XXX's Data Analysis Report

The report is written to demonstrate how to apply data and statistical methods to evaluate, analysis and forecast XXX's business performance. The report is organized in the following sessions. Note that the report is based on the limited data available by July 6 2015. Inaccurate conclusion may be introduced in the report due to incompleteness of database.

In this report, I focus on analyzing labor category, which has a much smaller category set than "job category". But the same analysis approach can be applied to job category in the second step. Labor Category and job category are closely correlated, therefore, I think it is proper to the use "labor category" instead in the first exploratory stage.

Session I

<u>Analysis and forecast of job requisitions from clients – Labor demand</u>

I begin with exploring data from the job requisition report on XRM, with the purpose to answer the following questions and get a grand view about XXX's labor demand from its clients

- How many job requisitions XXX has received every year from 2003 to 2014
- How many job requisitions XXX has received in each labor category every year from 2003 to 2014
- What's the forecast for XXX's job requisition in 2015 and 2016

Criteria to select qualified job requisition entries

- A job requisition entry is qualified no matter its transaction status is successful or not in the end
- The date of the job requisition entry is based on its "Submitted Data"
- If a job requisition entry does not provide any information about its labor category , NTE Bill Rate and submitted date, it is considered as an unqualified entry

Part I: Job requisitions received every year 2003-2014

<u>Total Job Requisition</u>

Year	Number of Job Requisition	Changing Rate
2003	20	N/A
2004	42	110%
2005	19	-55%
2006	46	142%
2007	40	-13%
2008	45	13%
2009	33	-27%
2010	30	-9%
2011	423	1310%
2012	477	13%
2013	1530	221%
2014	1932	26%
By July 6 2015	1051+	N/A
Grand Total	5688+	

Table 1. Yearly Job Requisition from all XXX's clients 2003 - 2015

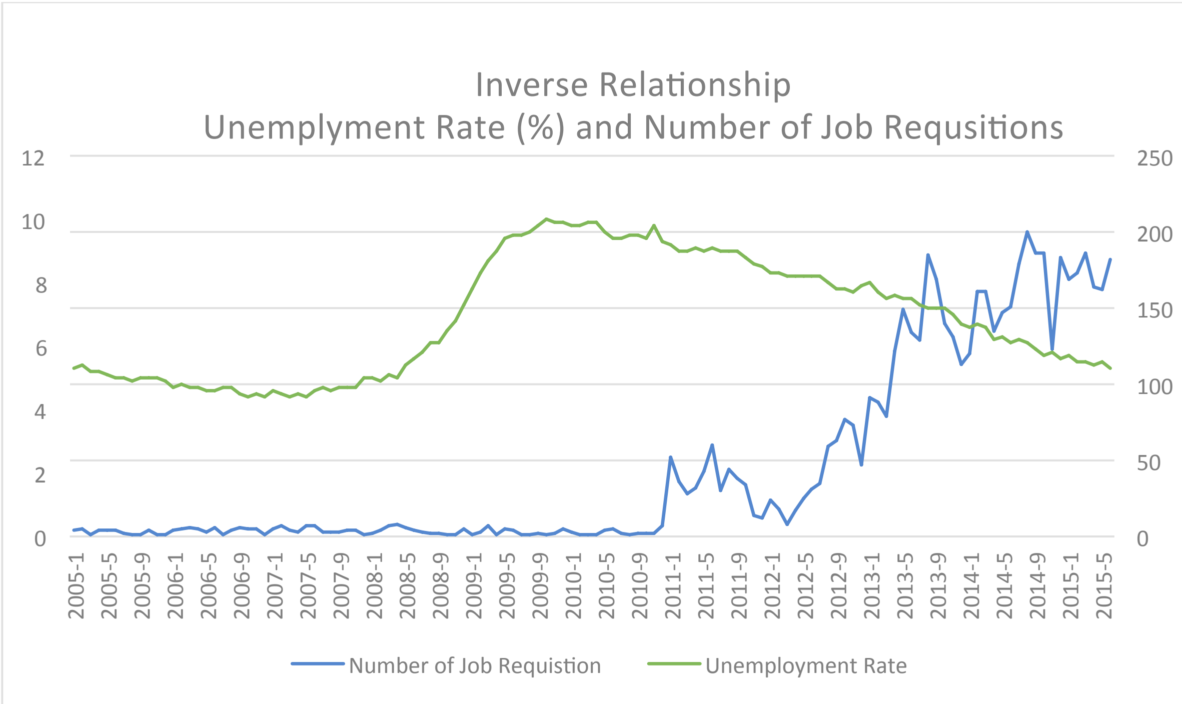


Figure 1. The Inverse Relationship between the Number of Yearly Job Requisitions and Unemployment Rate in the United States from 2010 -2014

	Unemployment Rate	Number of Job Requisition
Unemployment Rate	1	
Number of Job Requisition	-0.92	1

Table 2. The Correlation between Number of Yearly Job Requisitions and Unemployment Rate (%)

Table 1 and Figure 1 clearly Show that the XXX's clients' overall labor demand increased tremendously from 2010 to 2014. It may be because that XXX expanded its business faster and acquired more clients in that period. Moreover, the decreasing unemployment rate in the same period may be another significant explanatory factor to the increase of labor demand. Table 2 indicates that three exists strong inverse relationship between unemployment rate and XXX's yearly job requisitions, with correlation equal to -0.92.

Part II Job Requisition for Each Labor Category

12 Major Job Categories

First, I shrink 32 original labor categories in the database to construct a smaller labor category set with a broader range. There are 22 new labor categories in the database after the reconstruction. Please see the Table 4 below for the mapping rules.

New Labor Category	Old Labor Categories
Accounting/Finance	Accounting/Finance, Finance
Administrative	Administrative, Administrative/Clerical
Call Center/Customer Service	
Engineering	
Entertainment	
Food Related Services	
General	General, General Administration
Human Services/Insurance	
Information Technology	Information Technology, Information System and Technology, SAP
Laborer/Industrial	
Light Industrial	
Logistics	
Medical	
One-Off Orders	
Professional	Professional, corporate/professional/other
Professional/IT/Engineering	
Sales/Merchandising	
Scientific	
Security	
Tax/Media	Tax, Tax/Media, Media
Technical	
Trades	Trades,Trades2, Industries Trades

Table 4. 22 New labor categories

		2003-2015				By July 6 2015		
	Labor Category	Number	Percentage	Rank		Number	Percentage	Rank
1	Accounting/Finance	533	9.55%	4		79	8.37%	5
2	Administrative	459	8.22%	6		49	5.19%	7
3	Call Center/Customer Service	62	1.11%	12		12	1.27%	11
4	Engineering	458	8.21%	7		24	2.54%	9
5	Entertainment	3	0.05%			0	*0%*	
6	Food Related Services	5	0.09%			4	0.42%	
7	General	1298	23.26%	1		287	30.40%	1
8	Human Services/Insurance	39	0.70%			9	0.95%	
9	Information Technology	767	13.74%	2		101	10.70%	3
10	Laborer/Industrial	159	2.85%	10		33	3.50%	8
11	Light Industrial	515	9.23%	5		77	8.16%	6
12	Logistics	17	0.30%			3	0.32%	
13	Medical	207	3.71%	8		120	12.71%	2
14	One-Off Orders	9	0.16%			0	0%	
15	Professional	150	2.69%	11		24	2.54%	9
16	Professional/IT/Engineering	167	2.99%	9		20	2.12%	10
17	Sales/Merchandising	4	0.07%			0	*0%*	
18	Scientific	1	0.02%			0	*0%*	
19	Security	45	0.81%			4	0.42%	
20	Tax/Media	19	0.34%			6	0.64%	
21	Technical	631	11.31%	3		82	8.69%	4
22	Trades	33	0.59%			10	1.06%	12
	Grand Total	5581	100.00%			944	*100%*	

Table 5. Job requisition for 22 labor categories for 2003- 2015

Table 5. Shows the total number of job requisitions of each labor category received from 2003 to 2015 and the total number of job requisition of each labor categories received up to July 6 in 2015. I leave out the unsubstantial labor categories taking less than 1% and focus on analysis 12 major labor categories listed in the table 6.

No.	Labor Categories	Number of Job Requisitions	Percentage of Total Job Requisitions
1	General	1330	24%
2	Information Technology	768	14%
3	Technical	640	12%
4	Accounting/Finance	539	10%
5	Light Industrial	529	10%
6	Administrative	464	8%
7	Engineering	460	8%
8	Medical	229	4%
9	Professional/IT/Engineering	172	3%
10	Laborer/Industrial	162	3%
11	Professional	152	3%
12	Call Center/Customer Service	64	1%
	Grand Total	5509	100%

Table 6. 12 Major Labor Categories 2003 - 2015

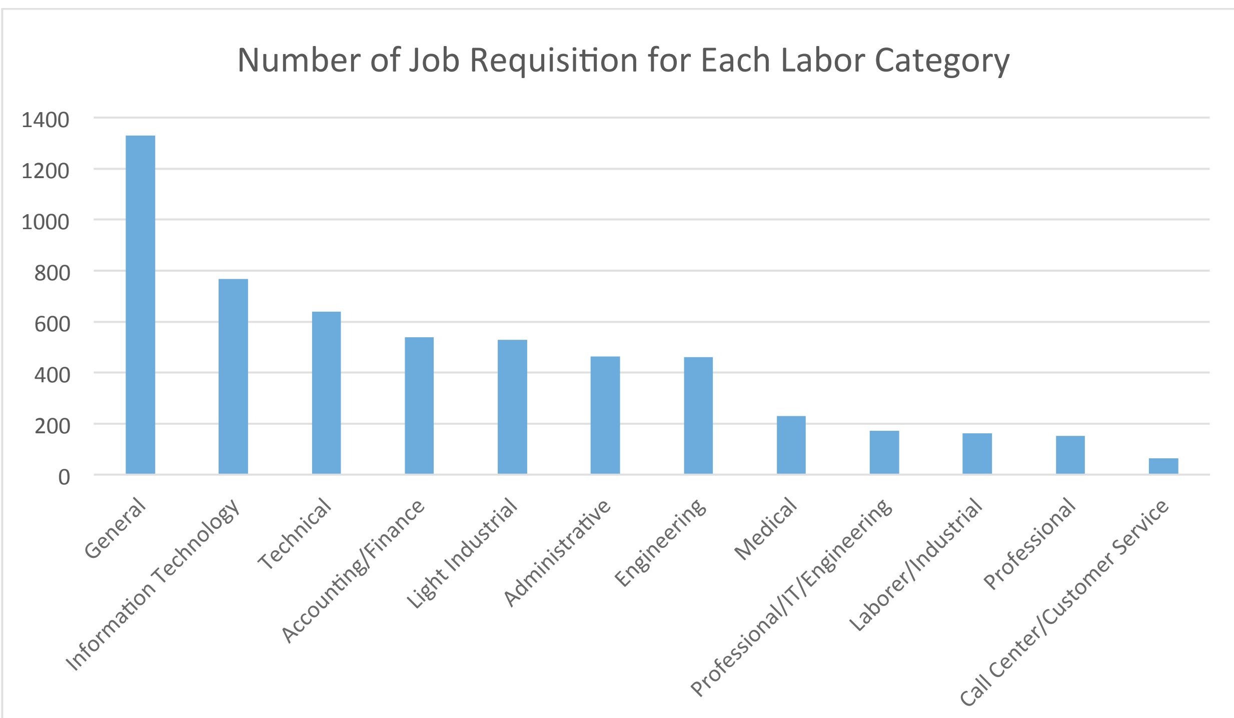


Figure 4. Percentage of 12 labor categories 2003 -2015

Table 6 and Figure 4 show that XXX's highest labor demanding in the following labor categories: "General", "Information Tech","Technical","Accounting and Finance" and "lighting industry".

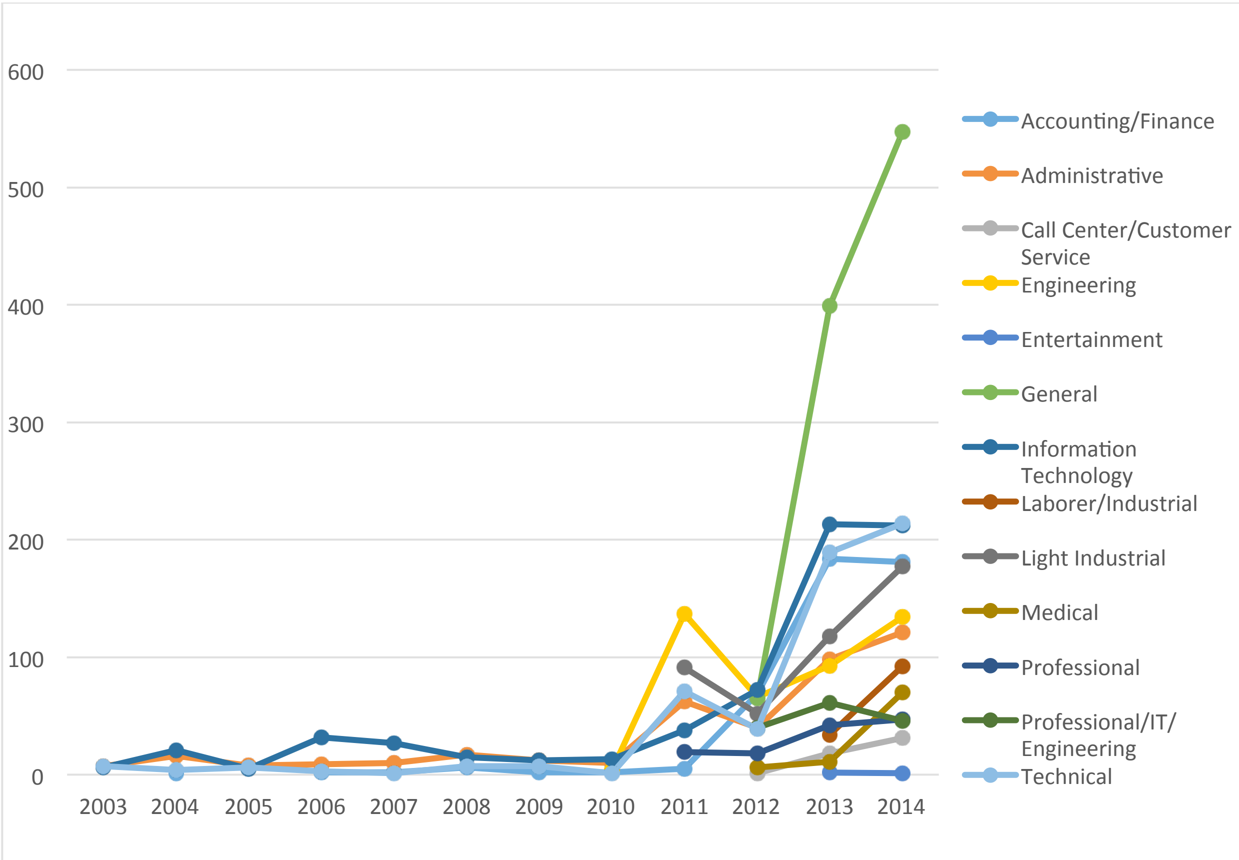


Figure 5. Yearly Job requests trends for 12 labor categories 2003 -2014

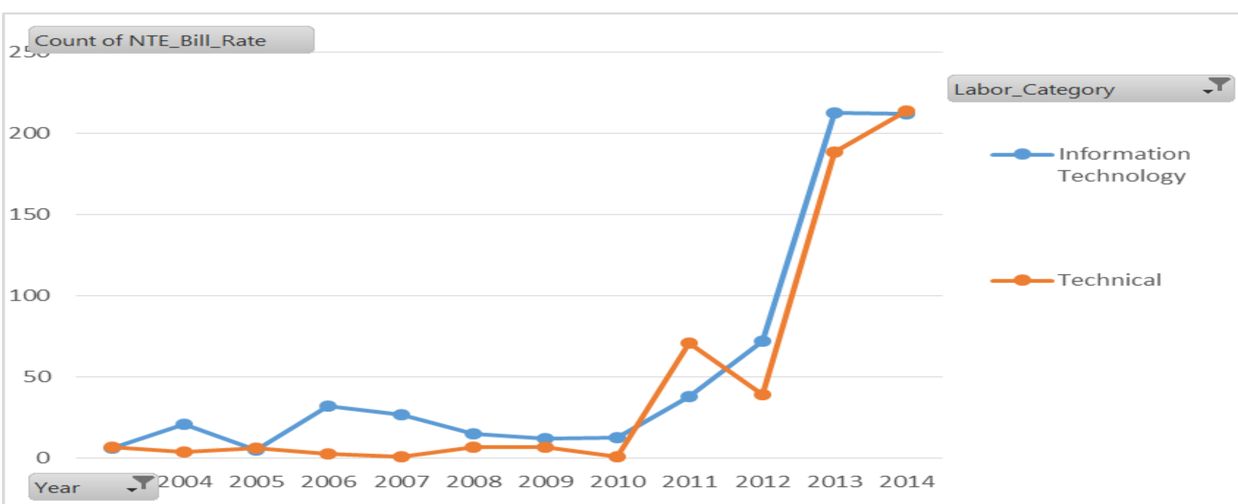


Figure 6. Yearly Job requests trends for "Information Technology" and "Technical" 2003 -2014

Year	Information Technology
2003	6
2004	21
2005	5
2006	32
2007	27
2008	15
2009	12
2010	13
2011	38
2012	72
2013	213
2014	212
Grand Total	666

Table 7. Number of yearly job requests for information technology 2003-2014

2012-2014	Increasing Rate
General	744%
Technical	448%
Information Tech	190%

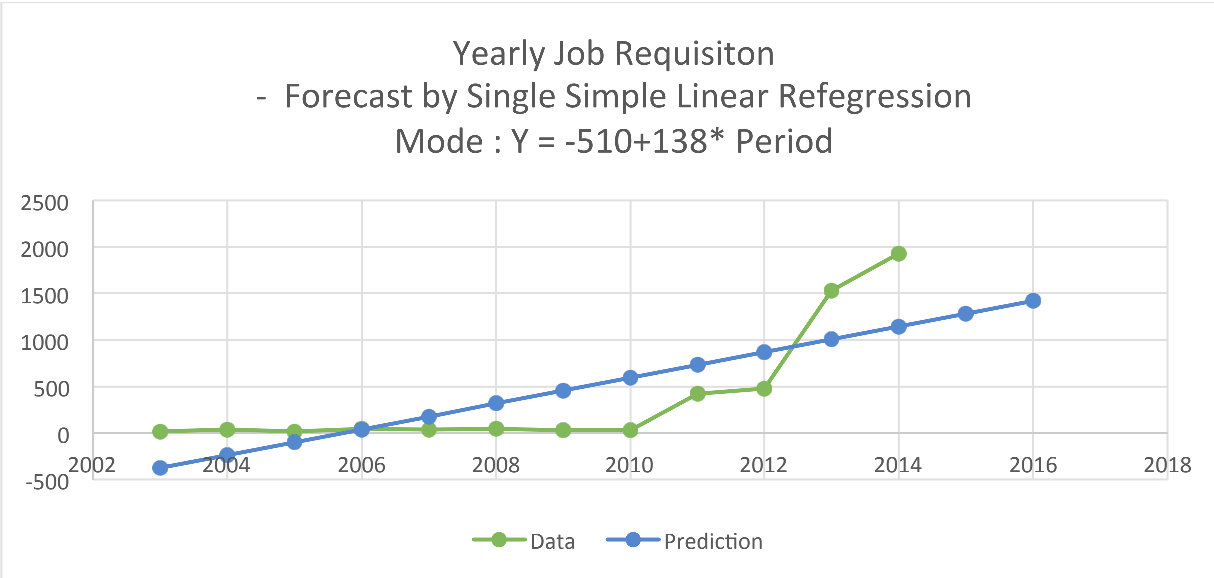
Table 8. Three Labor Categories having highest increasing in labor demand

As shown in figure 5, the demands for 12 major labor categories all hold upwards trends in general after 2012, though in different degrees. The demand for "General" labor category in 2014 is 7 times more than that in 2012. The demand for "Technical" increases approximately 448% from 2012 to 2014, followed by "Information Tech", 190%.

