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Decoding Job Market Trends: ChatGPT's Influence on Soft and Hard Skill Demands

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As the abilities of Artificial Intelligence (AI) grow, automation anxiety (the fear of being replaced by technology) has plagued the workforce—especially after the launch of the advanced Generative AI tool ChatGPT. To avoid structural unemployment, workers may need to invest in developing skills not easily replaced by AI. Some scholars argue that AI is less able to replicate soft skills than hard skills, but the literature lacks studies that indicate a causal effect across industries and occupations. This paper investigates how the public release of ChatGPT has influenced the demand for soft skills relative to hard skills in the U.S. job market. Analyzing 342,213 Indeed job listings from January 2019 to December 2023, the regression controls for role, company, industry, and macroeconomic factors. The findings suggest a statistically significant, positive effect of ChatGPT's release on the relative demand for soft skills.

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1. Introduction

As Artificial Intelligence (AI) becomes more adept at completing complex tasks in a fraction of the time it takes a human, many individuals are experiencing automation anxiety: the fear of being replaced by technology. Automation anxiety has haunted the labor force since the days of the Roman Empire (Frey, 2019). Workers worry new technology will make their skills obsolete, threatening their livelihood—and history validates their automation anxiety. Technological innovations such as light bulbs, computers, and robots led to structural unemployment, displacing workers who needed to adapt their skills to meet the new labor market demands. Previous literature supports the idea that computerization and other technologies tend to replace low-wage workers, often changing skill requirements for jobs (Friedberg, 512). These disruptions can profoundly impact society; for example, research indicates that computerization led to over half the growth in demand for female workers from 1975 to 1993, increasing women's economic independence (Weinberg, 290). The root cause lies in the types of skills required for jobs affected by computerization. While men held a comparative advantage in jobs requiring physical strength, women held a comparative advantage in the computer-based roles that replaced them (Weinberg, 291).

Artificial Intelligence is the new computer, fueling today's technological revolution. John McCarthy, who coined the term in 1955, defined AI as "the science and engineering of making intelligent machines" (Reed, 2011). Many modern definitions, such as that of McKinsey & Company, compare the abilities of humans and machines: "Artificial intelligence is a machine's ability to perform the cognitive functions we usually associate with human minds" (McKinsey & Company, 2023). In the National Artificial Intelligence Act of 2020, the U.S. Department of State defined AI as "a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments" (U.S. Department of State, 2020). Other definitions emphasize AI systems' ability to learn and improve. In the AI Guide for Government, the U.S. General Services Administration outlines several definitions for AI, including: "Any artificial system that performs tasks under varying and unpredictable circumstances without significant human oversight, or that can learn from experience and improve performance when exposed to data sets" (*AI Guide for Government*, n.d.) For this paper, I will use a definition that combines the previous definitions: "AI is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions using cognitive functions we usually associate with human minds. AI systems can also learn from data, improve their performance, and contextualize information." Just as the introduction of the computer shifted the types of skills in demand, Artificial Intelligence may displace certain types of skills and increase the demand for others. In fact, the McKinsey Global Institute estimated that automation and AI are disrupting the global economy 10 times faster than and 300 times the magnitude of the Industrial Revolution (Dobbs et al., 2015). However, it is largely unknown how job skill requirements will change.

Numerous articles claim that AI is leading to an emphasis on soft skills, arguing that these interpersonal abilities (such as creativity and problem-solving) are inherently more difficult to automate than hard skills (Daniel, 2021; McGinty, 2024). Others assert that the growth of AI has skyrocketed demand for technical skills such as data analysis and cybersecurity, but warn that long-term, soft skills are key to maintaining a competitive advantage over technology (Iliadis, 2018). However, I have not found evidence pointing to a causal effect across the entire job market in the existing literature; the articles either theorize or point to employee surveys, rather than demonstrate a causal relationship through data. The recency of companies' widespread AI integration limits the data on corporate AI use, contributing to the lack of empirical research.

Because of this lack of data, I will explore the topic by analyzing the effect of ChatGPT's public release on the relative demand for soft skills compared to hard skills. ChatGPT is a chatbot built on OpenAI's large language models, specifically the GPT (generative pre-trained transformer) series. A form of Generative AI, ChatGPT responds with human-like text to a variety of user-submitted prompts, from writing code to creating a travel itinerary (Marr, 2023). McKinsey & Company describes Generative AI as "algorithms (such as ChatGPT) that can be used to create new content, including audio, code, images, text, simulations, and videos" (McKinsey & Company, 2024). ChatGPT's inclusion in this definition points to its influence in the field. Five days after OpenAI released the first public demo on November 30, 2022, ChatGPT garnered over one million users (Marr, 2023). Though the foundation for Generative AI was laid in 1906, ChatGPT's sophisticated models, vast quantity of training data, cost-free availability, and user-friendly interface enabled it to become the catalyst for Generative AI's recent popularity (Zewe, 2023). While the use of Generative AI tools like ChatGPT has become widespread among individuals, businesses have been slower to adopt—but are increasingly using them to streamline their operations (The Economist, 2024).

Therefore, the public release of ChatGPT proves a pertinent case study of the effect of new AI technology on the relative demand for soft skills in the U.S. job market. Employing a dataset of Indeed.com job postings from January 2019 to December 2023, I will use Python to calculate each listing's relative demand for soft skills, defined as the number of identified soft skills divided by the sum of the number of identified soft skills and the number of identified hard skills. I will then perform a regression analysis that tests for a causal relationship between the launch of ChatGPT and the relative demand for soft skills. Based on previous research, I hypothesize that the release of ChatGPT increased the relative demand for soft skills in the job market. Furthermore, I anticipate this relationship will change over time as the labor market adapts to the new technology. Utilizing the Indeed data as a representative sample of national trends, the regression provides evidence supporting this hypothesis. This analysis indicates that the release of new AI tools may increase companies' demand for soft skills.

The following sections outline the structure of this paper. Section 2 reviews the existing literature, after which Section 3 presents the data and methodology. Next, Section 4 analyzes the regression results. Finally, Section 5 offers concluding remarks.

2. Literature Review

2.1 What is a skill?

The term "skill" carries different connotations across disciplines. In this paper, the word "skill" will reflect this study's focus on the skills that employers demand in the labor market. Three general concepts of skill form the basis for the prototype of The Occupational Information Network (O*NET), a free online database sponsored by the U.S. Department of Labor that outlines occupations based on the knowledge, skills, and abilities workers need to succeed in these positions. According to the O*NET prototype document, the three primary definitions of skills that employees can gain are "developed capacities that facilitate learning," "developed capacities that facilitate performance in a variety of job settings," or "procedures needed to acquire and perform various job tasks" (Peterson et al., 1995). Highlighting the learned nature of skill, this framework emphasizes skills' impact on job performance. Additionally, the O*NET model emphasizes the ability for skills to change with the needs of the job market.

Swinburne University of Technology economist and linguist Alexis Esposto synthesized the O*NET concepts with other economic definitions of skill, describing skills as "those generalizable attributes of individuals that confer advantage in the labor market" (Esposto, 2008). As a form of human capital, skills must have the capability of generating a return, according to Esposto. However, because certain generalizable attributes could potentially fall under Esposto's definition and not be considered skills—such as socioeconomic background, race, and gender—it requires a slight modification that incorporates the learned nature of skills. Thus, the term "skill" in this paper refers to "those generalizable *learned* attributes of individuals that confer advantage in the labor market."

2.2 What are soft and hard skills?

While schools, businesses, and academia often contrast "soft skills" and "hard skills," placing a skill in one category or the other can be more challenging than their apparent dichotomy would suggest. The term "soft skills" reportedly first appeared in a 1972 U.S. Army training to describe essential job-related abilities that entail minimal interaction with machines. (Lamri & Lubart, 2023). Given that new technologies have made machine-based work universal, many modern definitions of soft skills now focus more on human interaction and less on machine interaction. O*NET describes soft skills as "interpersonal and thinking skills needed to interact successfully with people and to perform efficiently and effectively in the workplace" (O*NET, n.d.). Similarly, AI researcher Jeremy Lamri and creativity researcher Todd Lubart state that soft skills enable individuals to adeptly manage interpersonal situations, build and maintain relationships, solve problems, and collaborate effectively (Lamri & Lubart, 2023). They contrast this human-centric nature with hard skills' machine dependency, defining hard skills as "technical, tangible, and quantifiable abilities related to the use of equipment for a specific job" (Lamri & Lubart, 2023). Other definitions of hard skills center on the requirement of specific knowledge, rather than a physical tool (Lyu & Liu, 2021). Many modern definitions of soft and hard skills stem from the distinction between machine-aided and not machine-aided tasks, playing into the dichotomy between humans and machines. For this study, the term "soft skills" will refer to the O*NET definition while "hard skills" will refer to "technical, tangible, and quantifiable abilities."

Despite society's and literature's emphasis on the distinction between soft skills versus hard skills, many authors believe these skills are a continuum, rather than a dichotomy (Andrews & Higson, 2008; Dell'Aquila et al., 2016; Hendarman & Cantner, 2017; Lyu & Liu, 2021). The categorization of a skill as "hard" or "soft" can be affected by the context in which an individual uses the skill, and many are interconnected and interdependent. For example, the soft skill communication can include writing (a hard skill) while the hard skill programming requires problem-solving (a soft skill) in order to be effective (Lamri & Lubart, 2023). As such, future studies may benefit from incorporating contextual analysis and skill mapping to gain a more nuanced understanding of AI's impact on the demand for soft and hard skills in the labor market.

While scholars have not reached a consensus on whether soft skills or hard skills benefit individuals and businesses more, the evidence generally appears to favor soft skills. According to some studies, not only do soft skills often serve as a more accurate predictor of workplace success (Lamri & Lubart, 2023; Deming, 2017) but they also become obsolete more slowly than hard skills (Dominici; Schultheiss and Backes-Gellner). Most research suggests soft skills—especially those related to critical thinking, change management, communication, and teamwork—are increasing in demand over time, with some scholars asserting that the demand for hard skills—particularly those involving routine tasks—is decreasing (Doherty & Stephens, 2023; Deming, 2017; Ojanperä et al., 2018). A 2017 study found that between 1980 to 2012, wages and employment grew significantly for social skill-intensive occupations and jobs with both high social skill and math requirements. However, occupations with high math but low social skill requirements declined in employment during this period (Deming, 2017). Other studies suggest that hard skills bring equal returns (Balcar, 2016) or bring relatively more success than soft skills for employees and employers within science, technology, engineering, and math (STEM) disciplines (Lyu & Liu, 2021; Deming, 2017). Furthermore, research indicates that combining soft and hard skills improves success more than using either type of skill on its own (Succi & Canovi, 2019). Overall, the literature demonstrates that both soft and hard skills bring value to the workplace, but their relative demand and return in the job market have fluctuated over time.

