Continuous Transitions in Job Posting Trends Across Fields: A Temporal Perspective

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Abstract

As of February 2025, job searching remains challenging, raising the question of whether job postings have declined over time across different fields. In this note I analyze the evolution of job postings on Indeed, revealing a continuous transition in job market trajectories, starting with civil engineering, which stabilizes at a higher level, and ending with software development, which exhibits a pulse-like pattern returning to its initial state. Using principal component analysis (PCA) and ordinary least squares (OLS) regression, I find that job posting trends can be described by two principal components: a general trend and a field-specific trajectory. Fields that rose gradually tended to stabilize, whereas those that surged rapidly experienced a decline. To explain these patterns, I propose a mathematical model based on coupled nonlinear differential equations, suggesting that variations in acceleration rates and hiring costs (negative feedback) drive field-specific differences. The model successfully reproduces key features observed in the data, offering insights into the underlying mechanisms shaping job market dynamics.

1 Introduction

The difficulty of finding a job has become a widely discussed topic on social media. On Reddit, the subreddit r/recruitinghell serves as a support group where job seekers share their frustrations. Similarly, LinkedIn features numerous posts from individuals reporting prolonged unemployment. YouTube channels dedicated to job searching have also analyzed why finding a job has become increasingly difficult between 2023 and 2025 [1, 2, 3]. Even mainstream media, such as CNBC's report "Why Getting a 'Good' Job Feels So Difficult" [4], has covered this issue.

However, these discussions may reflect the experiences of specific communities rather than the broader job market. To gain a clearer understanding, it is essential to analyze hiring trends across different fields over time. This analysis can help answer key questions: Are job opportunities scarce in specific industries or across the board? Is there a common factor driving this perception? Fortunately, the Indeed Hiring Lab tracks job postings over time, providing a comprehensive and publicly available dataset [5] (see Figure 1). Here, I argue that the number of job postings serves as a useful proxy for hiring patterns across industries.

Here I characterize hiring trends using a combination of unsupervised machine learning and mathematical modeling. All time trajectories have their particular features, but my analysis shows that they are interrelated. I show this via a combination of principal component analysis (PCA) and ordinary least squares (OLS) regression. I show how the weight of the second component characterizes each trajectory, and is also can be used as a proxy for the performance for each field. My mathematical analysis suggests that hiring costs drives a negative feedback that affects each field differently.

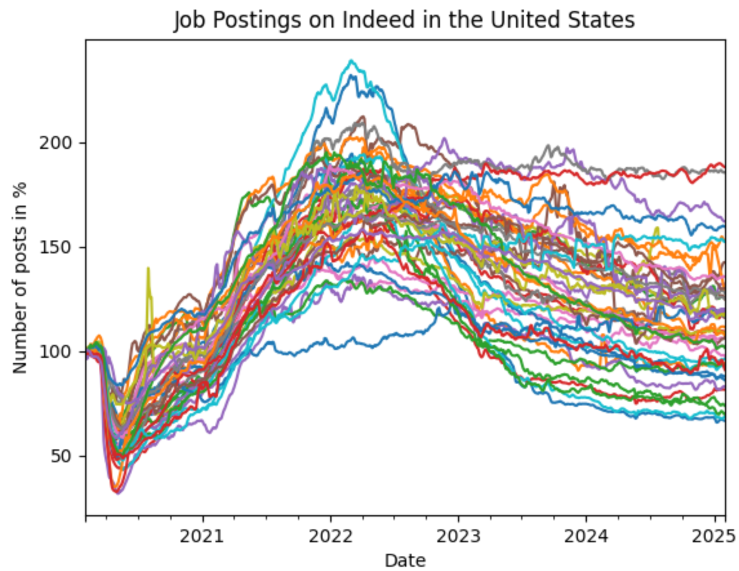

Figure 1: Time series showing the percentage of jobs posted in Indeed for different fields. February 1st 2020 is used as a reference point with the assigned value of 100%. Data from the Indeed Hiring Lab obtained via the FRED