Hence, "General", "Information Tech","Technical" have largest demands while having highest growth rate in the same time. In Session II, I deeply explore how XXX fits those increasing demands by analysis XXX's labor supply side.

Part III: Forecast for Yearly Job Requisition in 2015-2016

i. Method 1 : Single Simple Linear Regression



The single linear regression model could not capture the overall trend of the data from 2003 to 2014 because it has a large jump from 2010 to 2011, which result in large prediction errors.

Year	Period	Data	Prediction	Residuals	MSE	Changing Rate
2003	1	20	-372	392	1405	-33%
2004	2	42	-234	276		
2005	3	19	-96	115		
2006	4	46	41	4		
2007	5	40	179	-139		
2008	6	45	317	-272		
2009	7	33	455	-422		
2010	8	30	593	-563		
2011	9	423	731	-308		
2012	10	477	869	-392		
2013	11	1530	1007	522		
2014	12	1932	1145	786		
2015	13	1051+	**1283**	N/A		
2016	14	N/A	**1421**	N/A		

Table 6. Prediction by Single Simple Linear Regression

ii. Method 2: Two-period Linear Regressions Model

Year	Period	Data	Prediction	Residuals	Mean Square Error	Changing Rate
2011	1	423	253.5	169.5		
2012	2	477	811.5	-334.5		
2013	3	1530	1369.5	160.5	203.96	22%
2014	4	1932	1927.5	4.5		
2015	5	N/A	**2485.5**	N/A		
2016	6	N/A	**3043.5**	N/A		

Table 7. Prediction by Two-Period Linear Regressions

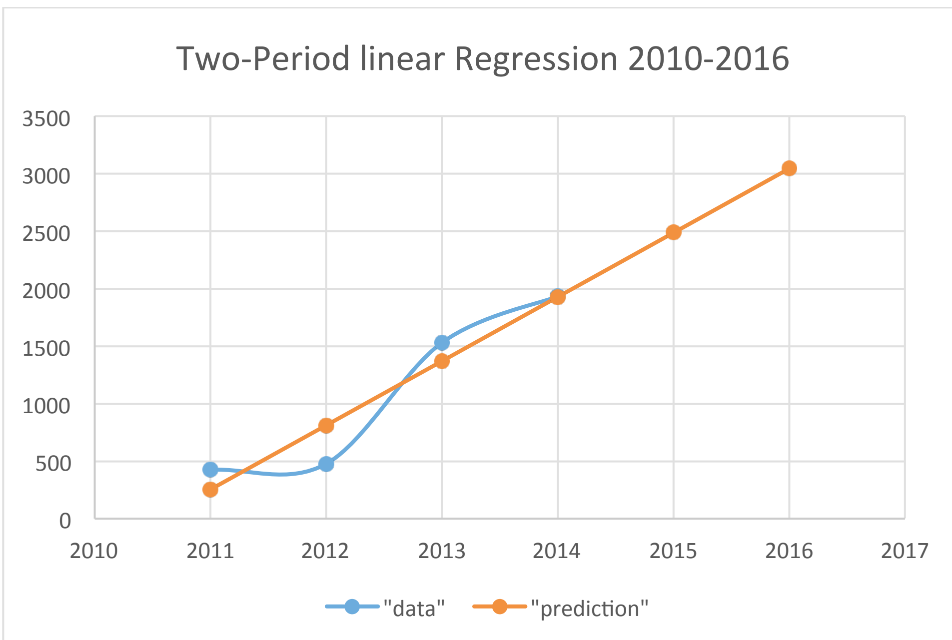


Figure 7. Two-Period Linear Regression

I fit two simple linear regressions, one from 2003 to 2011 and the other one from 2011 to 2014. This method produces significant lower mean square error and increases the prediction accuracy level. Under this model, the forecast for yearly job requisition is 2485.5 in 2015 and 3043.5 in 2016 ,with annual changing rate of 22% on average.

iii. Method 3: Relationship between Accumulative Labor demands and yearly labor demands

	Q1	Ratio	Prediction	Q1-2	Ratio	Prediction	Q1-2-3	Ratio	Prediction	Q1-2-3-4
2003				6			17			20
2004	14	0.33		22	0.50		36	0.85		42
2005	10	0.52		14	0.73		18	0.94		19
2006	15	0.32		29	0.63		40	0.86		46
2007	16	0.40	0.38	26	0.65	0.64	35	0.87	0.89	40
2008	13	0.28	0.40	31	0.68	0.66	38	0.84	0.88	45
2009	11	0.33	0.32	21	0.63	0.66	25	0.75	0.85	33
2010	4	0.13	0.33	14	0.46	0.65	19	0.63	0.80	30
2011	116	0.27	0.22	251	0.59	0.56	363	0.85	0.71	423
2012	50	0.10	0.24	123	0.25	0.56	280	0.58	0.77	477
2013	258	0.16	0.16	663	0.43	0.42	1146	0.74	0.67	1530
2014	442	0.22	0.17	875	0.45	0.41	1440	0.74	0.72	1932
2015			**0.18**			**0.408022**			**0.714777**	

Table 8. Prediction by Percentage

	Q1	*Q1-2*	*Q1-2-3*	*Q1-2-3-4*
Q1	1			
Q1-2	0.99	1		
Q1-2-3	0.98	0.99	1	
Q1-2-3-4	0.97	0.99	0.99	1

Table 9. Correlation between Accumulative Quarterly Job Requisition and Total Yearly Job Requisition.

Table 9 shows that there is a strong correlation between the accumulative job request by certain quarter and yearly total job requests. Therefore, I first estimate the ratio of accumulative job requests divided by yearly total using the historical data, and then calculate total job requests for 2015.

Here, I apply the technique of weighted moving average. I assume that a recent data reveals more accurate information about future trend than elderly data. Hence, more weight is placed on the most recent observations when making the forecasts of future values. The prediction of that ratio at time t is the average of three previous data points at t-1,t-2,t-3, weighted by 0.5,03,02 respectively. I select this set of weight parameter because it leads to the approximately lowest mean square error.

By July 6 2015, very close to the end of second quarter of 2015, XXX has received 1051 job requisitions. Therefore, I forecast that there will be 2576 (1051/0.408022) job requisition in total in 2015, which is very close to the result 2485 by method 2. Assuming the job requisition in 2015 is 2576, the prediction for 2016 is 3142(2576*(1+22%), with yearly increasing rate of 22% by method 2.

iv. Method 4. Relationship with Unemployment Rate

Economists forecast that the U.S. unemployment Rate continues to decrease in the near future years. Due to the inverse relationship between unemployment rate and XXX's job requisition, I expect XXX's labor demand will continuous to grow. However, the slope coefficient is not significant in the simple regression model of labor demand over unemployment rate. We need to search for more advanced model if we want to use unemployment rate as a quantitative variables in a model to make accurate prediction.

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	60.24748	21.41467	2.813374	0.005702
Unemployment Rate	-2.24883	3.002567	-0.74897	0.455295

v. Method 5: Forecast for each job category

A time series is a sequence of data points, typically consisting of successive measurements made over a time interval. Time series forecasting assumes that a time series is a combination of a pattern and some random error.

Step 1: Graph and Decomposition

The Purpose of the sequence plot is to give a visual impression of the nature of the time series. The goal is to separate the patterns from the error by understanding the pattern's trend, its long term increase or decrease, and tis seasonality if existence, the change caused by the seasonal factors.

Step 2: Forecasting

Several method of time series forecasting are available such as : Linear Regression, Moving Average, Exponential Smoothing, and ARIMA. The optimal method is the one that minimizes the root –mean-square error. RMSE is defined as follows.

$$RMSE = Sqrt(\frac{SSE}{df})$$

The forecasting method of demand in each labor category is likely to be different each other because every labor demand time series has its unique pattern and characteristics.

Note that a qualified time series should not contain any missing data that would lead to one or several gap periods over the selected time interval. In this report, I use the time series of "General", "Information Tech" and "Technical" labor categories as examples.

1. Information Tech

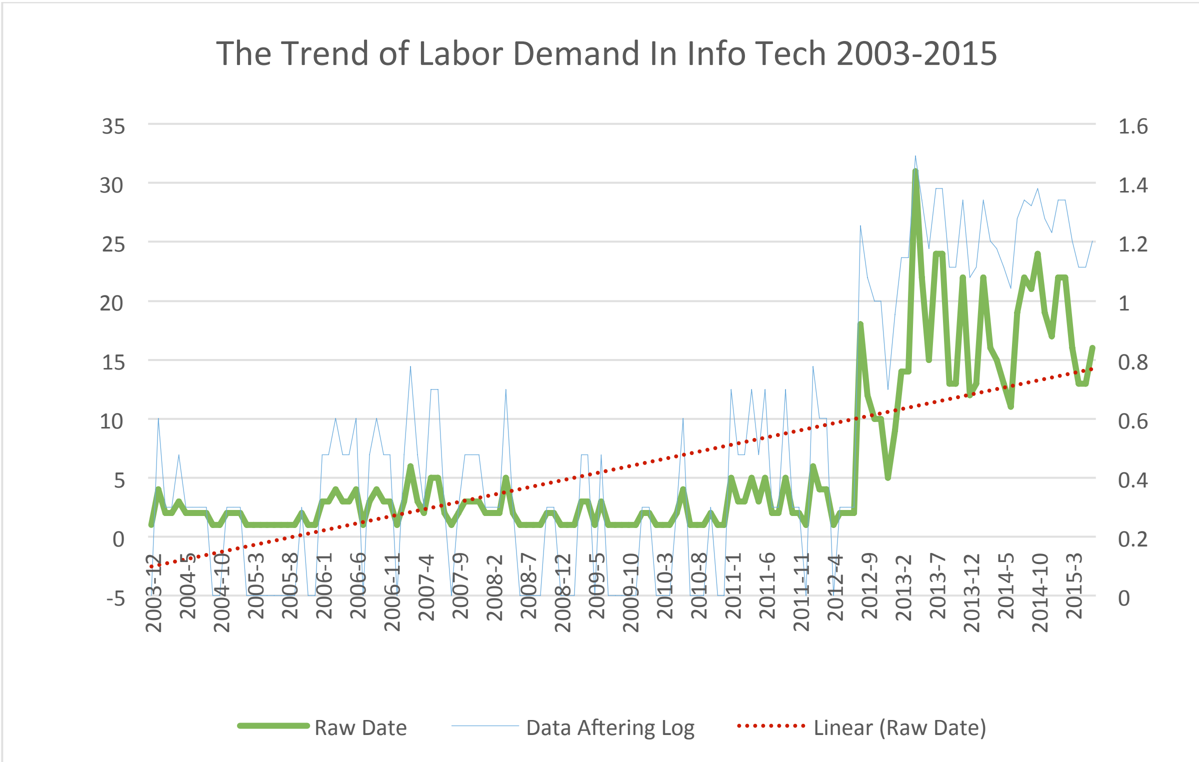


Figure 8

Linear Trend

The red line in Figure 8 shows that the labor demand in the "Information Technology" labor category from 2003 to 2014 holds an upwards trends overall.

Seasonality

Table 10 indicates that there is no large difference of job requisitions in the "Info Tech" labor category among each month. Figure 9 also supports that there is no consistent pattern repeated every year, and hence no strong and obvious indicator of seasonality. I will confirm the non-existence of strong seasonality using statistical time series decomposition method, in the following session.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2003												1
2004	4	2	2	3	2	2	2	2	1	1	2	2
2005	2	1	1	1	1	1	1	1	1	2	1	1
2006	3	3	4	3	3	4	1	3	4	3	3	1
2007	3	6	3	2	5	5	2	1	2	3	3	3
2008	2	2	2	5	2	1	1	1	1	2	2	1
2009	1	1	3	3	1	3	1	1	1	1	1	2
2010	2	1	1	1	2	4	1	1	1	2	1	1
2011	5	3	3	5	3	5	2	2	5	2	2	1
2012	6	4	4	1	2	2	2	18	12	10	10	5
2013	9	14	14	31	22	15	24	24	13	13	22	12
2014	13	22	16	15	13	11	19	22	21	24	19	17
2015	22	22	16	13	13	16						
Month-Total Applicants	**72**	**81**	**69**	**83**	**69**	**69**	**56**	**76**	**62**	**63**	**66**	**47**
Month-Mean Applicants	**6**	**6.75**	**5.8**	**6.9**	**5.8**	**6**	**5.4**	**7.4**	**6.1**	**6.2**	**6.4**	**3.9**

Table 10. Time Series of Job requisition For Info Tech

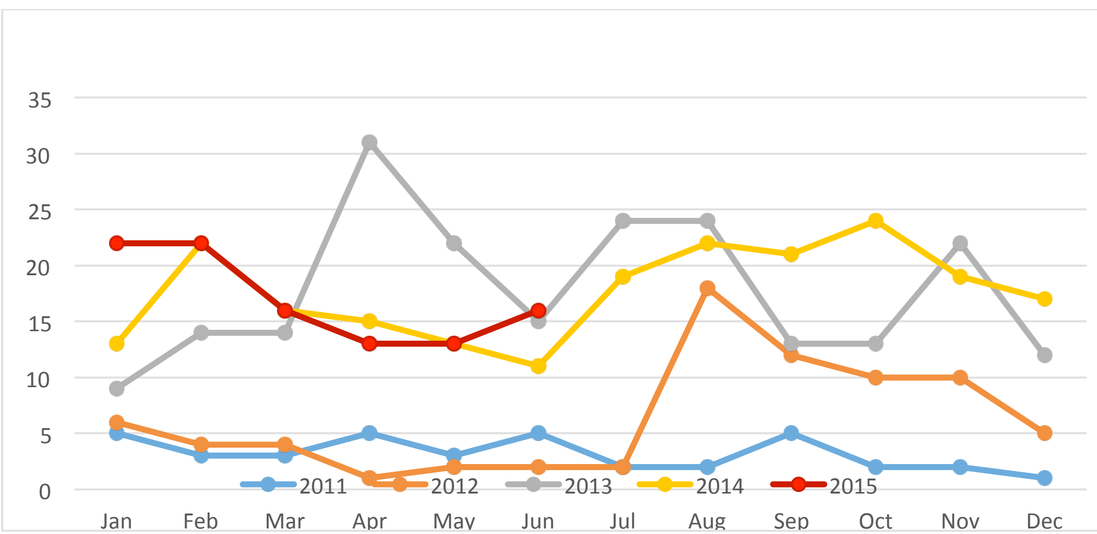


Figure 9 Monthly Seasonality Trend for Labor Demand in Info Tech

Decomposition – Trend + Seasonality + Residual

There are two models we can apply when making time series decomposition and forecasting. The addictive model has an implicit assumption that the different components affected the time series additively.

Data = Trend + Seasonal Effect + Residual

For monthly data, an additive model assumes that the difference between the January and July values is approximately the same each year. In other words, the amplitude of the seasonal effect is the same each year.

The multiplication model, otherwise, requires that the July value has the same proportion higher or lower than the January value in each year, rather than assuming that their difference is constant. The multiplication model can be transferred to an additive model by taking logarithms of both sides of the model.

Data = Trend * Seasonal Effect * Residual

I favor the multiplication model for this time series because the season effects become larger in the recent years.

