Technology Job Market

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Research Statistics 3

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Rationale

Over the years, the tech industry had rapidly changed and expanded. Though the market for tech graduates has grown, it also is unstable as companies go through hiring and layoff sprees, and has been greatly impacted by events like the dot com bubble and COVID-19. The strength of the tech job market cycles with time and also depends on the economy.

During the dot com bubble, the demand for computer science graduates was high and starting salaries were high. However, the bubble burst in the year 2000, which resulted in job losses and lower salaries for many tech workers. A study by Sandvig et al. (2005) found that graduates with internship experience and high GPAs have higher starting salaries and faster job placement. During times with worse market conditions, internship experience becomes even more important to getting hired and obtaining higher starting salaries. Furthermore, larger tech firms have more job stability than smaller firms, who tend to over-hire during economic upturns and layoff employees during economic downturns. This study shows how the economy and stock market influences how easy it is for someone to be employed in the tech industry. It could be expanded to see how the job market correlates with the number of layoffs and hires in the tech industry.

Additionally, COVID-19 significantly impacted the job market for computer science graduates. According to a study by Cerioli et al. (2023), the numbers of ads posted related to tech jobs dropped between 15 and 48% during the first half of 2020. However, the market recovered and the number of ads targeting tech related jobs reached a peak in 2021. According to BER Staff and Zafri (2023), the start of COVID-19 caused many people to lose their jobs, and it decreased the demand for computer scientists. However, government programs, low interest rates, and increased work from home opportunities caused the tech job market to boom again in the second half of COVID through 2021, making it a good time to be hired for new employees. COVID-19 is an example of how fiscal and monetary policy affects the strength of the tech job market, where lower interest rates and increased demand means more job openings. It would be helpful to see how layoff and hiring numbers increased or decreased as time went on.

A study by Hossen et al. found that it is most likely for high-tech companies to lay off their employees due to organizational change or financial issues (2023). Recently, workplace culture has become more transactional between employers and employees, so there is less job stability. High-tech companies will lay off many workers during economic downturns. Especially during recessions, employers cite reasons for laying off employees to be due to financial reasons and business demand. It would be helpful to see how layoffs and quits are impacted by these issues.

The purpose of this study is to examine what layoff and hiring trends can reveal about the number of open jobs and overall strength of the job market. As someone who will go to university and pursue a computer science degree, I hope to be able to better understand the job market by looking at statistics for layoffs, quits, and hires. This is especially important to me because the job market for computer science is not the best right now, and I hope to learn if it will improve with time. I am investigating the question: what is the relationship between layoffs, hires, quits, and the number of open positions in tech?

Study Design

Sampling

The Job Openings and Labor Turnover Survey collects data on job openings, hires, quits, layoffs and discharges, other separations, and total separations, for various industry sectors (like information, construction, mining, etc.) each month, starting from the year 2000. The researchers select a stratified random sample from this dataset of 21,000 non-farm businesses, including factory, office, store, and government workers in all 50 states and DC. Strata are chosen from groups divided by ownership, region, industry sector, and establishment size class.

The sample is chosen from the 9 million businesses in the Quarterly Census of Employment and Wages (QCEW) program from the Bureau of Labor Statistics (BLS) and the Federal Railroad Administration (FRA). The QCEW program has information from 95% of non-farm companies in the US, and gets its information from state unemployment insurance (UI) and the Unemployment Compensation for Federal Employees (UCFE) program. Employees are counted if they are full-time, part-time, permanent, short-term, seasonal, salaried, or hourly. Data on railroad companies from the FRA are added to the sampling frame to create the JOLTS database.

I chose to use this dataset because it contained information about thousands of employees in various industry sectors, including information for 280 businesses in the information industry for each month over the course of 24 years.

