The Gender Pay Gap in Executive Compensation in China

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Table of Contents

1 Introduction

Throughout the past decades, many efforts have been made to narrow down the gender pay gap in China. In the 1990s, the enforcement of the "Law of the People's Republic of China on the Protection of Women's Rights and Interests" guaranteed equal rights for women in the field of politics, education, work, ownership of property, as well as personal rights and rights of marriage and family (Dasgupta et al). More recently, last year the Ministry of Human Resources and Social Security of the People's Republic of China enforced new regulations on recruitment practices to further promote women's labor force participation rate, fining companies up to $7400 if they ever posted gender discriminated recruitment information.

Quantifying the effects of efforts made to shrink the gender pay gap, in 2019, 43.7 % of the workforce in China were women. In urban areas, on average women earned a monthly wage of 6,995 yuan (about 1,009 U.S. dollars), up 7.7 percent year on year (Xinhuanet). This improvement, asides from the political and social influences, has also been attributed to the change of women themselves. Throughout the years we have observed a drastic increase in women's education level, work capabilities and the desire to advance their professional career by diving into STEM jobs, which on average pay 25-33% higher than non-STEM positions (BOSS).

Nevertheless, despite the narrowing gaps, gender disparities in the workplace still exist. In particular, women often reach an invisible "glass ceiling" as they climb up the corporate ladder. The result of the "glass ceiling" is that women are underrepresented in executive-level jobs even though their professional capabilities are comparable or even better than men's. In 2019, only 25.4 percent of executive-level positions in Chinese enterprises were taken by women despite the fact that women accounted for 49.6 percent of graduate students and 52.5 percent of full-time college students (Xinhuanet). This drastic difference signals a disheartening but unavoidable fact that women on average receive less return for the investments they have made, both financially and mentally. A more poignant fact is that gender inequality in the workplace has been present for such a long time that even some of the women themselves have the mindset that women are inferior to men in terms of professional capabilities. In the "2020 Report on the Current Situation of Chinese Women in the Workplace" published by Zhaopin, data shows that 32.59% of the female respondents prefer to work with a male executive while only 6.92% of them prefer to work with a female executive.

2 Literature Review

What factors then have hindered women's opportunity to achieve equal pay? A lot of researchers tried to answer this question. Initially, the human capital theory, developed by Becker and Mincer, was prevalent in the research field. The theory suggests that women had less schooling and work experience than men, and therefore resulted in the gender pay gap. But as more and more women became educated and participated in the labor force, the human capital theory alone is insufficient to account for the factors involved in the gender pay gap.

Later on, as researchers continued to examine, critique and build upon existing literature, the gender pay gap has become a multi-faceted issue including factors covering demographics, economic, social, political and psychological influences. In specific, American scholars Blau and Kahn categorized these factors into traditional and new in the article *The gender wage gap: Extent, trends, and explanations*. Traditional factors include labor force participation, selection bias, education and mathematics test scores, labor force experience and work hours, formal training and turnover, motherhood, occupations, industries and firms and labor market discrimination. In this list of factors, we can observe that although women and men have almost reached equilibrium on a majority of the factors such as education, labor force experience and participation, motherhood and selection bias still present issues in narrowing down the gender pay gap because of the fixation in completely reverting the scene. Difficulties associated with motherhood, for example, will not be resolved in the near future unless women spend significantly less time taking care of the children or men decide to take much more parenthood responsibilities.

Another thing we notice from this list is the last factor about discrimination, which is special because it is often associated with cognitive recognition that makes it harder to measure compared to other factors. One theory trying to explain the rationale of the discrimination is social identity theory, which suggests that people have a tendency to evaluate the competencies of in-group members more positively than those of out-group members (Tajfel 1982; Tajfel and

Turner 1979; Hogg and Terry 2000). Gender, in this case, is one of the perceived attributes of in-group favoritism and thus male directors evaluate male executives more favorably than female executives, resulting in a higher gender pay gap at the executive level (Shin 2012).