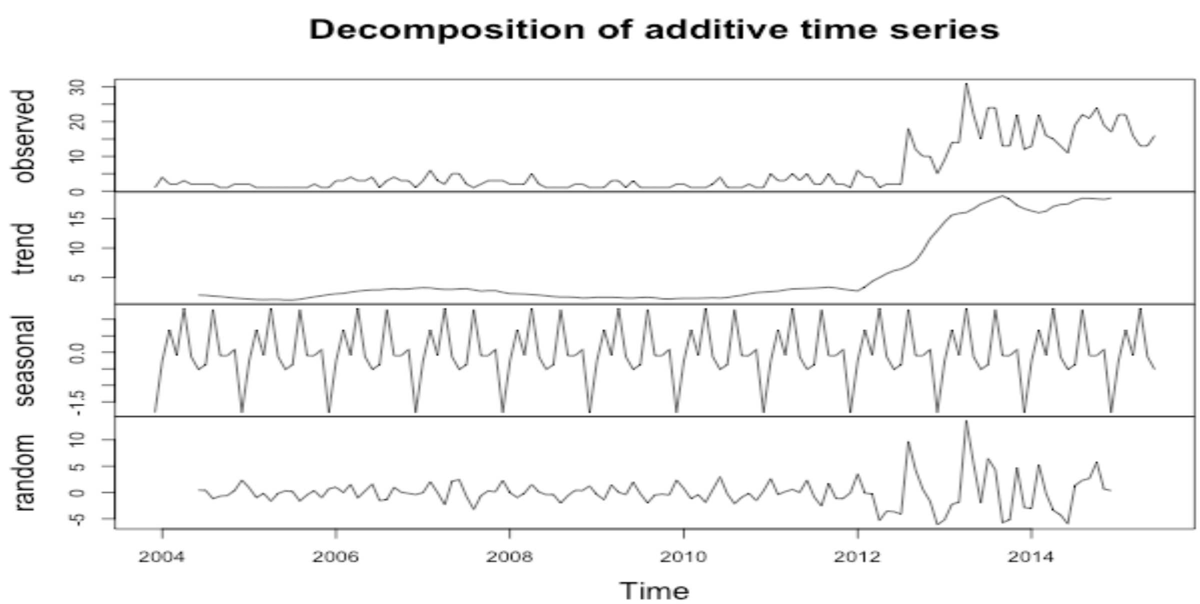


Figure 10 Decomposition of Time Series of Labor Demand in Info Tech

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
-0.27	0.68	-0.09	1.33	-0.13	-0.52	-0.38	1.30	-0.10	-0.10	0.09	-1.82

Table 11a. Seasonal Adjustment

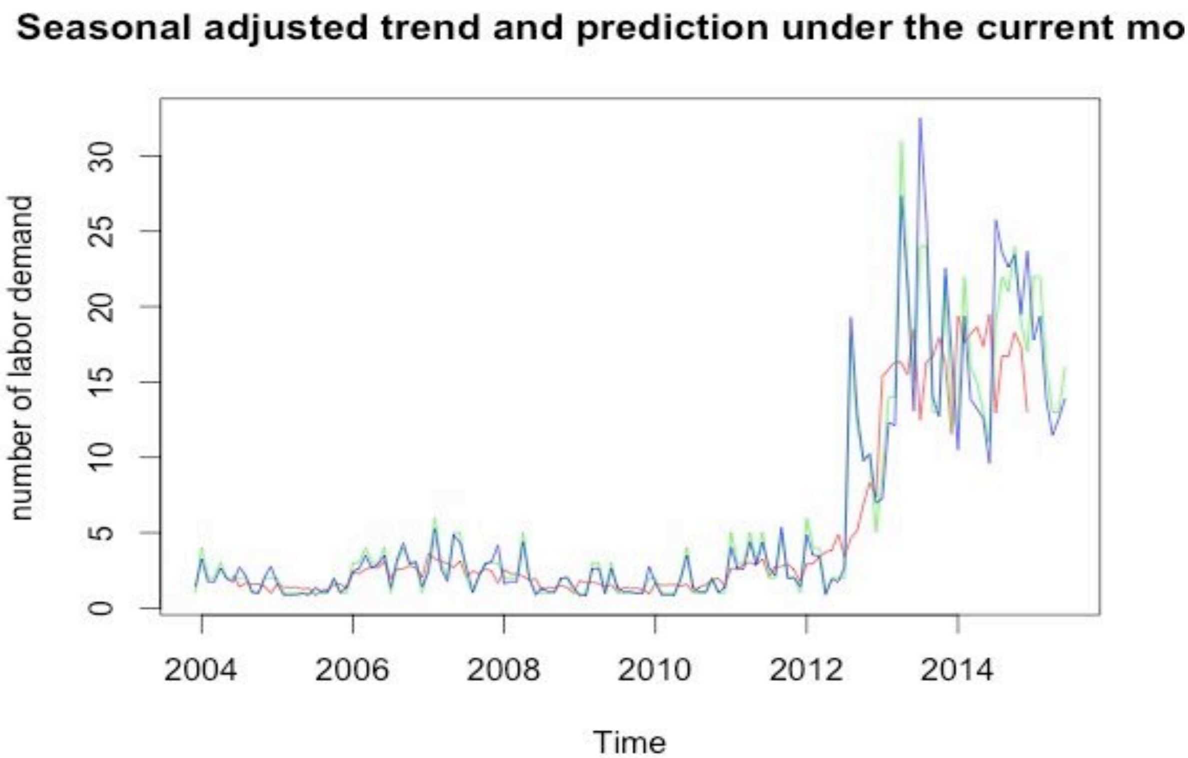


Figure 11

The red line represents the decomposed trend of the labor demand in Info Tech. The green line is the original data. The blue line is seasonal-adjusted data.

According to the Figure 10, the seasonal component does not vary a lot among every month and all of them are less than 1 unit, which are not substantial. Moreover, the green line for the original data and the blue line representing the data after seasonally adjustment in the Figure 11 almost match. I notice that the demand in the first and second quarter is relatively higher than that in the last two quarters during a year because most negative seasonal component values are located in the third and fourth quarter in the Table 11.

All those points suggest that there is moderate but no strong and obvious seasonality.

Forecasting

Linear Regression Method

Model:

In the simple linear regression model of labor demand of "Info Technology" over "Time", the labor demand has a positive relationship with "Time", which is statistical significant with a large t-value. In mathematical form,

Y (Number of Job requisitions) = 0.12*X (Time) – 2.64, for X (Time) = 1, 2, 3…

The slope coefficient 0.12 says that the labor demand for the "Info Tech" increase for 0.12 people (unit) on average every month from Dec 2003 to June 2015, which is 1.44 people (unit) every year.

Regression Statistics	
Multiple R	0.704605
R Square	0.496468
Adjusted R Square	0.492792
Standard Error	4.940798
Observations	139

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-2.64811	0.842689	-3.14245	0.002054	-4.314466846	-0.98175
P	0.121386	0.010444	11.62231	3.72E-22	0.100733359	0.142039

Table 11b Simple Linear Regression Result

Prediction:

	Prediction Value	80% Lower Bound	80% Upper Bound
2015-7	14.35	7.89	20.80
2015-8	14.47	8.01	20.92
2015-9	14.59	8.13	21.05
2015-10	14.71	8.25	21.17
2015-11	14.83	8.37	21.29
2015-12	14.95	8.49	21.42
2016-1	15.07	8.61	21.54
2016-2	15.20	8.73	21.66
2016-3	15.32	8.85	21.79
2016-4	15.44	8.97	21.91

2016-5	15.56	9.08	22.04
2016-6	15.68	9.20	22.16
2016-7	15.80	9.32	22.28
2016-8	15.92	9.44	22.41
2016-9	16.05	9.56	22.53
2016-10	16.17	9.68	22.65
2016-11	16.29	9.80	22.78
2016-12	16.41	9.92	22.90

Table 11c Forecast by Linear Regression and 80% Prediction Interval

In July 2015, the prediction of labor demand of "Info Tech" under the linear regression model is 14.35. 80% prediction Interval represents that the actual labor demand of this labor category in July 2015 should lie between 7.89 and 20.80 with probability 0.8.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	sum	%Change
2003												1	1	
2004	4	2	2	3	2	2	2	2	1	1	2	2	25	2400%
2005	2	1	1	1	1	1	1	1	1	2	1	1	14	-44%
2006	3	3	4	3	3	4	1	3	4	3	3	1	35	150%
2007	3	6	3	2	5	5	2	1	2	3	3	3	38	9%
2008	2	2	2	5	2	1	1	1	1	2	2	1	22	-42%
2009	1	1	3	3	1	3	1	1	1	1	1	2	19	-14%
2010	2	1	1	1	2	4	1	1	1	2	1	1	18	-5%
2011	5	3	3	5	3	5	2	2	5	2	2	1	38	111%
2012	6	4	4	1	2	2	2	18	12	10	10	5	76	100%
2013	9	14	14	31	22	15	24	24	13	13	22	12	213	180%
2014	13	22	16	15	13	11	19	22	21	24	19	17	212	0%
2015	22	22	16	13	13	16	14	14	15	15	15	15	190	-10%
2016	15	15	15	15	16	16	16	16	16	16	16	16	188	-1%

Table 11d Yearly Total and Changing Rate by Using Mean of Prediction

	Total	Changing
Mean-2015	190	-10%
80%Low-2015	151	-29%
80%High-2015	229	8%
Mean-2016	188	-11%
80%Low-2016	111	-48%
80%High-2016	267	26%

Table 11 e

The prediction for 2015 under the simple linear regression model is 10% lower than that in 2014, though the total labor demand for the first two quarters in 2015 is approximately equal to what XXX had in the same period of 2014. The prediction interval in 2016 is wider than that in 2015, which shows increasing uncertainty with time far from current date.

Exponential Smoothing

Exponential smoothing is a procedure for continually revising a forecast in the light of more recent experience. Exponential Smoothing assigns exponentially decreasing weights as the observation get older. In other words, recent observations are given relatively more weight in forecasting than the older observations.

I apply the Holt-Winter Exponential Smoothing method to make forecast, with alpha =0.78, beta=0.17, and gamma = 0.54, with because this combination of coefficients is optimized and produces the approximately lowest error, with SSE (Residual of Sum of Square) equal to 69.30.

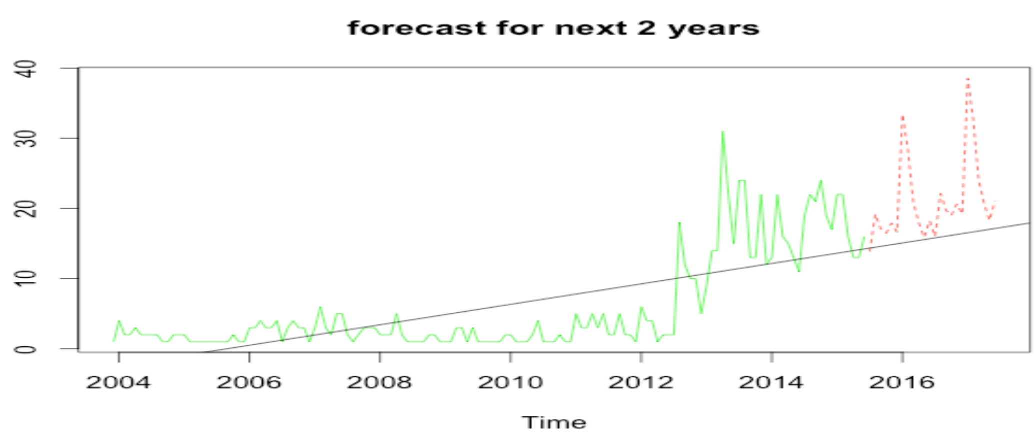


Figure 12a Forecast of XXX's Labor Demand for next 4 Years 2015 -2019

The green line is the original data and red line represents the forecasting values under the exponential smoothing. The black line is the simple linear regression line over time.

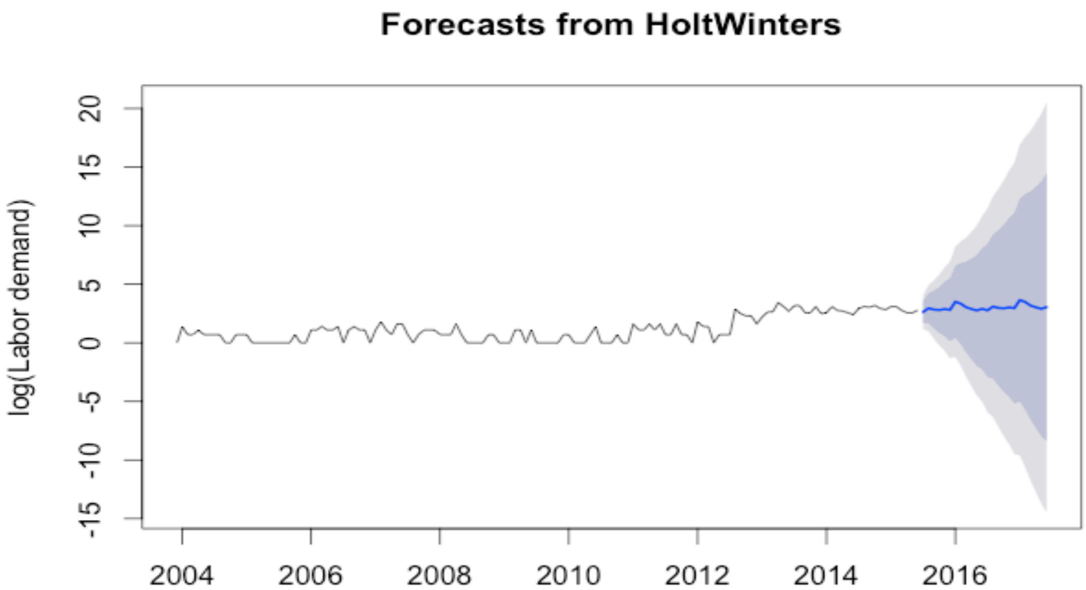


Figure 12b Forecast of XXX's Labor Demand for next 4 Years 2015 -2019

The black line is the log of origin data. The blue line repents predictions under the model using the log of original data. The dark blue region represents 80% prediction region and the light blue region represents 90% prediction region.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	sum	Changing
2003												1	1	
2004	4	2	2	3	2	2	2	2	1	1	2	2	25	2400%
2005	2	1	1	1	1	1	1	1	1	2	1	1	14	-44%
2006	3	3	4	3	3	4	1	3	4	3	3	1	35	150%
2007	3	6	3	2	5	5	2	1	2	3	3	3	38	9%
2008	2	2	2	5	2	1	1	1	1	2	2	1	22	-42%
2009	1	1	3	3	1	3	1	1	1	1	1	2	19	-14%
2010	2	1	1	1	2	4	1	1	1	2	1	1	18	-5%
2011	5	3	3	5	3	5	2	2	5	2	2	1	38	111%
2012	6	4	4	1	2	2	2	18	12	10	10	5	76	100%
2013	9	14	14	31	22	15	24	24	13	13	22	12	213	180%
2014	13	22	16	15	13	11	19	22	21	24	19	17	212	0%
2015	22	22	16	13	13	16	14	19	17	16	18	17	203	-4%
2016	33	28	21	18	16	18	16	22	20	19	21	19	252	24%

Table 12a forecast of XXX's Labor Demand for next 4 Years 2015 -2019 – Mean Predictions

Point	Forecast	Low Bound 80%	High Bound 80%	Low Bound 95%	High Bound 95%
2015-7	14	5	36	3	59
2015-8	19	5	69	3	136
2015-9	17	3	87	1	204
2015-10	16	2	118	1	333
2015-11	18	2	183	1	626
2015-12	17	1	246	0	1023
2016-1	33	2	725	0	3693
2016-2	28	1	913	0	5734
2016-3	21	0	1012	0	7893
2016-4	18	0	1325	0	12916
2016-5	16	0	1803	0	22114
2016-6	18	0	3249	0	50459
2016-7	16	0	4703	0	95281
2016-8	22	0	10387	0	269451
2016-9	20	0	14954	0	499932
2016-10	19	0	23489	0	1018346
2016-11	21	0	42271	0	2391078
2016-12	19	0	65600	0	4870480

Table 12b 80% and 95%Prediction Interval for forecasting

From Table 12 a, I figure out that the labor demand in 2015 is approximately equal t0 2014, which is consistent with my expectation. But the Table 12b also shows that this method has very large perdition interval, making the forecasting less reliable and practical.

ARIMA

ARIMA is short for Autoregressive Integrated Moving Average, which produces better result by taking correlations in the data into account.

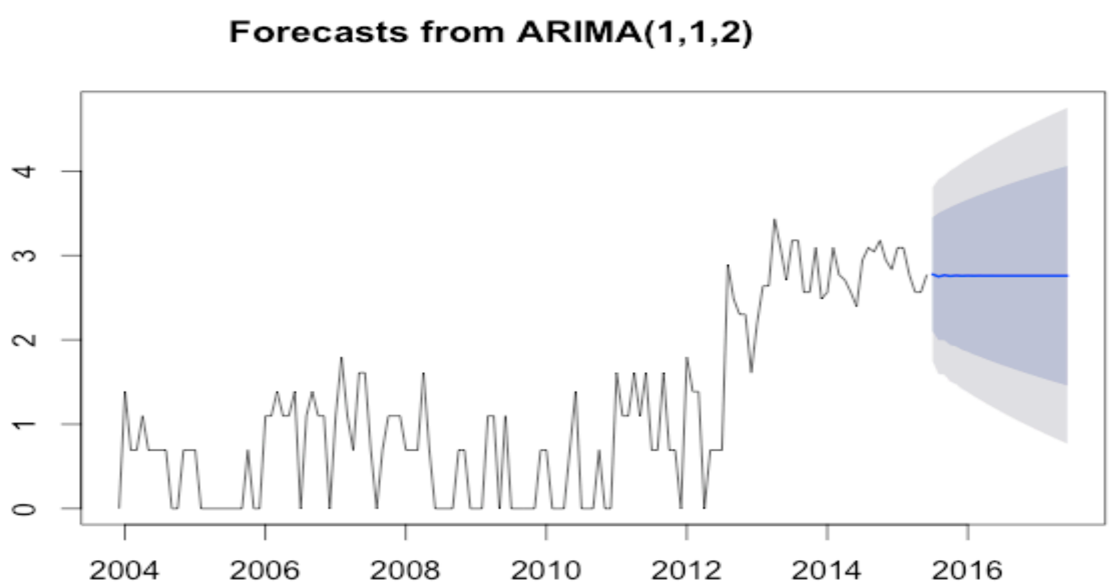


Figure 13c Prediction under ARIMA model

Month	Year	Forecast	Lo80	Hi80%	Low95%	High95%
Jul	2015	16	8	31	6	45
Aug	2015	16	7	33	5	50
Sep	2015	16	7	34	5	52
Oct	2015	16	7	36	5	55
Nov	2015	16	7	37	4	57
Dec	2015	16	7	38	4	60
Jan	2016	16	6	39	4	63
Feb	2016	16	6	40	4	66
Mar	2016	16	6	41	4	68
Apr	2016	16	6	42	3	71
May	2016	16	6	43	3	74
Jun	2016	16	6	45	3	77
Jul	2016	16	5	46	3	80
Aug	2016	16	5	47	3	83
Sep	2016	16	5	48	3	86
Oct	2016	16	5	49	3	89
Nov	2016	16	5	50	3	92
Dec	2016	16	5	51	3	95

Table 13c Prediction and 80%, 95% Prediction Interval

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total	Changing
Mean-2015	22	22	16	13	13	16	16	16	16	16	16	16	197	-7%
80%Low-2015	22	22	16	13	13	16	8	7	7	7	7	7	145	-31%
80%High-2015	22	22	16	13	13	16	31	33	34	36	37	38	311	47%
Mean-2016	16	16	16	16	16	16	16	16	16	16	16	16	197	-7%
80%Low-2016	6	6	6	6	6	6	5	5	5	5	5	5	67	-54%
80%High-2016	39	40	41	42	43	45	46	47	48	49	50	51	541	74%

Table 13d Yearly Changing Interval Using 80% Prediction Interval

ARIMA method produces more realistic results with comparatively narrow prediction interval and lower errors.

Conclusion

	Regression		Exponential Smoothing		ARMIA	
2014	212		212		212	
2015	190	-10%	203	-4%	197	-7%
2016	188	-1%	252	24%	197	-7%

Table 13 e

In conclusion, I prefer the result think the demand of labor in Info Tech would be a slightly lower than that in 2014. The overall trend would be moderate but a slight downside trend,-7%.