Results

A. Summary of variables

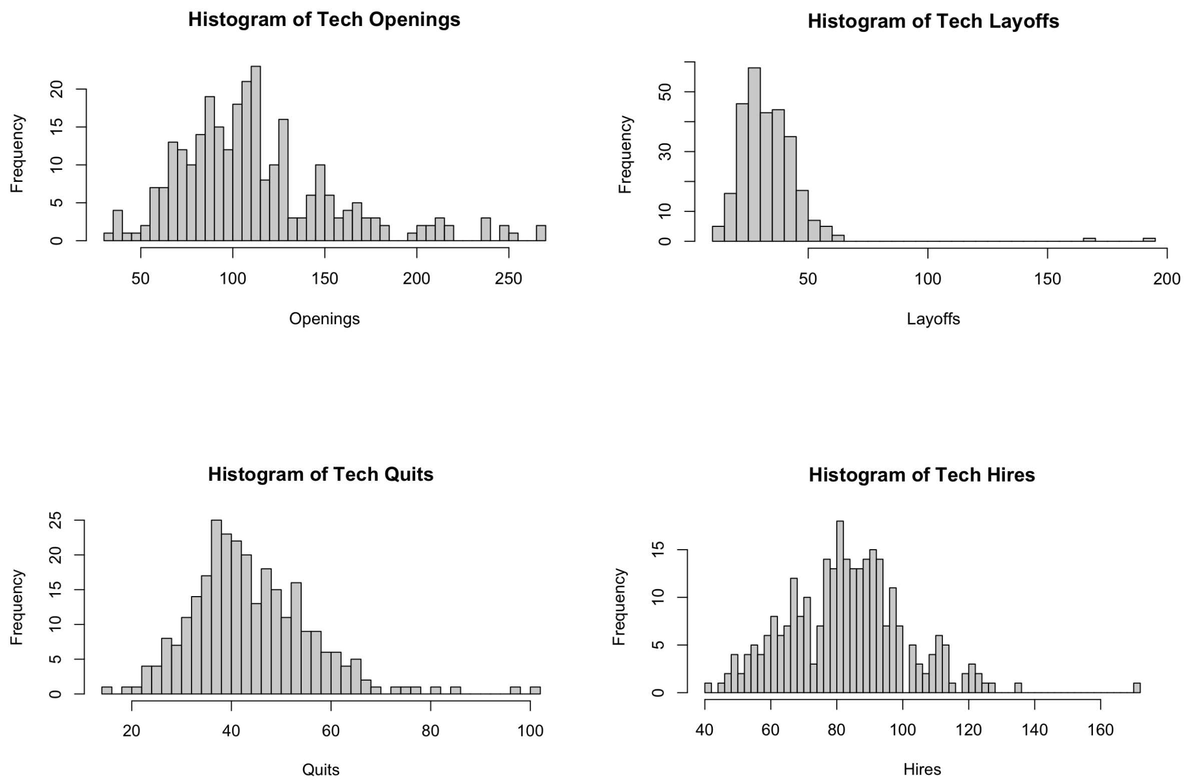

Figure 1. Histograms of variables analyzed.

Tech openings were the number of open tech positions in thousands at the end of each month from 2000-2024. Tech layoffs were the number of reported layoffs in thousands in the tech industry for each month from 2020-2004. Tech quits were the number of people in thousands who quit a job in the tech industry for each month from 2000-2024. Tech hires were the number of people in thousands who were hired in the tech industry for each month from 2000-2024. All of these graphs (with the exception of hires) have a slight right skew. Before is a table of descriptive statistics (in thousands) for the number of tech layoffs, quits, hires, and job openings.

Variable <chr>	min <dbl>	Q1 <dbl>	median <dbl>	Q3 <dbl>	m... <dbl>	mean <dbl>	sd <dbl>	n <int>
Layoffs	11	26.00	32	40	192	34.11071	15.92473	280
Quits	14	37.00	43	52	102	44.50357	12.19289	280
Hires	41	70.75	83	93	171	83.39643	18.12333	280
Openings	34	85.00	107	130	268	113.20000	43.16646	280

Figure 2. Summary statistics for variables analyzed.

B. Multiple regression model with all predictors

I created a multiple regression model with job openings as the dependent variable, and hires, layoffs, and quits as the independent variables. I checked for conditions including linearity, zero mean, equal variances, independence, randomness, and normality.