Traditional variables, however, do not capture the whole picture. There is almost always a considerable portion of unexplained variances to which traditional variables alone cannot be fully attributed (Blau and Kahn 2017). Therefore, researchers have been trying to switch gears and explore other alternatives of explanations. What they found out was that these new factors were often associated with social norms, psychological attributes and noncognitive skills. In specific, the differences in the average propensity to negotiate, the willingness to compete, the preference of risk appetite, gender stereotypes have all affected wage inequality. As such, it is worth noting that these dividing social norms have accelerated the gender segregation of occupation (Tharenou 2012). Using real-life examples, in 2018, mining jobs, which are commonly thought of as a man-only position, topped the chart of the industry-wide gender pay gap. Meanwhile, the education industry, which is often associated with words such as "caring", "kind", "children", is among the lowest on the chart because women have more career opportunities in this industry (BOSS).

The list of factors may never be exhaustive, and the gender pay gap is thus a challenging task to conquer both in real life and in research. Therefore, in our research paper, we have decided to examine this issue in a more targeted approach using the compensation data for only executives. The reasons are as follows. The group of executives tends to be much more homogeneous than the entire labor force because people in senior management often share similar social, political and financial backgrounds. Additionally, it is worth pointing out that the gender pay gap declined much more slowly at the top of the wage distribution (Blau and Kahn 2017). Last but not least, the concept of "trickle-down effect" suggests that all members of society benefit from growth, and that growth is most likely to come from those with the better resources and skills (Investopedia). A significant improvement or even elimination of the gender pay gap among women executives, who have above average resources and skills, will certainly trigger more compassion, courage, strength and confidence leading to advocacy events that help fellow women.

As mentioned above, there has been a wide range of literature on factors influencing biased executive compensation. However, not much research has been focused on how the gender pay gap is different between one city and another. Social culture and political background vary across different cities, and therefore ultimately lead to different policies or corporate characteristics that may have or have not increased the gender pay gap. In this paper, we investigate how the gender pay gap varies between Shanghai and Beijing, the top two mega-cities in China. Both cities are top tier cities in the global market, yet each has distinctive characteristics - one known as the commercial hub and another one as the political center of China.

According to the Wall Street Journal, Shanghai, a city with higher economic development and urbanization brought by its favorable coastal location, was rated as the most liberal city in the country by researchers at MIT in 2015. The city government itself also provides beneficial policies for start-ups to land in the city. In 2016, the Shanghai government started compensating venture capital firms for losses incurred in the early stage as a way to incentivize more tech startups (Technode). This move has opened up a more vibrant market for job seekers and entrepreneurs. According to government data, 55% of new internet companies in China are founded by women (World Economic Forum). Therefore, taking the beneficial policies targeting Shanghai's startups into consideration, it is believed that women can find more equal opportunities in Shanghai than in other conservative cities. On the other hand, Beijing, the country's political and cultural center, has the largest tertiary sector, also known as the service sector, the proportion of GDP among all cities in China. Traditionally, people would perceive Beijing as a more conservative city than Shanghai as it shoulders more political responsibility.

Another aspect we believe that is interesting to investigate is how the gender wage gap is different in tech and non-tech industries. The characteristics of tech occupations provide more flexibility for people to work since it has less client-facing work, and thus less rigid on when and where to get the job done (Goldin 2014). These features allow women in tech professions to get paid in proportion to the hour they work and help to better eliminate unfair pay. Additionally, from the aforementioned data, we can notice that a major portion of IT startups entrepreneurs includes women, which potentially leads to a smaller gender wage gap in that industry.

2.1 Research Hypotheses

Based on our literature review, it is evident that the gender pay gap is a pressing issue in China despite the various efforts made to narrow down the gap. Previous studies also suggest that situations such as in-group favoritism and "glass ceiling" result in a larger gender pay gap in senior management level, indicating that female executives face more gender pay inequality than female employees with more junior-level roles. Thus, based on this background, we develop our Hypothesis 1.

H1: In China, on average female executives earn less than male executives in public traded companies.

Moreover, previous research has shown that Shanghai is a more liberal city than Beijing. Benefiting from its location and policies, the city gains more competence globally and thus able to provide more career opportunities. Meanwhile, Shanghai has a much more inclusive culture because of its active role in the global market. Therefore, we develop our second hypothesis as follows.

H2: In China, on average Beijing executives have a larger gender gap than Shanghai executives in public traded companies.