2. General

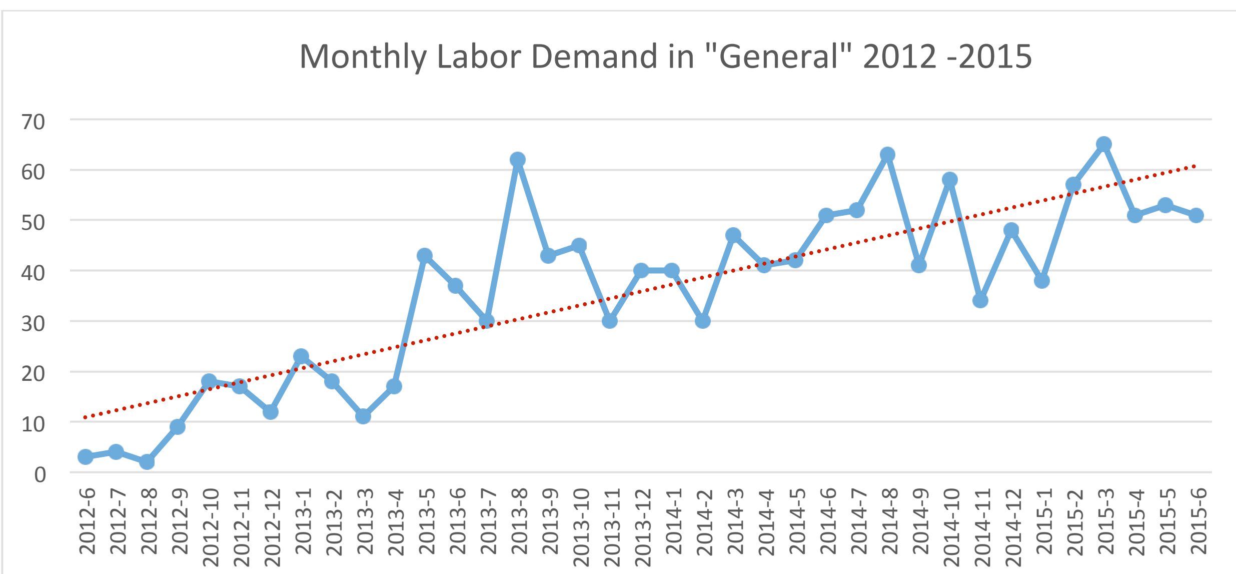


Figure 13.

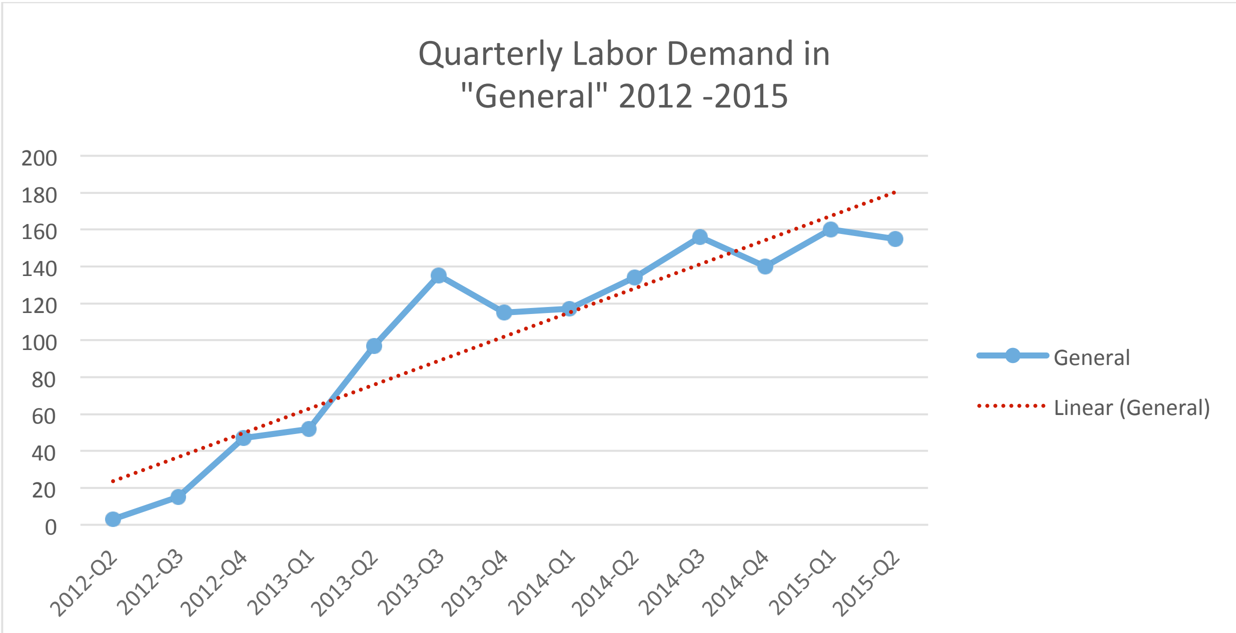


Figure 14.

	Qtr1	Qtr2	Qtr3	Qtr4
2012		3	15	47
2013	52	97	135	115
2014	117	134	156	140
2015	160	155		

Table 13. Quarterly Labor Demand in General

Compared to "Info Tech", the labor demand of "General" labor category has a shorter period of time series data from June 2012 to June 2015. Figure 13 shows that the monthly labor demand in "General" holds an upwards trends and the seasonality effect is approximately constant over the time. According to Figure 14, the demand in the Fourth quarter seems to be lower than the others. In next pages, I will explore the trend and seasonality using statistical methods.

Linear Trend

Based on the monthly time series data of labor demand in "General", I regress the "labor demand" over time. See Table 13 for the results. The mathematic representation of the model is

Y (Labor Demand In Genera) = 1.38*X (Time) +9.5045, for Time = 1,2,3…37

The slope coefficient of the regression model is 1.38, and the positive trend is statistical significant with P-vale less than 5%. The coefficient says that the labor demand of General labor category increase 1.38 unit every month on average from 2012 to July 6 2015. The same procedure can be also applied to the quarterly time series data, which result in similar conclusion.

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	9.504505	3.452507	2.752928	0.009299	2.495541834	16.51346717	2.495541834	16.51346717
time	1.385965	0.158412	8.749121	2.48E-10	1.064371649	1.707558175	1.064371649	1.707558175

Table 13. Regression result table: Demand over Time

Seasonality

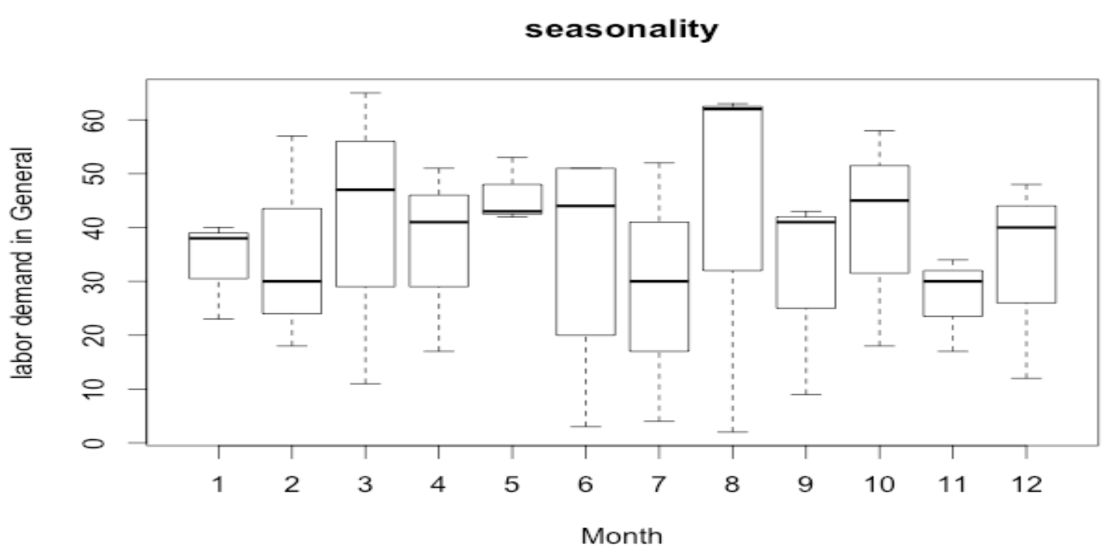


Figure 15

The boxplot in Figure 15 shows that the labor demand of "General" has highest demand in August and lowest demand in Feb and Nov on Average.

Decomposition– Trend + Seasonality + Residual

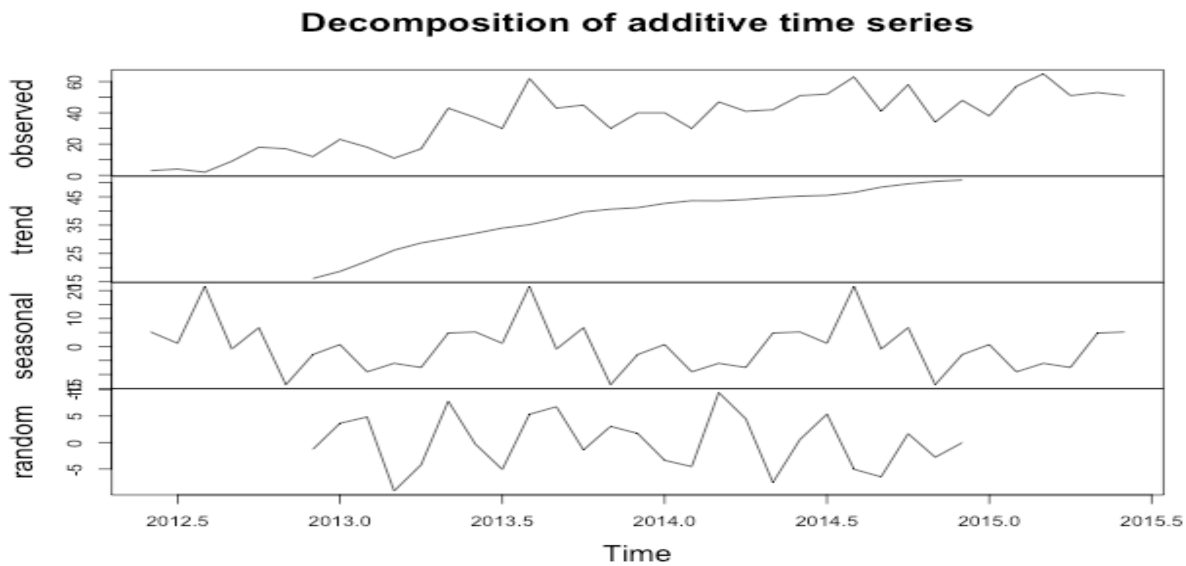


Figure 16 Decomposition of Monthly Data

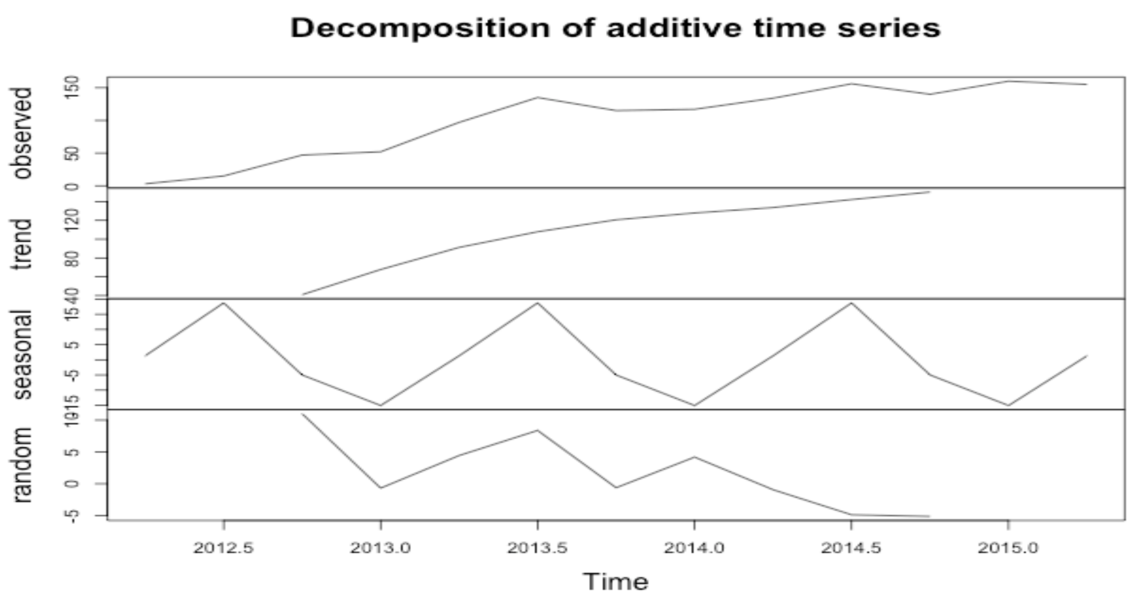


Figure 17 Decomposition of Quarterly data

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0.69	-9.07	-6.01	-7.51	4.80	5.19	1.13	21.51	-0.93	6.74	-13.68	-2.89

Table 14 Monthly Seasonal Adjustment

Qtr1	Qtr2	Qtr3	Qtr4
-15.06	1.31	18.75	-5

Table 15 Quarterly Seasonal Adjustment

The statistical decomposition method confirms our observations that the labor demand of "General" labor category has strong seasonality. From Figure 17, we can tell that the demand is comparative high in second and especially third quarter while it is low in the first and fourth quarter. The numerical adjustment data for every month and quarter are shown in Table 14 and Table 15.

I infer that weather status may be an influential factor. The first and fourth quarter usually have bad weather situations, such as low temperature, snow storm, which significantly reduce the frequency of human activity and the demand of service and consumption. Hence, the demand of "General" is low. This inference need to be confirm by further exploration and I will leave it out in this paper.

Forecast

<u>Exponential Smoothing</u>

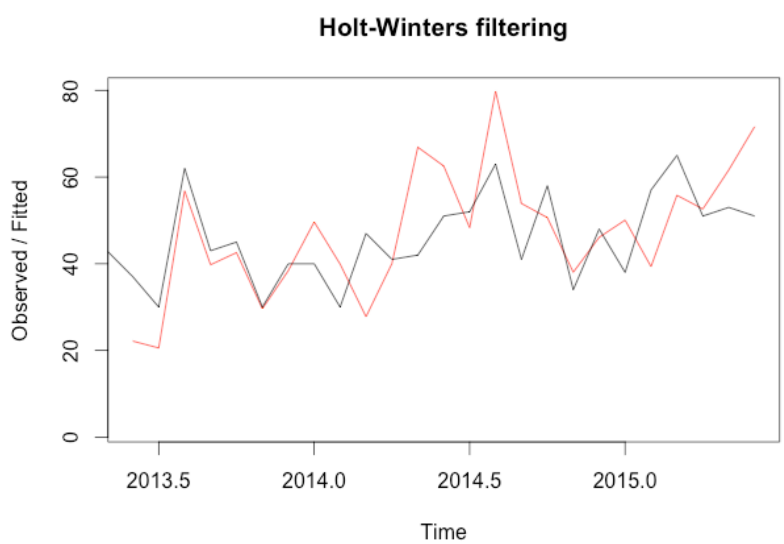


Figure 18a Fitted Value – Monthly Data

The black line represents the monthly raw data and red line is the fitted value under holt-winter filtering using smoothing parameter: alpha =0.34, beta =0, gamma=1. This set of coefficients minimizes the SSE of the model.

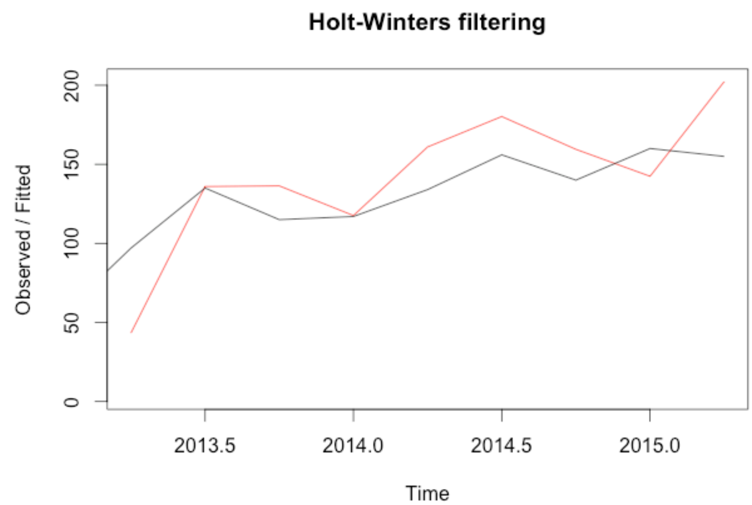
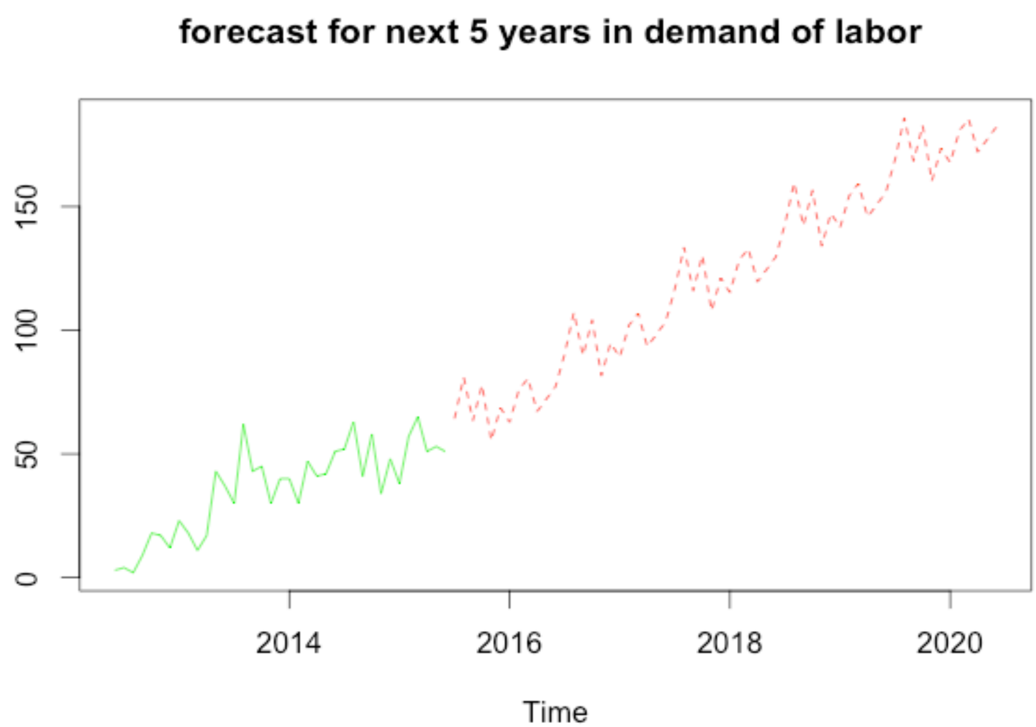


Figure 18b Quarterly Data

The black line represents the quarterly raw data and red line is the fitted value under holt-winter filtering using smoothing parameter: alpha =0.91, beta =0, gamma=0. This set of coefficients minimizes the SSE of the model.



