ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis [Programme Data Science and Marketing Analytics]

The Paradox of Pay: Exploring the Decline of Employer Recommendation Likelihood for Top Earners

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Abstract

This paper explores the influence of income on the likelihood of an employee to recommend their employer. Exploring a European dataset of employer reviews on Kununu, it discovers and empirically proves a curvilinear, inverted U-shape relationship where the likelihood of recommending an employer first rises with increasing salary, before reaching a plateau up to a certain inflection point after which it starts decreasing with increasing salary. Employing Logistic Regression and Random Forest, we then explore which factors are most influential in determining the likelihood of recommending an employer, determining that satisfaction with the various facets of a person's workplace is a far more powerful predictor than a person's salary. To shed light on the changing nature of the relationship, we employ LDA to uncover and compare the most salient topics discussed before and after the point of inflection. We find that the most influential topics include interpersonal issues with colleagues and management, career advancement opportunities, and discrepancies between a person's expectations and the reality. We also find that higher earners are more concerned with money despite earning more.

"Don't just work for the money; that will bring only limited satisfaction" – Kathy Ireland

Keywords: Income, Salary, Job Satisfaction, Happiness, Logistic Regression, Random Forest, Latent Dirichlet Allocation, Topic Analysis, Inverted U-shapes, Online Employer Recommendations

1. Introduction

Whether or not money buys happiness is a topic that is widely debated and researched. Recent studies on the US labor market have had differing findings, with some arguing that money does buy life satisfaction, but only up to a certain threshold (Kahneman & Deaton, 2010), while others argue that an individual's well-being continues to rise even above that threshold (Killingsworth, 2021). The exact nature of the relationship between income and well-being has been debated and revisited over the years, with multiple arguments for the relationship being linear or curvilinear. Even more recent literature corrects past studies by characterizing important differences, suggesting that happiness does not taper off but rather accelerates at higher income levels for the happiest group of people, but confirms the tapering off effect for less happy individuals (Killingsworth et. al, 2023). The nature of income and job satisfaction is complex as well. Most individuals' main motivation to work is to earn an income. Then, is income what truly makes us satisfied or not with our work? This relationship is also highly debated; other personal and work-related factors also influence job satisfaction (Parker & Brummel, 2016). This study explores the role of income on job satisfaction. However, it also acknowledges the importance of income on life satisfaction and the interaction between life satisfaction and job satisfaction in the overall context.

Other factors also play an important role in job satisfaction and must be considered when considering the role of income. An individual's job or vocation is a crucial and significant part of their lives and where they spend a large portion of their waking hours. Work improves self-esteem, community involvement, and identity for many individuals, playing a substantial role beyond just meeting economic needs (Anderson & Winefield, 2011). Bowling et al. (2010) also reported a positive relationship between job satisfaction and other facets of subjective well-being apart from income, including life satisfaction, happiness, positive affect, and the absence of negative affect. This supports the spillover hypothesis that satisfaction in one life domain, such as work, can *spill over* into the other facets of life satisfaction and well-being (Bowling et al., 2010). Job satisfaction also influences both mental and physical health outcomes, and high levels of job satisfaction are linked to lower levels of burnout, higher self-esteem, and reduced symptoms of depression and anxiety (Faragher et al., 2005). Thus, for an individual striving for a fulfilling work life and overall better health and well-being, finding a workplace which is conducive to job satisfaction is paramount.

Happiness with one's work is thus vital for an individual's overall well-being. However, even from a management perspective, it is wise to ensure that a company's employees are satisfied, as higher employee satisfaction can improve company performance (Latif et al., 2013), financial measures (Bae et al., 2010; Chi & Chen, 2021; Symitsi, 2016), lead to better employee retention (Messmer, 2005), and even company profits (Chi & Gursoy, 2009; Stamolampros et al., 2019). Understanding what factors make individuals satisfied or dissatisfied with such an integral part of our lives and an influential determinant of employee and company performance, therefore, is essential to both organizations for optimizing Human Resources (HR) policy and employees when deciding on an employer.

Employer reviews can provide valuable insights into employee satisfaction (Hollig, 2021). When employees recommend the company on such websites, we assume they are satisfied with their workplace and are dissatisfied when they do not recommend the employer. This study aims to investigate the relationship between income and employee recommendations by examining a European dataset from Kununu, one of such online employer review websites. Specifically, it aims to explore whether the relationship between income and the likelihood of leaving a positive employee recommendation is linear or curvilinear and proves the relationship is best modeled as a curvilinear, inverted U-shape relationship. Next, it compares the strength of the relationship between income and the likelihood of recommending an employer relative to other predictors. Finally, we explore what factors could contribute to the decrease in the likelihood of recommending an employer beyond the point of inflection, where the nature of the relationship displays a shift. The research question this paper seeks to answer is the nature of the relationship between income and the likelihood of employer recommendations on employer reviews on the online platform Kununu is?

More specifically, (1) Is the relationship between income and the likelihood of giving a positive recommendation best modeled as a linear or curvilinear relationship? (2) Is income a stronger predictor of job satisfaction relative to the other predictors? (3) What topics are discussed before and after the point of inflection, and how are they different?

2. Literature Review

2.1. Theoretical Frameworks of Job Satisfaction

The question of whether money buys happiness is a topic of ongoing research and debate. Intuitively, it seems logical to assume that more money, earning a higher salary, leads to more happiness because money is a means through which individuals improve their purchasing power, security, and socioeconomic status. Correspondingly, there has been research that confirms that higher income can lead to greater life satisfaction or well-being for some individuals (Diener & Biswas-Diener, 2001; Kahneman & Deaton, 2010). However, the true nature of this relationship has proven much more complicated and difficult to generalize for all individuals. Since happiness is a broad term, we will consider Subjective Well-Being (SWB) as a reliable measure of happiness (Diener, 2000) when exploring what past studies have uncovered. This section explores some foundational theories and hypotheses regarding job satisfaction and SWB and their relationship with income.

While the primary focus of this study is job satisfaction and income, it is crucial to consider SWB and life satisfaction because job satisfaction does not exist in isolation. Following the spillover hypothesis, satisfaction in one area of life can spill over into other domains of life, which in turn leads to a positive influence on overall life satisfaction and SWB (Bowling et al., 2010). Thus, examining SWB and life satisfaction as well lead to a more holistic understanding of job satisfaction and income, and acknowledges that job satisfaction is a critical component of overall well-being. To comprehensively examine the findings of past studies, we will consider that satisfaction measured in any domain is positively correlated with job satisfaction (Bowling et al., 2010).

So why would income and SWB be related and influenced by one another? The theoretical frameworks explored in Diener and Biswas-Diener's (2001) study offer possible explanations for the relationship between income and SWB, which can be summarized into the following reasons for the influence of income. Income can improve SWB by facilitating the fulfilment of basic human needs, such as food, shelter, and security. This can explain the stronger effects of income on SWB at lower income levels, where basic needs are unmet, and the plateau in SWB for relatively higher earners, where these basic human needs have been fulfilled. However, even beyond these essential needs, income can facilitate higher-level needs such as self-respect, status, and self-actualization. Also, people assess their well-being by comparing it to several relative standards, including past experiences and the experiences of their peers. This highlights the role of social comparisons, as also highlighted by Ferrer-i-Carbonell (2005), and can explain the ever-lasting effect of unmet desires. Individuals also socialize within their respective cultures to adopt certain values, goals, and behaviors, and are happier when they meet the respective goals of their cultures, the attainment of which income can facilitate. In this context, income enables participation in valued cultural activities, explaining why even relatively poor individuals report high SWB if engaged in respected activities.

With this theoretical understanding of why income can affect life satisfaction, we now examine what past research has found regarding how income affects SWB, life satisfaction, and job satisfaction.

2.2. Shape of the Relationship Between Income and Job Satisfaction

So, how does income affect SWB and job satisfaction? Is it a linear relationship, or is it better modeled as a curvilinear relationship? Moreover, how can we methodically prove a U-shaped or an inverted U-shaped relationship? This section examines the past conflicting findings in the literature.

A linear relationship is characterized by a constant rate of change between two variables, often depicted as a straight line on a graph. In contrast, a curvilinear relationship is one where the rate of change varies, resulting in a curved line on the graph, indicating that the association between the variables is not constant (Schumacker & Lomax, 2016, p. 53). Many influential studies have found a curvilinear relationship (Kahneman & Deaton, 2010; Diener & Biswas-Diener, 2001), but this relationship has been debated in the recent literature. Killingsworth (2021) challenges this threshold effect by presenting evidence that well-being continues to rise with income, even beyond the $75,000 mark previously found (Killingsworth, 2021). Stevenson & Wolfers (2008) also challenge the concept of a satiation point and find a clear positive relationship between GDP per capita and subjective well-being. Thus, one cannot deny that higher income levels can also be associated with greater SWB. For many individuals, income will increase their SWB, and some argue that it will continue to increase it indefinitely.

Kahneman and Deaton (2010) found that higher income improves emotional well-being but only up to a certain point, beyond which additional income has a diminishing effect on happiness (Kahneman & Deaton, 2010). This notion of a threshold effect suggests that while money can alleviate financial stress and provide comfort, it does not necessarily equate to continuous increases in emotional well-being in every situation. This relationship was also found by Diener and Biswas-Diener (2001), who claim that the relationship between income and life satisfaction is curvilinear, finding the effect of income on life satisfaction to diminish as income increases. Their study concluded that "while money can increase SWB, especially at lower income levels, its impact is limited by diminishing returns and moderated by other significant factors such as relationships and cultural context" (Diener & Biswas-Diener, 2001). Recent literature also points out the nuanced differences in income's impact on well-being among different groups of people. Others argue that the relationship between income and happiness does not taper off for the happiest individuals but does so for the least happy, that "happiness accelerates at higher income levels for the happiest group of people, but confirms the tapering off effect for the least happy group of people"

(Killingsworth et al., 2023). Thus, generalizations are not easy to make, as people from different backgrounds and situations may react differently to increases in income.

Adding to the complexity, Parker and Brummel (2016) also identified a linear relationship between income and overall job satisfaction but a curvilinear relationship between income and pay satisfaction. However, they found that after a certain point, people began reporting decreasing pay satisfaction above certain income levels (Parker & Brummel, 2016). This suggests that additional pay beyond certain income levels may not significantly enhance overall satisfaction and may even lead to decreased satisfaction, probably due to higher expectations or increased job pressures outweighing the added benefits of a higher income.

This study properly tests for the existence of an inverted U-shape in the data before assuming the shape of the relationship is linear or curvilinear. According to Haans et al. (2016), many researchers fall into the trap of assuming a U-shaped or inverted U-shape relationship without performing sufficient testing to prove that a U-shaped relationship exists. A U-shaped relationship exists if the dependent variable Y first decreases with the independent variable X at a decreasing rate to reach a minimum, after which Y increases at an increasing rate as X continues to rise. An inverted U-shaped relationship exists if Y first increases with X at a decreasing rate to reach a maximum, after which Y decreases at an increasing rate. (Haans et al., 2015). This study will take all the necessary and sufficient testing using the three-step procedure proposed by Lind and Melhum (2010), which Haans et al. (2015) recommend to prove the presence of an inverted U-shape. The exact steps are detailed in section 3.4.