Last but not the least, As Claudia Goldin previously stated in her research, the gender gap in the IT industry is significantly smaller than other professions. However, such research only has been done on the U.S market. Given the fact that the Chinese tech industry has been booming, our last hypothesis is to study the current difference of gender pay gap in IT and non-IT industry in China.

H3: In China, on average IT industry executives have a smaller gender gap than Non IT industry executives in public traded companies.

3 Data

The data was originally collected from China Stock Market & Accounting Research (CSMAR) Database. Our sample includes domestic A-share publicly listed firms and A shares in either on or both of the Shenzhen and Shanghai stock markets over the period of 2005 to 2020. Observations with missing values are excluded.

Align with these executives' salary, we have also included other variables including their *Age, Sex,* company's *Total Assets, Return on Asset growth, Net Margin, Operating Growth, Return on Asset, Return on Investment, Return on net asset, Margin Growth, Operating Margin, Year, City* and *Industry*. Before we do the following analysis, we conducted basic data cleaning as below:

1. **Log**: After we have completed the data cleaning steps, we did logarithmic transformation to two variables: company's *Total Asset* and manager's *Salary* because these two variables are not normally distributed and taking logarithm transformation to them will make data more normalized. Since we want to do linear regressions for the following analysis, doing such a transformation will improve the fit of the model with less prediction error.

2. **Fixed Effect:** Our data is panel data that ranges across different years, therefore we conducted a fixed effect which is we minus the original data with the mean value of that industry in that year to control for the influences of different industries and different years.

3. **Scale:** We include a number of variables in the regression in order to cover different aspects of potential factors and increase predicting power. However, different factors have different numerical scales. For example, *Total Asset* are usually measured in million, but *Return on Asset* and other ratios are measured in percent. Therefore, we decide to standardize all of the numerical variables before conducting regression. By regressing on standardized variables, we could better assess on how each independent variable contributes to the effect on the dependent variable.

4. **PCA:** We use a list of ratios, which measure companies' performances, to assess the effect of companies' performances on executives' compensations. To avoid collinearity but retain sufficient predicting power at the same time, we decide to conduct principal components transformation on these ratios. As mentioned above, we would like to standardize all of the numerical variables, so we derive the principal components based on the correlation matrix of the ratio variables. From Table 8, we could see the weights and loadings of the principal components. According to the loadings, we decide to name the first component as "*Return on Asset*", the second component as "*Operating Efficiency*", the third component as "*Growth Potential*", and the last component as "*Return on Investment*". The cumulative variance explained by four principal components reaches 64.2%. Therefore, we confirm that four principal components are sufficient to summarise ratio variables.

3.1 Descriptive Statistics

Table 1 demonstrates the variables which we use in our regression analysis. *Salary* is the dependent variable. Our major focus is to test for gender pay gap, therefore *Sex* is the primary independent variable. We also include some control variables. Variable *Age* is to control for executives' ages and experiences. Variable *Total Asset* is to control for companies' sizes. Variables *Return on Asset, Return on Investment, Growth Potential, Operating Efficiency* are all to control for companies' performances. Variables *City, Year, Industry* are to control for location, date, industry respectively. We also have two specific variables. Variable *BJSH* is to control for city of Beijing and city of Shanghai. Variable *IT* is to control for Technology industry. For more details, please see Table 1.

Table 2 presents the descriptive statistics for the whole sample, male subgroup and female subgroup. By briefly observing the table, we find that the sample size of male, 195,803 observations, is much larger than that of female, 36778 observations. Additionally, when we compare the means of the variables between two groups, we find that some means are significantly different between two groups, such as *Age, Salary and Total Asset.* To prove our estimation, we conduct t-tests among every pair of the variables. The results show that the means of *Salary, Age, Total Asset, and Operating Efficiency* are significantly different between male and female. The significant difference in average salary drives us to check the validity of the t-test in regression analysis.