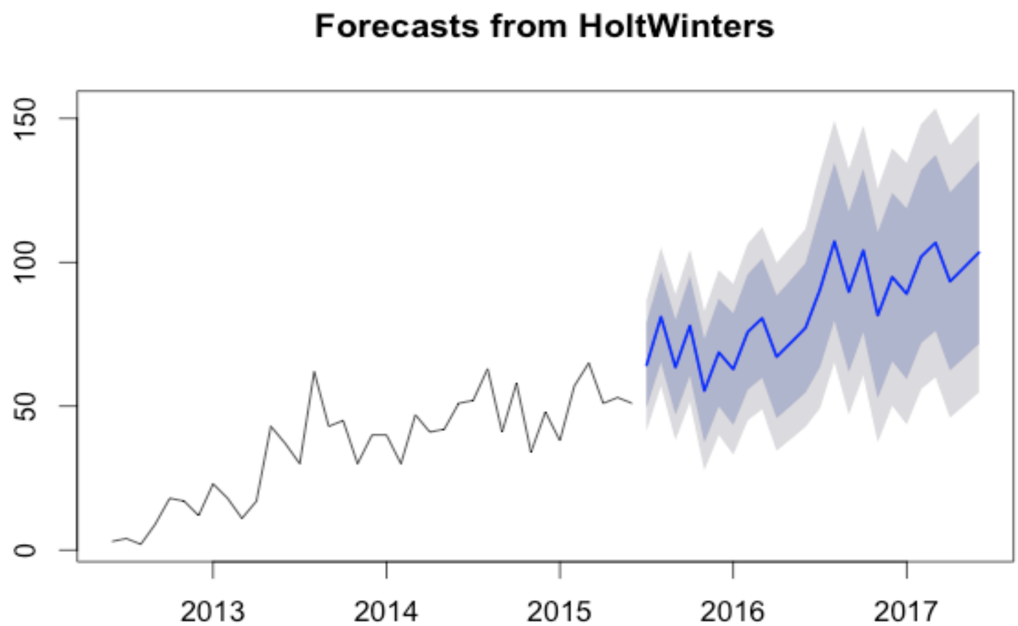


Figure 19 Monthly prediction 2015 -2020

Green line represents the raw data and green line is prediction under the holt-winter filtering using monthly data

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Sum
2015	38	57	65	51	53	64.3	81.0	63.5	78.0	64.3	55.34	68.69	734
2016	62.8	75.8	80.6	67.2	72.1	77.2	90.5	107.3	89.7	104.2	81.56	94.91	1003.8
2017	89.1	102.0	106.8	93.4	98.3	103.4	116.7	133.5	115.9	130.4	107.78	121.13	1318.4
2018	115.3	128.2	133.0	119.6	124.6	129.7	142.9	159.7	142.1	156.6	134.00	147.35	1633.1
2019	141.5	154.4	159.3	145.8	150.8	155.9	169.2	185.9	168.4	182.8	160.22	173.57	1947.7
2020	167.7	180.6	185.5	172.0	177.0	182.1							

Table 16 Monthly Prediction 2015-2020

Year	Demand	Increase Rate	Average Increasing Rate
2013	376		31.81%
2014	507	35%	
2015	733	45%	
2016	1004	37%	
2017	1318	31%	
2018	1633	24%	
2019	1948	19%	

Table 17 Increasing Rate

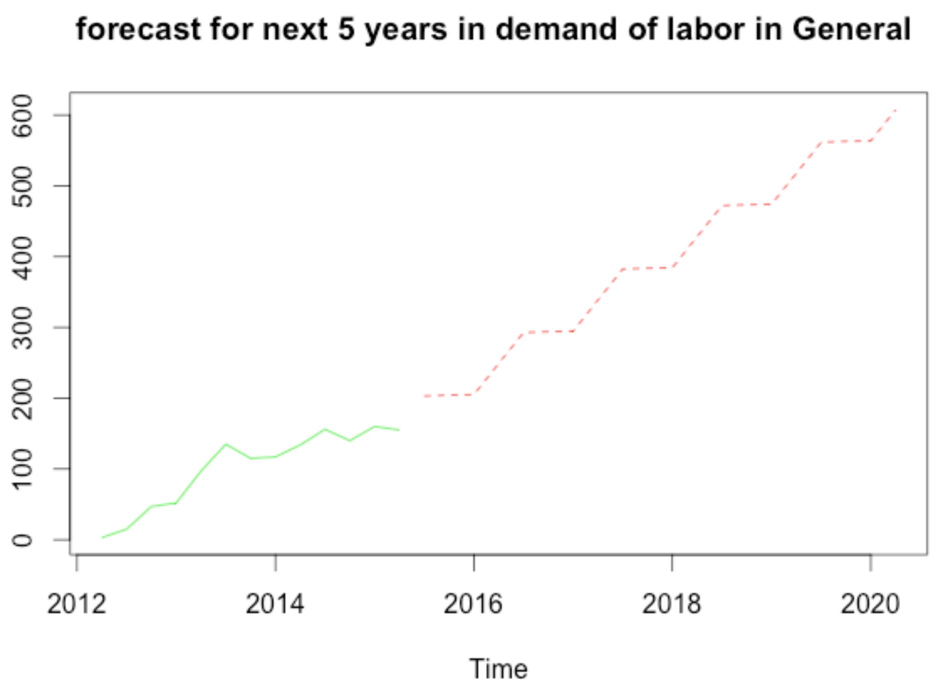


Figure 20 Quarterly prediction 2015 -2020

Green line represents the raw data and green line is prediction under the holt-winter filtering using quarterly data

	Qtr1	Qtr2	Qtr3	Qtr4	Total-by	Total-by	Total-by

					Quarter Prediction	Month Prediction	Average
2015	160	155	203.1	204	722	734	728
2016	205	249	292.7	294	1040.6	1003.8	1022
2017	294.7	339	382.4	384	1399.2	1318.4	1359

Table 18

Here, I applied the holt-winter model twice by using monthly and quarterly data and use the average of the predictions as its final prediction of labor demand in "General". The increasing rate from 2014 to 2015 is 44%. The result is not very different when solely using the monthly prediction and quarterly prediction.

3. **Technical**

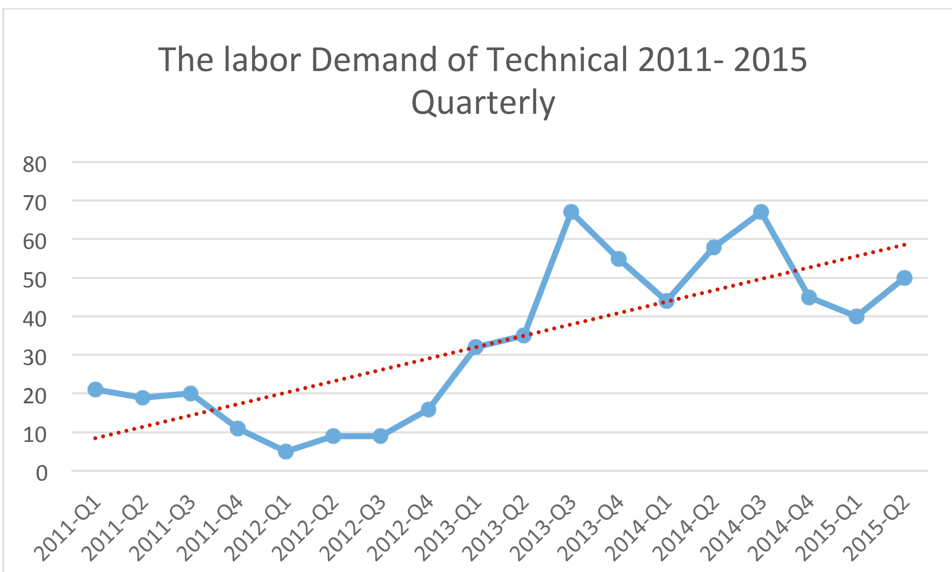


Figure 21

Trend

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*

Intercept	5.490196078	6.768109041	0.811186	0.42916	-8.8576	19.8379463
Time	2.948400413	0.625266714	4.715428	0.00023	1.62289	4.273906633

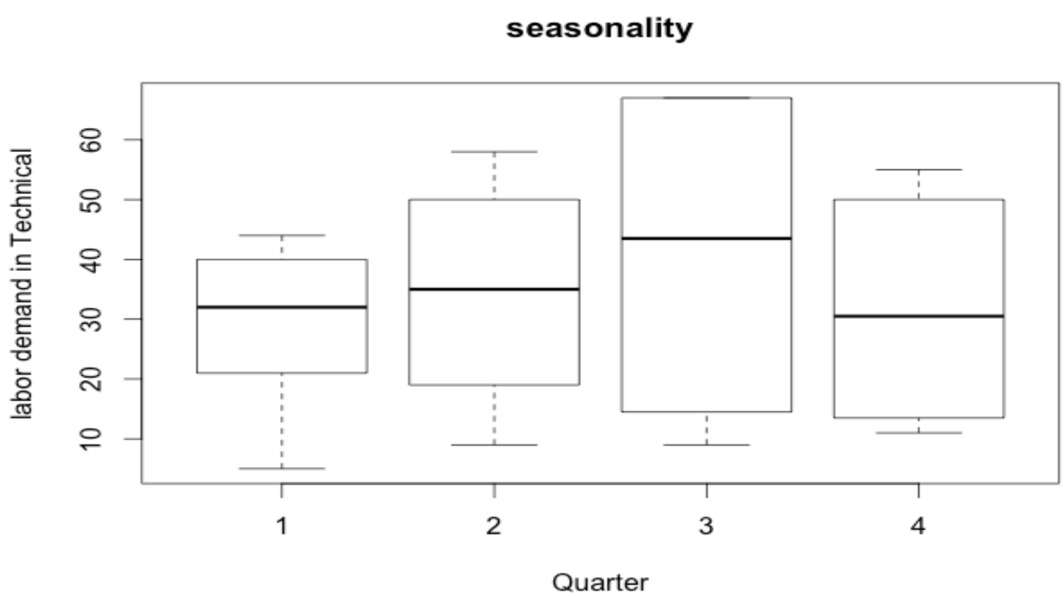
Table 19 Linear Regression of Demand over Time

Figure 21 and Table 19 shows that the labor demand in "Technical" labor Category holds an upwards trend over time. The regression function is

Y (Demand) = 2.94X (Time) +5.49, X= 1, 2, …, 18.

The slope coefficient means that the labor demand of technical increases 2.94 units every quarter on average from 2011 to 2015.

Seasonality



	Qtr1	Qtr2	Qtr3	Qtr4
Seasonal Adjustment	-4.833333	-1.208333	8.302083	-2.260417

Figure 22

Figure 22 shows that the demand in Technical labor is highest in the third quarter and lowest in the first quarter over a year.

Decomposition

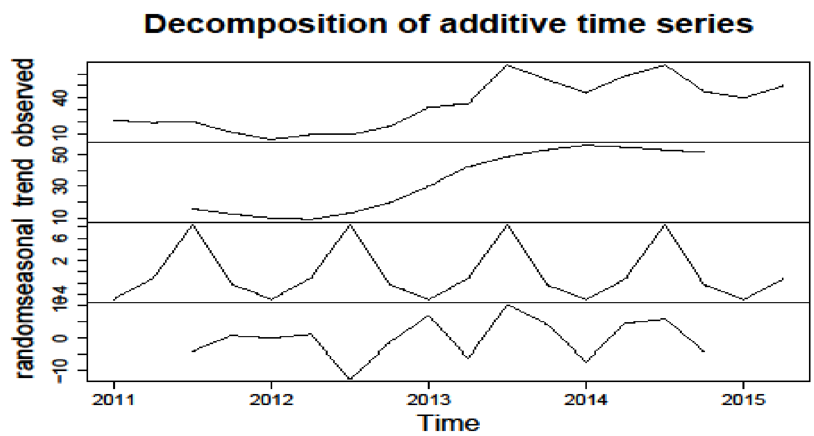
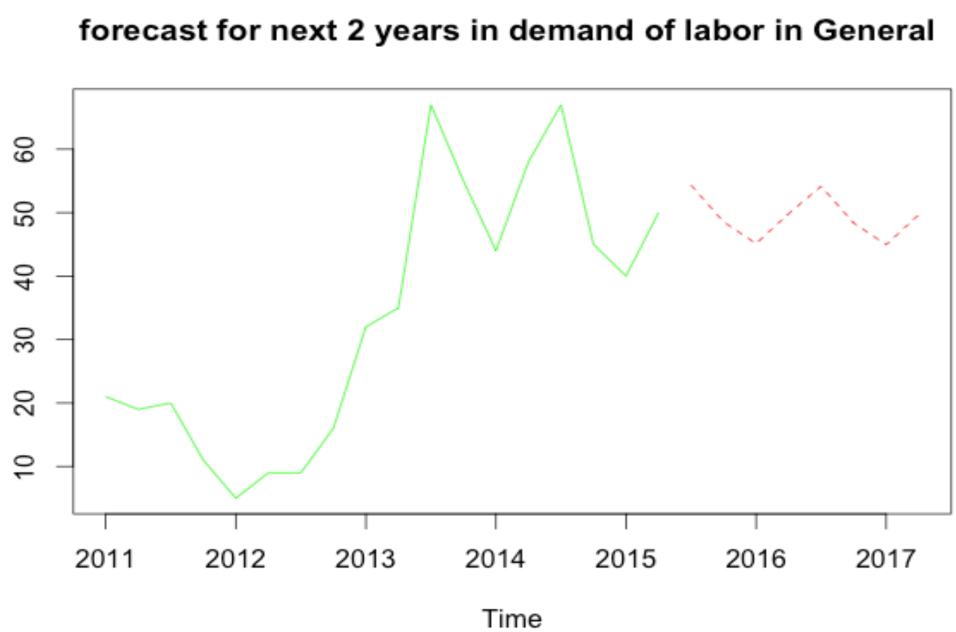


Figure 23

Forecast

Exponential Smoothing



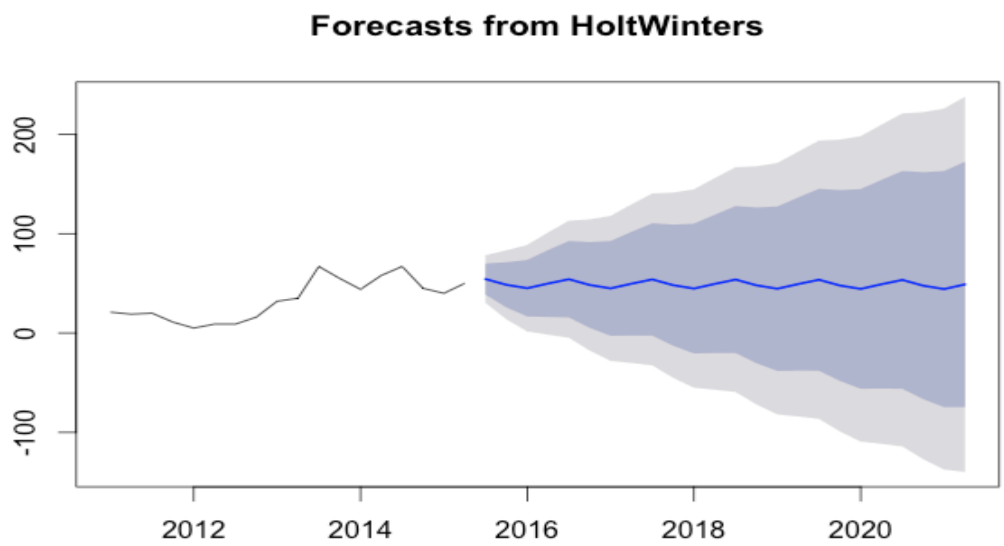


Figure 24a

	Qtr1	Qtr2	Qtr3	Qtr4	Total	Changing Rate%
2011	21	19	20	11	71	
2012	5	9	9	16	39	-45%
2013	32	35	67	55	189	385%
2014	44	58	67	45	214	13%
2015	40.0	50.0	54.3	48.5	192.8	-10%
2016	45.1	49.8	54.2	48.4	197.4	2%
2017	44.9	49.7				

Table 20a Forecast of Labor Demand in Technical

Table 20 shows that compare to 2014, the labor demand in Technical will decrease 10% in 2015. This forecasting is not surprising because the data for the first quarter and second quarter in 2015 is lower than those in the same period of 2014. However, compared to 2011, the labor demand for technical has increased tremendously. I forecast the demand in Technical will stay in a relative high level but with moderate variation in the following years.