2.3. Reasons for Declining Satisfaction with Increasing Income

As discussed, most past studies have, up until this point, debated whether the relationship between income and satisfaction is truly linear or whether it is curvilinear, in that the effect of increasing income displays diminishing returns after a certain point. However, few papers explore whether there is in fact an inverted U-shape? Could increasing income negatively influence job satisfaction at some point, and why could this be the case? In this section, we explore potential reasons for the decrease in satisfaction with rising income.

Higher income is not an infallible indicator of the number of desires that can be met because some individuals with high incomes can develop lofty material aspirations (Diener & Biswas-Diener, 2001). Proto & Rustichini (2013) also propose that as income increases, aspirations also increase continuously and raise their expectations and desires for income, which can lead to dissatisfaction if these aspirations are not met, or their desires rise at a faster rate than their income. A gap between said aspirations and realized income is negatively perceived, which can offset the positive effects of higher income (Proto & Rustichini, 2013). Individuals who prioritize material wealth over other values generally experience lower SWB, except for those who are already wealthy. This suggests that the pursuit of material goals can hinder happiness unless basic needs and financial security are not already met, and the chronic salience of desires combined with increasing material aspirations can explain why increases in income at both the individual and national levels have not always enhanced SWB (Diener & Biswas-Diener, 2001).

Further, at high income levels, the benefits of additional income may be outweighed by costs such as increased stress or lack of work-life balance that naturally are expected with higher paying jobs. Parker & Brummel (2016) have found that task satisfaction decreases as income increases beyond a certain point, indicating that higher-paying jobs may come with less satisfying tasks. Kahneman et al. (2006) argue that the common belief that higher income leads to greater happiness is largely a misconception, as it does not significantly increase moment-to-moment happiness and is often accompanied by more tension and stress.

Higher income levels may also lead to higher expectations and comparisons with others, even resulting in decreased satisfaction if these expectations are not met. It is also possible that people who achieve higher incomes compare their pay to others who are at even higher levels rather than people at equivalent or lower levels (Parker & Brummel, 2016). Graham and Pettinato (2002) found that upwardly mobile individuals often experienced a "frustrated achievers" phenomenon, where despite objective economic gains, their subjective well-being was negatively skewed due to rising aspirations and increased comparison with wealthier groups and concluded that the subjective well-being of individuals was more influenced by relative income differences and economic instability than by absolute income levels. Further, individuals tend to place more weight on upward comparisons (comparing themselves to those earning more) than downward comparisons (comparing themselves to those earning less). This upward comparison has a significant impact on life satisfaction, further emphasizing the importance of relative rank over absolute income (Boyce et al., 2010). Additionally, people can develop more luxurious, expensive tastes when they start earning more money. The amount of money people believe is necessary to meet their basic needs and desires also rises with income (Graham & Pettanino, 2002; Van Praag & Frijters, 2002).

2.4. Non-monetary Drivers of Job Satisfaction and SWB

So far we have suggested possible reasons in the literature why SWB might decline with rising income. But it is also important to also consider other important factors that may influence job satisfaction. As mentioned, the effects of income might be moderated by other non-monetary factors. Once a person's income reaches a level where basic needs met and they can lead comfortable lives, income’s impact on job satisfaction appears to diminish. Arguably, people do not work just to earn an income, they also work for their mental and overall well-being, as it is a very big and important part of an individual’s life. Anderson and Winefield (2011) find that work provides more than just economic benefits, but it also contributes to self-esteem, community involvement, and personal identity (Anderson & Winefield, 2011). Of course, we all need to work to survive, but what happens when a person becomes comfortable and no longer needs to work to survive?

At higher income levels, job satisfaction is more significantly influenced by other factors such as relationships with coworkers and opportunities for promotions, suggesting a declining importance of financial motivation (Parker and Brummel, 2016). This section explores what these other factors might be, giving a more nuanced and holistic understanding of satisfaction. Returning to Diener and Biswas-Diener (2001), they noted diminishing returns on happiness as income increases and suggest that non-monetary factors such as social relationships and a sense of purpose play significant roles in determining SWB. They find that while higher income can help improve SWB for very poor individuals and those living in less wealthy societies, more money does not necessarily enhance long-term SWB for middle-class or upper-class individuals in wealthy nations, and other factors become more important. Latif et al. (2013) further support this and find that higher-level employees, who probably earn more, derive more satisfaction from intrinsic rewards like recognition and self-esteem, whereas lower-level employees, who probably earn relatively less, find more satisfaction in extrinsic rewards such as salary and benefits. The importance of income thus seems to play a less and less influential role the higher an individual starts to earn, and other factors become the main determinants of satisfaction and SWB.

Another critical perspective is provided by Ferrer-i-Carbonell (2005) and Boyce et al. (2010), emphasizing the role of comparisons. They find that "individuals care about their relative income as much as about their absolute income" (Ferrer-i-Carbonell, 2005). Thus job satisfaction is not solely determined by one's own income but also by how it compares to the income of their peers. Boyce et al. (2010) also find that individuals gain satisfaction from being higher in the income rank within their comparison group and lose satisfaction if their rank is lower. In fact, they found that the ranked position of an individual's income predicted general life satisfaction better than absolute income or reference income. Thus, it is not just one's salary that determines how satisfied they are, but their performance relative to their colleagues and peers.

Finally, the study by Roelen et al. (2008) identifies several key factors that significantly contribute to overall job satisfaction. The primary determinants of job satisfaction include task variety, working conditions, workload, career perspectives, and job autonomy. Interestingly, salary was not even a significant predictor in the study (Roelen et al., 2008). Jung and Suh (2019) also identify key factors including vacation, organizational culture, work intensity and efficiency, working hours, self-development, and human resource management. The study finds that senior management is the most important factor for overall job satisfaction, then followed benefits and compensation, and concludes that self-development and general welfare as being highly important for employees rating their satisfaction as very high.

With an understanding of the relationship between income and satisfaction, and the other factors driving job satisfaction we now move on to the reason companies might want to keep their employees satisfied.

2.5. Importance of Satisfaction for Organizations

We assume in this study that greater happiness is good for individuals, and more happiness leads to a better life, hence why it is important. The goal of most businesses is to make money, and not necessarily to make people happy, so why would organizations be interested in keeping their employees happy and satisfied so long as they are making money?

From a managerial perspective, ensuring one's employees are satisfied can lead to better company goals and results. The success and growth of an organization are affected by employee satisfaction, as it boosts productivity and improves work quality (Latif et al., 2013; Messmer, 2005; Chi & Chen, 2021; Bae et al., 2010; Chi & Gursoy, 2009; Symitsi et al., 2019). The paper by Latif et al. (2013) finds that satisfied employees contribute to a better working environment, increased productivity, and improved organizational reputation, leading to reduced absenteeism and lower turnover rates (Latif et. al, 2013). Further, Messmer (2005) finds that employers are recognizing the increasing importance of retaining their top performers and the key to keeping these valued employees is maintaining a high level of job satisfaction. The practices, policies, and programs that a company establishes are the foundation for efforts throughout the organization to maintain high morale and retain staff.

The benefits of keeping employees satisfied are not limited to performance, and companies can even find benefits to their financial bottom lines by keeping employees happy. Chi and Chen (2021) found that "the average employee rating of a firm and sentiment measures based on text analytics of employee comments regarding a firm are both negatively correlated with its cost of debt" (Chi & Chen, 2021). Moreover, the paper by Bae et al. (2010) finds that firms that treat their employees more favorably tend to maintain lower debt ratios. Keeping employees happy can even lead to better profitability (Chi & Gursoy, 2009). Symitsi et al. (2019) also find that firms with higher average employee ratings tend to exhibit better stock market performance. They also find that employee reviews provide valuable insights into a firm's future stock returns, beyond traditional financial metrics. Thus, treating one's employees well can lead to better financial outcomes, incentivizing companies to keep employees satisfied, if only for their own self-interest.

For the overall well-being of not just individuals but for companies as well, decision-makers would be well-advised to attempt to keep their employees satisfied, and policymakers should keep employee satisfaction in mind when deciding on internal policies. Given the importance of satisfaction, how can we best understand what drives employee satisfaction from review data, particularly the text reviews?

2.6. Topic Analysis on Employer Reviews

So how useful are employer reviews in providing insights into what could be causing the mentioned inverted U-shape? We can examine the key topics that dominate both the positive and the negative reviews. Employer reviews can provide valuable insights into employee satisfaction, workplace culture, and changes in employee satisfaction over time. They also offer insider knowledge and linguistic styles used in the reviews. (Hollig, 2021). This section shall discuss the main findings past papers have found by employing similar analysis.

Symitsi et al. (2020) find that positive feedback often centers on compensation/benefits, company reputation, career progression, task variety, and management, while negative feedback frequently highlights issues with management/leadership, office conditions, career progression, job roles, and compensation. The study also finds that rating scores and review text from the mentioned reviews are valuable indicators for predicting employee turnover and firm profitability. Stamolampros et al. (2019) identify leadership, career progression, and cultural values as critical determinants of employee satisfaction. While compensation and benefits are found to be important, they are considered basic needs, and their improvement alone does not significantly boost overall satisfaction. Sainju (2020) found that salient topics affecting employee satisfaction discuss issues such as management and leadership, advancement opportunities, pay and benefits, work-life balance, and company culture. The study reveals that management and leadership, as well as a stressful work environment, are the most influential factors determining whether an employee is satisfied.

3. Data

3.1. Dataset Description

<u>Dataset Source</u>

The dataset is collected from Kununu, a German employer review website where employees leave reviews based on their experiences within the company. The initial dataset in this study consists of 405,250 observations across 63 variables, each observation representing a review left by an employee, either current or former, about their employer. The responses span from reviewers spread across three countries: Germany, Austria, and Switzerland. Most respondents come from Germany, with 337,438 observations, 45,094 from Austria, and 22,718 from Switzerland.

<u>Dependent Variable</u>

The dataset contains a binary variable indicating whether the employee would recommend this employer or not, which is this study's primary dependent variable of interest.

Primary Control Variable

A salary amount variable indicates the amount of yearly compensation earned by the employee and the salary currency, indicating whether it is in Euros or in Swiss Francs.

Review Rating Variables

On the Kununu website, reviewers are asked to rate various aspects of the workplace on a scale of 1 to 5 for 13 different features of working at said employer, with 1 being least satisfied and 5 being most satisfied. These features are divided into 4 main categories: Corporate Culture, Diversity, Work Environment, and Career and Salary. Next to each rating, the employee is also asked to leave an optional text to elaborate further on the rating they receive. The text variables include a mandatory title, an optional improvement text, and two additional comment boxes. A date variable is also present, indicating the date the review was created. The text reviews are all in German.