Table 3 and 4 includes the descriptive statistics for Beijing and Shanghai cities. In table 3, there are 7693 Beijing people in total, in which 6951 of them are male, 1102 of them are female. The number of male executives takes up 90% of the whole Beijing dataset. From table 3 we can see that the mean of almost every variable in men's dataset greatly surpasses each corresponding variable in women's dataset. Moreover, by conducting t-tests, we can also see that these gaps are all statistically different. Also, by comparing women's columns with the whole Beijing dataset, almost every variable is greatly below the mean level of the whole city. For *Salary*, men's salary is 3.66 times women's on average. The difference between men and women in Beijing is also significant in *Age*, *Total Asset*, *Return on Assessment*, *Return on Investment*, and *Operating Efficiency*. From table 4, we can see that there are 8690 Shanghai people in total. 7280 of them are male and 1410 of them are female. The number of male executives takes up 83.78% of the whole Shanghai dataset. Comparing with Beijing, although it is not significant, sex distribution is more even in Shanghai. For salary, women's mean level of salary is 27.33% of men's mean salary and is 30.5% of the whole city's mean salary. By conducting t-tests, we find out that the difference between men's salary and women's salary is also significant. Similar to Beijing, every aspect of women's data in this dataset is lower than men's, including *Age, Total Asset, Return on Asset, Return on Investment, Operating Efficiency*, and *Growth Potential.* The difference between men's and women's mean value is also significant in *Age, Operating Efficiency, Growth Potential,* and *Return on Assessment.* Overall, from these two tables, we could initially prove our hypothesis 2 that the gender gap of Beijing is slightly bigger than Shanghai, and we will further discuss this hypothesis using regression analysis.

In Table 5, we extract all IT industry people and divide them into male and female subsets. There are 13268 people in the IT industry in total: 10,817 of them are male and 2,451 of them are female. Male executives take up 82% of the IT industry and female executives take up 18% of it. Focusing on *Salary*, we could see the same pattern for the IT industry: the mean salary of women is way below the mean salary of men, and a p-value of almost zero means that the difference between the two samples' mean salary is quite significant. With a higher standard deviation, men's salary is more spread out than women's. Also, both the lower bound and upper bound of women's salary is below men's. Finally, comparing the other variables, all variables in the women subset are below men's except for *Growth Potential* and *Return on Investment.* The t-test shows that the difference between men's and women's mean value in IT subset is also significant in *Age*, *Total Asset*, and *Operating Efficiency*.

Table 6 presents the correlation matrix of the numerical variables (all of them are already standardized). From the table, we can see that *Salary* is positively correlated with *Total Asset* to a relatively strong degree. It suggests that an increase in the total assets of the companies might increase the salaries of the executives. The correlation between *Age* and *Salary* is negative, indicating that older executives might receive lower salaries than younger executives do. The correlations between the principal components and *Salary* are positive, except for *Return on Investment (ROI)*, which shows a slightly negative correlation with *Salary*. Moreover, the independent variables are not significantly correlated with each other. This satisfies the requirement of non-collinearity among independent variables.

4.1.1 Model 1

Our primary focus of the study is to test whether on average female CEOs earn less than male CEOs in China. To test this theory, we built our first linear regression model with the salary as the dependent variable, dummy variables - *Sex, Industry, Date, City,* and numerical variables - Ag*e, Total Asset, Return on Asset, Return on Investment, Growth Potential, Operating Efficiency* as the independent variables. We are only interested in investigating the effect of gender on salary, and therefore we chose to control for the effects of other independent variables on *Salary*.

4.1.2 Regression analysis

$$Salary = \beta_0 + \beta_1 \times Sex + \beta_2 \times Age + \beta_3 \times Total\ Asset + \beta_4 \times Return\ on\ asset + \beta_5 \times Operating\ Efficiency + \beta_6 \times Growth\ Potential + \beta_7 \times Return\ on\ investment + \beta_8 \times Industry + \beta_9 \times Year + \beta_{10} \times City$$

We present the details of the regression coefficients in the first column of Table 7. Given the fact that coefficient of *Sex* 1 is 0.227 and *Sex* is a significant predictor, we conclude that when we control for other variables and hold all numerical variables constant, male (*Sex*=1) would earn 0.227 more units of *Salary* than female (*Sex*=0). Moreover, because we ran the regression based on standardized data, we can estimate the contribution of each independent variable to the dependent variable. We find that *Sex* influences *Salary* in a relatively strong way, suggesting that gender is still an important factor for companies to consider when they offer salaries. For control variables, *Total Asset, Return on asset, Operating Efficiency* and *Growth Potential* display positively statistical correlations with *Salary*. *Return on Investment* and *Age* show negative statistical correlations with *Salary*. Because *Industry, Year, City* are categorical variables, they have different correlations with *Salary* according to the different categories respectively.