2 Data analysis via principal components analysis (PCA) and ordinary least squares (OLS) regression

The dataset consists of 45 different fields published by the Indeed Hiring Lab [5] (Figure 1). The time series begins on February 1, 2020, which serves as the reference point, assigned a value of 100%. Subsequent values represent percentage changes in job postings over time. To analyze the dataset, I first applied principal component analysis (PCA). The first two principal components capture 96% of the dataset's variance. The first component exhibits an overshoot pattern, while the second shows an initial increase followed by a sharp drop (Figure 2). Next, I assessed how well these two components describe each job posting trajectory X_i, where i indexes the fields. I performed a linear regression

$$\hat{X}_i = \theta_1 PC_1(t) + \theta_2 PC_2(t) \tag{1}$$

where θ_1 and θ_2 indicate the contribution of each principal component to X_i. The model fits well,

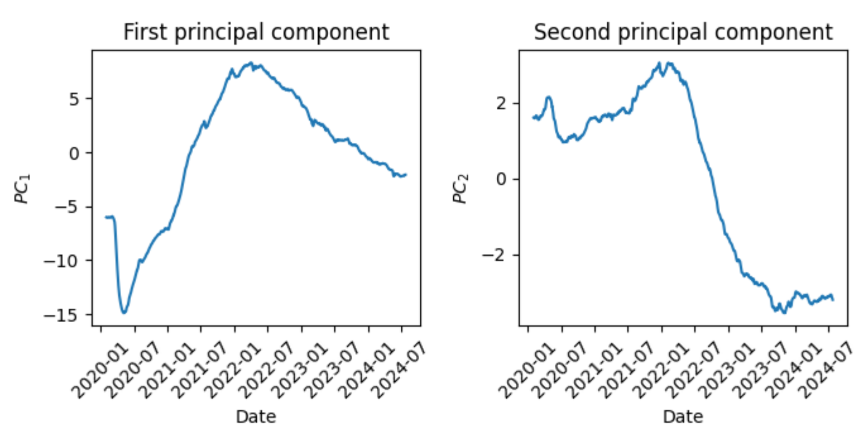

Figure 2: First two principal components obtained from the Indeed job posting time series.

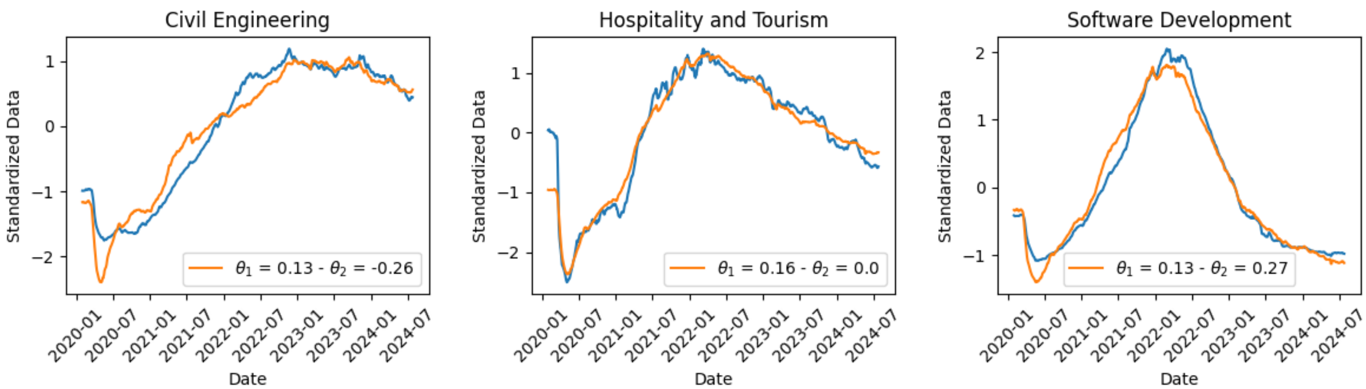

Figure 3: Examples of three different times series (standardized data) along with their with their linear regression fit given by Eq.(1). The values of θ_1 and θ_2 correspond to the regression parameters.

with an average coefficient of determination $R^2 = 0.96 \pm 0.03$.