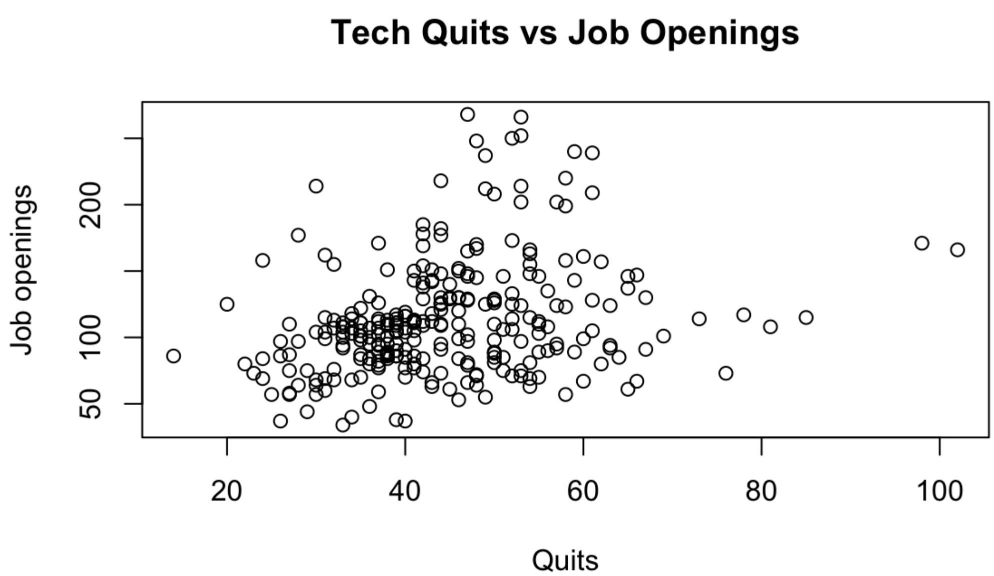

Figure 3. Scatter plot of tech quits vs tech openings.

The relationship between tech quits and job openings has a weak, positive relationship with some curvature. The r value between quits and job openings is 0.248, but increases to 0.29 when tech quits undergoes a log transformation.

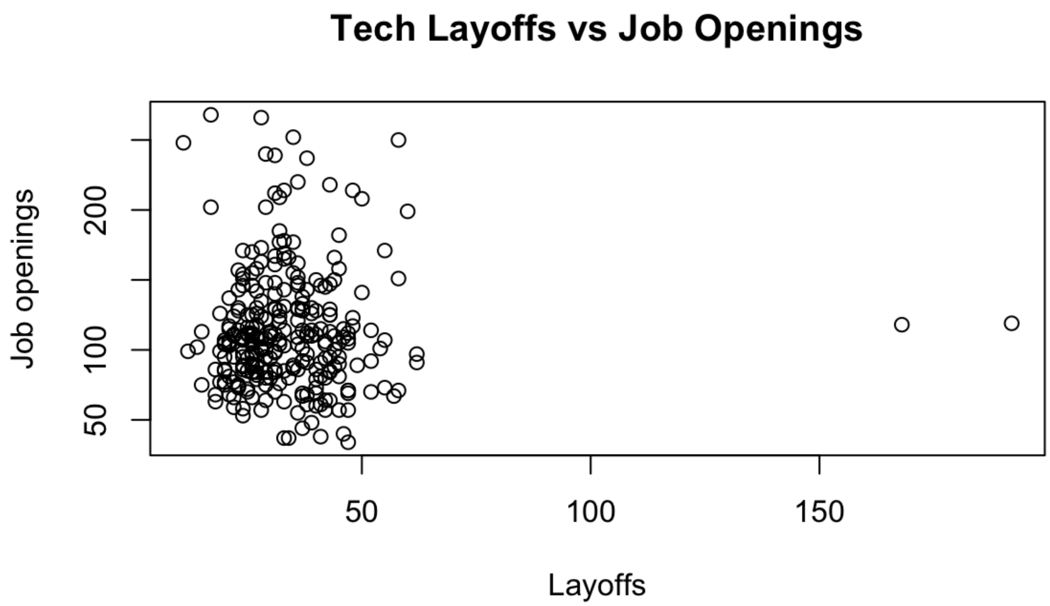

Figure 4. Scatter plot of tech layoffs vs tech openings.

It does not seem like the relationship between tech layoffs and job openings is linear, so we must proceed with caution. The highest r value was when layoffs underwent a transformation and became layoffs squared, with an r value of 0.011.