The four main pillars are comprised of the below specific ratings:

1 - Career & Salary: Salary/Social benefits, Image, Career/Training

2 - Corporate Culture: Working atmosphere, Communication, Colleagues, Work-life balance, Superior behavior, Interesting tasks

3 - Work Environment: Working Conditions**,** Environmental/Social Awareness

4 - Diversity: Equality**,** Dealing with older colleagues

There is further a Total Score variable, which is the average of all the overall ratings of the individual components. A decision to take the Total Score variable over the individual four pillars into the final models is based on concerns over collinearities, as well as correlation scores as seen in Table 6.4.

Additional Reviewer Information

An “Active” variable indicates whether the employee was active at the time of review. There are several variables in the data related to employment details: job status, indicating whether an employee is an active or former employee of the company, job position, a variable indicating whether the employee is an intern or not, the department in which the employee works spread across 15 different departments, the name of the company being reviewed, and the country identifier for the company. User career level also indicates whether an employee is a regular employee or a CEO, director, or team lead. The industry variable describes which industry the reviewer is associated with. There are two unique identifier columns, one for identifying the employee and the other for identifying the company per review. Further is a column for the number of reviews per company and a column indicating the respondent’s gender, whether Male, Female, Diverse or they will not disclose.

Date Range

The date range for the final dataset contains reviews from the 1st of January 2019 until the 12th of April 2021. It is important to note that the coronavirus pandemic took place and was at its peak during this timeframe, and thus might influence the topics and overall text analysis.

3.2. Data Wrangling Steps

Removed Variables

Four variables contain many missing values. “ex_job” and “prak_job” had 392,402 and 405,077 missing values, respectively. Due to the extremely high proportion of missing values, these variables were excluded from the study. Further, two variables also had an excessive number of missing values, “user_years_of_experience” and “user_has_direct_reports,” with 43,283 and 45,138 missing observations, respectively.

They thus were also excluded entirely from the study. “employmenttype” is a binary variable with only three observations as 1 and 405,247 as 0. This variable is thus deemed not meaningful and has also been excluded. Omitting the remaining missing observations within observations leaves 364,746 observations across 58 variables.

Added Variables

A variable indicating whether the review was left on a weekday or on a weekend is created for this study to examine whether there is a significant difference in the number of reviews left being positive or negative during the week as opposed to on a weekend.

Removed Observations

To accurately assess the impact of salary on job satisfaction across different nations, it is essential to establish that salaries are distributed in a statistically comparable way among the countries studied. For this purpose, Welch two sample t-tests are performed to evaluate the null hypothesis that no significant difference exists in average salaries between Germany and Austria, and between Germany and Switzerland. This step is critical to ensure that any observed variations in job satisfaction are not attributable to underlying salary discrepancies or other country-specific factors that may confound the results. After all, the average German salary in the dataset is €48,377.73, while in Switzerland, it is much higher €86,190.61, and in Austria, it is €44,467.16. To establish whether they are comparable, a two-sample t-test is implemented. The results, which can be found in Table 6.1 in the Appendix, empirically prove that salaries are significantly different in the other two countries than in Germany.

Such disparities in mean salaries suggest that Austria and Switzerland operate within a distinct economic and labor market context relative to Germany. Given these differences, including all three countries within the study and interpreting the results as homogeneous would be inappropriate as the relationship between salary and employee satisfaction might be confounded across different economic environments.

Thus, focusing on only Germany since it has the most significant number of observations would help to isolate and examine the influence of salary within a more controlled and homogeneous context, leading to more specific insights applicable to the German labor market and ensuring that the data remains consistent and comparable across all observations. This also removes the added layer of complexity stemming from each country's separate labor laws and regulations, which are unique to each. Therefore, this study focuses on only Germany and isolates only German observations; the dataset is left with 301,751 observations. Further, the study shall only look at observations of respondents who make at least the minimum wage in Germany, as observations that make less are presumably either purposely under-reporting, have made an error, or are part-time employees, and these observations are also omitted. Thus, the study looks only at full-time employees, and the dataset is left with 276,368 observations. Finally, after removing observations that are outliers, the final dataset is left with 273,501 observations.

Re-operationalized Variables

Several variables have been re-operationalized to suit the chosen methodology better. Some reference categories are changed to become the largest category within that variable. Many of the categorical variables had many categories with a very low number of observations. These small categories are combined as below:

For job positions, the categories are redefined as **employee** (80.09%), **management** (14.68%), or **other** (5.23%). For the department variable, the categories have been re-operationalized as such: Admin and Support (19.77%), Technical (13.81%), Operational (14.61%), Sales and Marketing (22.45%), and Other (29.37%). Please refer to Table 6.2 in the Appendix for an exact breakdown of what roles are contained in each category.

Scaling, centering, and adding polynomials

When comparing salaries, it is essential to consider the scale when analyzing its effect on job satisfaction due to how people perceive change. According to Weber's law, the principle that perception of a just noticeable difference varies depending upon its relation to the strength of the original stimulus (Kahneman & Deaton, 2010). After all, a €10,000 a year increase in salary would not have the same effect on an individual that earns €100,000 a year and a person that earns just €10,000 a year. While it might be a nice bonus for the high earner, it might be life-changing for the lower earner. Thus, a new variable for the logarithmic transformation of income will be used in order to understand the increase in salary on a percentage increase in happiness in accordance with studies performed in the past (Kahneman & Deaton, 2010; Ferrer-i-Carbonell, 2005; Jebb et al., 2018). Log transformation is a common practice in economic research that normalizes income data and stabilizes variance (Wooldridge, 2016; Cameron & Trivedi, 2005). It is also important to note that logistic regression does not require the independent variables to follow a normal distribution but rather to maintain a linear relationship with the logit of the dependent variable Stoltzfus, J. C. (2011). The Total Score variable, however, did not display such a linear relationship but instead displays a bimodal distribution with most observations clustered around either 1 star or 5 stars. Thus, for the logistic regression, the polynomial of Total Score is added to capture the nature of this variable. Since the Income variable will also be proved to follow a curvilinear relationship, the Square of the Log of Salary will also be added as a variable. Both the Salary and Total Score variables are centered and scaled to avoid multicollinearity concerns with a variable and its square.

Text Data

For text analytics, the German text reviews are translated into English. Windsor et al. (2019) found that machine translation using Google Translate is effective at providing translations for analyzing non-English text. They found that human and machine translations of the same corpus produce similar results in a term-document matrix and similar topic models. Hence this study uses Google Translations in order to translate the German text reviews into English. The text columns were exported as a .csv file from R, uploaded into Google Sheets, and translated from German to English using the googletranslate function and then imported again into English into R for text analytics. Standard text cleaning, removal of stop words, and stemming of the corpus are performed before performing feature extraction. Properly cleaning the text data is necessary before applying text analytics to a corpus of text. The pre-processing of the subsets containing employee text reviews involves loading the data and removing unnecessary rows or columns. Next, we addressed encoding issues within the text data to ensure consistent and clean text for analysis. We implemented custom functions to clean the text of problematic characters, such as non-standard quotation marks, symbols, and emojis, and remove extraneous whitespace. Once the text data was cleaned, we combined the individual columns of text into a single column for each dataset. This consolidated column was necessary for creating an interpretable corpus of text that could be analyzed using LDA.

4. Empirical Analysis

4.1. Model-free Evidence

Figure 4.1 shows the relationship in the data, without any model, between the likelihood of a review giving a positive recommendation to an employer and the amount of salary earned. Interestingly, an inverted U-shape can be obviously seen, with the data first showing rising likelihood to recommend an employer, before reaching a plateau, then a declining likelihood to recommend.

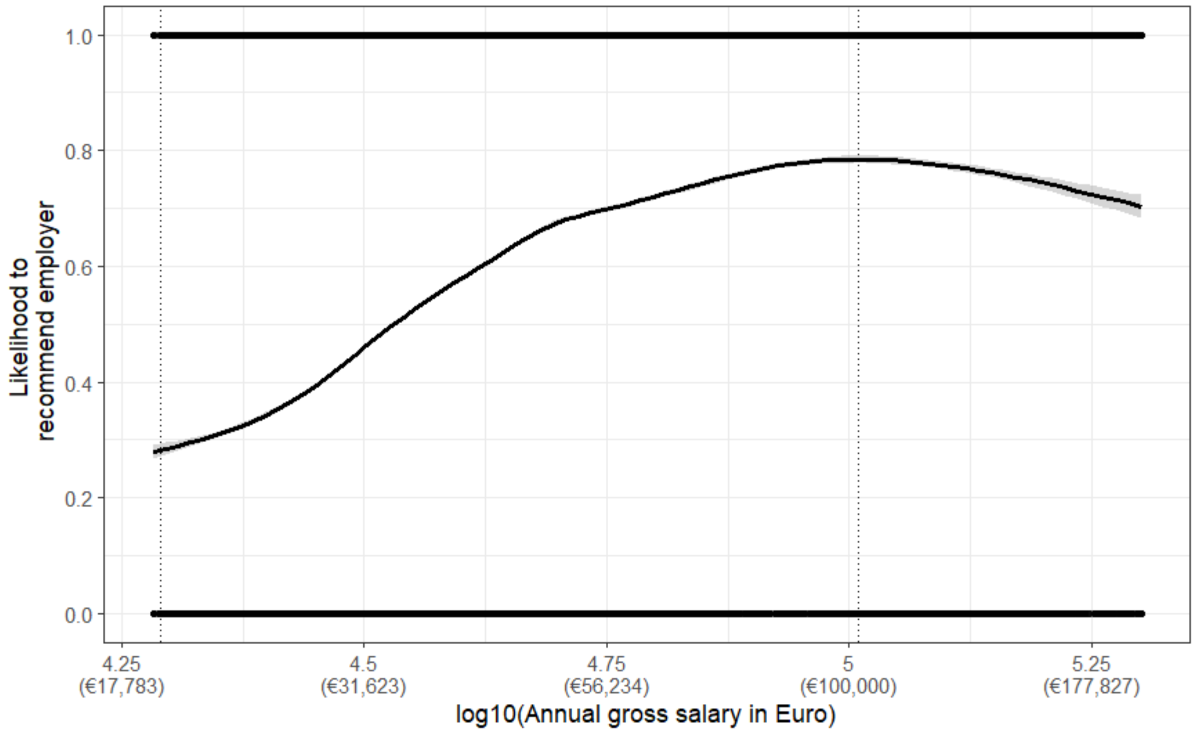

Figure 4.1: Graph of Likelihood to Recommend an Employer against the Log of Salary. *Note:* Actual Salary values between parentheses.

This visual evidence provides an initial expectation of the relationship between income and job satisfaction. This aligns with the literature suggesting that the effects of income diminish after a certain point and that employees might experience declining satisfaction beyond a certain range (Kahneman & Deaton, 2010; Diener & Biswas-Diener, 2001; Parker & Brummel, 2016).