ARIMA

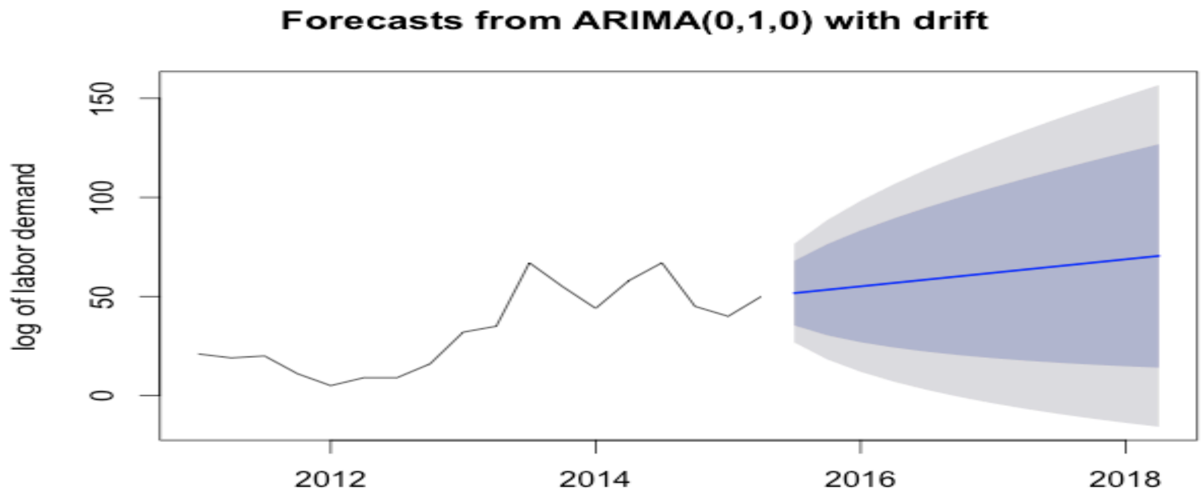


Figure 24b

Year	Quarter	Forecast	80%LOW	80High	95%Low	95% High
2015	Q3	52	35	68	27	77
2015	Q4	53	30	76	18	89
2016	Q1	55	27	83	12	98
2016	Q2	57	24	89	7	107
2016	Q3	59	22	95	3	114
2016	Q4	60	20	100	-1	121
2017	Q1	62	19	105	-4	128
2017	Q2	64	18	110	-7	134
2017	Q3	65	17	114	-9	140
2017	Q4	67	16	118	-12	146

Year	Q1	Q2	Q3	Q4	Total	Change
2014	44	58	67	45	214	
Low-2015	40	50	35	30	155	-28%
Mean-2015	40	50	52	53	195	-12%
High-2015	40	50	68	76	234	10%
Low-2016	27	24	22	20	93	-52%

Mean-2016	55	57	59	60	231	18%
High-2016	83	89	95	100	367	66%

Table 20b

Conclusion

Linear Regression		Exponential Smoothing		ARIMA		Average	
214		214		214		214	
240	12%	192	-10%	195	-9%	209	-2%
287	34%	197	-8%	231	8%	238	11%

Table 20c

Compared with 2015, the demand of "Technical" labor will still stay at a high level in 2015 and 2016 but it shows some slight drawbacks compared to 2014. As I mentioned previously in Table 8, "General" take the first place in the growth rate of labor demand using the demand in 2014 as a base, followed by "Technical" and "Info Tech". After taking a deeper analysis, I find that labor demand in "General" still have strong potential to continue to grow in future while demand in " Info Tech" and " Technical" has meet some unbound after years of growth. The demand in "Info Tech" and "Technical" will still be high in near future, but with some moderate level of ups and downs.

vi. Method 6: Forecast for each client

I use two approaches to forecast the labor demand for a specific clients.

1. Overall Trend Approach
2. General - Job Category Approach
3. Individual- Job Category Approach

In the Overall Trend Approach, I fit an appropriate model, linear or nonlinear, according to the pattern and trend of client's overall labor demand data

In the General Job Category approach, I first estimate the client's demand weight allocation in each labor category based on the historical data. Then, I estimate the individual demand of each labor category in general, as what I did in Method 5 for "Info Tech", "General" and "Technical". Lastly, I calculate the total labor demand by aggregating all the demand in each major labor categories. The approach is reasonable with the assumption that the client's job demand shares some similarities with the overall labor demand for each labor category in the market.

The steps of Individual-Job Category Approach is the same as in the General-Job Approach except I make the prediction solely based on client's time series data. The result is customized for the client only but the prediction accuracy level will be reduced if the clients has relative a few data.

In both labor category approaches, not only can we provide the client its overall amount of labor demand but also the demand for each specific labor category.

In this report, I use client BAEES demonstration.

Overall Trend Approach

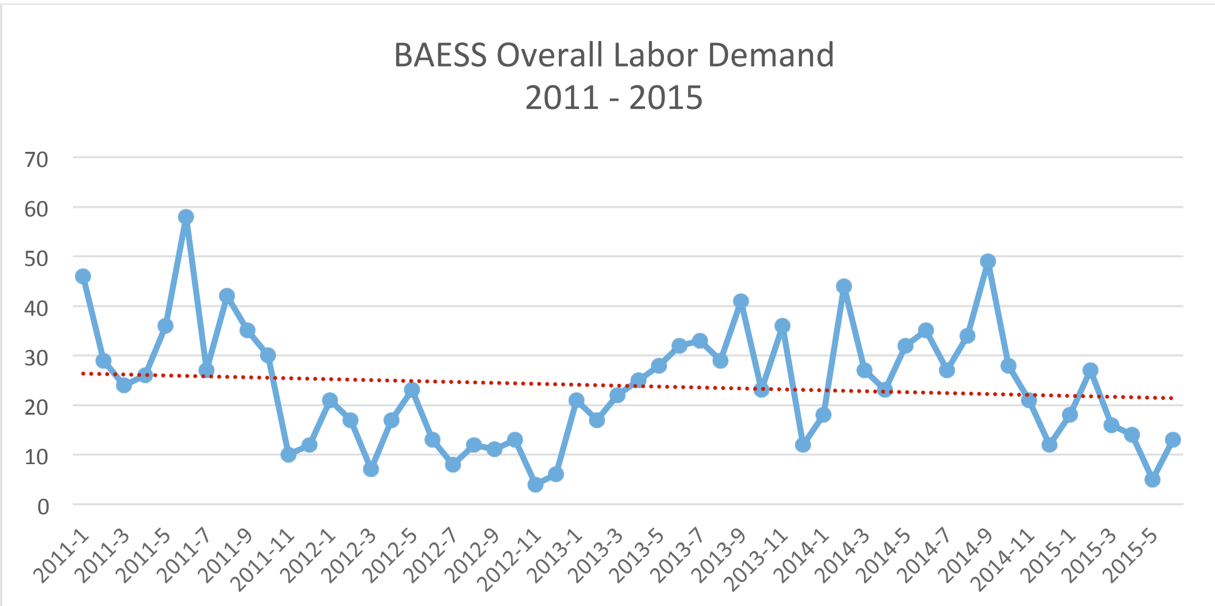


Figure 25

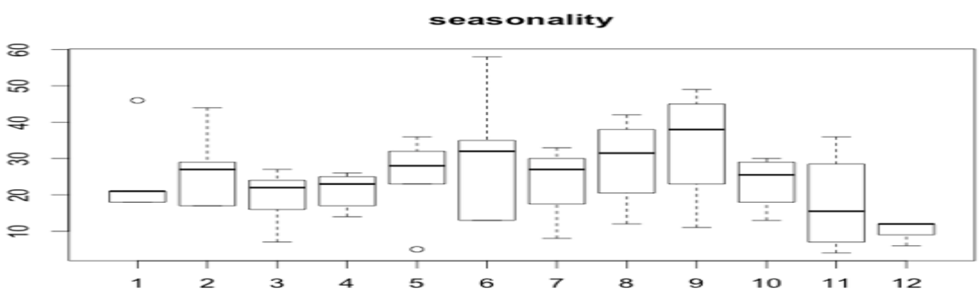
Regression Statistics	
Multiple R	0.122728
R Square	0.015062
Adjusted R Square	-0.00388
Standard Error	12.0186
Observations	54

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	26.44375	3.317013	7.972156	1.41E-10	19.78767	33.09982
Period	-0.09358	0.104937	-0.89175	0.376636	-0.30415	0.116994

Table 21a Linear Regression Result

The red line in Figure 25 shows that BAESS's overall labor demand displays a slight downwards trend from 2011 to 2015. However, the small t value in Table 21 does not reject the possibility that the slope coefficient could be 0 or even a small positive number. The R square is 0.01 around zero, which means the simple linear regression model of labor demand against time only improve the prediction accuracy by 1% percent compared to using its mean value. Hence, I think the BAESS's overall trend of labor demand is approximately constant and does not change with time a lot in this period. The linear regression model is not appropriate in this case.

Seasonality



Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
-2	4	-4	-1	5	4	-1	5	10	-1	-6	-12

Figure 26

Figure 26 shows that client's labor demand is highest in September and is lowest in December.

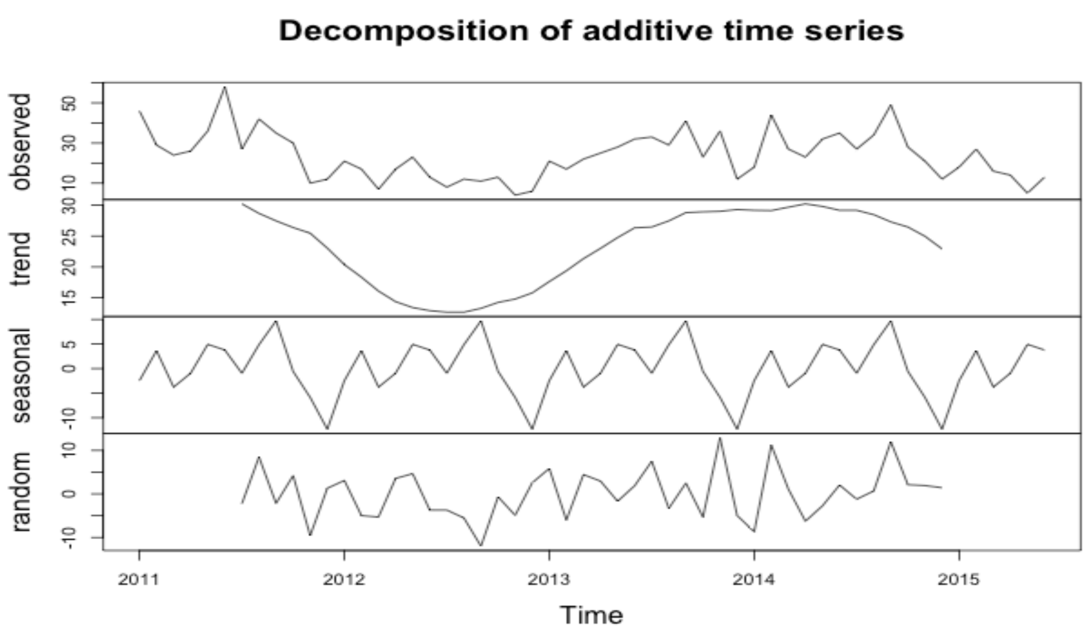


Figure 27

Forecasting – ARIMA

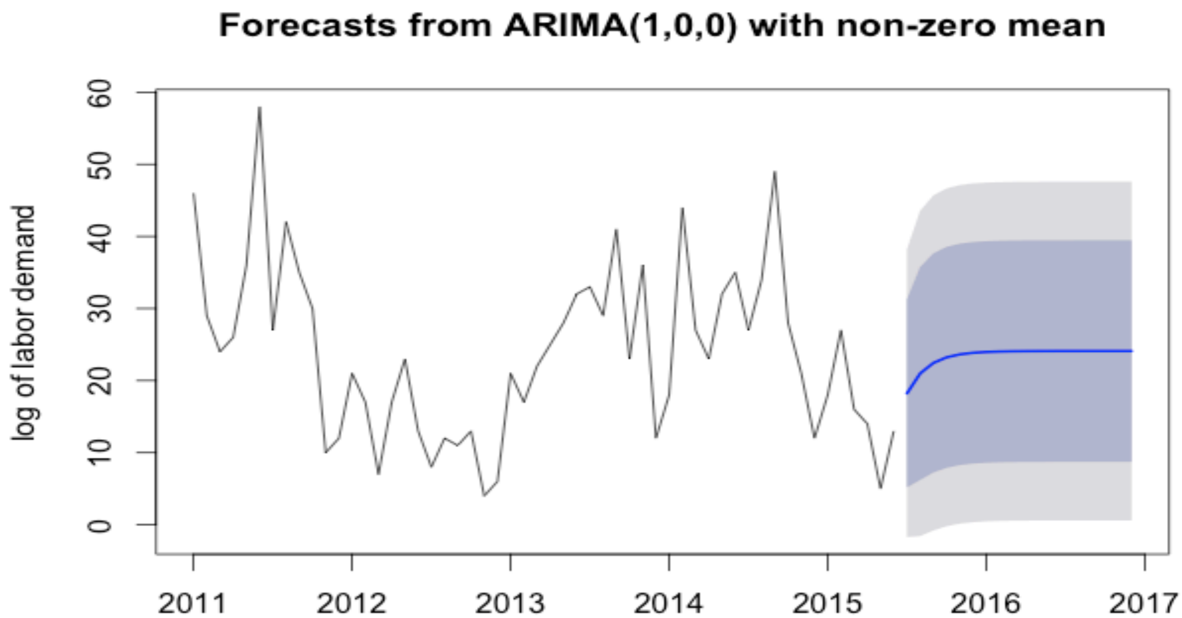


Figure 28

The Figure 28 shows that the clients' labor demand will decrease in 2015 around 36%. In the first two quarters of 2015, clients' demand has shrank to half of the size in the same period of 2014.

Date	Point	Forecast	80%LOW	80%High	05%LOW	95%High
Jul-15	2015	18.2	5.2	31.2	-1.7	38.1
15-Aug	2015	21.0	6.2	35.7	-1.6	43.5
15-Sep	2015	22.4	7.3	37.6	-0.8	45.7
15-Oct	2015	23.2	7.9	38.5	-0.2	46.6
15-Nov	2015	23.6	8.3	39.0	0.2	47.1
15-Dec	2015	23.9	8.5	39.2	0.4	47.3
16-Jan	2016	24.0	8.6	39.3	0.5	47.4
16-Feb	2016	24.0	8.7	39.4	0.5	47.5
16-Mar	2016	24.1	8.7	39.4	0.6	47.5
16-Apr	2016	24.1	8.7	39.4	0.6	47.6
16-May	2016	24.1	8.7	39.4	0.6	47.6
16-Jun	2016	24.1	8.7	39.4	0.6	47.6
16-Jul	2016	24.1	8.7	39.4	0.6	47.6
16-Aug	2016	24.1	8.7	39.4	0.6	47.6

16-Sep	2016	24.1	8.7	39.5	0.6	47.6
16-Oct	2016	24.1	8.7	39.5	0.6	47.6
16-Nov	2016	24.1	8.7	39.5	0.6	47.6
16-Dec	2016	24.1	8.7	39.5	0.6	47.6

Table 21b

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total	Changing
2011	46	29	24	26	36	58	27	42	35	30	10	12	375	
2012	21	17	7	17	23	13	8	12	11	13	4	6	152	-59%
2013	21	17	22	25	28	32	33	29	41	23	36	12	319	110%
2014	18	44	27	23	32	35	27	34	49	28	21	12	350	10%
2015	18	27	16	14	5	13	18	21	22	23	24	24	225	-36%
2016	24	24	24	24	24	24	24	24	24	24	24	24	289	28%

Table 21c

Year	Total	Change
2014	214	
Low-2015	136	-61%
Mean-2015	225	-36%
High-2015	314	-10%
Low-2016	105	-70%
Mean-2016	289	-17%
High-2016	367	35%

Table 21 d

General - Labor Category Approach

Job Category	Admin	Engineering	Information Technology	Light Industrial	Professional	Technical	Grand Total
BAEES	9.71%	27.14%	2.93%	29.99%	4.39%	25.83%	100.00%
Changing 2015	-14%	-68%	-7%	3%	N/A	-9%	
Overall 2015	**-22%**	[9.71*14+27.14*(-68)+2.93*(-7)+29.99*(-3)+25.83*(-9))]/(100-4.39)					

Table 22

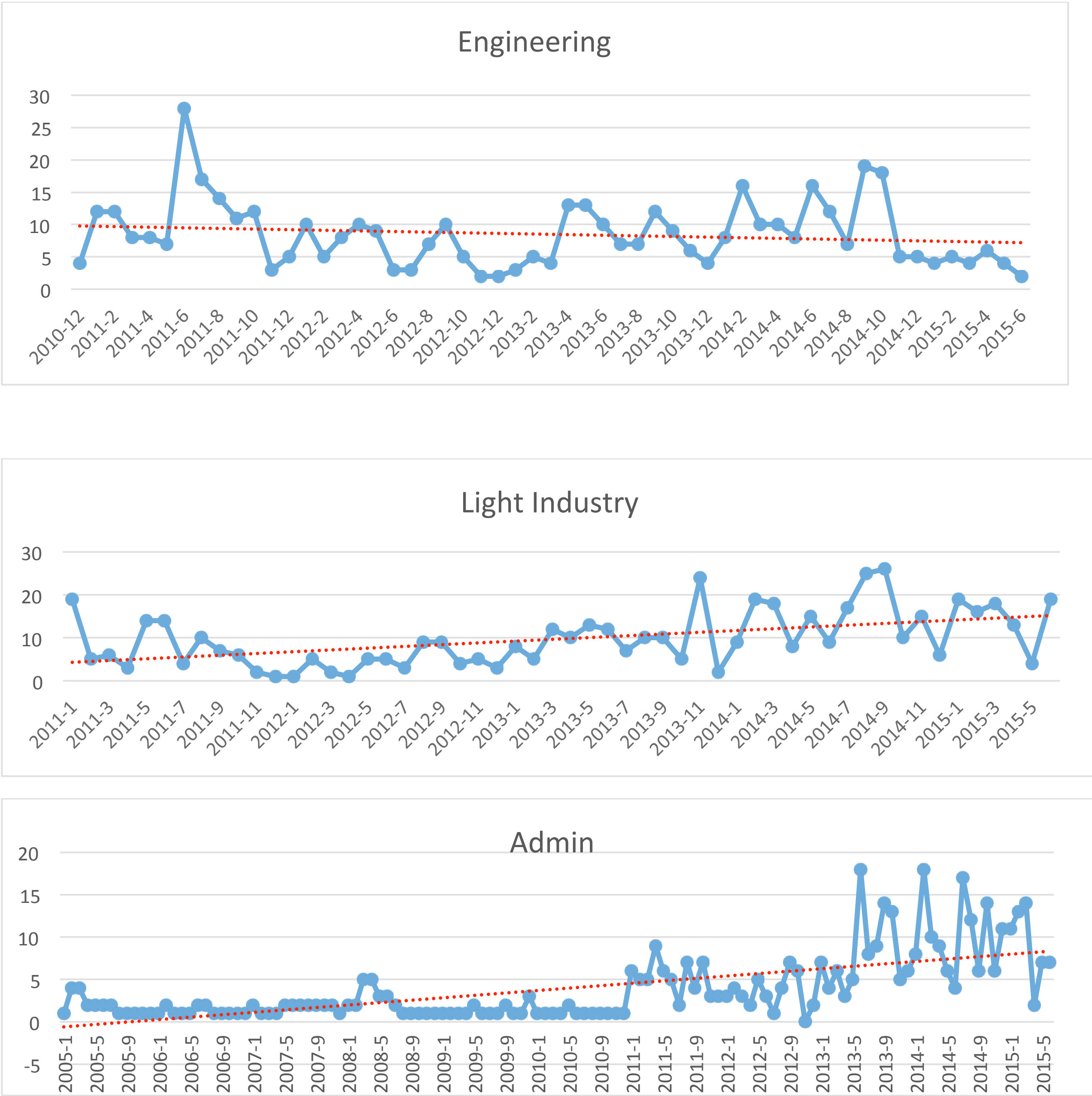


Figure 28

Engineer	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Sum	Changing Rate	Overall
2011	12	12	8	8	7	28	17	14	11	12	3	5	137		
2012	10	5	8	10	9	3	3	7	10	5	2	2	74	-46%	
2013	3	5	4	13	13	10	7	7	12	9	6	4	93	26%	
2014	8	16	10	10	8	16	12	7	19	18	5	5	134	44%	
2015	4	5	4	6	4	2	2.9	2.71	5.36	4.1	1.37	1.3	42.78	-68%	-13%

2016	1.8	2.65	2.334	3.77	3.24	2.5	2.9	2.71	5.36	4.1	1.37	1.3	34.08	-20%	

Admin	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Sum	Changing Rate	0verall
2011	6	5	5	9	6	5	2	7	4	7	3	3	62		
2012	3	4	3	2	5	3	1	4	7	6	0	2	40	-35%	
2013	7	4	6	3	5	18	8	9	14	13	5	6	98	145%	
2014	8	18	10	9	6	4	17	12	6	14	6	11	121	23%	
2015	11	13	14	2	7	7	6	10	8	11	7	7	104	-14%	
2016	8	9	8	6	9	8	6	10	8	11	7	7	97	-7%	22%

Light	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	sum	Changing Rate Overall	
2011	19	5	6	3	14	14	4	10	7	6	2	1	91		
2012	1	5	2	1	5	5	3	9	9	4	5	3	52	-43%	
2013	8	5	12	10	13	12	7	10	10	5	24	2	118	127%	
2014	9	19	18	8	15	9	17	25	26	10	15	6	177	50%	
2015	19	16	18	13	4	19	13.7	22	22.5	11	19.6	5.4	182.9	3%	
2016	14	15.1	15.76	9.03	6.788	17	13.8	22	22.5	11	19.6	5.4	171.3	-6%	26%

Table 23 Prediction of Labor Demand in 2015 and 2016, Using Data for all the client

Session II

<u>Analysis and forecast of job bid applicants – Labor Supply</u>

I study XXX's overall labor supply of different labor categories, states and clients from 2003 to July 6, 2015 and compare it to the corresponding labor demand. I create the supply-demand ratio as a key performance indictor to check if the supply and demand in a specific field is well balanced.