Figure 3 presents three standardized trajectories alongside their linear fits and corresponding parameters θ_1 and θ_2. Notably, the trajectory for Hospitality and Tourism has no contribution from the second component $\theta_2 = 0$. Comparing it with Civil Engineering (which has the highest negative θ_2) and Software Development (which has the highest positive θ_2) highlights the role of PC_2. When θ_2 is negative, it slows the increase after the first minimum and maintains higher values (Figure 5, Civil Engineering). A positive θ_2 accelerates the initial increase but suppresses final values, creating a pulse-like pattern (Figure 5, Software Development).

The modulatory effect of PC_2 is further illustrated in Figure 4 (left panel), where the scatter plot of θ_1 vs θ_2 follows an approximately hyperbolic shape. Additionally, Figure 4 (middle panel) shows a decreasing relationship between θ_2 and the final observed value, confirming PC_2's repressive effect. Since θ_2 effectively characterizes each trajectory, I use it as a proxy for field performance. To categorize fields systematically, we applied the Freedman-Diaconis rule [6] to determine histogram bin sizes (Figure 4 left panel). Fields are classified as follows:

- **Far better**: θ_2 between -0.257 and -0.153
- **Better**: θ_2 between -0.153 and -0.048
- **Recovered**: θ_2 between -0.048 and 0.056
- **Worst**: θ_2 between 0.056 and 0.161
- **Far worst**: θ_2 between 0.161 and 0.265

Table I summarizes the results.

Interestingly, despite discussions of a "white-collar recession," highly skilled fields appear in both the "far worse" and "far better" categories. Banking & Finance, Scientific R&D, Mathematics, and Software Development fall into the "far worse" category, while Civil Engineering, Physicians & Surgeons, Dental Jobs, and Veterinary fields fall into the "far better" category. This suggests that job posting trends are driven by industry-specific factors rather than skill level alone.

3 Dynamical systems model for job posting patterns

The results suggest two key insights: (1) job posting patterns are well described by two principal components, indicating that all trajectories follow a common process, and (2) PC_2 acts as a modulator, implying that a varying parameter influences this process. To explain these observations, I propose a causal model using a dynamical systems approach [7].

The model consists of two variables: $H(t)$, representing hiring (directly corresponding to the job postings time series), and $C(t)$, representing hiring-related costs. Hiring $H(t)$ drives costs $C(t)$, which in turn exert negative feedback on hiring. The system is governed by the equations:

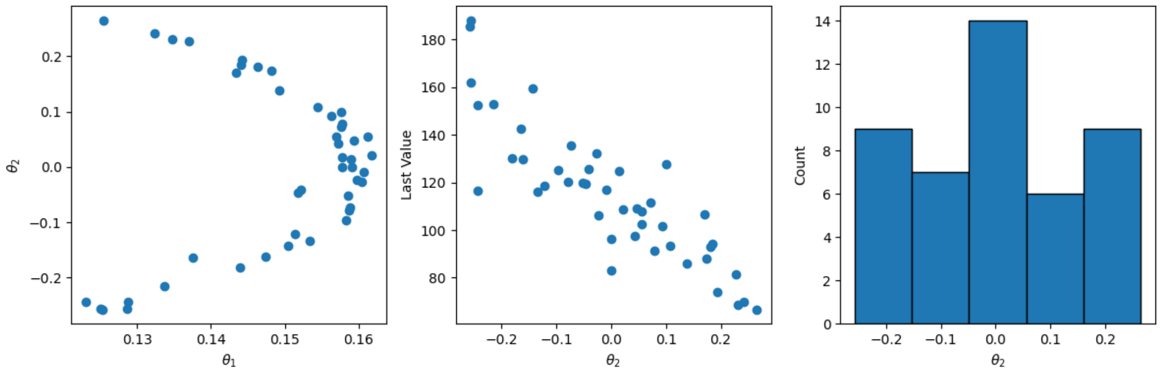

Figure 4: Left panel: θ_1 vs θ_2, the cloud of points shows a hyperbolic shape where that θ_1 with θ_2. Center panel: The last value observed in the time series along with their θ_2 value. The trend shows the repressive effect of PC_2 . Right panel: Histogram for θ_2, the bin size was chosen via the Freedman-Diaconis rule.