4.2. Logistic Regression

This study employs a hierarchical regression framework to build the final Logistic Regression models to understand the relationship between the predictors and the likelihood of recommending an employer. Logistic regression was chosen because it is well suited for binary dependent variables and benefits from high interpretability (Hosmer et al., 2013; Menard, 2002).

Logistic regression is a statistical method for analyzing datasets in which there are one or more independent variables that determine an outcome. The outcome is typically binary, meaning it has two outcomes. Logistic regression aims to find the best-fitting model to describe the relationship between the dependent variable (binary outcome) and the independent variables. It is formed on the concept of the estimation of maximum likelihood in predicting the probabilities of the two classes of a binary dependent variable, Y. The dependent variable is nominal, signifying no natural order amongst the classes. The formula for Logistic Regression is found below (Dodge, 2008):

$$Logit(P) = \ln \frac{p}{1-p} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_k X_k$$

To establish a foundational understanding of the effect of salary on likelihood to recommend employer, the first step is to establish the baseline model, the simplest nested model upon which the next regressors will be added is simply a model of salary on the likelihood to recommend employer. The ensuing models will be compared based on accuracy. The effects of each variable or sets of variables included in the final model can be isolated by entering the new predictors one step at a time. They can help to understand the complex dynamics and their influences. This framework can help determine which variables would lead to a better model. To compare the incremental effects of adding variables, models will be compared on their respective Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) values, as well as the McFadden's R^2 value, with lower AIC and BIC values indicating a better-fitting model and higher McFadden's R^2 values indicating greater explanatory power. Variance Inflation Factors (VIFs) values shall be examined for every model to ensure that multicollinearity does not significantly affect the model.

VIF values identify the extent of multicollinearity that the variables introduce into a given model. VIF for a regression model variable equates to the ratio of the model variance to the model variance with the inclusion of solely a single independent variable. This ratio value is computed for each of the independent variables. In other words, this is calculated by taking an independent variable, and regressing said variable against the other independent variable predictors. The formula for the calculation is found below:

$$\frac{1}{1 - R_i^2}$$

The general rule of thumb for whether a VIF score is too high, meaning that multicollinearity has become a problem, is summarized below (Dodge, 2008):

• 1 = Uncorrelated

• Values between 1 and 5 = Moderate Correlation

• Greater than 5 = Strong Correlation

Any variable that introduces a VIF value higher than 5 shall be removed from the model.

The Likelihood Ratio Test (LRT) is used to compare the goodness-of-fit between two nested models, the simpler model and the other being a more complex model that includes additional predictors. The LRT helps evaluate whether including new variables significantly improves the model's explanatory power at every step of the hierarchical regression framework. The LRT gives an objective measure of whether adding a variable is meaningful. When performing the LRT, the null hypothesis states that the simpler model (baseline) is sufficient and that the additional predictors in the more complex model do not significantly improve the model fit. If the LRT yields a p-value below a chosen significance level (e.g., 0.05), the null hypothesis is rejected, indicating that the more complex model provides a significantly better fit to the data. Incrementally adding the variables one at a time, each variable was included in the final model if it was deemed to contribute significantly to the variation captured as indicated by the LRT and whether it does not introduce unacceptable levels of multicollinearity with the other predictors, as well as whether the predictor does not increase the AIC and the BIC.

The formulas for the calculation of the AIC and the BIC are as follows:

$$AIC = 2k - 2\log(L)$$

$$BIC = \log(T)\,k - 2\log\,(L)$$

Where k is the number of parameters, L is the maximal total likelihood of the data set, and T is the sample size. The AIC focuses on the goodness of fit and the simplicity of the model. At the same time, the BIC also includes a penalty for the number of parameters in relation to the sample size, thus favoring more parsimonious models (Dodge, 2008).

Thus in following the above steps, the final models are built. Since the Total Score was found to be the strongest predictor, we examined the effects of removing this variable to understand its overall impact on the model and the relative importance of other predictors, and to examine the influence of income with and without this predictor. The summary of the Regression Model is found in Table 4.2.

4.3. Assumptions of Logistic Regression

The following assumptions are necessary for Logistic Regression (Stoltzfus, 2011), and below are the suggested steps to test that the assumptions hold:

1 – Binary Outcome Variable: We fulfill this assumption by ensuring that the dependent variable is binary, having only two possible outcomes

2 – Independence of Observations: Observations should be independent. This is checked by reviewing the study design and data collection process to ensure that there is no inherent correlation

3 – Linearity of the Logit: The relationship between each predictor variable and the outcome's log-odds should be linear. The proposed test is to examine scatterplots of

the predictors against the logit values or by including interaction terms and polynomial terms to check for and model any non-linear relationships

4 – No Perfect Multicollinearity: There should be no perfect multicollinearity among the predictor variables. The suggested test is to ensure that there are no VIF values greater than 10

5 – Large Sample Size: As a rule of thumb, it is recommended to have at least 10 cases per predictor variable

6 – Absence of Outliers: Outliers can be identified by examining standardized residuals and leverage values. Observations with large residuals or high

Each of the assumptions is verified to hold, and where necessary, the model is adjusted. The dependent variable (whether an employee recommends an employer or not) only has two possible outcomes. Independence of observations would be impossible for this study to confirm, as that would require access to the website. However, we will assume it holds since we have no reason to suspect that they are dependent on one another. For linearity in the logit, each numeric variable's scatterplot is examined and the interaction terms test performed, and any variables that exhibit a polynomial relationship have the polynomial term included in the regression. VIF values are examined at each step of the model-building framework, and no values greater than 10 appear. The dataset is large and has far more than 10 cases per predictor. Finally, leverage values were checked, and any outliers were removed.

4.4. Proving the Relationship

Many papers assume an inverted U-shape without properly and sufficiently testing for such a relationship (Haans et al., 2016). To ensure that the inverted U-shape does exist objectively within our dataset, the formal three-step test proposed by Lind and Mehlum shall be followed (Lind & Mehlum, 2009). The steps are described below:

1. **Significance and Expected Sign of β_2**: The coefficient β_2 from the quadratic term must be significant and have the expected sign. A significant and positive β_2 indicates a U-shaped relationship, while a significant and negative β_2 indicates an inverted U-shaped relationship.
2. **Slope Tests at Data Range Extremes**: The slope of the relationship must be sufficiently steep at both ends of the data range. This involves calculating the slope at the low end (X_L) and the high end (X_H) of the X-range. Specifically, the slope at X_L, which is $\beta_1 + 2\beta_2 X_L$, should be positive and significant, and the slope at X_H, which is $\beta_1 + 2\beta_2 X_H$, should be negative and significant. Both slope tests must be significant; otherwise, a simpler model might better represent the relationship, such as a logarithmic or exponential function.
3. **Turning Point Within Data Range**: The turning point of the U-shaped or inverted U-shaped curve must be located well within the data range. This is determined by taking the first derivative of the quadratic equation and setting it to zero, yielding the turning point at $-\beta_1 / (2\beta_2)$. The 95% confidence interval for this turning point must lie within the observed range of the data. If the confidence interval extends beyond the data range, it suggests that only the data captures only part of the curve.

Including the first-order term of the salary in this situation in the regression equation is essential to avoid making the strong assumption that the turning point is at salary = 0. A significant and positive β_2 coefficient indicates a U-shaped relationship, while a significant and negative β_2 coefficient indicates an inverted U-shaped relationship. Although a significant β_2 is necessary, it is not sufficient to establish a quadratic relationship, and that is where many papers fall into the trap of stopping. (Haans et al., 2016). In fact, that is only the first step in the three-step procedure, and the next two are essential to prove the relationship. The three-step procedure and Logistic Regression results are found and elaborated on in section 4.5.

4.5. True Shape of the Relationship

Following these steps by Lind and Mehlum, we regress the dependent variable (likelihood of recommending an employer) on the independent variable (salary) and its square. The formula and results of this regression are found below in Table 4.1:

$$\text{Likelihood to Recommend} = \beta_0 + \beta_1 \cdot \text{Salary} + \beta 2 \cdot \text{Salary}^2$$

Table 4.1: Logistic Regression results for the relationship between Salary Scaled and the Square of Salary Scaled and Likelihood to Recommend an Employer

Variable Name	**Estimate**	**Std. Error**
Intercept	0.534***	0.005
Salary	1.366***	0.009
Square of Salary	-0.632***	0.013

Note: Significance Codes: ***: p < 0.001, ** : p < 0.01, * : p < 0.05, . : p < 0.1, (no symbol) : p ≥ 0.1

In accordance with the first step of Lind and Mehlum's (2009) proposed 3-step procedure, we find that the Square of Salary is indeed highly significant. This is the first essential step, but it is not sufficient alone, and that is where most papers erroneously stop. We find a positive, highly significant coefficient for Salary and a negative, highly significant coefficient for the Square of Salary, indicating the presence of an inverted U-shape.

The second step is having a sufficiently steep slope at the independent variable's low and high values. This is checked by calculating the first derivative of the regression equation and evaluating it at the minimum and maximum salary values. We can see from the table below that the slope is sufficiently steep and significant at both ends of the salary range. The test proves that the slope at the lowest point is $4.94e^{-05}$ and is highly significant, and the slope at the highest point is $-4.35e^{-05}$ and is also highly significant. The second step of the procedure further confirms the inverted U-shaped relationship, with a positive slope at the beginning and a negative slope at the upper end.

Finally, for the final step, we need to confirm that the turning point is within the salary range. We find the turning point to be at 115,412.20, with a 95% Confidence Interval between 112,235.82 and 118,588.63, well within our dataset range.

With all three steps confirming our hypothesized inverted U-shape relationship, we can empirically determine that this study's dataset does indeed exhibit an inverted U-shape in the relationship between salary and the likelihood to recommend an employer. This relationship starts by slowly rising, reaching a plateau until the inflection point, and then turning into a negatively correlated relationship. At the end of this section, we can answer the first research sub-question and conclude that the relationship between income and the likelihood of recommending an employer displays an inverted U-shape relationship.

4.6. Final Regression Models

Table 4.2 shows the results of two Regression Models, one with the Total Score variable included and one without the Total Score Variable. This section examines the results of the Models to shed light on the relationship between salary and the likelihood of recommending an employer. Since the Total Score was the strongest predictor, it was excluded from one model to understand its impact and compare the predictive power of income and other variables without it.