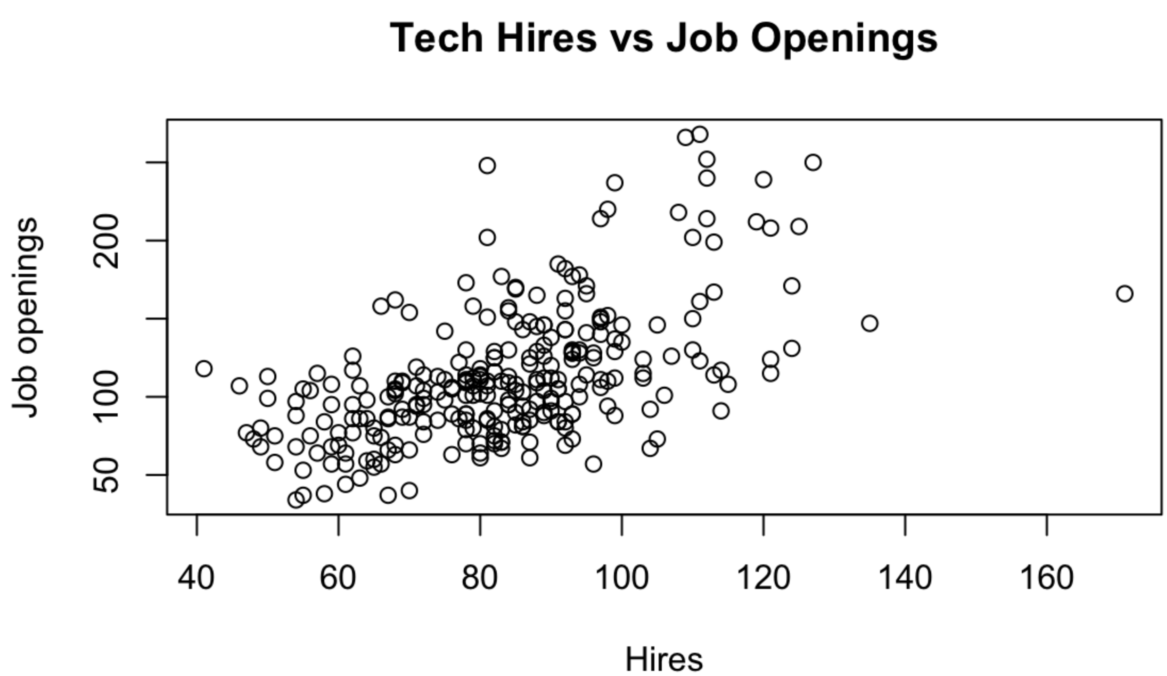

Figure 5. Scatter plot of tech hires vs tech openings.

The relationship between tech hires and job openings is positive, and it appears to be linear, with an r value of 0.564.