4.2.1 Model 2

For this section, we want to dig deeper into the data. Therefore, we choose Shanghai and Beijing as two main cities we want to further investigate: we want to test our hypothesis: In China, on average Beijing executives have a larger gender gap than Shanghai Executives in public traded companies. To test this hypothesis, we first built a subset of data of companies based in Beijing and Shanghai and created a new dummy variable named *BJSH*: Beijing was coded as 1 and Shanghai was coded as 0. We built a linear regression model with *Salary* as the dependent variable, *Sex* and *BJSH* as the independent variable. Meanwhile, we control for *Return on Assessment, Return on Investment, Growth Potential, Total asset, Operating Efficiency* and *Age.* Furthermore, we added an interaction term between city and sex to find out the relationship between these two variables.

4.2.2 Regression analysis

$$\begin{aligned} Salary = \; & \beta_0 + \beta_1 \times Sex + \beta_2 \times BJSH + \beta_3 \times Sex{:}BJSH + \beta_4 \times Age + \beta_5 \times Total\ Asset \\ & + \beta_6 \times Return\ on\ Asset + \beta_7 \times Operating\ Efficienct + \beta_8 \times Growth\ Potential \end{aligned}$$

We will explain the coefficient meaning and our test result in Table 7 here. As the coefficient of *Sex* 1 is 0.081, it means that holding other variables constant, male (*Sex* = 1) will earn 0.081 units more salary than female (*Sex* = 0). The coefficient of *BJSH* is -0.195, which means that holding everything else constant, Beijing people (*BJSH* = 1) will earn 0.195 unit less salary than

Shanghai People. One unit increase of age will result in 0.168 units of decrease in salary, holding everything else constant. For control variables: *Age* has a significant negative effect on salary; *Total Asset* has a significant positive effect on salary; *Return on Asset* has a significant positive effect on salary; *Operating Efficiency* has a significant positive effect on salary; *Return on Investment* has a significant negative effect on salary; *Growth Potential* has a non significant negative effect on salary. Since the interaction term has a positive coefficient, we can interpret that adding *BJSH* intensified the gender gap. We could also see this result from below analysis:

- Shanghai Female (BJSH = 0, Sex = 0): Salary = 0.196 + 0.081*0 -0.195*0 + 0.099*0*0 = 0.196
- Beijing Female (BJSH = 1, Sex = 0): Salary = 0.196 + 0.081*0 -0.195*1 + 0.099*0*1 = 0.196 - 0.195
- Shanghai Male (BJSH = 0, Sex = 1): Salary = 0.196 + 0.081*1 -0.195*0 + 0.099*1*0 = 0.196 + 0.081
- Beijing Male (BJSH = 1, Sex = 1): Salary = 0.196 + 0.081*1 -0.195*1 + 0.099*1*1 = 0.196 + 0.081 - 0.195 + 0.099

Therefore, compared with the baseline, Shanghai Female, Beijing Female is 0.195 unit below; Shanghai Male is 0.081 units above; Beijing Male is 0.015 units below. The gap between Beijing male and female is 0.18 units, and the Shanghai male and female gap is 0.081. **Overall, we proved our hypothesis that Beijing executives have a larger gender gap than Shanghai executives in Chinese public companies.**

4.3.1 Model 3

In this section, we chose the IT industry as our primary investigation object. We want to test our hypothesis 3: In China, on average IT industry executives have a smaller gender gap than Non IT industry executives in public traded companies. We coded a new dummy variable as IT: IT industry as 1, non-IT industry as 0. We built a linear regression model using the whole dataset with *Salary* as the dependent variable, *Sex* and *IT* as the independent variable. We also controlled for *Return on Assessment, Return on Investment, Growth Potential, Total Asset, Operating Efficiency* and *Age.* Furthermore, we added an interaction term between industry and sex to find out the relationship between these two variables.