Table 4.2: Logistic Regression Models Comparison With and Without Total Score with Diagnostics

Coefficient	**With Total Score**	**Without Total Score**
(Intercept)	1.016 (0.040) ***	1.137 (0.018) ***
log_salary_scaled	0.056 (0.028) *	1.097 (0.013) ***
I(log_salary_scaled^2)	-0.289 (0.039) ***	-0.573 (0.017) ***

total_score_scaled	10.393 (0.065) ***	
I(total_score_scaled^2)	3.080 (0.154) ***	
user_genderDIVERSE	-0.233 (0.147)	-1.003 (0.066) ***
user_genderFEMALE	0.119 (0.028) ***	0.252 (0.013) ***
user_genderWONT_TELL	-0.206 (0.039) ***	-0.611 (0.018) ***
job_position_reopmanagement	0.062 (0.036) .	0.270 (0.016) ***
job_position_reopother	0.165 (0.067) *	0.658 (0.027) ***
department_reopOperational	0.042 (0.041)	-0.463 (0.019) ***
department_reopOther	-0.072 (0.034) *	-0.297 (0.016) ***
department_reopSales and Marketing	-0.251 (0.037) ***	-0.158 (0.017) ***
department_reopTechnical	-0.363 (0.042) ***	-0.052 (0.020) *
day_typeWeekend	-0.005 (0.033)	-0.266 (0.015) ***
job_statusMISC_MISS	-0.146 (0.193)	-0.728 (0.078) ***
job_statusREVIEW_STATUS_EX	-1.076 (0.029) ***	-2.016 (0.014) ***
industry_cleanedBusiness	-0.070 (0.040) .	0.249 (0.018) ***
industry_cleanedEducation	-0.034 (0.089)	-0.064 (0.040)
industry_cleanedEngineering	0.051 (0.050)	-0.046 (0.024) .
industry_cleanedHigh-Tec	-0.180 (0.041) ***	0.086 (0.019) ***
industry_cleanedLegal and Public & Health	0.134 (0.046) **	0.085 (0.021) ***
industry_cleanedManufacturing	0.050 (0.035)	-0.323 (0.016) ***

industry_cleanedOthers	0.041 (0.043)	-0.072 (0.020) **
McFadden's R2	0.793	0.189
BIC	54,286.43	210,678.43

Note: Significance Codes: Standard Errors in Parentheses *** : p < 0.001, ** : p < 0.01, * : p < 0.05, . : p < 0.1, (no symbol) : p ≥ 0.1

The VIF values for both models report no worrisome multicollinearity values, and are found in Table 6.3 in the appendix.

The primary purpose of the Regression Models in this study is to analyze the relationship between income and other factors and their effect on the likelihood of recommending an employer. We aim to answer whether income is a more powerful predictor relative to the other variables. In the model that includes the Total Score variable (total_score_scaled), the coefficients for income (log_salary_scaled) and its quadratic term capture the curvilinear relationship between income and recommendation likelihood and confirm the relationship even with the presence of other controls. As income increases, the likelihood to recommend initially increases but decreases after reaching a certain point. The total score variable has a very high positive coefficient (10.393) and is indeed the highest coefficient of our predictors, indicating that higher overall scores are strongly associated with a higher likelihood of recommending the employer. Interesting to note is that the total score variable is by far the most influential predictor in the model and is a far more powerful predictor than salary (0.056), indicating that satisfaction with different aspects of one's job is a much stronger predictor of likelihood to recommend employer than a person's salary.

For comparison purposes we remove the total score variable in the second model to check the effects and compare the two models. The coefficients for Salary (1.097) and its quadratic term (-0.573) are significantly larger, suggesting that income plays a stronger role when the Total Score, and hence satisfaction with the different facets of one's job, is not considered. Clearly, the Total Score variable captures a significant portion of the variation in the likelihood of recommending an employer, which is otherwise distributed among other predictors in the model without it.

The McFadden's R^2 for the model with the total score (0.792) is significantly higher than that for the model without the total score (0.189), indicating a much better fit when the Total Score is included. The BIC is also much lower for the model with the Total Score (54,286.43) compared to the model without it (210,678.43), suggesting that the model with the total score is preferred.

To further confirm the superior performance of the model with Total Score, predictions are made on the validation set. Diagnostics are found below in Table 4.3:

Table 4.3: Model Predictions Diagnostics

Metric	Model With Total Score	Model Without Total Score
Accuracy	0.943	0.733
Precision	0.927	0.734
Recall	0.933	0.555
F1-Score	0.930	0.632

Clearly, employing the Total Score variable leads to much more accurate predictions and gives us a superior model.

4.7. Random Forest and Variable Importance Plots

A Random Forest Model can be useful to rank the importance of the variables in regression and classification problems (Biau & Scornet, 2016) and is chosen to further confirm variable importances and to help answer the question of which variables are most influential in determining likelihood of recommending an employer. Random Forest is an ensemble machine learning method first introduced by Breiman (2001). Random Forest provides us with Variable Importance Plots, calculated utilizing two concepts to determine how influential a predictor or a feature is in explaining overall variance. The concepts are the Mean Decrease Accuracy (MDA) and the mean Decrease Gini (MDG). MDA measures how much the accuracy of the Random Forest decreases when a particular feature's values are randomly shuffled. The model's accuracy is first calculated using out-of-bag data. Then values of a certain feature are randomized and the accuracy is recalculated. The more the accuracy drops due to this randomization, the variable is deemed higher in importance. MDG measures how each feature contributes to the homogeneity of the nodes and the leaves of the model's decision tress. The goal of decision trees is to make the resulting nodes as pure as possible. The MDG is a measure of how pure groups are. The more likely it is that a feature will creatues more pure nodes dplits, the higher the MDG score (Breiman, 2001). For the sake of consistency, the Random Forest Model will have all variables pre-processed the exact same way as the Logistic Regression Model, and will use the exact same final dataset without any outliers even though the Random Forest is not sensitive to outliers. Figure 4.2 below shows the results of the Variable Importance Plot for the Random Forest Model.

Variable Importance Plots for Random Forest Model

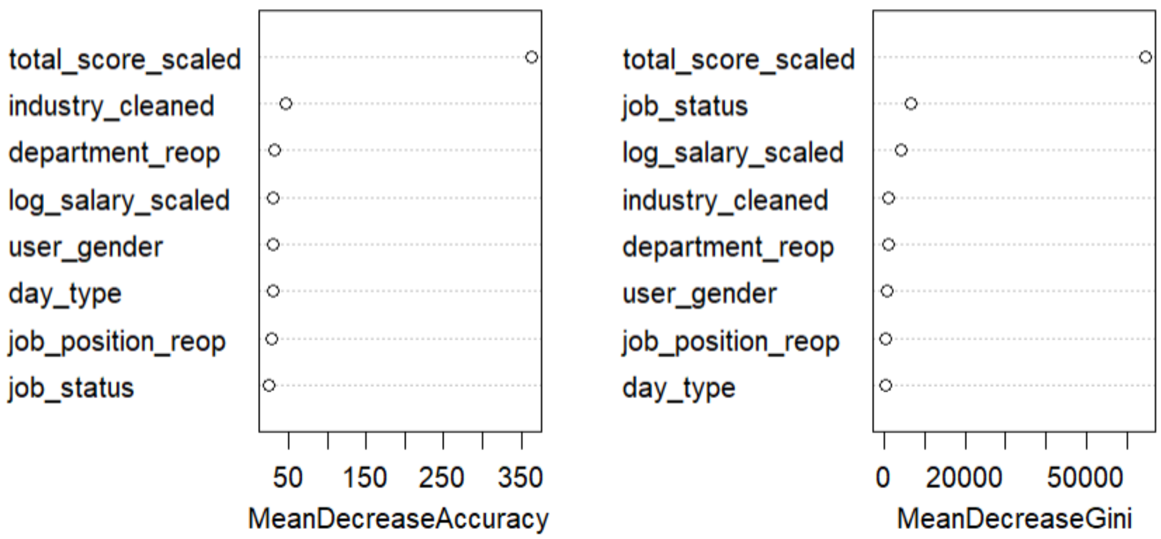

Figure 4.2: Mean Decrease Accuracy and Mean Decrease Gini Plot for Random Forest Model

Both the MDA and the MDG indicate that the Total Score variable is the most important by far. MDA shows salary as the 4th most important variables and MDG shows salary as the 3rd most important. The Random Forest model confirms the finding that being satisfied with the overall factors of one's work is a far more important predictor than a person's salary and is the single most powerful predictor.

5. Text Analytics

5.1. Model-Free Evidence

To get an idea of the topics that are present across all reviews that will be analyzed with the LDA model, a word cloud is generated, as seen below in Figure 5.1:

Figure 5.1: Word Cloud of most frequent words across both subsets.

From the wordcloud, we can see that the most salient topics refer to management and colleagues, and communication. Training and opportunities (presumably for self and career development) are also expected to be salient topics. Slightly less frequent we see mentions of salary, indicating that we can expect less mentions of income, possibly due to both subsets being relatively high earners.

5.2. Latent Dirichlet Allocation

This study attempts to discover the most salient topics before and after the inflection point with the past literature in mind, testing whether a topic is present or absent, or much more dominant in one subset than the other to gain insight into the nature of pay and satisfaction. The chosen method for finding said topics is Latent Dirichlet Allocation (LDA) for its simplicity and interpretability. LDA is a generative probabilistic model used to identify the latent topics within a large collection of documents, introduced by Blei et al. (2003). LDA considers each document a mixture of a finite number of topics and that each word in the document is attributable to one of the document's topics. The results of an LDA model represent the probability of a topic appearing in a document and the probability of each word appearing in a topic. At the basis of the model lies the idea that a collection of documents, or corpus, is made up of a random mixture of latent topics. The generative process for each document i in corpus C is summarized by the following formulas:

Topic Distribution for Document n:

$$\theta_n \sim \text{Dir}(\alpha \ldots \alpha),$$

where θ_n is the vector representing topic probabilities for document n and α is a fixed predetermined parameter determining the distribution of θ_n.

Word Distribution for Topic k:

$$\beta_k \sim \text{Dir}(\delta \ldots \delta),$$

where β_k is a vector representing word probabilities for topic k and δ is the predetermined hyperparameter governing the prior distribution of β_k.

Word Generation for Each Word w in Document i:

$$z_{wn} \sim \text{Multinomial}(\theta_n)$$

where each topic k is selected for each word i based on a multinomial distribution

Topic Assignment for Word w in Document n:

$$w_{wn} \sim \text{Multinomial}(\beta_{zwn})$$

where each word w is given a certain topic k and the word distribution belonging to topic k

LDA is applied to the two subsets of employee review data, referred to as the higher subset, the subset where the phenomenon of decreasing likelihood to recommend an employer with increasing salary occurs, and the range subset, a subset of similar number of observations (8,718 for the higher salary range, 8,835 for the lower salary range) right before the inflection point where likelihood to recommend was still increasing steadily to uncover the latent thematic structures within each subset. Understanding the difference between these two subsets is the key to understanding why the shift in behavior occurs before and after the inflection point. The higher subset contains 8,718 observations, and the range subset contains 8,835 observations. The steps involved in applying LDA are detailed below.

With the data prepared, a corpus is created for each dataset. The corpus was then preprocessed to remove punctuation, convert text to lowercase, remove stop words, strip whitespace, and apply stemming. Additionally, we defined a custom function to remove frequently occurring but uninformative words such as “good,” “great,” and “employee.”