2.3 The impact of artificial intelligence on demanded skills

Given the relatively recent prevalence of AI, especially Generative AI, in the workplace, limited research exists on its effect on employers' skill demands. Most studies on the topic are theoretical, do not empirically examine a causal relationship, or focus on specific jobs or industries. For instance, a systemic literature review of AI's effect on the software engineering labor force observed a growing emphasis on skills related to communication, problem-solving, creativity, and teamwork, alongside complementary software and AI-specific proficiencies (Necula, 2023). One study included in the review anticipates that AI will automate many engineers' routine tasks, which tend to rely on hard skills (Dam, 2019). Collectively, the studies in the literature review suggest that new AI tools will increase the demand for soft skills, as hard skills are more likely to be automated.

A content analysis study using interviews with 40 AI experts concluded that the majority of managerial skills (which tend to be soft skills) will likely be enhanced by AI-manager collaboration. For example, managers can use an AI's pre-analysis in their decision-making. With AI's ability to manage straightforward and repetitive cognitive tasks (Decker et al., 2017) the authors suggest that it may assume control of certain administrative functions (Kolbjørnsrud et al., 2017) as well as analytical and cognitive processes (Huang et al., 2019). Skills of considerable complexity, such as emotional intelligence, and abstract skills, such as systemic thinking, are unlikely to be replaced or enhanced by AI (Giraud et al., 2022). Artificial Intelligence's capabilities are typically confined to specific problem sets (Lu et al., 2018), making it currently incapable of skills such as creativity, empathy, judgment, storytelling, and motivational speaking (Plastino & Purdy, 2018; Wilson, 2017). As AI can only draw from previous ideas, it lacks the capacity for imagination (Rometty, 2016). While replacing some hard skills may mean a greater emphasis on managers' soft skills, leaders may also need more AI-related hard skills to successfully integrate this technology into organizations (Giraud et al., 2022).

A study on security analysts provided evidence supporting the idea that AI will redirect high-skilled workers toward tasks dependent on social skills and advanced cognitive abilities (Grennan & Michaely, 2020). Moreover, the research indicated that AI functions both as a direct substitute and a complement to the work of security analysts. By leveraging variations in AI capabilities across different stocks, the authors demonstrate that analysts with portfolios more exposed to AI tended to shift their focus towards soft skills, adjust their coverage towards stocks with lower AI involvement, and even transition out of the profession. Notably, the redirection of employees' time towards tasks reliant on social skills contributed to improved consensus forecasts.

2.4 Discussion

The ongoing discourse surrounding the dichotomy, or continuum, of soft and hard skills reflects the dynamics of the modern workforce. Historical definitions framed soft and hard skills in the context of machine interaction, and contemporary perspectives expand on this understanding with a more nuanced view factoring in the relational and contextual aspects of these skills. The introduction and rapid evolution of Artificial Intelligence in the workplace bring a fresh layer of complexity to this conversation.

Available literature suggests that while AI might edge out certain hard skills by automating routine tasks, it accentuates the value of soft skills, particularly those that revolve around human judgment, empathy, and creativity. Even in professions that traditionally rely on hard skills, such as security analysis and software engineering, research indicates a shift towards soft skills.

While these targeted studies help in understanding the effect on their intended demographic, larger trends remain unknown. There is a clear need for empirical, cross-industry research that examines the broader implications of AI on skill demands, especially considering the profound consequences for our society and economy.

3. Data and Methods

To estimate how the public release of ChatGPT has affected the relative demand for soft skills and hard skills, this study uses job listings from the popular job board Indeed. Describing itself as “the #1 job site in the world” according to the total number of site visits, Indeed receives over 350 million unique monthly visitors (Indeed, n.d.). Due to the need for historical data and Indeed’s anti-web scraping protections, Scripps College Professor and Dr. Taro Yamane Chair in Economics Roberto Pedace generously purchased the data with his endowed chair funds. The data is from PromptCloud’s JobsPikr platform and comprises 500,000 Indeed job postings from January 1, 2019, to December 31, 2023. By including dates from the beginning, middle, and end of each month, the dataset ensures a balanced representation and avoids bias from sampling only one time period per month. As this study focuses on the effect in the United States, the data only consists of jobs located within the United States, excluding U.S. territories. The relevant variables in the purchased data are the job category, company name, state, posting date, job description, inferred department name, inferred industry, and salary offered.

Before the data could be analyzed, the data required cleaning. I first dropped all job postings that did not contain a value for the job category, state, inferred department name, or inferred industry, leaving 473,707 observations. Second, I cleaned the job description and salary columns using Python, fixing problems such as character encoding issues. For example, “Master,Äôs Degree in Accounting or related field” was corrected to “Master’s Degree in Accounting or related field.” After extracting 318,275 salaries from the salary column’s sentences using regular expression operations, I noticed all observations from 2019 and the beginning of 2020 lacked salaries in that column. Through regular expression operations, I extracted another 24,265 salaries from the job descriptions of this period. If a job posting provided a salary range rather than a number, I took the average of the minimum and maximum salary. Next, I extracted the salary time unit from the salary column or job description, transforming all pay into an annual salary. To ensure the variables were on similar scales, the log of *yearly_salary* was taken. Additionally, I converted the state, job category, department, and industry to dummy variables through one-hot encoding.

To account for potential variation between full-time and part-time jobs, I created the *is_part_time* dummy variable. If an observation's job description contains "part time", "part-time", or "parttime" (case-insensitive), its *is_part_time* value is 1. Due to anti-web scraping protections of websites with company size information, I was unable to control for this factor. Instead, I created the dummy variable *is_public_company*, assigning a value of 1 if the company is listed on NASDAQ, NYSE, or AMEX, according to dumbstockapi.com. Finally, I created the two independent variables of interest: *days_since_release* and *sq_days_since_release*. These capture the number of days after ChatGPT's public release the job was posted (0 if it was before the release), as well as the square of this number to capture nonlinear effects, such as a gradual decrease in the impact over time.

To extract the skills from the job descriptions, I compiled 108,305 soft and hand skills from several sources: a soft skills dataset from the EPJ Data Science journal article "Responsible team players wanted: An analysis of soft skill requirements in job advertisements" (Calanca et al., 2019); a hard skills list from O*NET; a categorized list of hard and soft skills from the European Skills, Competences, Qualifications and Occupations (ESCO) classification (*Skills & Competences*, n.d.); and hard skills from lists of top software products for businesses during 2019-2024 (*Best Software Products for 2019*, 2019; *Best Software Products for 2020*, 2020; *Best Software Products for 2021*, 2021; *Best Software Products for 2022*, 2022; *Best SaaS Software &*

Top B2B Apps of 2024, 2024). The latter addition aimed to ensure the hard skills list reflected current software skills, given the rapid evolution of the software industry.

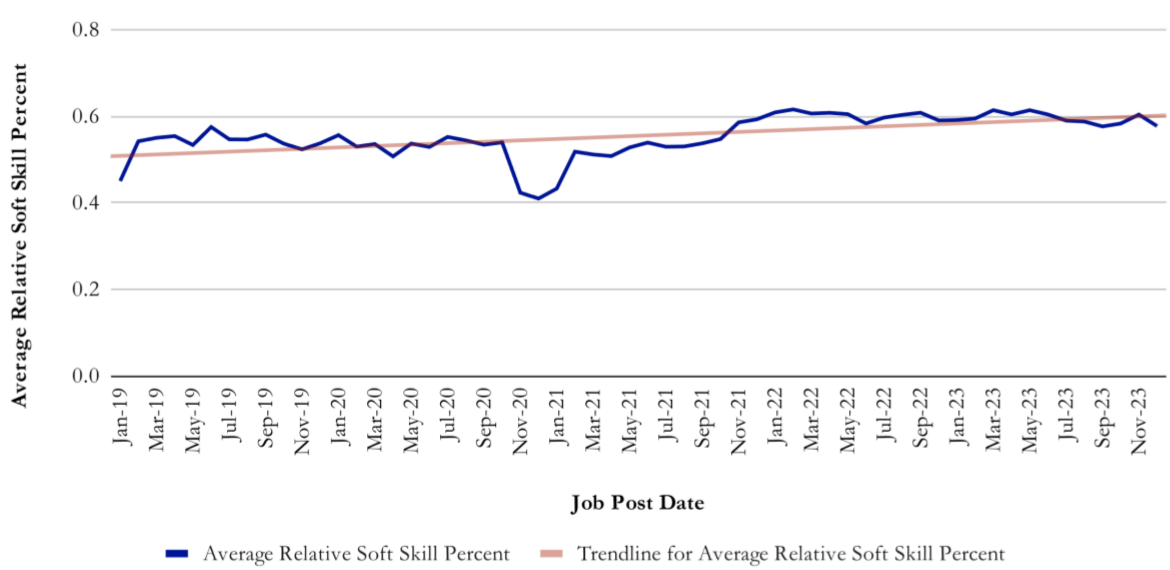
Because the sources included several ways a skill could be worded in a job description, I used regular expression operations to delete skills that contained the whole text of another skill. This aimed to prevent the double-counting of skills. After this deduplication, 58,358 skills remained, consisting of 57,315 hard skills and 1,043 soft skills. The ratio reflects the more specific nature of the wording of hard skills (such as certain technologies) compared to the more general wording of soft skills. Table 1 provides a sample of seven hard skills and seven soft skills from the list.