4.3.2 Regression Analysis

$$Salary = \beta_0 + \beta_1 \times Sex + \beta_2 \times IT + \beta_3 \times Sex{:}IT + \beta_4 \times Age + \beta_5 \times Total\ Asset + \beta_6 \times Return\ on\ Asset + \beta_7 \times Operating\ Efficienct + \beta_8 \times Growth\ Potential + \beta_9 \times City$$

The coefficients of these variables are presented in Table 7, and we will interpret the coefficients below. The coefficient of *Sex* 1 is 0.230, which means that holding other variables constant, male (*Sex* = 1) will earn 0.230 unit more salary than female (*Sex* = 0). The coefficient of *IT* is -0.050, which means that holding every other thing constant, IT people (*IT* = 1) will earn 0.050 unit less salary than non-IT People. One unit increase of *Age* will result in 0.146 units of decrease in salary, holding everything else constant. For control variables: *Total Asset* has a significant positive effect on salary; *Return on Asset* has a significant positive effect on salary; *Operating Efficiency* has a significant positive effect on salary; *Return on Investment* has a significant negative effect on salary; Growth Potential has a non-significant negative effect on salary. However, since the coefficient of interaction is not significant, we cannot conclude that IT industry companies have a smaller gender gap than non-IT industry companies in China.

5 Conclusion

Our study mainly emphasizes the widely discussed sensitive social topic, gender gap. We approached this problem by first testing its existence under the context of executive salary in Chinese listed firms. Then we discussed two important factors that may cast influence on the gender pay gap, that is firm location and industry.

To test the relationship between executive salary and gender, we extract the data of Chinese listed firms from the CSMAR database from the year 2005 to 2020. After conducting the necessary cleaning process strictly following previous studies, we established a sample containing 232,481 observations. We included 7 control variables to control for various factors that may influence executive salary from executive experience to firm size. From the testing result, it can be observed that the *Salary* is positively related to *Sex=1*, which offers valid evidence for our first hypothesis. Reasons for the result can be derived from our research about gender inequality. While a young female with an entry level position shares an almost equal payment with her male counterparts, the pay gap is widened throughout their future career development, which explains the statistically significant result we have over executive salary.

The development of our second hypothesis seeks to test for the influence of firm location on executive salary and gender pay gap. Two iconic cities of China, Beijing and Shanghai, are selected. First, we find that executives of Shanghai based firms have higher salaries than Beijing based ones. From our literature review, this is probably because Shanghai is the economic hub of China and has prosperous commercial activity. Executives benefit from the enhanced information flow and make better business decisions and thus are more valued in the companies. Second, we found that in Shanghai, the gender pay gap is narrower. This result is also in line with our presumption that females enjoy a more equal environment in Shanghai.

Our third hypothesis emphasizes the gender gap in the information technology (IT) industry which is a prosperous industry that has recently emerged in the past 15 years. Our result suggests that executives of IT firms have lower salary levels compared to executives of firms in non-IT companies. This is probably due to the fact that these firms are relatively new and are still investing most of their retained earnings into future development instead of compensating their management team. Also, there's no significant difference in gender pay gap between IT and non-IT firms, suggesting that the situation of gender inequality is not better in this young industry.

In conclusion, we confirmed the existence of a gender pay gap among executives of Chinese listed firms. Executives in Shanghai are better paid compared to their counterparts in Beijing and Shanghai's female executives have more equal salary as well. Executives of IT firms earn less than those in non-IT companies and there's no evidence that the gender pay gap in IT firms is significantly smaller.

6 Limitations

Our study suffers from the following limitations.

Firstly, the observations studied are limited to executives in Chinese listed firms due to the availability of data. We do not have data about the salary of non-managerial roles nor lower-level positions. Also compared to large firms, small and medium sized firms lack transparency and it is very hard to acquire data concerning their performance. This limitation is worth highlighting because executives of listed companies only account for the top tier group of people and may not be able to represent the whole picture of the employment environment in China. Thus, the scope of our research constrains the application of my findings.

Secondly, our study does not involve all possible economic characteristics that can influence executive salary, such as the level of their education. Due to the unavailability of data, we do not take this into consideration and simply used *Age* to control for their experience.

Lastly, we recognize that our regression models have a relatively low R-squared value. However, it is worth noting that the study of gender pay gap has an inherently greater amount of unexplainable variation, such as behavioral factors that are hard to measure and quantify. Nevertheless, for future research, it is likely that the R-squared value could be improved by adding more independent variables including education level, GDP and CPI and so on.