After preprocessing, Document-Term Matrices (DTMs) are created from the cleaned corpora. DTMs represent the frequency of terms (words in the corpus) across documents and are the key for fitting the LDA model. To reduce the dimensionality and focus on more relevant terms, we removed sparse terms from the DTMs, retaining terms that occurred in a sufficient number of documents.

Subsequently, we split the data into training and validation sets. This step involved randomly selecting 80% of the documents for the training set and using the remaining 20% for validation. This split allowed us to train the LDA model and later validate its performance on unseen data. We then proceeded to fit the LDA model using the training data.

Perplexity and Complexity plots help determine the optimal number of topics. The optimal number of topics for each subset was different for each subset, but 10 was determined to be a good compromise. For both subsets, we set the number of topics for both subsets the same at 10 and utilized Gibbs sampling for model estimation in order to make the comparison between the two subsets more appropriate. Perplexity is a measure of how well a probability model predicts a sample. In the context of LDA, lower perplexity indicates better generalization performance of the model, implying that the model is better at predicting new data. Coherence measures the degree of semantic similarity between high-scoring words in the topic. Higher coherence scores indicate topics that are more human-interpretable and semantically meaningful. Below are figures 3.3 to 3.6, showing the Perplexity and Coherence Plots for both Subsets:

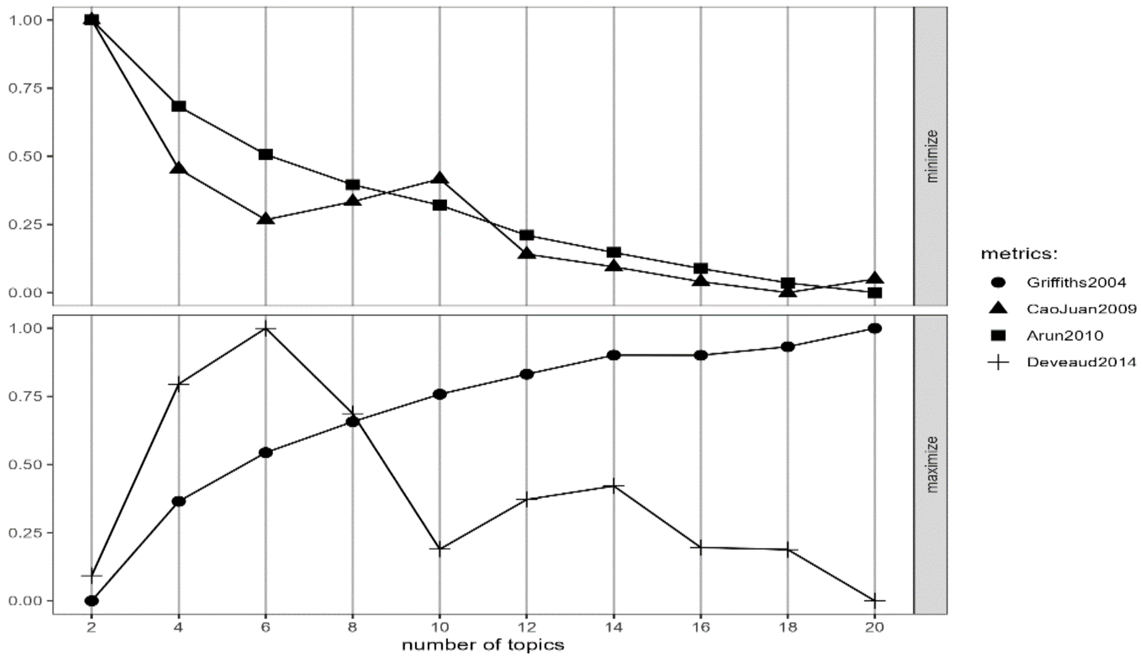

Figure 5.2: Coherence Plot for the Higher Subset

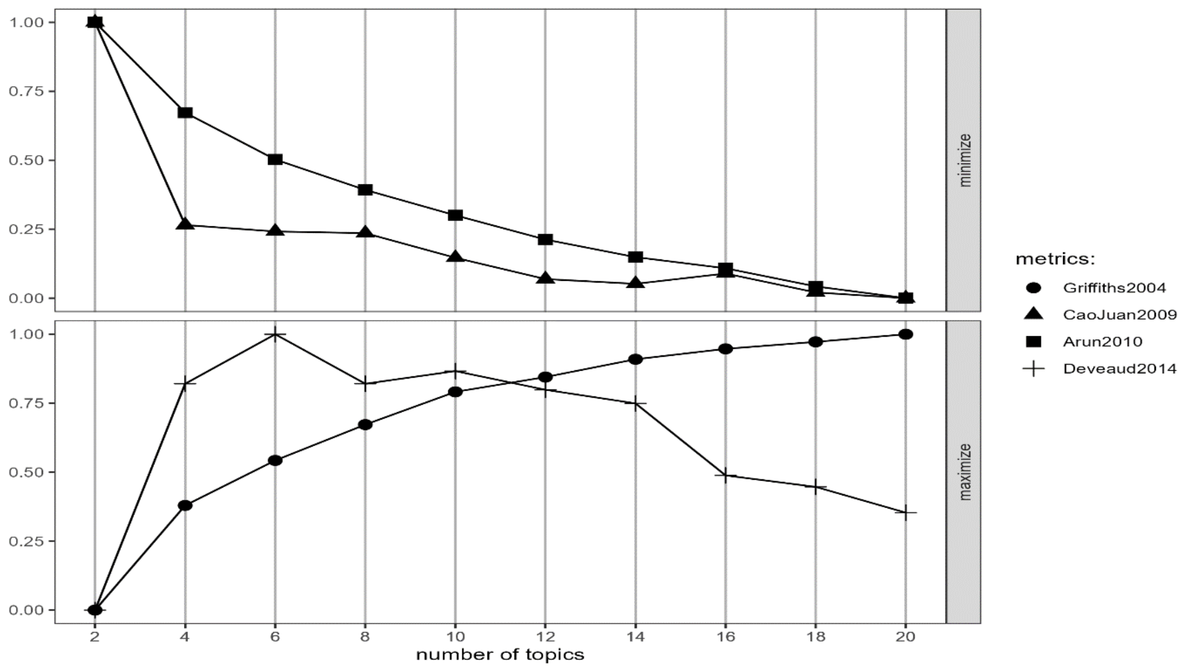

Figure 5.3: Coherence Plot for the Range Subset

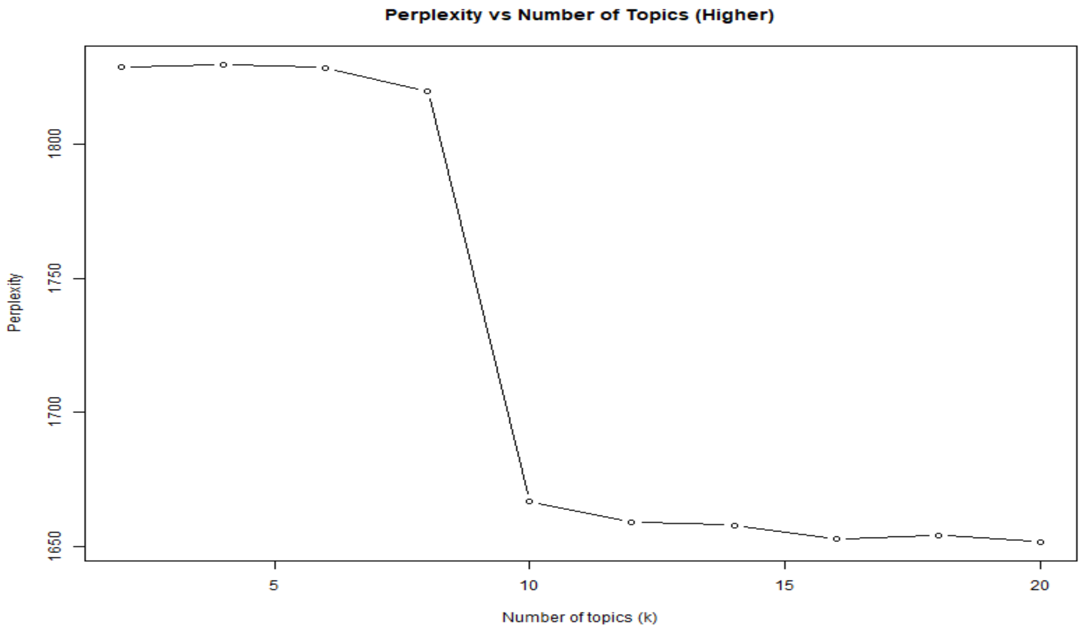

Figure 5.4: Perplexity Plot for the Higher Subset

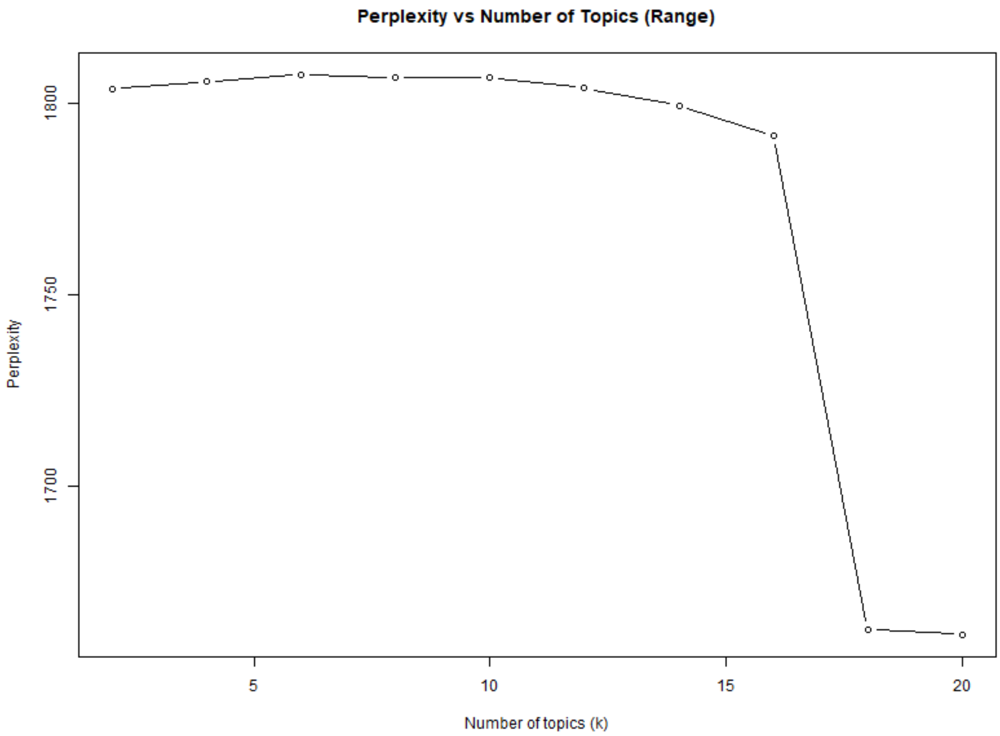

Figure 5.5: Perplexity Plot for the Range Subset

The model parameters included a burn-in period of 200 iterations plus 10 times the number of topics and 700 iterations plus 10 times the number of topics. The alpha and delta hyperparameters were set to 0.1 to control the distribution of topics across documents and words across topics, respectively.