Table 1: Sample of Hard Skills and Soft Skills

Skill Name	**Skill Type**
3D modeling	Hard skill
installing coffered ceiling	Hard skill
train actors to use weapons	Hard skill
assemble tube hinges	Hard skill
clearing accident scene	Hard skill
primary care	Hard skill
Adobe Premiere Pro	Hard skill
open to new ideas	Soft skill
undertake multiple tasks	Soft skill
communicate	Soft skill
English	Soft skill
enthusiastic	Soft skill
detail oriented	Soft skill
present proposals	Soft skill

Using the list of skills, I extracted the *relative_soft_skill_percent* dependent variable for each job description, dividing the number of identified soft skills by the number of total identified skills. I dropped 327 job descriptions that lacked any identified soft and hard skills, leaving 342,213 observations for analysis. Figure 1 below shows the monthly average *relative_soft_skill percent*, without accounting for any of the control variables. With the trendline's positive slope of .00163, this data indicates that on average, the relative demand for soft skills increased by .163% per month from January 2019 to December 2023. This is consistent with previous literature that has found the demand for soft skills to increase over time. Notably, the economic shock of COVID-19 and the resulting restrictions likely affected the composition of job listings. In the regression model, variables capturing macrofluctuations (inflation, unemployment, and the Brave-Butters-Kelley Real Gross Domestic Product Index) aim to control for this shock.

Figure 1: Monthly Average Relative Soft Skill Percent Over Time



Additionally, the data includes five variables to control for economic conditions: the monthly Brave-Butters-Kelley Real Gross Domestic Product Index (from Federal Reserve Economic Data), the unemployment rate (from Federal Reserve Economic Data), the monthly inflation rate (from Bureau of Labor Statistics), the Daily Treasury Bill Rates (from the Treasury), and the daily Effective Federal Funds Rate (from the Federal Reserve Bank of New York). If a job listing's posting date did not exactly match a daily control variable's date, the closest date with a daily value was used.

Table 2 below contains descriptive statistics for the main variables, including the number of observations, mean, standard deviation, minimum value, and maximum value. For the full descriptive statistics table, see Appendix Table 1. To see a list of all variables and their definitions, see Appendix Table 2.

Table 2: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
days_since_release	342,213	65.849	115.070	0	396
sq_days_since_release	342,213	17577.090	36727.180	0	156816
log_salary	342,213	10.691	0.511	8.600	18.421
yearly_salary	342,213	53549.270	319835.100	5434	1.00e+08
is_remote	342,213	0.026	0.158	0	1
is_part_time	342,213	0.075	0.264	0	1
is_public_company	342,213	0.013	0.114	0	1
num_soft_skills	342,213	12.635	8.385	0	89
num_hard_skills	342,213	9.898	6.557	0	60

relative_soft_skill_percent	342,213	0.558	0.160	0	1
inflation	342,213	4.174	1.751	1.2	6.6
unemployment	342,213	4.638	1.452	3.4	14.8
fedfundrate	342,213	1.920	2.187	0.04	5.33
treasurybillrate	342,213	1.870	2.177	-0.04	5.78
bbkmgdp	342,213	2.579	7.082	-68.494	46.184

If the sample of job posts has a lower or higher representation of groups (such as states, industries, and job categories), the model may understate or overstate any effect the release of ChatGPT may have had on the relative demand for soft skills. Figure 2 compares state representation in the sample to each state's U.S. population percentage according to the 2023 U.S. Census, suggesting the sample reflects population trends (*State Population Totals and Components of Change: 2020-2023*, 2023).

Figure 2: State Representation in Sample

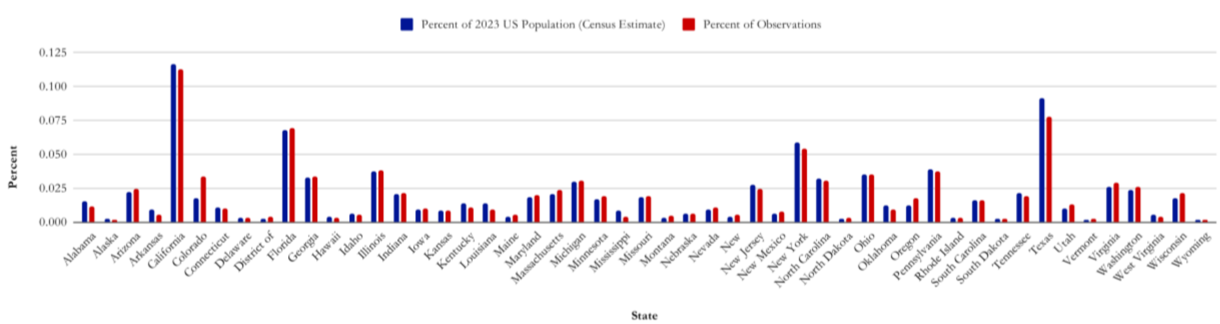


Figure 3 shows the sample's industry distribution, while Figure 4 displays U.S. employment distribution by industry based on the 2022 Bureau of Economic Analysis (BEA) estimates (*Employment by Major Industry Sector*, 2023). Though the industry breakdowns are different in the two datasets, certain industries may be underrepresented, while some may be overrepresented. For example, the retail industry comprises 0.9% of the sample but about 9.4% of the U.S. workforce. If the skill requirements of jobs in the retail industry are less impacted by the public release of ChatGPT, then this model could overstate the impact of ChatGPT's release.

However, since the BEA data represents employment rather than job openings, it may not be representative of hiring trends in these industries. For instance, the Professional & Business Services industry comprises a significant portion of the U.S. workforce, but if turnover is lower than in other industries, then there may be relatively fewer Professional & Business Services job postings on Indeed. Thus, this comparison may be less indicative of sample representation issues.

Figure 3: Industry Representation in Sample

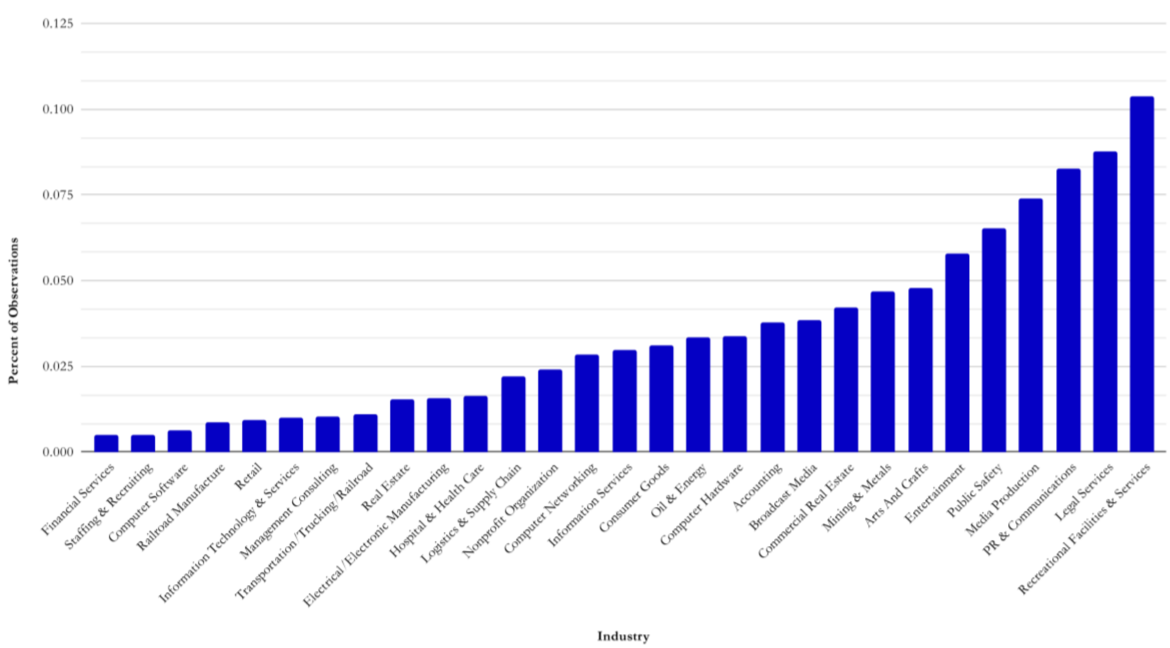
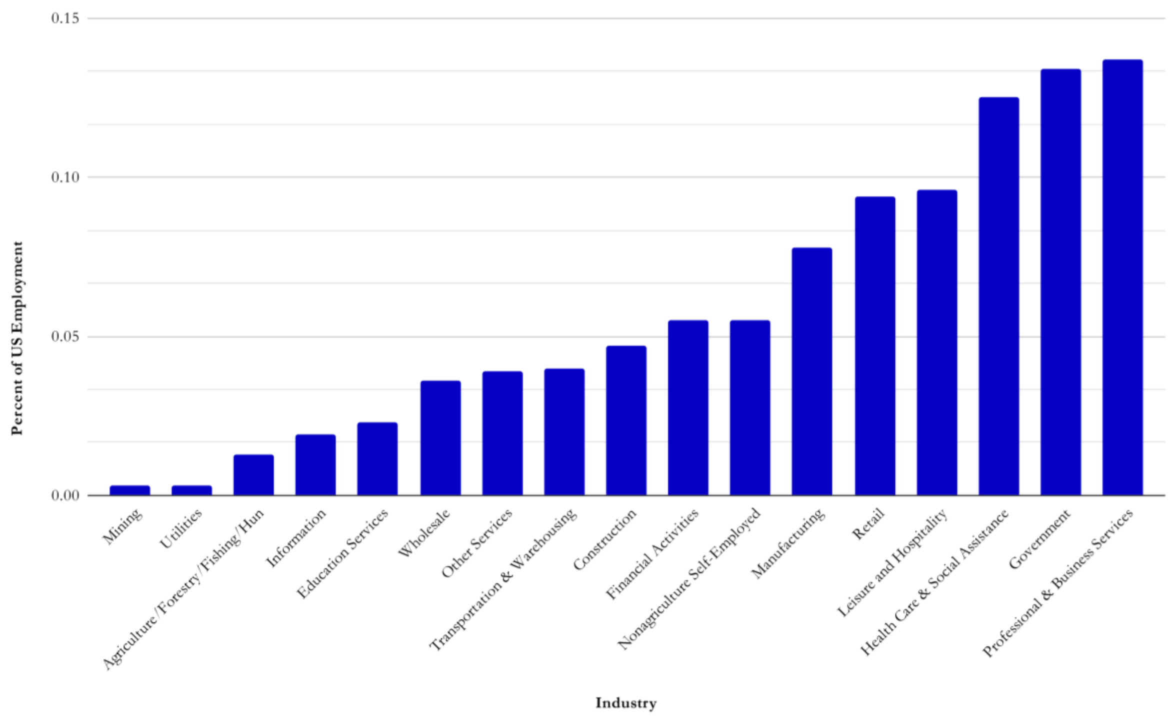
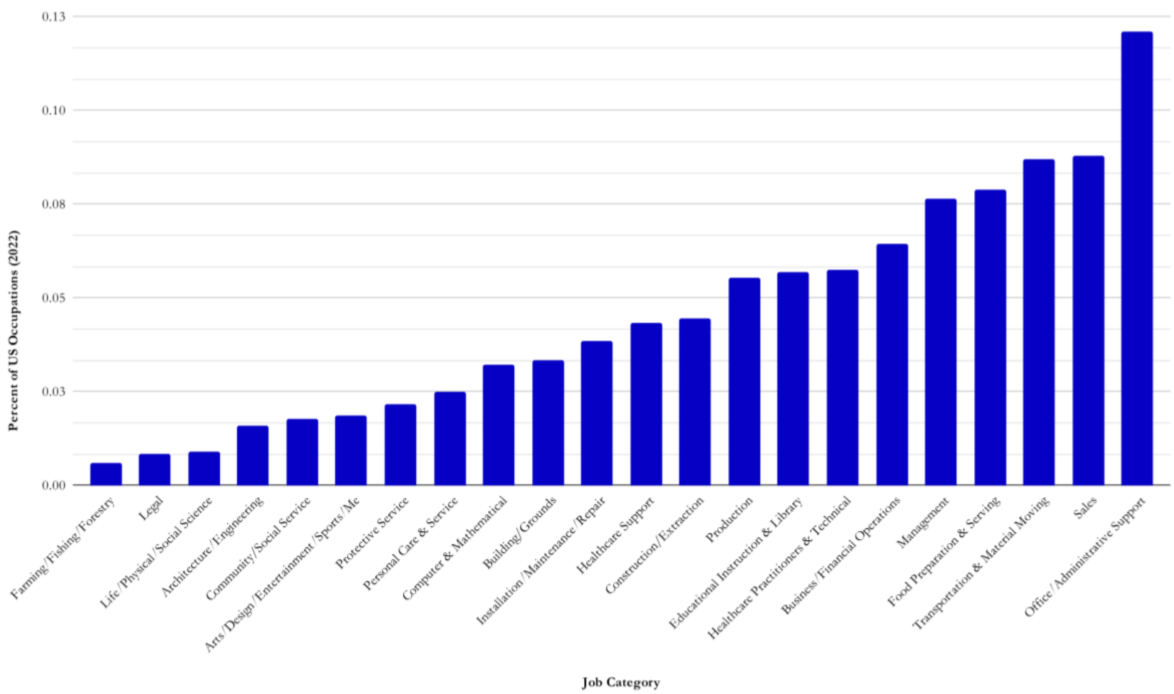


