understanding of turnover (Griffeth et al., 2000). Hence, future study could fill the research gap by incorporating macroeconomic indicators, such as crude oil, gold price and exchange rate in forecasting labour turnover rate.

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