Once the LDA models were fitted, we extracted the top terms for each topic to facilitate interpretation. The detailed results of the LDA analysis are presented in section 4.3.

5.3. Term-Topic Distribution Analysis

Lower Earners Subset

The Lower Earners Subset topics can shed light on why employees are still becoming more satisfied with their employers. Although they are Lower Earners compared to the Higher Earners subset, they are not low earners in absolute terms. They can still be considered comfortable and comparable to the Higher Earners. This subset still experiences rising likelihood of employer recommendations up until the point of inflection and are still relatively high earners. Understanding the differences between the topics discussed between both subsets can shed light on the reasons for the nature of the inverted U-shape relationship. What do employees talk about in this subset that makes them more satisfied than the Higher subset? Figure 5.6 below gives us an overview of the most salient topics and the words that contribute most to each topic.

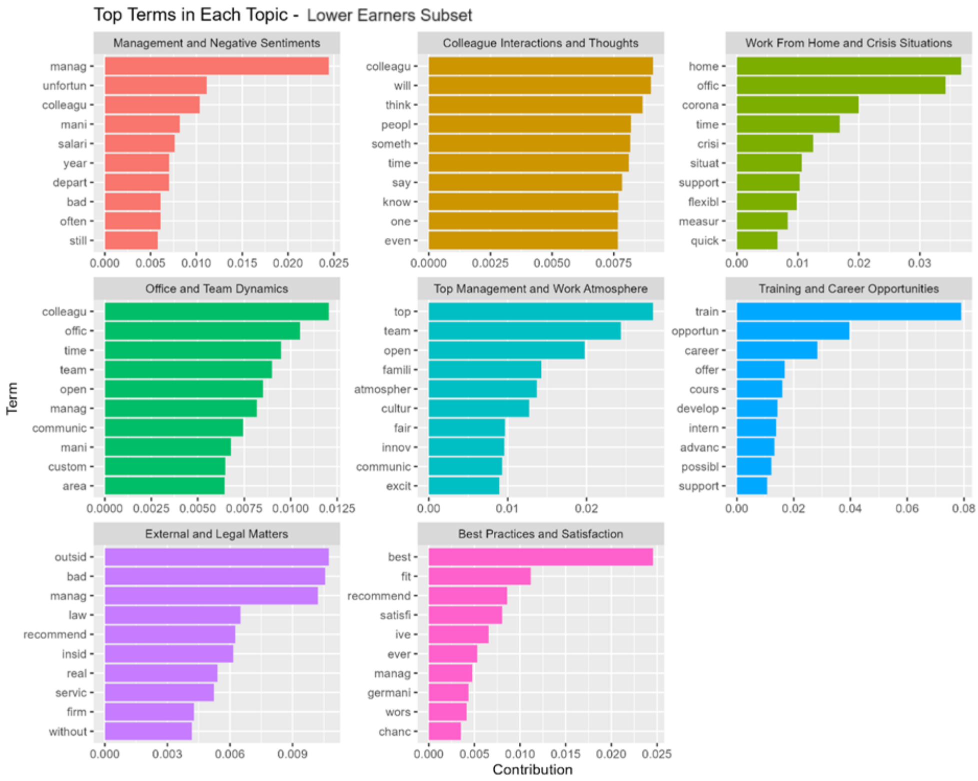

Figure 5.6: Term-Topic Distributions for the Lower Earners Subset

The first topic is mostly about negative sentiments towards management and colleagues. Interpersonal relationships at work are clearly important as they emerge as another topic in a less negative light, this time highlighting thoughts amongst colleagues. As mentioned, the timeframe of our dataset is within the peak of the coronavirus pandemic. Thus, it is no surprise that it would emerge as an important topic given the pandemic's tremendous impact on workers' daily lives. Flexible working conditions, the possibility to work from home, and proper adaptation to times of crisis all emerge as important factors influencing employee satisfaction. Open communication between colleagues and management appears again, and the dimension of time, perhaps hinting towards work-life balance, plays an important role. The work atmosphere and culture from top management are also critical, as are training and advancement opportunities. Bad management can lead to external legal matters and inner conflict within a firm, and feeling a good fit with one's company is important for an employee.

Thus, the key topics emerging from the Lower Earners Subset discuss interactions with colleagues and management, flexibility and appropriate adaptation to change, training and career advancement opportunities, supportive company culture and finding a good fit with one's company culture, and handling of external legal matters and inner conflict. Interestingly, there has been no mention of salary in this subset, possibly indicating that it is not an issue of great concern to reviewers at this point along the salary range.

Higher Earners Subset

Below is the term-topic distribution plot for the Higher Earners subset in Figure 5.7:

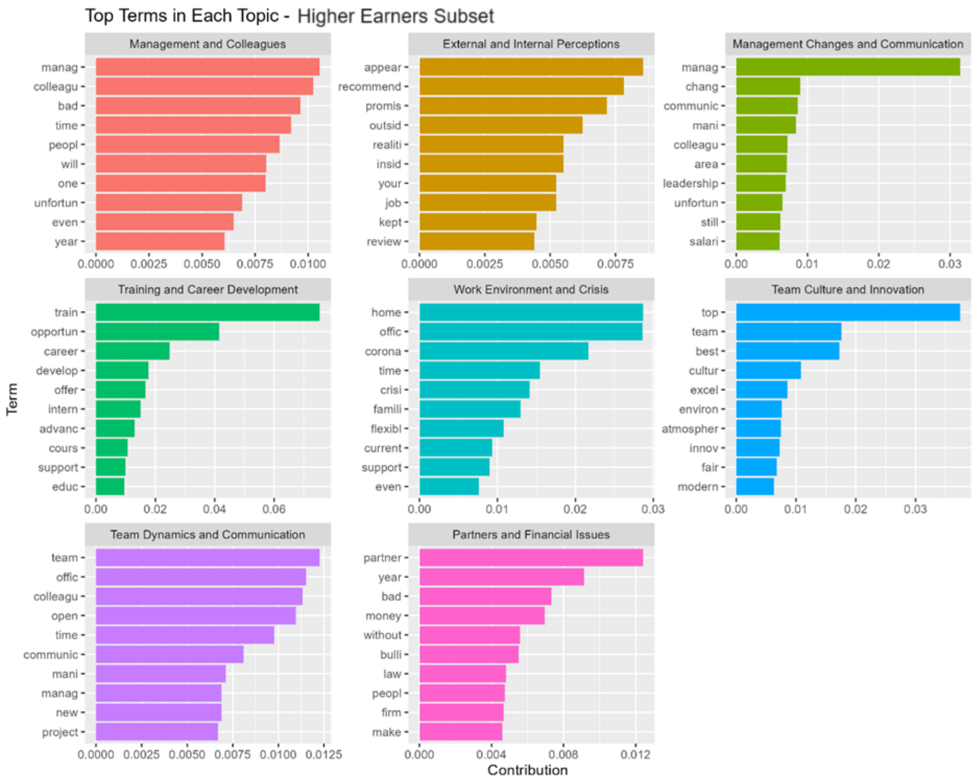

Figure 5.7: Term-Topic Distributions for the Higher Earners Subset

Even in the Higher Earners subset, interactions with management and colleagues are significant in multiple topics. Interactions with top management and leadership seem to be a very salient factor for all employees even at the highest incomes. The importance of a flexible response to crises and the possibility of a home office are also common themes with the Lower Earners subset, as are career advancement and development opportunities. However, in the Higher Earners subset, we see two mentions of financial aspects, with terms like money and salary, that were not present in the Lower Earners subset. Interestingly, money is mentioned only by the higher earners. Another unique topic discusses perceptions. It seems there is a rift between expectations and reality that employees experience at the higher end of the salary scale.

Comparison of the Lower Earners and Higher Earners Topics

While both subsets have overlapping topics and similar terms, one key difference can be noticed. Money and salary are not mentioned once in the Lower Earners subset, while it is in the Higher Earners subset. Interestingly, the subset that earns more is more concerned with money than the one that earns less. We can learn a lot from the absence of a term, not just from its presence. Despite earning more, the Higher Earners subset is more concerned with money than the Lower Earners subset. Another difference is the topic regarding a rift between expectations and reality in the Higher Subset, not seen in the Range subset.

6. Conclusion

6.1. Discussion

This section answers our research sub-questions individually before coming to an overall conclusion. Regarding the first research sub-question:

Is the relationship between income and the likelihood of giving a positive recommendation best modeled as a linear or curvilinear relationship?

The relationship between salary and the likelihood of recommending an employer, and by extension of job satisfaction, is best modeled as a curvilinear, inverted U-shaped relationship rather than a linear relationship, where the likelihood to recommend an employer, and by extension satisfaction with one’s job, rises steadily at lower income levels, before reaching a plateau and then starting to decrease beyond an inflection point. This is in line with past studies that have found a curvilinear relationship (Kahneman & Deaton, 2010; Diener & Biswas-Diener, 2001) and decreasing pay satisfaction (Parker & Brummel, 2016) after a certain point on the salary scale.

Is income a stronger predictor of job satisfaction relative to the other predictors?

Based on the regression analyses and the Random Forest Variable Importance plots, it is clear that while income is a significant predictor of the likelihood of recommending an employer, it is not the strongest predictor. The inclusion of the Total Score variable drastically improves the model fit, as evidenced by the much higher McFadden's R^2 and lower BIC values. When included, the Total Score, the aggregate of the overall facets of job satisfaction, has a much larger coefficient than income, indicating that it is a far more powerful predictor of whether an employee would recommend their employer. While the log of salary and its square are significant predictors in both models, it is that clear being satisfied with the other aspects of one’s work are a much more powerful predictor of likelihood to recommend employer rather than salary. The Variable Importance Plots further confirms this finding, and the Total Score appears as the single most influential variable by far. We can conclude satisfied with the overall factors of one’s work is more important than the amount of money one makes in predicting likelihood to recommend an employer, as evidenced by the relative power of the Total Score variable as a predictor in comparison to the Salary variable. This is in line with previous findings (Diener & Biswas-Diener, 2001) that higher income does not significantly enhance SWB for middle-class or upper-class individuals in wealthy nations such as Germany, and with Roelen at al. (2008) that the primary determinants of job satisfaction are not monetary, as evidenced by the dominance of the Total Score variable. The fact that the higher earners are less satisfied with their pay than lower earners confirm the findings that people even begin reporting decreasing pay satisfaction above certain income levels (Parker & Brummel, 2016).