Figure 4: 2022 U.S. Employment Distribution by Industry

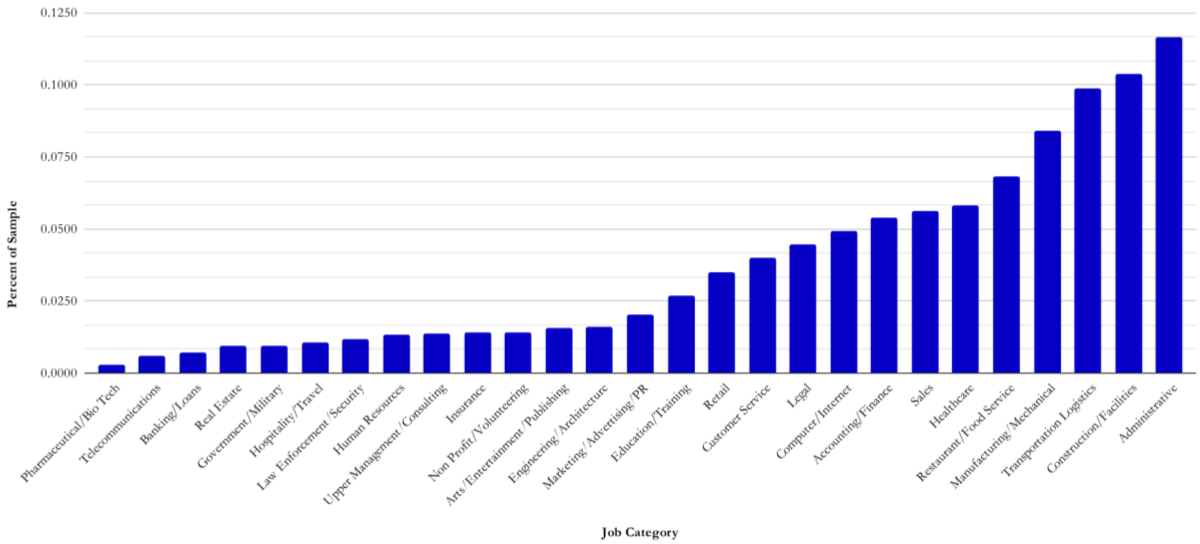


Similarly, the representativeness of the sample regarding job categories could affect the accuracy of the model. Figure 5 and Figure 6 offer some insight into how the sample's job category representation compares to the 2022 employment distribution of occupations according to the U.S. Bureau of Labor Statistics (*Employment by Detailed Occupation*, 2023). Several of the major segments, such as Transportation/Logistics (compared to Transportation & Material Moving), Restaurants/Food Service (compared to Food Preparation & Serving), and Administrative (compared to Office/Administrative Support), appear to have similar distributions. Others, such as Upper Management/Consulting (compared to Management), have a significantly different representation in the sample. If the effect of the release of ChatGPT is significantly different in these underrepresented or overrepresented groups compared to the rest of the sample, this may lead to the model overstating or understating the effect. Though this consideration remains relevant, the caveat for the industry representation comparison also applies to occupation representation. As the BEA data reflects total employment rather than job openings, it might not accurately depict the distribution of job postings across these occupations. This caveat raises doubts about the extent to which this comparison reflects sample representation issues.

Figure 5: 2022 U.S. Employment Distribution by Occupation



<u>Figure 6: Job Category Representation in Sample</u>



4. Model and Results

A multiple linear regression tested the effect of the public release of ChatGPT on the relative demand for soft skills compared to hard skills. Below is the regression equation, with vectors representing the dummy variables related to the state, job category, department, and industry. To avoid the dummy variable trap, the regression omitted the dummy variables *categoryconstructionfacilities, california, departmentfacilities*, and *industryrecreationalfacilitiesan*. Dropping one dummy variable from each group is necessary, as it can be predicted from the other dummy variables in that group, leading to perfect multicollinearity (known as the dummy variable trap). The control variables *fedfundrate* and *treasurybillrate* were removed from the regression due to their VIFs of 128.66 and 119.10, respectively, indicating high multicollinearity. With their removal, only *days_since_release* and *sq_days_since_release* had VIFs higher than 3.60, with VIFs of 23.44 and 18.23, respectively.

These variables' higher colinearity is expected since *sq_days_since_release* is a transformed version of *days_since_release* intended to account for any nonlinear effects, which *days_since_release* cannot capture. It is unlikely that this colinearity significantly affects the model, as the coefficients and R^2 values are of a reasonable magnitude. When *sq_days_since_release* is removed from the regression, the R^2 decreases by just .0008. Additionally, when either *days_since_release* or *sq_days_since_release* is omitted from the regression, their counterpart maintains the same magnitude and p-value, suggesting that the colinearity does not significantly affect the model. For the full table of VIF values, see Appendix Table 3. Applying the Breusch–Pagan/Cook–Weisberg test for heteroskedasticity yielded a p-value of 0.0000, indicating the presence of heteroskedasticity. To address this, robust standard errors were computed.

<u>Regression Equation</u>

$$relative\_soft\_skill\_percent \ = \beta_0 \ + \beta_1 days\_since\_release + \beta_2 sq\_days\_since\_release + \ \beta_3 log\_salary \ + \ \beta_4 is\_remote + \beta_5 is\_part\_time \ + \ \beta_6 is\_public\_company + \ \beta_7 inflation + \ \beta_8 unemployment + \beta_9 bbkmgdp + \sum_{i=1}^{50} \beta_{state_i} state_i + \ \sum_{j=1}^{26} \beta_{category_j} category_j + \sum_{k=1}^{24} \beta_{department_k} department_k + \ \sum_{l=1}^{28} \beta_{industry_l} industry_l$$

With a p-value of 0.0000, the regression model was statistically significant ($R^2 = 0.1281$, $F(137, 342075) = 353$). Table 3 displays the result of this regression for the non-dummy variables. To view the full regression results, see Appendix Table 4. The two variables that capture the effect of ChatGPT's release, *days_since_release* and *sq_ days_since_release*, are both statistically significant, with p-values of 0.000. The *days_since_release* coefficient of 0.0003265 indicates that the relative demand for soft skills increases by .03265% each day after the release of ChatGPT. While *days_since_release* has a positive coefficient, *sq_days_since_release* has a smaller, negative coefficient of -5.17e-07. This suggests that the effect of ChatGPT's public release slightly decreases over time and may eventually decline or enter a steady state. However, this relationship may change in the future as OpenAI releases improved versions of ChatGPT.