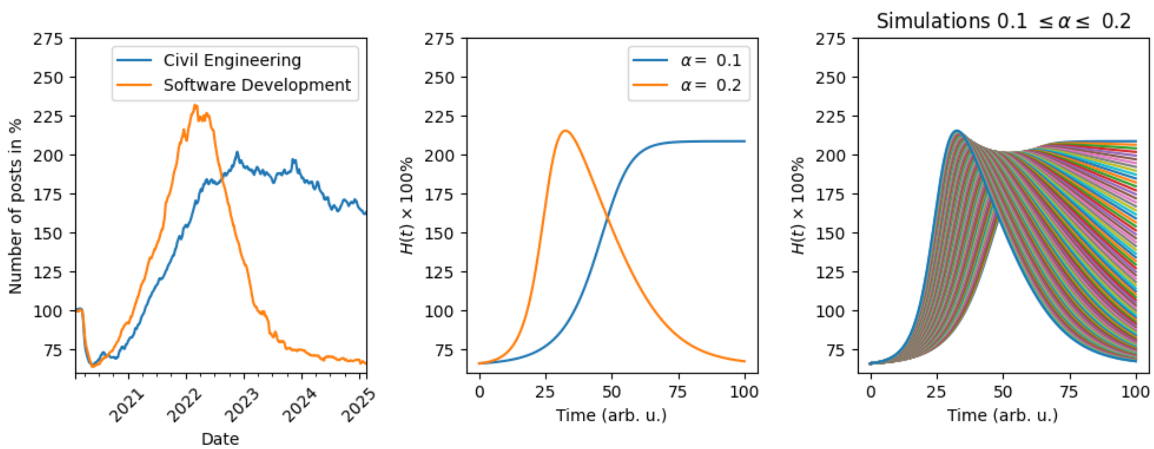

Figure 5: Left: Time series corresponding to $\theta_2 = -0.26$ (Civil engineering) and $\theta_2 = 0.27$ (Software development) Center: Simulations corresponding to $\alpha = 0.1$ and $\alpha = 0.2$. Right: All simulations performed with values between $0.1 \leq \alpha \leq 0.2$.

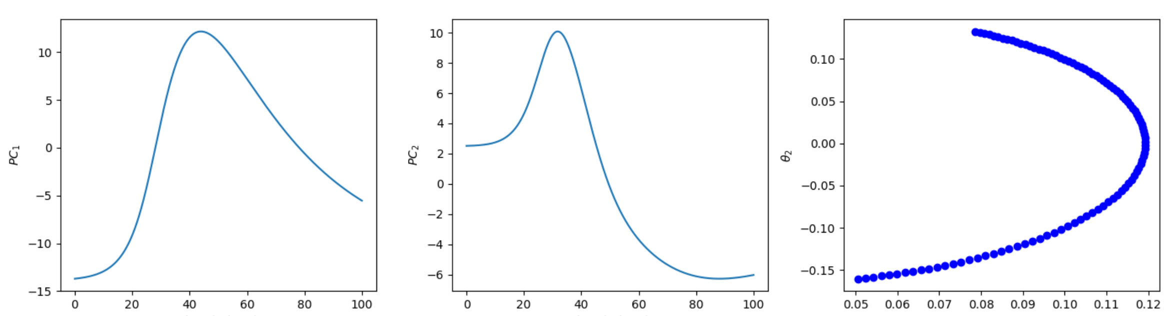

Figure 6: Left: First principal component from simulation. Center: Second principal component from simulation. Right: θ_1 vs θ_2 from simulations.

Table 1: Job fields categorized by their performance

Performance Classification				
Far Worst	Worst	Recovered	Better	Far Better
Software Development	Manufacturing	Construction	Nursing	Civil Engineering
Banking and Finance	Sales Job	Hospitality and Tourism	Electrical Engineering	Driving
Marketing	Customer Service Job	Accounting	Childcare	Physicians and Surgeons
Human Resources	Logistic Support	Retail	Medical Technician	Dental Job
Scientific R&D	Medical Information	Project Management	Social Service	Beauty and Wellness
Information Design and Documentation	Arts and Entertainment	Food Preparation and Service	Personal Care and Home Health	Veterinary
Mathematics		Management	Installation and Maintenance	Therapy
Loading and Stocking		Legal		Education and Instruction
Media and Communications		Cleaning and Sanitation		Sports
		Insurance		
		Architecture		
		Pharmacy		
		Security/Public Safety		
		Administrative Assistance		