Moreover, we could also apply the time series analysis tools to analyze the labor supply side, like what I did for labor demand in Session I. Hence, we can see the trend and forecast for the future labor supply. Moreover, I can demonstrate how the labor demand and supply for a specific labor category change with time and how they relate to each other. Despite of “Labor category”, the same procedure can also be applied to “job category “to figure out how the labor demand and supply vary with time for a specific job category, such as “programmer”. However, the labor supply entry in the Job Bid Report does not associate with a “Time” variable, which stops me further analysis the data. I suggest to add a “time” related variable to each job bid entry later on.

Part I: Labor Supply and Demand Ratio

Total Labor Supply and demand

No.	Labor Category	Total Number of Labor Bids	%	Rank	Total Number of Labor requisitions	Supply Demand Ratio
1	Accounting/Finance	7409	9.49%	4	533	13.9
2	Administrative	4433	3.36%	8	459	9.7
3	Call Center/Customer Service	643	0.63%	10	62	10.4
4	Engineering	5318	11.70%	2	458	11.6
5	General	9104	7.77%	5	1298	7.0
6	Information Technology	15278	42.12%	1	767	19.9
7	Laborer/Industrial	306	0.21%	11	159	1.9
8	Light Industrial	6124	5.76%	7	515	11.9
9	Medical	2	0.00%	12	207	0.0
10	Professional	1697	2.20%	9	150	11.3
11	Professional/IT/Engineering	2285	6.14%	6	167	13.7
12	Technical	8133	10.62%	3	631	12.9
	Grand Total	60732	100.00%		5406	11.2

Table 1. Total Job Bids received from 2003 to June 2015 for each Job Category

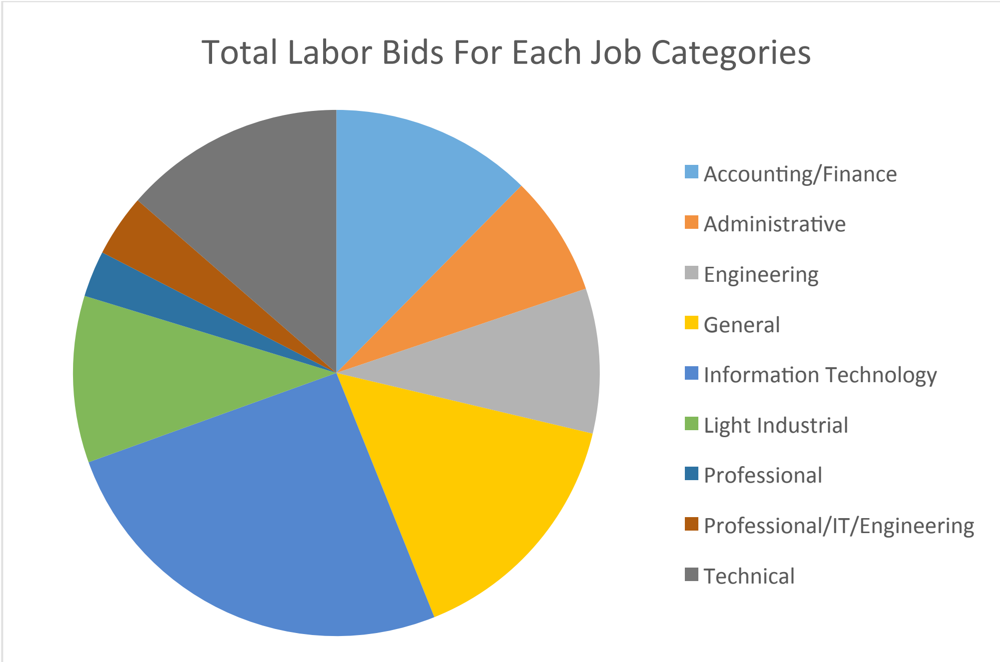


Figure 1. Total Job Bids Received from 2003 to June 2015 for each Job Category.

Table 1 and Figure 1 indicates that XXX received largest amount of labor bids in the Information Technology labor categories, Engineer and Technical taking the second and third place. It shows that XXX has powerful access to labor market in the technical area.

The supply demand ratio in the last column of Table 1 is calculated by the total number of job bids divided by the total number of job requisition for each labor categories, which measures how many job bids XXX receives on average for each job requisition in that specific labor category. In general, XXX is capable to provide 11 candidates for a job requests, regardless the labor categories.

The Information Technology labor categories has the highest supply demand ratio of 19.9, which means that XXX is able to provide around 20 candidates for each job request received in the Information Technology labor category. The supply demand ratios are also relatively high in the Accounting/Finance, Engineering, Technical, Professional, and Light Industry etc. However, The XXX's labor supply is intense in the Medical and Labor/Industry category. Medical has approximately 0 supply demand ratio and Labor/Industry category has 1.9, which indicates XXX has difficulty to find potential candidates to fulfill the demand. Although both two labor categories together take only approximate 7% of total job requisitions and has relative small impact on XXX's the overall performance, they may be potential areas that XXX can work on to serve it clients and make more profit.

Labor Supply and Demand in each State

No	State	Total Labor Supply	%		Total Labor Demand	%	State Supply Demand Ratio
1	Michigan	22693	34.64%		1297	28.32%	17.5
2	New Hampshire	13220	20.18%		929	14.77%	14.2
3	New Jersey	11909	18.18%		1674	29.50%	7.1
4	Texas	7875	12.02%		435	9.43%	18.1
5	New York	1344	2.05%		136	1.84%	9.9
6	Illinois	1172	1.79%		75	1.38%	15.6
7	Virginia	998	1.52%		90	2.22%	11.1
8	North Carolina	883	1.35%		50	0.66%	17.7
9	South Carolina	860	1.31%		128	1.14%	6.7
10	Massachusetts	725	1.11%		51	0.89%	14.2
11	Florida	576	0.88%		60	0.90%	9.6
12	Kansas	500	0.76%				
13	Tennessee	432	0.66%		17	0.12%	25.4
14	Georgia	349	0.53%		8	0.12%	43.6
15	California	311	0.47%		19	0.40%	16.4
16	Indiana	287	0.44%		27	0.44%	10.6
17	Ohio	274	0.42%		7	0.10%	39.1
18	Pennsylvania	245	0.37%		9	0.12%	27.2
19	Kentucky	207	0.32%		2	0.06%	103.5
20	Nebraska	117	0.18%		3	0.02%	39.0
21	Utah	117	0.18%		5	0.03%	23.4
22	Alabama	83	0.13%		5	0.04%	16.6
23	Arkansas	63	0.10%		3	0.03%	21.0
24	Colorado	49	0.07%		3	0.03%	16.3
25	Wisconsin	43	0.07%		3	0.02%	14.3
26	Mississippi	42	0.06%		5	0.09%	8.4
27	Hawaii	31	0.05%		5	0.11%	6.2
28	Connecticut	29	0.04%		2	0.01%	14.5
29	Louisiana	21	0.03%		5	0.03%	4.2
30	Oregon	16	0.02%		1	0.01%	16.0
31	Arizona	14	0.02%		512	7.08%	0.0
32	Maine	8	0.01%		3	0.02%	2.7
33	Maryland	6	0.01%		2	0.02%	3.0
34	Missouri	6	0.01%		3	0.03%	2.0
35	Nevada	6	0.01%		3	0.02%	2.0
	Grand Total	65511	100.00%		5577	1	11.7

Table 2. Labor Supply and Demand in each state

Table 2. Shows that most of job applicants are from Michigan, New Hampshire, New Jersey and Taxes, which are consistent with the rank of total amount of labor demand.

I define state-supply-demand ratio as the amount of total job bids received in a state from 2003 to June 2015 divided by the corresponding amount of job requests received in that state in the same period of time. This ratio measures that how many candidates XXX have on average for a job requests in a state, regardless of the labor categories. We should keep it in cautious that I have not taken the effect of labor categories in consideration. If certain state has a high demand in a labor categories that XXX hardly access to, it may produce a high state-supply-demand ratio.

For example, Kentucky has highest state-supply-demand ratio, 103.5, meaning that for every job request in that state, XXX approximately receives 103 applicants on average, regardless of the labor categories required for the job. Most high labor demanding states have higher state-supply-demand ratio, which are good indicators showing that XXX has sufficient labor sourcing pools in its major markets. However, Arizona takes 7% of total job requests but XXX could not cover those job demand because of lacking of enough applicants. The data suggests that XXX should work on souring and expanding its labor supplier in Arizona to better serve its clients.

In the end of session I , I would like to take a further analysis of the labor demand and supply by introducing the factor of labor categories in XXX's major markets: Michigan, New Hampshire, New Jersey, Texas and Arizona.

Michigan			
	Labor Demand	Labor Supply	SUPPLY-DEMAND RATIO
Accounting/Finance	171	1883	11.0
Administrative	238	2447	10.2
Call Center/Customer Service			
Engineering	56	666	11.8
General	5		0
Information Technology	651	14712	22.5
Laborer/Industrial			
Light Industrial	5	25	5
Medical	1		0
Professional	58	621	10.7
Professional/IT/Engineering			
Technical	108	1168	10.8
Grand Total	1293	21522	16.6

Table3. Michigan Labor Demand and Supply in 12 Labor Categories

New Hampshire			
	Labor Demand	Labor Supply	Supply-Demand Ratio
Accounting/Finance	89	852	9.5
Administrative			
Call Center/Customer Service	247	3119	12.6
Engineering			
General	27	431	15.9
Information Technology			
Laborer/Industrial	259	4111	15.8
Light Industrial			
Medical	44	525	11.9
Professional			
Professional/IT/Engineering	263	4182	15.9
Technical	929	13220	14.2
Grand Total	89	852	9.5

Table4. New Hampshire Labor Demand and Supply in 12 Labor Categories

New Jersey			
	Labor Demand	Labor Supply	Supply – Demand Ratio
Accounting/Finance	158	1703	10.7
Administrative	10	88	8.8
Call Center/Customer Service	45	643	14.2
Engineering	16	202	12.6
General	909	6943	7.6
Information Technology	4	15	3.7
Laborer/Industrial	134	306	2.2
Light Industrial	9	55	6.1
Medical	167	2	0.01
Professional	4	4	1
Professional/IT/Engineering			
Technical	176	1553	8.8
Grand Total	1632	11514	7.0

Table5. New Jersey Labor Demand and Supply in 12 Labor Categories

Texas			
	Labor Demand	Labor Supply	Supply – Demand Ratio
Accounting/Finance	158	3513	22.2
Administrative	26	234	9
Call Center/Customer Service			
Engineering	6	39	6.5
General	91	1783	19.5
Information Technology	1	5	5
Laborer/Industrial			
Light Industrial	17	213	12.5
Medical			
Professional			
Professional/IT/Engineering	133	2006	15.08
Technical	3	7	2.3
Grand Total	435	7800	17.9

Table6. Texas Labor Demand and Supply in 12 Labor Categories

Arizona			
	Labor Demand	Labor Supply	Supply – Demand RATIO
Accounting/Finance	17		
Administrative	2	4	2
Call Center/Customer Service	17		
Engineering			
General	251		
Information Technology	66		
Laborer/Industrial	25		
Light Industrial			
Medical	39		
Professional			
Professional/IT/Engineering			
Technical	1		
Grand Total	418	4	

Table7. Arizona Labor Demand and Supply in 12 Labor Categories

Table3 and Table 4 show that XXX is able to fulfill clients' requests in almost all the labor categories in its top two markets, Michigan and New Hampshire. Table 5 indicates that New Jersey has a Medical Supply-Demand Ratio of 0.0. It means that the state has a high labor demand in Medical category while XXX is not able to attract even one applicant in general. The phenomena of labor supply shortage in medical category is shown in most states. Table 7 show that Arizona has a labor shortage almost in every labor categories.

Session III

Analysis of Replacement Time

In this session, I will focus on analysis the replacement for each labor category. This session can be helpful to answer an important question to our client: how long it takes for XXX to fulfill a position?

Despite "Labor category", the same procedures can also be applied to "Job Category". However, job category need to be shrunk to have a proper set size. Therefore, we need to regroup the job category first before we can perform this tasks.

Note that I change the negative replacement time to "0" in the database and ignore the entries that have blank "replacement time". However, the blank 'replacement" time may mean that XXX is never able to find any people in this positon. Leaving out them may lead to the calculated yearly average replacement time lower than the actual mean.

Yearly Average Placement Time

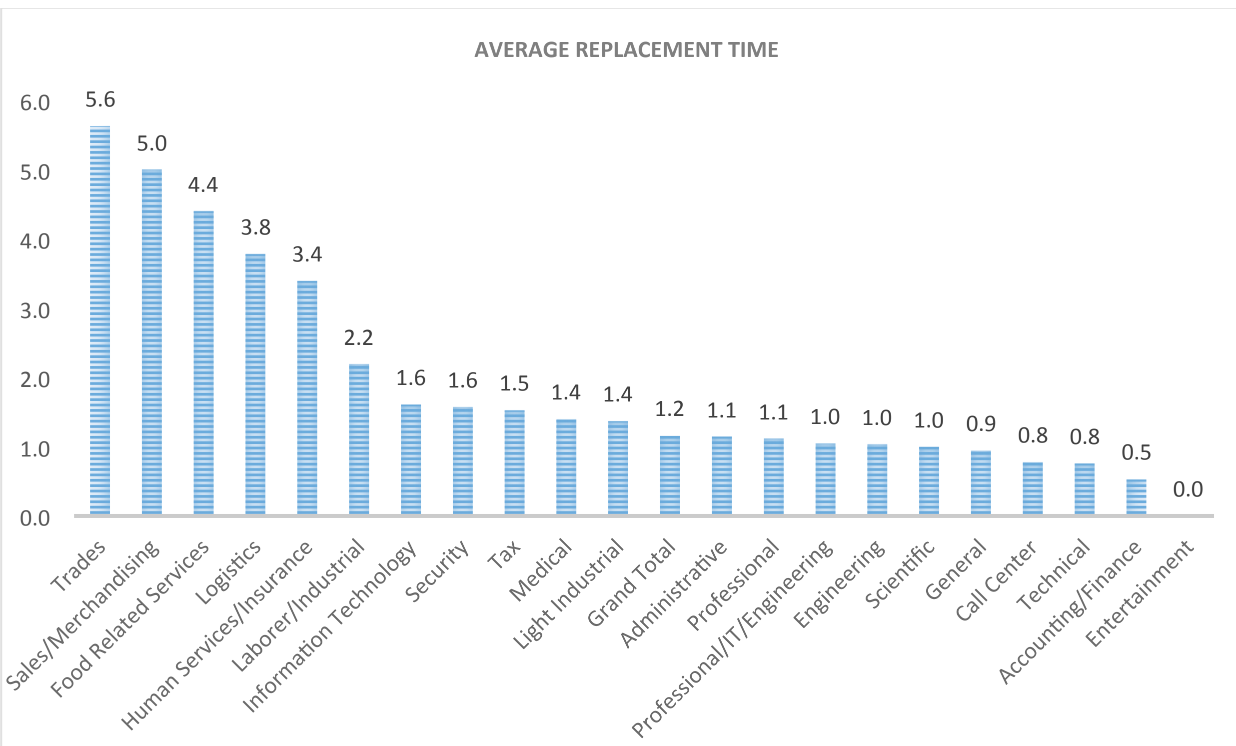


Figure 1 Average Replacement Time

Labor Category	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Average
Accounting/Finance		0.0		2.0	1.0	0.8		0.0	0.0	0.9	0.5	0.4	0.6	0.5
Administrative	0.2	1.9	0.4	0.7	1.2	1.4	0.2	0.6	1.0	0.2	0.9	1.7	1.5	1.1
Call Center										13.0	1.0	0.5	0.3	0.8
Engineering								6.0	1.0	0.7	0.5	1.7	0.4	1.0
Entertainment											0.0	0.0		0.0
Food Related Services												1.0	5.3	4.4
General										1.9	1.0	0.8	0.9	0.9
Human Services/Insurance											5.6	2.1	2.5	3.4
Information Technology	0.7	3.6	1.4	0.3	0.7	1.0	0.0	0.7	1.4	1.0	0.8	3.4	1.1	1.6
Laborer/Industrial											1.8	2.3	2.3	2.2
Light Industrial									3.6	1.6	0.7	1.3	0.2	1.4
Logistics											5.2	3.6	1.3	3.8
Medical										10.6	0.3	1.8	0.9	1.4
Professional									1.2	1.7	1.0	1.3	0.5	1.1
Professional/IT/Engineering										1.0	0.9	1.3	0.9	1.0
Sales/Merchandising										5.0	5.0			5.0
Scientific											1.0			1.0
Security											1.0	1.9	3.5	1.6
Tax										2.0	0.5	2.0	1.6	1.5
Technical	3.3	0.8	1.0	2.5	1.0	1.3	0.0		1.5	0.6	0.8	0.5	0.6	0.8
Trades										5.0	14.3	3.9	2.0	5.6
Grand Total	1.1	2.5	0.9	0.6	0.9	1.2	0.1	0.8	1.7	1.3	1.0	1.3	0.9	1.2

Table 1 Average Replacement Time for Each Labor Category

Figure 1 and Table 1 show that “Trades”, “Sales and Merchandising”, “Food Service”, “Human Resource”, “Logistics” have longest replacement time, more than 3 days.