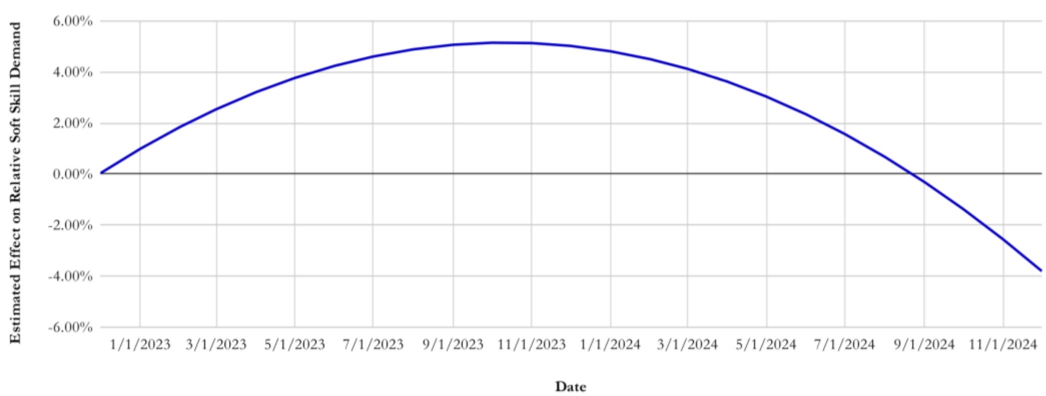
Table 3: Robust Linear Regression Model

Variable	Coefficient	Std. Err.	t	P>|t|	Lower 95%	Upper 95%
days_since_release	0.0003265	0.00001	30.18	0.000	0.00031	0.00035
sq_days_since_release	-5.17e-07	2.95e-08	-17.52	0.000	0.00000	0.00000
log_salary	-0. 0097723	0.00060	-16.25	0.000	-0.01095	-0.00859
is_remote	-0. 0075091	0.00128	-5.87	0.000	-0.01002	-0.00500
is_part_time	0. 0045536	0.00096	4.73	0.000	0.00267	0.00644
is_public_company	-0. 0004074	0.00191	-0.21	0.831	-0.00416	0.00334
inflation	0. 0222965	0.00027	83	0.000	0.02177	0.02282
unemployment	-0. 0014695	0.00034	-4.37	0.000	-0.00213	-0.00081
bbkmgdp	0. 0001807	0.00004	4.72	0.000	0.00011	0.00026
constant	0. 5269358	0.00695	75.81	0.000	0.51331	0.54056

To test if *days_since_release* and *sq_ days_since_release* were capturing a coincidental correlation with other factors that were concurrently changing, the variables *time_trend* and *post_gpt* were created. The *time_trend* variable counts the days since the initial observation, starting at 1. The *post_gpt* dummy variable equals 1 for job listings posted after the public release of ChatGPT on November 30, 2022, and 0 otherwise. Substituting *days_since_release* and *sq_days_since_release* with these variables in a robust linear regression produced a statistically significant model (R^2 = 0.1273, $F(137, 342075)$ = 351.30, p = 0.0000). *Post_gpt* exhibited a p-value of 0.000 and a coefficient of .0446766, while *time_trend* had a p-value of 0.001 and a coefficient of -6.26e-06. These results suggest that the findings are robust; it is likely that *days_since_release* and *sq_days_since_release* capture the impact of ChatGPT rather than another influence. Overall, this evidence supports the idea that Generative AI may replace automatable hard skills and encourage workers to focus on soft skills.

While the results are more reliable in the short run, Figure 7 forecasts the effect of ChatGPT's release on the relative demand for soft skills. The model indicates that the effect peaked on October 12, 2023, at 5.15484% and may dissipate on August 22, 2024. However, OpenAI has announced that it will release a markedly improved generative AI tool, GPT 5, in the summer of 2024. Among other improvements, GPT-5 will be capable of executing tasks autonomously (Cuthbertson, 2024). Based on the results of this study, the release of GPT-5 may increase the relative demand for soft skills, offsetting any potential decline in the effect of the original version's release.

Figure 7: Estimated Effect of ChatGPT's Release on Relative Soft Skill Demand Over Time



5. Conclusion

This study uses Indeed data to investigate how the public release of ChatGPT has influenced the demand for soft skills relative to hard skills in the job market. Analyzing 342,213 job listings from January 2019 to December 2023, the regression controls for role, company, industry, and economic factors. The findings suggest a statistically significant, positive impact of ChatGPT's release on the relative demand for soft skills.

In light of previous research, these results suggest that new AI tools might replace automatable hard skills and redirect employees toward tasks dependent on social skills and advanced cognitive abilities. Considering the effect on the total job market, this shift toward soft skills outweighs any increased demand for AI-related hard skills. Workers dependent on routine hard skills may need to enhance their soft skills as AI reshapes their roles. Failure to do so could lead to temporary structural unemployment until these workers acquire new skills. If future AI tools continue to increase the relative demand for soft skills, education and training should further emphasize soft skill development.

When interpreting the results, the limitations of the study should be taken into account. Because OpenAI released ChatGPT around the end of most COVID-19 pandemic restrictions, the regression may have conflated these two effects. I attempted to control for this through variables capturing macrofluctuations: inflation, unemployment, and the Brave-Butters-Kelley Real Gross Domestic Product Index. The regression also did not take into account the release of the more advanced GPT-4 model, available with the ChatGPT Plus paid plan starting March 14, 2023. This launch may have caused an increase in the relative demand for soft skills that is not factored into my regression. Though I aimed to include as many skills as possible, there are likely some not captured by the list of 58,358 skills. If the skill count error changes over time, this may lower the accuracy of the results. Additionally, certain industries and positions, such as gig workers, are less likely to use job boards such as Indeed. Because of their exclusion, the model may overstate or understate the effect of ChatGPT if it impacts these industries and roles differently.

To counter this, future studies should include job postings from multiple job boards as well as company websites. More sophisticated skill extraction—such as identifying relevant sections of the listing with Latent Dirichlet Allocation (LDA) topic modeling—will also increase the accuracy of findings. Furthermore, to better help workers prepare for shifts in skill demand, future research should investigate which specific soft and hard skills are increasing and decreasing in demand due to AI tools like ChatGPT.

Understanding how technology shapes our society is crucial to enable preparation and response. With insights into how an upcoming AI tool will influence skill demand, job seekers can invest in learning valuable skills, enhancing their employability and income prospects. This study suggests that current Generative AI capabilities may favor hard skills over soft skills, potentially signaling a shift or decline in some jobs requiring mainly automatable hard skills.

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Appendix

Table 1

Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
days_since_release	342,213	65.849	115.070	0	396
sq_days_since_release	342,213	17577.090	36727.180	0	156816
log_salary	342,213	10.691	0.511	8.600	18.421
yearly_salary	342,213	53549.270	319835.100	5434	1.00e+08
is_remote	342,213	0.026	0.158	0	1
is_part_time	342,213	0.075	0.264	0	1
is_public_company	342,213	0.013	0.114	0	1
num_soft_skills	342,213	12.635	8.385	0	89
num_hard_skills	342,213	9.898	6.557	0	60
relative_soft_skill_percen	342,213	0.558	0.160	0	1
inflation	342,213	4.174	1.751	1.2	6.6
unemployment	342,213	4.638	1.452	3.4	14.8
fedfundrate	342,213	1.920	2.187	0.04	5.33
treasurybillrate	342,213	1.870	2.177	-0.04	5.78
bbkmgdp	342,213	2.579	7.082	-68.494	46.184
categoryaccountingfinance	342,213	0.035	0.183	0	1
categoryadministrative	342,213	0.076	0.265	0	1
categoryartsentertainmentpublish	342,213	0.010	0.099	0	1
categorybankingloans	342,213	0.004	0.067	0	1
categorycomputerinternet	342,213	0.031	0.174	0	1
categoryconstructionfacilities	342,213	0.068	0.251	0	1

categorycustomerservice	342,213	0.026	0.159	0	1
categoryeducationtraining	342,213	0.017	0.131	0	1
categoryengineeringarchitecture	342,213	0.010	0.101	0	1
categorygovernmentmilitary	342,213	0.006	0.077	0	1
categoryhealthcare	342,213	0.037	0.190	0	1
categoryhospitalitytravel	342,213	0.007	0.083	0	1
categoryhumanresources	342,213	0.008	0.092	0	1
categoryinsurance	342,213	0.009	0.095	0	1
categorylawenforcementsecurity	342,213	0.008	0.088	0	1
categorylegal	342,213	0.029	0.166	0	1
categorymanufacturingmechanical	342,213	0.054	0.227	0	1
categorymarketingadvertisingpr	342,213	0.013	0.113	0	1
categorynonprofitvolunteering	342,213	0.009	0.095	0	1
categorypharmaceuticalbiotech	342,213	0.002	0.042	0	1
categoryrealestate	342,213	0.006	0.077	0	1
categoryrestaurantfoodservice	342,213	0.044	0.206	0	1
categoryretail	342,213	0.023	0.149	0	1
categorysales	342,213	0.036	0.187	0	1
categorytelecommunications	342,213	0.004	0.063	0	1
categorytransportationlogistics	342,213	0.064	0.244	0	1
categoryuppermanagementconsulting	342,213	0.009	0.094	0	1

alabama	342,213	0.011	0.104	0	1
alaska	342,213	0.001	0.037	0	1
arizona	342,213	0.024	0.151	0	1
arkansas	342,213	0.005	0.073	0	1
california	342,213	0.108	0.310	0	1
colorado	342,213	0.032	0.177	0	1
connecticut	342,213	0.010	0.097	0	1
delaware	342,213	0.003	0.057	0	1
districtofcolumbia	342,213	0.004	0.060	0	1
florida	342,213	0.067	0.249	0	1
georgia	342,213	0.032	0.177	0	1
hawaii	342,213	0.003	0.056	0	1
idaho	342,213	0.005	0.073	0	1
illinois	342,213	0.036	0.187	0	1
indiana	342,213	0.020	0.140	0	1
iowa	342,213	0.009	0.095	0	1
kansas	342,213	0.008	0.088	0	1
kentucky	342,213	0.010	0.099	0	1
louisiana	342,213	0.009	0.095	0	1
maine	342,213	0.005	0.071	0	1
maryland	342,213	0.019	0.136	0	1
massachusetts	342,213	0.023	0.148	0	1
michigan	342,213	0.029	0.169	0	1
minnesota	342,213	0.018	0.134	0	1
mississippi	342,213	0.004	0.063	0	1
missouri	342,213	0.018	0.133	0	1
montana	342,213	0.004	0.065	0	1

nebraska	342,213	0.006	0.075	0	1
nevada	342,213	0.011	0.103	0	1
newhampshire	342,213	0.005	0.074	0	1
newjersey	342,213	0.024	0.152	0	1
newmexico	342,213	0.007	0.085	0	1
newyork	342,213	0.052	0.221	0	1
northcarolina	342,213	0.029	0.169	0	1
northdakota	342,213	0.003	0.053	0	1
ohio	342,213	0.034	0.181	0	1
oklahoma	342,213	0.009	0.093	0	1
oregon	342,213	0.017	0.128	0	1
pennsylvania	342,213	0.036	0.185	0	1
rhodeisland	342,213	0.003	0.053	0	1
southcarolina	342,213	0.015	0.123	0	1
southdakota	342,213	0.002	0.048	0	1
tennessee	342,213	0.018	0.134	0	1
texas	342,213	0.074	0.262	0	1
utah	342,213	0.013	0.113	0	1
vermont	342,213	0.003	0.051	0	1
virginia	342,213	0.028	0.164	0	1
washington	342,213	0.025	0.155	0	1
westvirginia	342,213	0.004	0.060	0	1
wisconsin	342,213	0.020	0.141	0	1
wyoming	342,213	0.002	0.040	0	1
departmentaccounts	342,213	0.038	0.192	0	1
departmentadmin	342,213	0.073	0.260	0	1
departmentagriculture	342,213	0.002	0.044	0	1