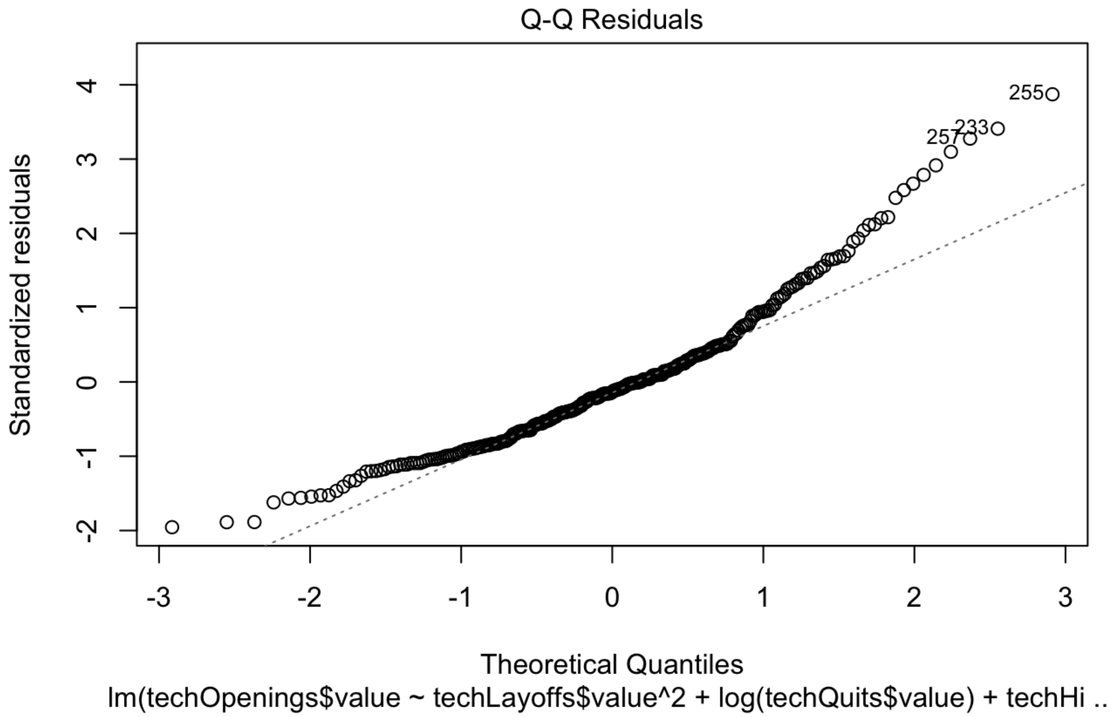

Figure 6. Normal probability plot of residuals for the multiple regression model.

The residuals are not approximately normally distributed, but a transformation of the tech openings to log(tech openings) makes the residuals much more evenly distributed.

C. Log transformation of the dependent variable (Job Openings)

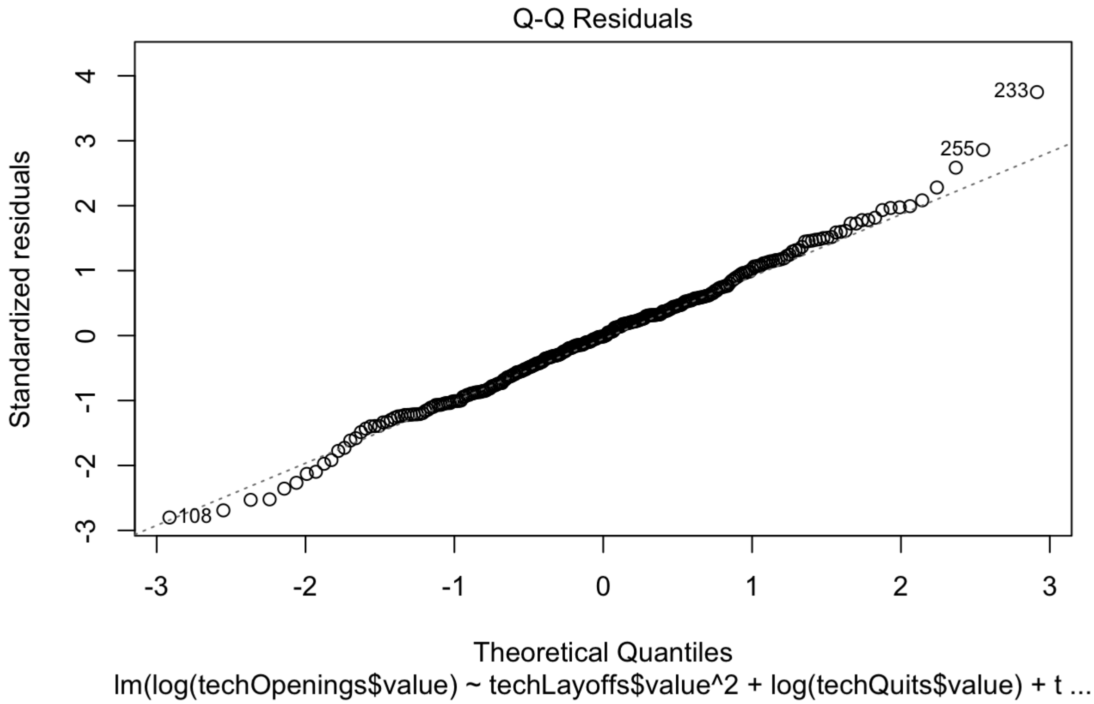

Figure 7. Normal probability plot of residuals for the multiple regression model after log transformation.