XXX’s major business areas, General has an average yearly replacement rate of 0.9, 1.6 for Info Tech, and 0.8 for Technical, which shows that XXX performs efficiently in those areas.

ow Labels	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
ccounting/Finance				2.8		1.2		0.0	0.0	1.9	1.1	1.2	1.2	1.2
dministrative	0.4	2.0	0.5	1.1	1.8	1.6	0.4	0.5	1.9	0.6	2.1	7.1	4.4	4.2
all Center/Customer ervice											1.6	0.8	0.5	1.9
ngineering									1.9	2.1	1.4	5.8	0.8	3.6
ntertainment											0.0			0.0
ood Related Services													1.5	2.3
eneral										7.9	2.1	2.2	7.3	4.4
uman Services/Insurance											14.5	4.5	4.3	9.1
formation Technology	1.6	13.1	1.9	0.8	1.7	2.0	0.0	1.8	3.9	1.5	1.8	13.5	2.4	7.6
aborer/Industrial											6.2	10.0	5.6	8.4
ght Industrial									13.2	2.6	1.5	3.3	0.6	5.8
ogistics											4.8	4.0	2.3	4.1
ledical										12.8	0.5	2.7	2.3	3.4
rofessional									3.9	2.4	2.6	3.5	0.9	2.9
rofessional/IT/Engineering										1.2	1.7	2.0	1.0	1.6
ales/Merchandising										1.4				1.0
cientific														
ecurity											2.2	2.5	4.4	2.6
ax											0.6	3.7	3.6	3.0
echnical	2.9	1.5	2.0	0.7		2.2	0.0		3.9	1.2	2.5	1.6	1.5	2.3
rades										7.1	36.9	7.0	4.5	18.1
rand Total	**2.1**	**9.2**	**1.5**	**1.1**	**1.7**	**1.7**	**0.3**	**1.7**	**6.9**	**3.9**	**3.7**	**5.8**	**4.7**	**5.0**

Table 2 Stand Deviation of Yearly Average Replacement Time

Table 2 shows that “Trade”, “Human Service and Insurance”,” Laborer/Industrial”, and “Info Tech” have higher variation in the yearly average replacement time. The SD for Info Tech is 7.6 and the 95% confidence interval is [0, 16.5]. It means with 95 percent probability that the replacement time for Info Tech is between 0 and 16.5 days.

Yearly Trend of Replacement Time

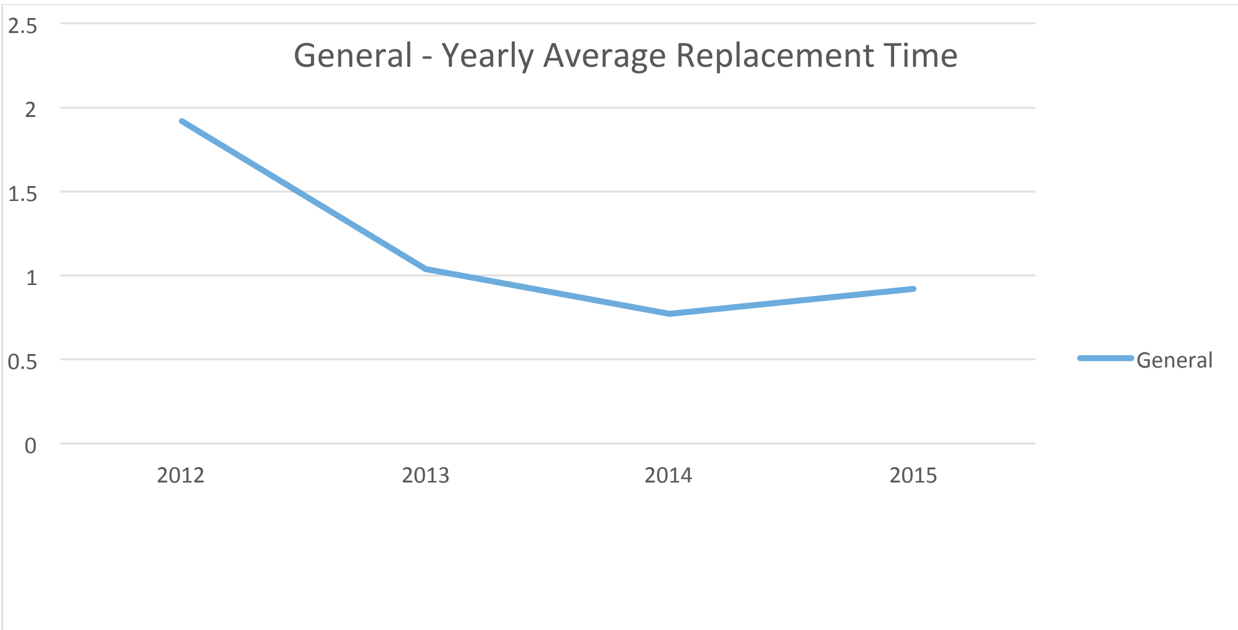


Figure 2a Yearly Trend – General

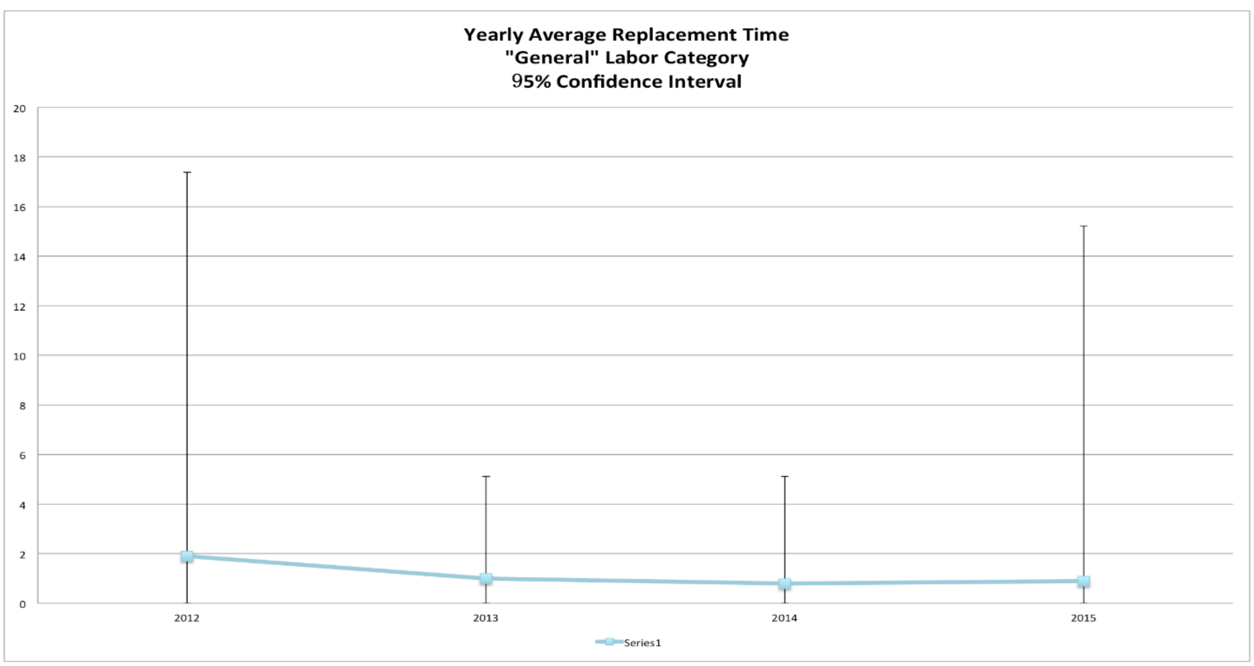


Figure 2b 95% Confidence Interval – General

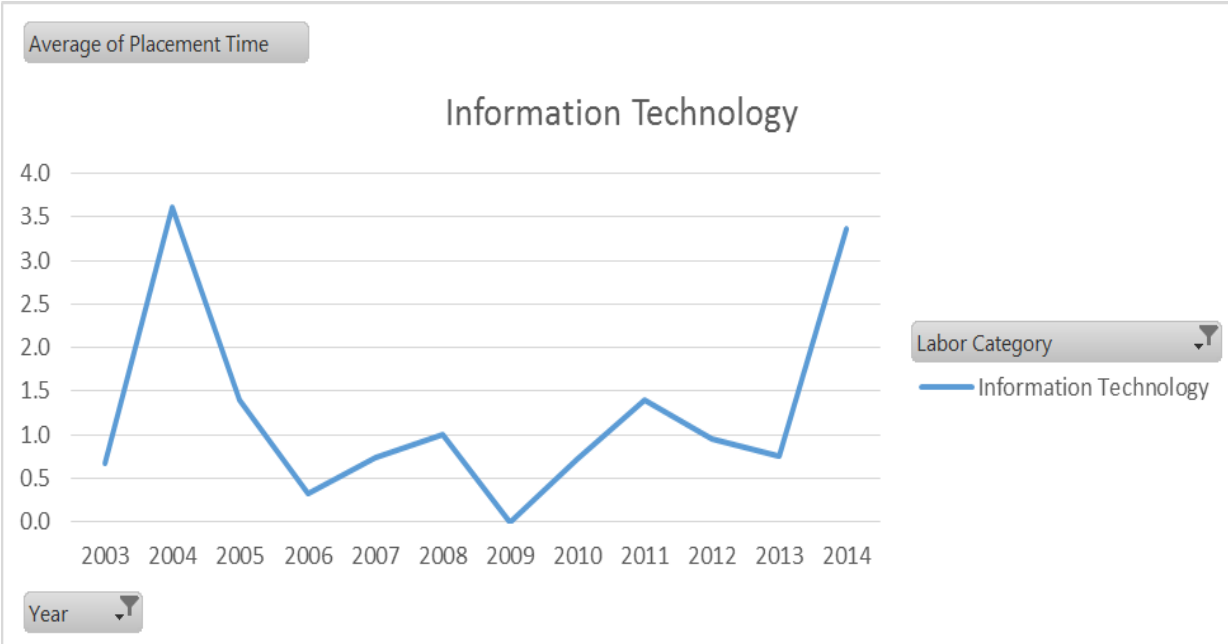


Figure 3a Yearly Trend – Info Tech

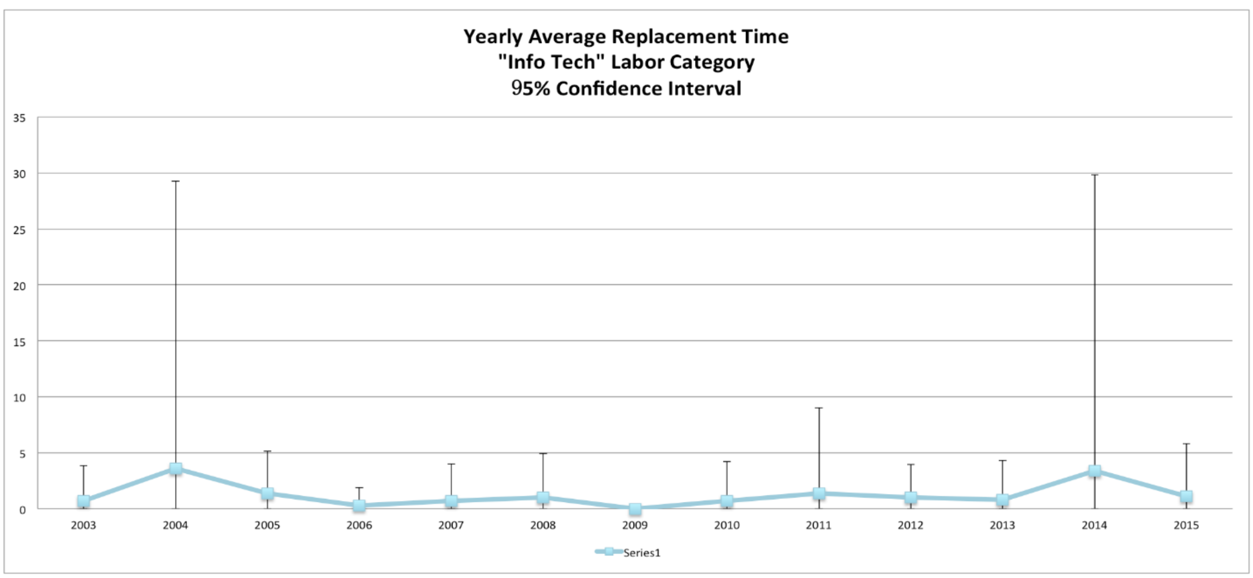


Figure 3b Confidence Interval - Info Tech

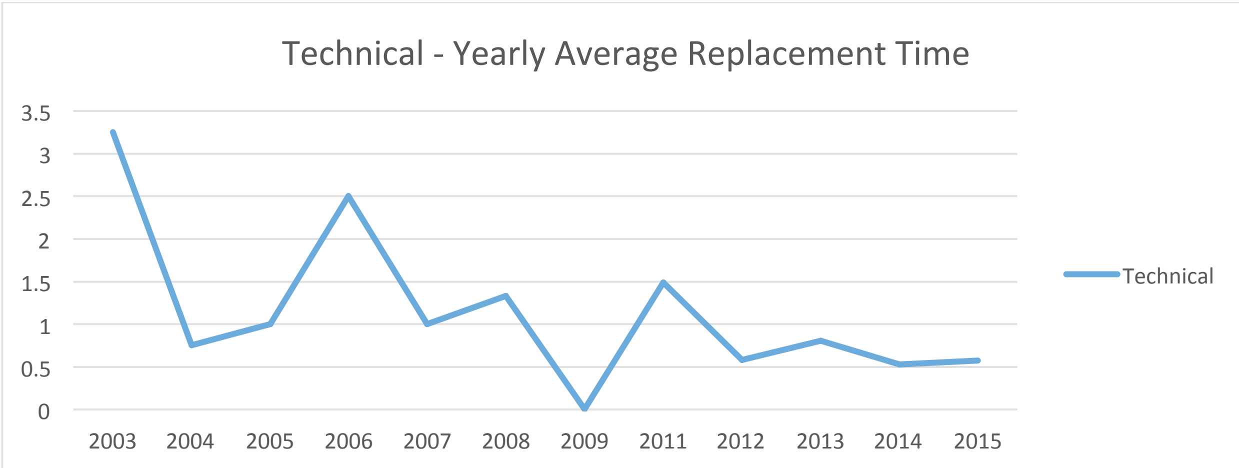


Table 4 a Yearly Trend – Technical

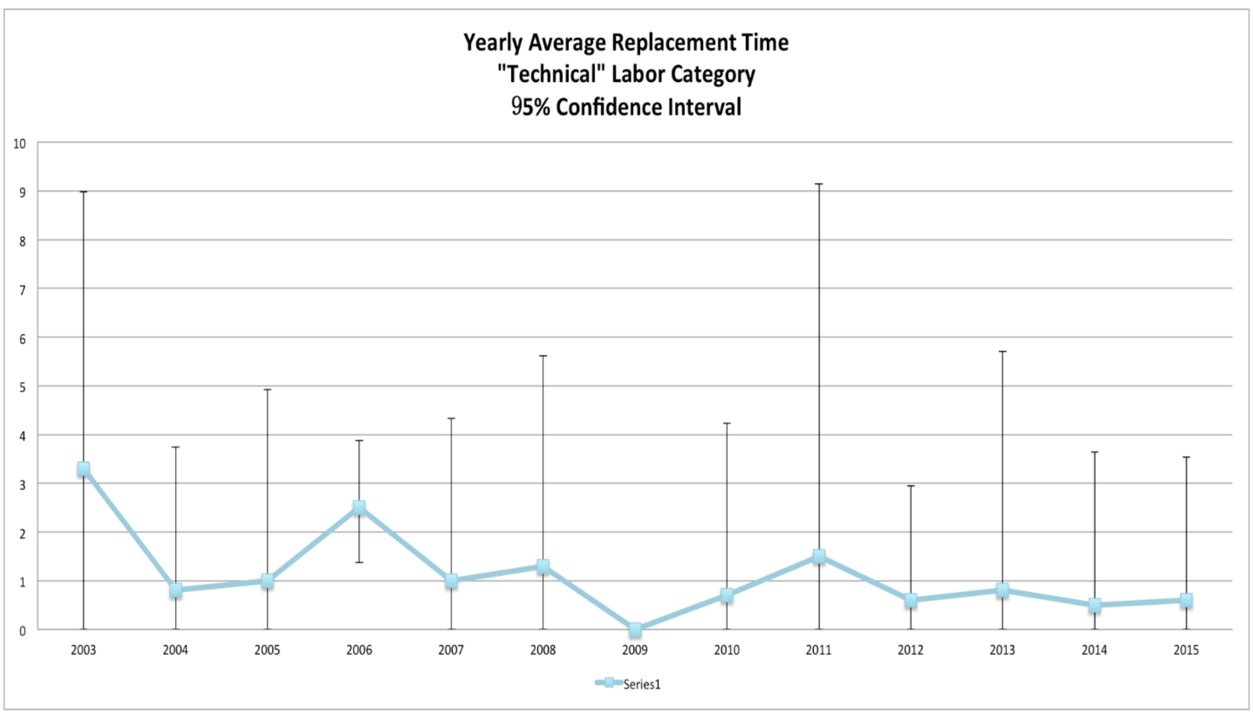


Table 4 b 95% Confidence Interval – Technical

Table 2 – 4a all show that the replacement time is decreasing from 2003 to 2014 in general for "General" and "Technical". "Info Tech's replacement time becomes longer and longer since 2009. Table 2-4 b show that 95% Confidence Interval for all the three labor categories in different years.