departmentartandarchitecture	342,213	0.022	0.147	0	1
departmentcustomerservice	342,213	0.030	0.170	0	1
departmenteducation	342,213	0.020	0.141	0	1
departmentelectrical	342,213	0.008	0.088	0	1
departmentfacilities	342,213	0.175	0.380	0	1
departmentfinance	342,213	0.010	0.101	0	1
departmenthr	342,213	0.017	0.129	0	1
departmenthealthcare	342,213	0.055	0.227	0	1
departmenthospitality	342,213	0.040	0.196	0	1
departmentit	342,213	0.048	0.214	0	1
departmentinternet	342,213	0.009	0.097	0	1
departmentlegal	342,213	0.039	0.193	0	1
departmentmanufacturing	342,213	0.060	0.238	0	1
departmentmarketing	342,213	0.009	0.096	0	1
departmentpublishing	342,213	0.008	0.090	0	1
departmentrealestate	342,213	0.014	0.118	0	1
departmentrestaurant	342,213	0.065	0.246	0	1
departmentretail	342,213	0.027	0.161	0	1
departmentsales	342,213	0.060	0.237	0	1
departmentscienceandenergy	342,213	0.002	0.045	0	1
departmentserviceandsecurity	342,213	0.093	0.291	0	1
departmenttravel	342,213	0.072	0.258	0	1
industryaccounting	342,213	0.038	0.191	0	1
industryartsandcrafts	342,213	0.048	0.214	0	1
industrybroadcastmedia	342,213	0.038	0.192	0	1

industrycommercialrealestate	342,213	0.042	0.201	0	1
industrycomputerhardware	342,213	0.034	0.181	0	1
industrycomputernetworking	342,213	0.028	0.166	0	1
industrycomputersoftware	342,213	0.006	0.079	0	1
industryconsumergoods	342,213	0.031	0.173	0	1
industryelectricalelectronicm anu	342,213	0.016	0.125	0	1
industryentertainment	342,213	0.058	0.233	0	1
industryfinancialservices	342,213	0.005	0.070	0	1
industryhospitalhealthcare	342,213	0.015	0.123	0	1
industryinformationservices	342,213	0.030	0.170	0	1
industryinformationtechnolo gyand	342,213	0.010	0.100	0	1
industrylegalservices	342,213	0.088	0.283	0	1
industrylogisticsandsupplych ain	342,213	0.022	0.146	0	1
industrymanagementconsulti ng	342,213	0.010	0.099	0	1
industrymediaproduction	342,213	0.074	0.261	0	1
industryminingmetals	342,213	0.047	0.211	0	1
industrynonprofitorganizatio nman	342,213	0.024	0.153	0	1
industryoilenergy	342,213	0.033	0.179	0	1
industrypublicrelationsandco mmun	342,213	0.083	0.276	0	1
industrypublicsafety	342,213	0.066	0.248	0	1
industryrailroadmanufacture	342,213	0.009	0.093	0	1
industryrealestate	342,213	0.016	0.124	0	1
industryrecreationalfacilities an	342,213	0.104	0.305	0	1

industryretail	342,213	0.009	0.096	0	1
industrystaffingandrecruiting	342,213	0.005	0.071	0	1
industrytransportationtrucki ngra	342,213	0.011	0.104	0	1

Table 2

Variable Definitions

Variable Name	**Description**
days_since_release	Number of days since the release of ChatGPT
sq_days_since_release	The value of days_since_release squared
yearly_salary	Annual salary. Average annual salary if salary is provided as a range
log_salary	Log of yearly_salary value
is_remote	1 if job is marked as remote on Indeed; 0 if else
is_part_time	1 if "part time", "part-time", or "parttime" present in job description; 0 if else
is_public_company	1 if company listed on NASDAQ, NYSE, or AMEX; 0 if else
relative_soft_skill_percent	Number of identified soft skills divided by number of total identified skills.
inflation	Monthly U.S. inflation rate from the Bureau of Labor Statistics
unemployment	Monthly U.S. unemployment rate from the Federal Reserve Bank of St. Louis
fedfundrate	Daily effective federal funds rate from the Federal Reserve Bank of New York
treasurybillrate	Daily treasury bill rate: 4-week bank discount from the U.S. Department of the Treasury
bbkmgdp	Brave-Butters-Kelley Real Gross Domestic Product from the Federal Reserve Bank of St. Louis

categoryaccountingfinance	1 if job category is accounting/finance; 0 if else
categoryadministrative	1 if job category is administrative; 0 if else
categoryartsentertainmentpublish	1 if job category is arts/entertainment/publishing; 0 if else
categorybankingloans	1 if job category is banking/loans; 0 if else
categorycomputerinternet	1 if job category is computer/internet; 0 if else
categoryconstructionfacilities	1 if job category is construction/facilities; 0 if else
categorycustomerservice	1 if job category is customer service; 0 if else
categoryeducationtraining	1 if job category is education/training; 0 if else
categoryengineeringarchitecture	1 if job category is engineering/architecture; 0 if else
categorygovernmentmilitary	1 if job category is government/military; 0 if else
categoryhealthcare	1 if job category is healthcare; 0 if else
categoryhospitalitytravel	1 if job category is hospitality/travel; 0 if else
categoryhumanresources	1 if job category is Human Resources; 0 if else
categoryinsurance	1 if job category is insurance; 0 if else
categorylawenforcementsecurity	1 if job category is law enforcement/security; 0 if else
categorylegal	1 if job category is legal; 0 if else
categorymanufacturingmechanical	1 if job category is manufacturing/mechanical; 0 if else
categorymarketingadvertisingpr	1 if job category is marketing/advertising/public relations; 0 if else
categorynonprofitvolunteering	1 if job category is non-profit/volunteering; 0 if else
categorypharmaceuticalbiotech	1 if job category is pharmaceutical/biotechnology; 0 if else
categoryrealestate	1 if job category is real estate; 0 if else
categoryrestaurantfoodservice	1 if job category is restaurant/food service; 0 if else
categoryretail	1 if job category is retail; 0 if else
categorysales	1 if job category is sales; 0 if else

categorytelecommunications	1 if job category is telecommunications; 0 if else
categorytransportationlogistics	1 if job category is transportation/logistics; 0 if else
categoryuppermanagementconsulting	1 if job category is upper management/consulting; 0 if else
alabama	1 if job in Alabama; 0 if else
alaska	1 if job in Alaska; 0 if else
arizona	1 if job in Arizona; 0 if else
arkansas	1 if job in Arkansas; 0 if else
california	1 if job in California; 0 if else
colorado	1 if job in Colorado; 0 if else
connecticut	1 if job in Connecticut; 0 if else
delaware	1 if job in Delaware; 0 if else
districtofcolumbia	1 if job in District of Columbia; 0 if else
florida	1 if job in Florida; 0 if else
georgia	1 if job in Georgia; 0 if else
hawaii	1 if job in Hawaii; 0 if else
idaho	1 if job in Idaho; 0 if else
illinois	1 if job in Illinois; 0 if else
indiana	1 if job in Indiana; 0 if else
iowa	1 if job in Iowa; 0 if else
kansas	1 if job in Kansas; 0 if else
kentucky	1 if job in Kentucky; 0 if else
louisiana	1 if job in Louisiana; 0 if else
maine	1 if job in Maine; 0 if else
maryland	1 if job in Maryland; 0 if else
massachusetts	1 if job in Massachusetts; 0 if else
michigan	1 if job in Michigan; 0 if else

minnesota	1 if job in Minnesota; 0 if else
mississippi	1 if job in Mississippi; 0 if else
missouri	1 if job in Missouri; 0 if else
montana	1 if job in Montana; 0 if else
nebraska	1 if job in Nebraska; 0 if else
nevada	1 if job in Nevada; 0 if else
newhampshire	1 if job in New Hampshire; 0 if else
newjersey	1 if job in New Jersey; 0 if else
newmexico	1 if job in New Mexico; 0 if else
newyork	1 if job in New York; 0 if else
northcarolina	1 if job in North Carolina; 0 if else
northdakota	1 if job in North Dakota; 0 if else
ohio	1 if job in Ohio; 0 if else
oklahoma	1 if job in Oklahoma; 0 if else
oregon	1 if job in Oregon; 0 if else
pennsylvania	1 if job in Pennsylvania; 0 if else
rhodeisland	1 if job in Rhode Island; 0 if else
southcarolina	1 if job in South Carolina; 0 if else
southdakota	1 if job in South Dakota; 0 if else
tennessee	1 if job in Tennessee; 0 if else
texas	1 if job in Texas; 0 if else
utah	1 if job in Utah; 0 if else
vermont	1 if job in Vermont; 0 if else
virginia	1 if job in Virginia; 0 if else
washington	1 if job in Washington; 0 if else
westvirginia	1 if job in West Virginia; 0 if else
wisconsin	1 if job in Wisconsin; 0 if else

wyoming	1 if job in Wyoming; 0 if else
departmentaccounts	1 if job department is accounting; 0 if else
departmentadmin	1 if job department is administration; 0 if else
departmentagriculture	1 if job department is agriculture; 0 if else
departmentartandarchitecture	1 if job department is art/architecture; 0 if else
departmentcustomerservice	1 if job department is customer service; 0 if else
departmenteducation	1 if job department is education; 0 if else
departmentelectrical	1 if job department is electrical; 0 if else
departmentfacilities	1 if job department is facilities; 0 if else
departmentfinance	1 if job department is finance; 0 if else
departmenthr	1 if job department is human resources; 0 if else
departmenthealthcare	1 if job department is health care; 0 if else
departmenthospitality	1 if job department is hospitality; 0 if else
departmentit	1 if job department is information technology; 0 if else
departmentinternet	1 if job department is internet; 0 if else
departmentlegal	1 if job department is legal; 0 if else
departmentmanufacturing	1 if job department is manufacturing; 0 if else
departmentmarketing	1 if job department is marketing; 0 if else
departmentpublishing	1 if job department is publishing; 0 if else
departmentrealestate	1 if job department is real estate; 0 if else
departmentrestaurant	1 if job department is restaurant; 0 if else
departmentretail	1 if job department is retail; 0 if else
departmentsales	1 if job department is sales; 0 if else
departmentscienceandenergy	1 if job department is science/energy; 0 if else
departmentserviceandsecurity	1 if job department is service/security; 0 if else
departmenttravel	1 if job department is travel; 0 if else