After the log transformation of the dependent variable, the residuals are more normally distributed.

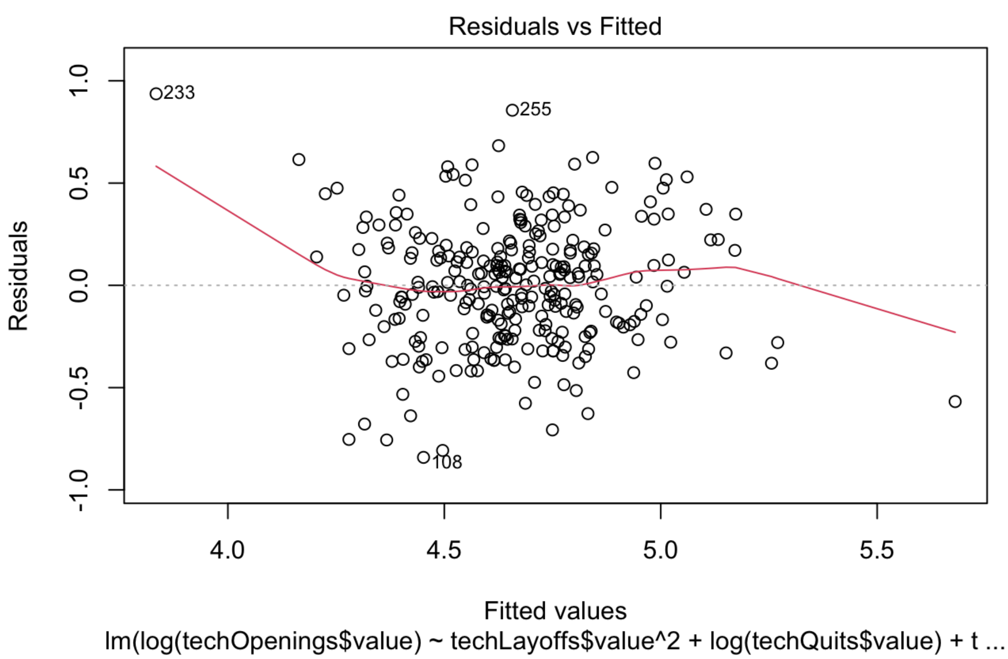

Figure 8. Plot of residuals vs fit for the multiple regression model after transformation.

After the log transformation, the residuals are evenly distributed around 0, satisfying the constant variance and zero mean condition.

	Estimate	Std. Error	t value	Pr(>|t|)	VIF
(Intercept)	4.304383039	0.278071655	15.479402	2.458142e-39	NA
techLayoffs$value	-0.002156954	0.001149204	-1.876912	6.158496e-02	1.028882
log(techQuits$value)	-0.190469148	0.089945535	-2.117605	3.510268e-02	1.817349
techHires$value	0.013752132	0.001354497	10.152946	8.709798e-21	1.851227

Figure 9. Table of coefficients and VIF for the multiple regression model.

All VIF values are below 5, so there is little evidence of multicollinearity. Observations are independent because the work status of one person (quit, layoff, or hire) does not affect the work status of another. Because data was selected from a stratified random sample, the randomness condition was met.

The equation for the multiple regression model is:

log(tech job openings) = 4.304 - 0.002*layoffs - 0.190*log(quits) + 0.014*hires

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Residual standard error: 0.3014 on 276 degrees of freedom
Multiple R-squared:  0.3398,    Adjusted R-squared:  0.3326
F-statistic: 47.34 on 3 and 276 DF,  p-value: < 2.2e-16
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Figure 10. Summary of the multiple regression model.

The R squared value of 0.3398 shows that 33.98% of the variability of the log of the tech openings is attributed to the multiple regression model.