$$\frac{dH}{dt} = (\alpha - C)(H - 0.65) - 0.0484(H - 0.65)^3 \tag{2}$$

$$\frac{dC}{dt} = 0.055(\alpha - 0.1)(H - 0.65) \tag{3}$$

where α is the model's sole free parameter. It determines both the initial hiring growth rate and the strength of hiring's influence on costs. Simulations were run with initial conditions $H(0) = 0.66$ and $C(0) = 0$, varying α from 0.1 to 0.2 in steps of 0.001. Using the Euler method with a time step of $\Delta t = 0.01$, the system was evolved for $T = 100$ (arbitrary units).

Figure 5 compares the job posting trends for Civil Engineering and Software Development (left panel) with the simulated outcomes for extreme values of $\alpha = 0.1$ and $\alpha = 0.2$ (right panel). These fields correspond to the observed extremes in θ_2. The model successfully replicates key features of the data, such as differences in initial growth rates and the contrast between a sustained increase and a pulse-like trajectory.Aggregating all simulations produces a model-based version of the original dataset (Figure 5, right panel).

Applying PCA and OLS to the simulated data yields principal components with similar patterns to those observed in the empirical analysis (Figure 6). The first component rises, overshoots, and stabilizes, while the second component peaks early and then declines sharply—mirroring trends in the actual job postings. Moreover, plotting θ_1 vs. θ_2 from the simulations reproduces the hyperbolic relationship seen in the original data, confirming that PC_2 acts as a modulator in both cases.

The model demonstrates that modulation by α captures key features of the real dataset. Specifically, stronger negative feedback follows a faster initial rise in $H(t)$, consistent with observed hiring patterns. This suggests that each field experiences a form of negative feedback, which I interpret as being related to hiring costs.

4 Conclusions

In this study, we analyzed the percentage of job postings over time on Indeed. While each field follows a distinct trajectory, our findings reveal that these patterns are interconnected. Using PCA and OLS, we showed that job posting trends follow a common process, transitioning smoothly from sustained growth to pulse-like behavior. This analysis allowed us to categorize fields based on their performance, demonstrating that job market trends are not determined by skill level alone.

Building on these insights, we developed a dynamical systems model that successfully reproduces key features of the data. The model suggests that all fields share a common process in which faster initial growth leads to stronger negative feedback. I speculate that hiring costs drive this feedback mechanism. Overall, this analysis provides a clearer understanding of how the job market has evolved in recent years.

5 Appendix

The code used in this note can be found here [8]

References

[1] T. Huang, "Why you can't find a job." [Online]. Available: https://www.youtube.com/watch?v=ElUtkHy3-zk

[2] D. Cassidy, "Why the job market is a complete joke." [Online]. Available: https://www.youtube.com/watch?v=UKlrSkekFWE

[3] ResumeGenius, "Why is it so hard to find a job?" [Online]. Available: https://www.youtube.com/watch?v=Q7G2vWjjwRQ

[4] "Why getting a 'good' job feels so difficult," *CNBC*. [Online]. Available: https://www.youtube.com/watch?v=R47vVwAp5yY

[5] "Indeed hiring lab data portal." [Online]. Available: https://data.indeed.com/#/

[6] D. Freedman and P. Diaconis, "On the histogram as a density estimator: L 2 theory," *Zeitschrift für Wahrscheinlichkeitstheorie und verwandte Gebiete*, vol. 57, no. 4, pp. 453–476, 1981.

[7] S. H. Strogatz, *Nonlinear dynamics and chaos: with applications to physics, biology, chemistry, and engineering (studies in nonlinearity).* Westview press, 2001, vol. 1.

[8] J. NegreteJr, "Jupyter notebook for this note." [Online]. Available: https://colab.research.google.com/drive/1F-JGrfA1Hgo_puMGbRqWEhqTfxn5hCdB?usp=sharing

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