industryaccounting	1 if job industry is accounting; 0 if else
industryartsandcrafts	1 if job industry is arts and crafts; 0 if else
industrybroadcastmedia	1 if job industry is broadcast media; 0 if else
industrycommercialrealestate	1 if job industry is commercial real estate; 0 if else
industrycomputerhardware	1 if job industry is computer hardware; 0 if else
industrycomputernetworking	1 if job industry is computer networking; 0 if else
industrycomputersoftware	1 if job industry is computer software; 0 if else
industryconsumergoods	1 if job industry is consumer goods; 0 if else
industryelectricalelectronicmanu	1 if job industry is electrical/electronic manufacturing; 0 if else
industryentertainment	1 if job industry is entertainment; 0 if else
industryfinancialservices	1 if job industry is financial services; 0 if else
industryhospitalhealthcare	1 if job industry is hospital and health care; 0 if else
industryinformationservices	1 if job industry is information services; 0 if else
industryinformationtechnologyand	1 if job industry is information technology and services; 0 if else
industrylegalservices	1 if job industry is legak services; 0 if else
industrylogisticsandsupplychain	1 if job industry is logistics and supply chain; 0 if else
industrymanagementconsulting	1 if job industry is management consulting; 0 if else
industrymediaproduction	1 if job industry is media production; 0 if else
industryminingmetals	1 if job industry is mining and metals; 0 if else
industrynonprofitorganizationman	1 if job industry is nonprofit organization management; 0 if else
industryoilenergy	1 if job industry is oil and energy; 0 if else
industrypublicrelationsandcommun	1 if job industry is public relations and communications; 0 if else
industrypublicsafety	1 if job industry is public safety; 0 if else
industryrailroadmanufacture	1 if job industry is railroad manufacturing; 0 if else

industryrealestate	1 if job industry is real estate; 0 if else
industryrecreationalfacilitiesan	1 if job industry is recreational facilities and services; 0 if else
industryretail	1 if job industry is retail; 0 if else
industrystaffingandrecruiting	1 if job industry is staffinf and recruiting; 0 if else
industrytransportationtruckingra	1 if job industry is transportation/trucking/railroad; 0 if else

Table 3

VIF Results from Breusch–Pagan/Cook–Weisberg Test for Heteroskedasticity

Variable	VIF	1/VIF
days_since_release	23.44	0.042654
sq_days_since_release	18.23	0.054862
unemployment	3.6	0.277554
inflation	3.3	0.30289
industryelectronics	2.27	0.441039
departmentengineering	2.17	0.460382
categoryretail	2.16	0.463732
categorylegal	2.14	0.468076
departmentlegal	2.07	0.48384
categorytransportationlogistics	1.86	0.539001
industrypublishing	1.76	0.567087
industrymining	1.71	0.584253
categoryadministrative	1.69	0.593392
departmentqualityassurance	1.67	0.597293
industrypublishing	1.62	0.616457
categoryaccountingfinance	1.6	0.62376

departmentsecurity	1.6	0.626906
departmentqualityassurance	1.56	0.641173
industrymisc	1.55	0.645702
industryentertainment	1.54	0.648255
departmentresearch	1.53	0.653916
categoryhealthcare	1.51	0.662525
departmentarchitecture	1.5	0.666624
departmentmanufacturing	1.49	0.669188
categorysales	1.49	0.673063
industryautomotive	1.48	0.673599
industryagriculture	1.48	0.676948
industryarchitecture	1.47	0.681167
departmenttraining	1.47	0.681615
categorymarketingadvertisingpr	1.42	0.706471
categoryconstruction	1.41	0.70831
texas	1.41	0.711603
departmentit	1.4	0.715268
industryoilgas	1.4	0.716783
categoryrestaurantfoodservice	1.39	0.719336
industrybreweries	1.39	0.719336
florida	1.37	0.728984
industryhardware	1.37	0.731081
industrylogistics	1.35	0.741718
log_salary	1.33	0.750848
industrycosmetics	1.33	0.751111
industryconsulting	1.32	0.760311
industryinsurance	1.31	0.761869
departmentmarketing	1.31	0.764418
departmentlegal	1.3	0.767438

departmentqualityassurance	1.3	0.770482
industryrealestate	1.3	0.767602
categoryarchitecture	1.29	0.776659
industrynonprofit	1.29	0.777839
newyork	1.28	0.779748
categorycustomer	1.27	0.789583
departmentfinance	1.26	0.795891
categoryeducation	1.25	0.799285
categoryrealestate	1.24	0.803379
departmenthumanresources	1.24	0.805987
departmentoperations	1.24	0.808099
departmentmanufacturing	1.22	0.816569
illinois	1.21	0.826551
pennsylvania	1.21	0.827776
ohio	1.2	0.831945
industryrealestate	1.2	0.832487
categoryhumanresources	1.2	0.833216
georgia	1.19	0.839475
industrytransportation	1.19	0.840178
departmentlegal	1.19	0.841706
colorado	1.19	0.842597
industryindustrial	1.18	0.847051
industryelectronics	1.18	0.848146
departmenttraining	1.18	0.84964
michigan	1.18	0.850573
northcarolina	1.17	0.852473
departmentengineering	1.17	0.855411
departmentconsulting	1.16	0.858627
categorylawenforcementsecurity	1.16	0.858676

virginia	1.16	0.861344
washington	1.14	0.874727
categorylegal	1.14	0.879312
newjersey	1.14	0.879984
arizona	1.14	0.880452
massachusetts	1.13	0.884694
industryrealestate	1.13	0.886
wisconsin	1.13	0.887451
categorynonprofitvolunteer	1.13	0.887457
indiana	1.13	0.888709
categoryhospitality	1.12	0.891481
categoryengineering	1.12	0.89221
categorybankingfinance	1.12	0.892497
maryland	1.12	0.896858
tennessee	1.11	0.900474
missouri	1.11	0.901199
industrymachinery	1.11	0.901385
minnesota	1.11	0.902382
oregon	1.1	0.908011
categorygovernmentpublicadministration	1.1	0.910551
industryretail	1.1	0.91119
southcarolina	1.1	0.911754
industryfinancialservices	1.09	0.919831
industryhardware	1.08	0.923247
categoryinformationtechnology	1.08	0.924463
categoryupsupplychain	1.08	0.927015
utah	1.08	0.928328
industrystorage	1.08	0.929289
alabama	1.07	0.934145

bbkmgdp	1.06	0.939488
kentucky	1.06	0.940205
nevada	1.06	0.940583
iowa	1.06	0.944334
louisiana	1.06	0.944725
categorytelecommunications	1.06	0.946153
oklahoma	1.06	0.946219
newmexico	1.06	0.946856
departmentcallcenter	1.06	0.94705
connecticut	1.06	0.947143
kansas	1.05	0.95286
categorypharmaceuticals	1.04	0.959904
is_part_time	1.04	0.963055
nebraska	1.04	0.965795
newhampshire	1.03	0.966596
is_remote	1.03	0.966742
idaho	1.03	0.967053
arkansas	1.03	0.967379
maine	1.03	0.967648
districtofcolumbia	1.03	0.971322
montana	1.03	0.97364
mississippi	1.03	0.974723
is_public_sector	1.02	0.97637
westvirginia	1.02	0.976665
delaware	1.02	0.977623
hawaii	1.02	0.979776
northdakota	1.02	0.981192
rhodeisland	1.02	0.982161
vermont	1.02	0.983431

departmentengineering	1.02	0.983517
southdakota	1.01	0.985587
wyoming	1.01	0.988161
departmentmanufacturing	1.01	0.988411
alaska	1.01	0.99094

Table 4

Robust Linear Regression Results

Variable	**Coefficient**	**Std. Err.**	**t**	**P>|t|**	**Lower 95%**	**Upper 95%**
days_since_release	0.00033	0.00001	30.18	0.000	0.00031	0.00035
sq_days_since_release	0.00000	2.95e-08	-17.52	0.000	0.00000	0.00000
log_salary	-0.00977	0.00060	-16.25	0.000	-0.01095	-0.00859
is_remote	-0.00751	0.00128	-5.87	0.000	-0.01002	-0.00500
is_part_time	0.00455	0.00096	4.73	0.000	0.00267	0.00644
is_public_company	-0.00041	0.00191	-0.21	0.831	-0.00416	0.00334
inflation	0.02230	0.00027	83	0.000	0.02177	0.02282
unemployment	-0.00147	0.00034	-4.37	0.000	-0.00213	-0.00081
bbkmgdp	0.00018	0.00004	4.72	0.000	0.00011	0.00026
categoryaccountingfinance	0.02402	0.00171	14.06	0.000	0.02067	0.02737
categoryadministrative	0.03972	0.00122	32.51	0.000	0.03732	0.04211
categoryartsentertainmentpublish	0.00659	0.00266	2.48	0.013	0.00138	0.01180
categorybankingloans	0.03708	0.00399	9.3	0.000	0.02926	0.04489

categorycomputerinternet	-0.02368	0.00172	-13.77	0.000	-0.02705	-0.02031
categorycustomerservice	0.02864	0.00165	17.32	0.000	0.02540	0.03188
categoryeducationtraining	0.03187	0.00225	14.16	0.000	0.02746	0.03628
categoryengineeringarchitecture	-0.01124	0.00239	-4.71	0.000	-0.01592	-0.00656
categorygovernmentmilitary	-0.01695	0.00326	-5.2	0.000	-0.02333	-0.01056
categoryhealthcare	0.03758	0.00171	21.99	0.000	0.03423	0.04093
categoryhospitalitytravel	0.03479	0.00318	10.94	0.000	0.02856	0.04102
categoryhumanresources	0.04351	0.00282	15.44	0.000	0.03799	0.04903
categoryinsurance	0.01509	0.00285	5.29	0.000	0.00950	0.02068
categorylawenforcementsecurity	-0.01284	0.00305	-4.21	0.000	-0.01882	-0.00686
categorylegal	0.04018	0.00236	17.03	0.000	0.03556	0.04481
categorymanufacturingmechanical	-0.01107	0.00137	-8.05	0.000	-0.01376	-0.00837
categorymarketingadvertisingpr	0.03473	0.00228	15.23	0.000	0.03026	0.03920
categorynonprofitvolunteering	0.05008	0.00236	21.24	0.000	0.04546	0.05470
categorypharmaceuticalbiotech	-0.00377	0.00633	-0.6	0.551	-0.01617	0.00863
categoryrealestate	0.03028	0.00341	8.89	0.000	0.02361	0.03696
categoryrestaurantfoodservice	0.03570	0.00190	18.77	0.000	0.03197	0.03943
categoryretail	0.04286	0.00193	22.18	0.000	0.03907	0.04665
categorysales	0.04906	0.00155	31.75	0.000	0.04604	0.05209