D. Backwards selection

Since the p value for layoffs was above 0.05, I got rid of the layoffs variable using backwards selection and created a new model with just tech hires and the log of tech quits. This changed the r value by slightly less than 0.1.

```
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)           4.247926   0.277696  15.297   <2e-16 ***
log(techQuits$value) -0.187323   0.090339  -2.074    0.039 *  
techHires$value       0.013405   0.001348   9.945   <2e-16 ***
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3027 on 277 degrees of freedom
Multiple R-squared:  0.3313,    Adjusted R-squared:  0.3265 
F-statistic: 68.63 on 2 and 277 DF,  p-value: < 2.2e-16
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Figure 11. Summary for the multiple regression model after eliminating layoffs.

Discussion

At the alpha = 0.05 level, tech quits and tech hires are statistically significant for predicting the log of tech job openings. For the model containing layoffs, hires, and quits, the R squared value is 0.34, meaning that 34% of the variability is attributed to the three variables. In the model excluding the importance of layoffs, the r squared value is only slightly lower (0.331). The tech layoffs also have a negative correlation with the total number of job openings, with a coefficient of -0.002 in the multiple regression model. However, it is so close to 0 that it is difficult to determine whether a correlation actually exists or if it is merely due to sampling variability. On the other hand, the number of quits and hires seem to be good predictors for the number of job openings in the tech industry. Quits have a negative correlation with job openings (with a coefficient of -0.19), while hires has a positive correlation (with a coefficient of 0.013). It makes sense that an increase in hires positively correlates to an increase in job openings, because more people will get hired if there are more openings. This is consistent with the study by Sandvig et al. (2005), which said that companies will over hire during economic upturns. In other words, there will be more hires when the job market is better and there are more open jobs. I was surprised that quits had a negative correlation with job openings, because I expected more people to quit their job to get another one when there are more jobs open. However, it also makes sense that people would stay in the job during times when the job market is strong, because pay is also better during these times. I was surprised to find that it is unlikely that layoffs correlated with the number of job openings. A study by Hossen et al. (2023) found that companies laid off more employees during economic downturns. However, my results found that there is little evidence for a correlation between layoffs and job openings. Maybe, layoffs are relatively constant throughout the year, but it seems like there are more layoffs during times with a weaker job market because fewer people get hired simultaneously. Another possible explanation is that some companies may not report their layoffs, making the data unrepresentative of the actual job market.

Future research could include comparing the tech job industry with other industries to see how each industry's job market is impacted differently. Another possibility for future research to focus on a specific period of time (like COVID-19 or the Great Recession) and see how those time periods impact the job market for technology. This can help people learn how current events impact the job market, so that people can realize that the job market will bounce back from negative events, and maybe help predict the job market in the case of important events in the future.

Reflection

This project helped me learn how to conduct literature reviews for APA articles. For example, I had to learn how to use search terms in order to find relevant literature on the databases. Additionally, using multiple regression models on real world data helped me learn how to apply my statistics knowledge to real life, and draw conclusions from actual data. It taught me how to conduct a multiple regression model on a large dataset, and how to filter out relevant data values for my project. I had to figure out how to extract data for the tech industry specifically in order to conduct data analysis. I also had to learn how to adjust the dataset so that it met the conditions for the multiple regression model.

References

BER staff, & Zafri, M. (2023). A Deep Dive into the Recent Tech Layoffs. *Berkeley Economic Review*, *XII*. https://econreview.studentorg.berkeley.edu/a-deep-dive-into-the-recent-tech-layoffs/

Bureau of Labor Statistics. (n.d.). *Job Openings and Labor Turnover Survey (JOLTS)*. https://download.bls.gov/pub/time.series/jt/

Bureau of Labor Statistics. (n.d.). Job Openings and Labor Turnover Technical Note. *Economic News ReleasePRINT:Print JOLTS JLT Program Links*. https://www.bls.gov/news.release/jolts.tn.htm

Cerioli, M., Leotta, M., & Ricca, F. (2023). COVID-19 impacts on the IT job market: A massive job ads analysis. *Electronics, 12*(15), 3339. doi:https://doi.org/10.3390/electronics12153339

Hossen, Md Nayem & Mollah, Md & Lipy, Nusrat & Hossain, Gazi & Rahman, Md. Shahinur. (2023). Factors Affecting Layoff in High-Tech Industry: Evidence from the USA. 15. 1-13.

Sandvig, J. C., Tyran, C. K., & Ross, S. C. (2005). Determinants of graduating MIS students starting salary in boom and bust job markets. *Communications of the Association for Information Systems, 16*, 29. doi:https://doi.org/10.17705/1CAIS.01629