What topics are discussed before and after the point of inflection, and how are they different?

This study confirms Jung and Suh’s (2019) findings of similar key factors that are most influential to job satisfaction, including organizational culture, self-development, and senior management. The prominence of management and interpersonal issues and the gap between promised and actual experiences align with Proto and Rustichini's (2013) notion that increasing income can raise expectations and aspirations, leading to dissatisfaction if these are unmet. Since both subsets are relatively high earners, and money is only mentioned in the higher subset, we confirm Kahneman et al. (2006) that more income does not necessarily lead to greater happiness but, in fact, might bring more tension and stress.

It appears that after an individual’s needs are comfortably met, the importance of an overall good working environment rises in importance. It might be best for a higher-earning individual to focus on finding an overall well-balanced workplace with good management and colleagues rather than continuously striving to rise on the salary scale without considering the other overall factors. However, this may not apply to individuals who are earning less than the point of inflection, and earning more may, in fact, lead to higher job satisfaction for said individuals. For companies striving to keep their employees satisfied, it is best to ensure the quality of management capable of empathetic communication and flexible adaptation to crises, having a supportive work environment that fosters good relations between colleagues, and provide employees with ample advancement and development opportunities, even at the highest salary ranges. It is important to manage employee’s expectations, and ensure there is not a great discrepancy between their expectations and the reality they face.

6.2. Implications

In conclusion, beyond a certain salary point and after one’s basic needs are met, continuing to pursue financial outcomes appears to lead to lower job satisfaction, and they would be better advised to prioritize more fulfilling work and supportive work environments rather than more income, as the increased job pressures might not be worth it in terms of improving the overall quality of their lives unless they are relatively lower earners. For companies seeking to enhance their employee's satisfaction, focusing solely on compensation is likely not the most effective course of action. Providing employees with flexible working conditions, a supportive work environment with ample development opportunities, and hiring empathetic management-level executives skilled at communication and capable of adapting adequately to new challenges would be a better investment than simply increasing their employee's salaries. This supports past findings that improving supervisor competency can significantly enhance employee satisfaction (Jung & Suh, 2019). Finally, we confirm that once a person reaches a comfortable income and their needs are met, the pursuit of material goals can hinder happiness (Diener & Biswas-Diener, 2001).

6.3. Limitations

It is important to note some of the limitations of this study and what further research can do to improve upon them. First, this study is performed on a German dataset, and thus, the external validity might not hold in other contexts or labor markets. Further, the timeframe of the reviews analyzed occurred during the peak of the coronavirus pandemic, and the findings might be skewed due to the profound impact it had on worker's lives. Employer reviews likely suffer from selection bias, and there is a higher tendency for people with extreme opinions to leave a review than people with moderate opinions (Marinescu et al., 2021). This leads to a self-selection bias, where the opinions of people who do not respond are not represented and might be significantly different than those who decide to leave a review. Future studies can employ the Heckman correction model, which can be useful in addressing self-selection bias in review data, particularly when reviews are clustered around extreme ratings, by adjusting for the over-representation of users with strong opinions and providing a more accurate estimate of overall satisfaction (Heckman, 1979). The relationship between happiness and success is not straightforward. Lyubomirsky et al. (2005) argue that happiness is not just a consequence of success but also a precursor to it and suggest that frequent positive affect contributes to success in various life domains, including work, health, and relationships. In fact, others have found that life satisfaction is shown to influence job satisfaction more strongly than the reverse (Białowolski & Węziak-Białowolska, 2020).

The nature of the dataset leads to some further inherent limitations. Responses are taken at a certain point in time, and do not follow the same individuals over the course of the progression of their career. It contains no demographic controls such as the age, educational background, or SWB levels of respondents. Such controls could have provided meaningful insights. The analysis of text data also carries some limitations that are difficult to correct for. The use of irony or sarcasm is not accounted for, and this might skew the ensuing topics. People often make spelling mistakes, and these mistakes might go through the data cleaning process undetected, and going through reviews to correct them would be too time consuming. This might lead to the loss of valuable observations or insights. Finally, the LDA models in this study only cover single word tokens, it would be interesting for future research to uncover what deeper insights might be gained by employing n-gram tokenization. LDA is useful in comparing two subsets due to its high interpretability, clear word-topic assignments, and standardized topic probabilities, but more complex approaches could also give meaningful insights. BERTopic could add contextual meaning to the text reviews. CorEx could help uncover hidden correlations between words that are not immediately obvious, and Non-negative Matrix Factorization (NMF) can offer more distinct topic separations.

Further, some decisions were made that affected the results of the data. The same number of topics was chosen for each subset for the topic analysis to keep the same level of granularity. However, one subset would have more coherent topics with a larger number of topics. The split of the subsets into the Higher Earners and the Lower Earners subset makes sense to get an overall view of how the topics these two subsets discuss differ, but a deeper look might provide even more valuable insights for future research. Namely, to look into both the positive and negative reviews in each subset, therefore building four topic models instead of the two built by this study. Finally, the Topic Analysis might benefit from differentiating between current and former employees, and building separate models for each and analyzing them separately might lead to interesting insights for future studies.

7. Appendix

Table 6.1: T-test of difference of means between Germany and other Countries

Comparison	t-Statistic	Degrees of Freedom	p-Value	95% Confidence Interval	Mean of Country A	Mean of Country B
Germany vs. Austria	30.348	57,946	0.00	[3658.00, 4163.12]	48,377.73	44,467.16
Germany vs. Switzerland	-152.95	22,612	0.00	[-38297.46, -37328.30]	48,377.73	86,190.61

Table 6.2: Re-Operationalization of the Department variable

Combined Category	Percentage	Included Departments
Admin and Support	19.77%	ADMIN (8.16%), BUYING (1.47%), DESIGN (1.40%), FINANCE (2.72%), HR (3.24%), LAW (1.04%), PR (0.81%), MANAGING (0.93%)
Technical	13.81%	IT (9.76%), RD (4.05%)
Operational	14.61%	ASSEMBLY (10.08%), WAREHOUSE (4.53%)
Sales and Marketing	22.45%	SALES (19.28%), MARKETING (3.17%)
Other	29.37%	MISS (29.37%)

Table 6.3: VIF Scores for Regression Models

Variable	VIF Model 1	VIF Model 2
log_salary_scaled	1.354	1.338
I(log_salary_scaled^2)	1.132	1.133
total_score_scaled	1.548	-
I(total_score_scaled^2)	1.5	-
user_genderDIVERSE	1.005	1.006
user_genderFEMALE	1.2	1.209
user_genderWONT_TELL	1.072	1.069
job_position_reopmanagement	1.095	1.108
job_position_reopother	1.027	1.069
department_reopOperational	1.803	1.719

department_reopOther	1.91	1.862
department_reopSales and Marketing	1.801	1.755
department_reopTechnical	1.777	1.703
day_typeWeekend	1.006	1.004
job_statusMISC_MISS	1.014	1.039
job_statusREVIEW_STATUS_EX	1.019	1.023
industry_cleanedBusiness	1.415	1.403
industry_cleanedEducation	1.076	1.071
industry_cleanedEngineering	1.252	1.223
industry_cleanedHigh-Tec	1.526	1.503
industry_cleanedLegal and Public & Health	1.335	1.32
industry_cleanedManufacturing	1.613	1.544
industry_cleanedOthers	1.307	1.276

Table 6.4: Correlation Matrix for Rec, Total Score, and Salary

Variable Name	rec	total_score	salary_amount
rec	1.000		
total_score	0.867	1.000	
salary_amount	0.236	0.274	1.000

Table 6.5: Correlation Matrix for rec, corporate culture, diversity, work environment, career and salary, and salary amount

Variable Name	rec	corporate_culture	diversity	work_environment	career_and_salary	salary_amount
rec	1.000					
corporate_culture	0.861	1.000				
diversity	0.766	0.869	1.000			
work_environment	0.798	0.889	0.820	1.000		
career_and_salary	0.831	0.904	0.820	0.869	1.000	
salary_amount	0.236	0.261	0.232	0.251	0.290	1.000

Table 6.6: Descriptive Statistics for Numeric Variables

Variable Name	Obs.	Mean	S.D.	Min	1st Qu.	Median	3rd Qu.	Max
rec	276,368	0.587	0.492	0	0	1	1	1
salary_amount	276,368	50,603	26,760	19,188	32,400	43,200	60,000	200,000
total_score	276,368	3.411	1.283	1	2.231	3.769	4.538	5
corporate_culture	276,368	3.413	1.305	1	2.167	3.833	4.667	5
diversity	276,368	3.701	1.389	1	2.5	4	5	5
work_environment	276,368	3.403	1.381	1	2	4	4.5	5
career_and_salary	276,368	3.218	1.363	1	2	3.333	4.333	5

Table 6.7: Distribution of Categorical Variables

Variable Name	Category	Frequency
user_gender	MALE	115,651
user_gender	DIVERSE	1,359
user_gender	FEMALE	56,140
user_gender	WONT_TELL	20,308
job_position_reop	Employee	155,462
job_position_reop	management	29,375
job_position_reop	other	8,621
department_reop	Admin and Support	38,568
department_reop	Operational	27,751
department_reop	Other	55,972
department_reop	Sales and Marketing	43,429
department_reop	Technical	27,738
day_type	Weekday	166,461
day_type	Weekend	26,997
job_status	REVIEW_STATUS_CURRENT	149,969
job_status	MISC_MISS	829
job_status	REVIEW_STATUS_EX	42,660
industry_cleaned	Goods and Services	46,130
industry_cleaned	Business	30,141
industry_cleaned	Education	3,607
industry_cleaned	Engineering	12,612
industry_cleaned	High-Tec	27,688
industry_cleaned	Legal and Public & Health	17,468
industry_cleaned	Manufacturing	37,455
industry_cleaned	Others	18,357

Table 6.8: Description of Variables

Variable Name	Description	Variable Type	Levels
rec	Whether employee recommends employer or not	Binary	0 = Not Recommended, 1 = Recommended
log_salary_scaled	Log-transformed and scaled salary amount	Continuous	-
I(log_salary_scaled^2)	Squared term of log-transformed and scaled salary amount	Continuous	-
total_score_scaled	Scaled total score	Continuous	-
I(total_score_scaled^2)	Squared term of scaled total score	Continuous	-
user_gender	Gender of the user	Categorical	MALE, FEMALE, DIVERSE, WONT_TELL
job_position_reop	Job position of the respondent	Categorical	employee, management, other
department_reop	Department of the respondent	Categorical	Admin and Support, Operational, Other, Sales and Marketing, Technical
day_type	Type of day	Categorical	Weekday, Weekend
job_status	Job status of the respondent	Categorical	REVIEW_STATUS_CURRENT, MISC_MISS, REVIEW_STATUS_EX

industry_cleaned	Industry classification of the respondent	Categorical	Goods and Services, Business, Education, Engineering, High-Tec, Legal and Public & Health, Manufacturing, Others

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