categorytelecommunications	0.00743	0.00385	1.93	0.054	-0.00012	0.01497
categorytransportationlogistics	-0.00264	0.00151	-1.75	0.081	-0.00561	0.00032
categoryuppermanagementconsulting	0.05535	0.00262	21.15	0.000	0.05023	0.06048
alabama	0.00215	0.00258	0.84	0.403	-0.00290	0.00721
alaska	-0.00399	0.00645	-0.62	0.536	-0.01662	0.00865
arizona	0.01407	0.00177	7.94	0.000	0.01060	0.01755
arkansas	-0.00507	0.00357	-1.42	0.156	-0.01206	0.00193
colorado	0.00864	0.00140	6.17	0.000	0.00589	0.01138
connecticut	0.01619	0.00268	6.05	0.000	0.01095	0.02143
delaware	0.03413	0.00465	7.34	0.000	0.02502	0.04324
districtofcolumbia	0.00125	0.00392	0.32	0.749	-0.00643	0.00894
florida	0.01391	0.00121	11.5	0.000	0.01154	0.01629
georgia	-0.00609	0.00176	-3.46	0.001	-0.00954	-0.00264
hawaii	0.00655	0.00501	1.31	0.191	-0.00326	0.01637
idaho	0.02790	0.00355	7.85	0.000	0.02093	0.03486
illinois	0.00097	0.00147	0.66	0.510	-0.00191	0.00385
indiana	0.01633	0.00195	8.39	0.000	0.01252	0.02015
iowa	0.00100	0.00284	0.35	0.723	-0.00456	0.00657
kansas	0.01720	0.00292	5.89	0.000	0.01147	0.02293
kentucky	0.01107	0.00272	4.06	0.000	0.00573	0.01640
louisiana	0.01101	0.00291	3.78	0.000	0.00530	0.01672
maine	0.02571	0.00347	7.4	0.000	0.01891	0.03252
maryland	0.00845	0.00189	4.47	0.000	0.00475	0.01216
massachusetts	0.01304	0.00178	7.33	0.000	0.00955	0.01652
michigan	0.01378	0.00165	8.34	0.000	0.01054	0.01702

minnesota	0.02035	0.00191	10.66	0.000	0.01661	0.02410
mississippi	-0.01574	0.00432	-3.65	0.000	-0.02421	-0.00728
missouri	0.00358	0.00201	1.78	0.075	-0.00036	0.00753
montana	0.02808	0.00373	7.53	0.000	0.02077	0.03539
nebraska	0.00465	0.00361	1.29	0.197	-0.00242	0.01173
nevada	0.01268	0.00256	4.95	0.000	0.00766	0.01770
newhampshire	0.01758	0.00369	4.76	0.000	0.01035	0.02482
newjersey	-0.00076	0.00188	-0.4	0.686	-0.00445	0.00293
newmexico	-0.01579	0.00313	-5.04	0.000	-0.02192	-0.00966
newyork	0.01481	0.00132	11.25	0.000	0.01223	0.01740
northcarolina	0.00317	0.00163	1.94	0.053	-0.00004	0.00637
northdakota	0.01806	0.00503	3.59	0.000	0.00821	0.02792
ohio	0.00707	0.00154	4.59	0.000	0.00405	0.01009
oklahoma	0.00337	0.00318	1.06	0.289	-0.00286	0.00959
oregon	0.00481	0.00187	2.57	0.010	0.00115	0.00848
pennsylvania	0.01282	0.00152	8.45	0.000	0.00984	0.01579
rhodeisland	0.01785	0.00505	3.54	0.000	0.00795	0.02774
southcarolina	-0.00003	0.00217	-0.01	0.990	-0.00428	0.00423
southdakota	0.01654	0.00579	2.86	0.004	0.00520	0.02789
tennessee	0.00991	0.00207	4.79	0.000	0.00586	0.01397
texas	0.01011	0.00116	8.69	0.000	0.00783	0.01239
utah	0.01721	0.00219	7.85	0.000	0.01291	0.02150
vermont	0.01169	0.00506	2.31	0.021	0.00177	0.02161
virginia	0.00973	0.00163	5.97	0.000	0.00653	0.01292
washington	0.00908	0.00162	5.6	0.000	0.00590	0.01226
westvirginia	0.01151	0.00463	2.48	0.013	0.00243	0.02059
wisconsin	0.01564	0.00196	7.98	0.000	0.01180	0.01948

wyoming	0.01510	0.00637	2.37	0.018	0.00261	0.02759
departmentaccounts	0.02828	0.00152	18.67	0.000	0.02531	0.03125
departmentadmin	0.03364	0.00120	28.1	0.000	0.03129	0.03598
departmentagricultur e	0.01846	0.00564	3.27	0.001	0.00741	0.02952
departmentartandarc hitecture	0.02396	0.00191	12.54	0.000	0.02022	0.02771
departmentcustomers ervice	0.02935	0.00162	18.08	0.000	0.02617	0.03254
departmenteducation	0.06905	0.00200	34.61	0.000	0.06514	0.07297
departmentelectrical	-0.03392	0.00283	-11.98	0.000	-0.03947	-0.02836
departmentfinance	0.02655	0.00242	10.99	0.000	0.02181	0.03128
departmenthr	0.02402	0.00194	12.38	0.000	0.02022	0.02783
departmenthealthcare	0.01976	0.00144	13.76	0.000	0.01695	0.02258
departmenthospitality	0.03125	0.00144	21.77	0.000	0.02843	0.03406
departmentit	-0.01776	0.00142	-12.47	0.000	-0.02055	-0.01497
departmentinternet	-0.00229	0.00243	-0.94	0.347	-0.00706	0.00248
departmentlegal	0.02733	0.00195	14.03	0.000	0.02351	0.03115
departmentmanufactu ring	0.02078	0.00120	17.28	0.000	0.01842	0.02313
departmentmarketing	0.04211	0.00239	17.65	0.000	0.03744	0.04679
departmentpublishing	-0.00361	0.00269	-1.34	0.180	-0.00889	0.00167
departmentrealestate	0.03029	0.00238	12.73	0.000	0.02562	0.03495
departmentrestaurant	0.04695	0.00161	29.24	0.000	0.04381	0.05010
departmentretail	0.02116	0.00160	13.23	0.000	0.01803	0.02430
departmentsales	0.05344	0.00124	43.23	0.000	0.05102	0.05586
departmentsciencean denergy	-0.02440	0.00540	-4.52	0.000	-0.03499	-0.01381

departmentserviceandsecurity	0.01302	0.00113	11.52	0.000	0.01080	0.01524
departmenttravel	0.00657	0.00137	4.8	0.000	0.00389	0.00925
industryaccounting	-0.00320	0.00160	-2	0.046	-0.00633	-0.00006
industryartsandcrafts	0.00395	0.00144	2.74	0.006	0.00113	0.00677
industrybroadcastmedia	-0.00068	0.00151	-0.45	0.655	-0.00364	0.00229
industrycommercialrealestate	0.00767	0.00147	5.21	0.000	0.00478	0.01055
industrycomputerhardware	-0.00853	0.00159	-5.36	0.000	-0.01165	-0.00542
industrycomputernetworking	0.01786	0.00190	9.39	0.000	0.01413	0.02159
industrycomputersoftware	0.01807	0.00341	5.3	0.000	0.01140	0.02475
industryconsumergoods	0.01055	0.00167	6.32	0.000	0.00728	0.01383
industryelectricalelectronicmanu	-0.01632	0.00223	-7.31	0.000	-0.02069	-0.01194
industryentertainment	0.00174	0.00138	1.26	0.207	-0.00096	0.00443
industryfinancialservices	0.04472	0.00367	12.17	0.000	0.03752	0.05193
industryhospitalhealthcare	0.04279	0.00246	17.4	0.000	0.03797	0.04761
industryinformationservices	-0.01779	0.00162	-11.01	0.000	-0.02096	-0.01462
industryinformationtechnologyand	-0.00046	0.00298	-0.15	0.878	-0.00630	0.00539
industrylegalservices	-0.01117	0.00139	-8.05	0.000	-0.01389	-0.00845
industrylogisticsandsupplychain	-0.01666	0.00216	-7.72	0.000	-0.02089	-0.01243
industrymanagementconsulting	0.00888	0.00276	3.21	0.001	0.00346	0.01430

industrymediaproduction	-0.00372	0.00127	-2.93	0.003	-0.00620	-0.00123
industryminingmetals	-0.03015	0.00147	-20.57	0.000	-0.03302	-0.02727
industrynonprofitorganizationman	0.01024	0.00170	6.03	0.000	0.00691	0.01357
industryoilenergy	-0.03050	0.00169	-18.01	0.000	-0.03382	-0.02718
industrypublicrelationsandcommun	-0.00256	0.00120	-2.12	0.034	-0.00491	-0.00020
industrypublicsafety	-0.02609	0.00125	-20.87	0.000	-0.02854	-0.02364
industryrailroadmanufacture	-0.02493	0.00270	-9.22	0.000	-0.03023	-0.01963
industryrealestate	0.02218	0.00222	9.99	0.000	0.01783	0.02653
industryretail	0.04466	0.00268	16.68	0.000	0.03941	0.04990
industrystaffingandrecruiting	-0.01494	0.00427	-3.5	0.000	-0.02331	-0.00657
industrytransportationtruckingra	-0.02531	0.00292	-8.67	0.000	-0.03103	-0.01959
constant	0.52694	0.00695	75.81	0.000	0.51331	0.54056