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Appendix

Table 1 Variable Definitions

Variable	Definition
Dependent Variables	
Salary	Standardized natural logarithm of the salary of each executive's salary after adjusted for time and industry
Independent Variables	
Sex	Dummy variable to control for gender (0-Female, 1-Male)
BJSH	Dummy variable to control for city location (0-Shanghai 1-Beijing)
IT	Dummy variable to control for industry (0-non-IT, 1-IT)
Control variables	
Age	Standardized form of the age
Total Asset	Standardized natural logarithm of the total asset of the company for which each executive works after adjusted for time and industry
Return on Asset	Principal component which is the combination of ROA growth rate, ROA, Return on net asset of the company for which each executive works after adjusted for time and industry
Operating Efficiency	Principal component which is the combination of Operating margin rate and Management expense ratio of the company for which each executive works after adjusted for time and industry.
Growth Potential	Principal component which is the combination of Net margin growth rate and Operating margin growth rate of the company for which each executive works after adjusted for time and industry
Return on Investment	Principal component which is entirely based on ROI (Return on Investment) of the company for which each executive works after adjusted for time and industry
City	Dummy variable (City Code) to control for the location of the company for which each executive works.
Year	Dummy variable to control for the time
Industry	Dummy variable to control for industry according to the industry classification code published by China Securities Regulatory Commission in the year of 2012

Table 2 Descriptive Statistics – Whole sample, female and male

	Whole Sample (n = 232481)				Sex=1 (n =195803）				Sex=0 (n = 36778)				Male-Female	
Variables	Min	Max	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	P-value	t-stat
Salary	-10.16	4.3306	-0.0003	0.9990	-10.16	4.33	0.0304	1.007	-5.716	3.135	-0.1639	0.943	0.0000	35.843
Sex	0	1	0.8418	0.3649	1	1	1	0	0	0	0	0		
Age	-3.230	4.93	-0.0001	1.0001	-3.23	4.93	0.058	0.993	-3.23	4.0002	-0.313	0.977	0.0000	-66.783
Total Asset	-4.780	5.34	-0.0009	0.9990	-4.78	5.34	0.019	1.006	-4.34	4.078	-0.1076	0.95	0.0000	23.249
Return on Asset	-0.798	0.220	0.0000	0.0100	-0.798	0.2197	-0.0001	0.0099	-0.7982	0.2197	0.00	0.0100	0.1070	-1.612
Operating Efficiency	-0.070	1.038	0.0000	0.0100	-0.0704	1.0376	-0.0004	0.0102	-0.0702	1.0376	0.0002	0.0084	0.0000	-5.533
Growth Potential	-0.038	0.719	0.0000	0.0100	-0.0376	0.719	-0.0000	0.0097	-0.0376	0.719	0.0004	0.0114	0.4389	-0.774
Return on Investment	-0.131	1.154	0.0000	0.0100	-0.1309	1.1549	0.0000	0.0095	-0.1309	1.1549	0.0005	0.0122	0.9368	-0.079

Table 3 Descriptive Statistics – Beijing, female in Beijing and male in Beijing

	Beijing (n= 7693)				Beijing Sex-1 (n = 6951）				Beijing Sex=0 (n= 1102)				Male-Female	
Variables	Min	Max	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	P-value	t-stat
Salary	-4.1733	3.2881	0.2249	0.9463	-3.7338	3.2881	0.2510	0.9495	-4.1733	1.9253	0.0686	0.9120	0.0000	6.1100
Sex	0	1	0.8568	0.3503	1	1	1	0	0	0	0	0	-	-
Age	-2.9975	4.1168	0.1836	1.0125	-2.9975	4.1168	0.2353	0.9901	-2.5310	3.4170	-0.1255	1.0878	0.0000	10.3200
Total Asset	-3.9567	3.5691	0.5252	1.2063	-3.9567	3.5691	0.5767	1.2200	-3.9567	3.5691	0.2174	1.0715	0.0000	10.0890
Return on Asset	-0.9655	4.5646	0.0438	0.5827	-0.9655	4.5646	0.0360	0.5809	-0.9655	4.5646	0.0906	0.5916	0.0045	-2.8422
Operating Efficiency	-0.7680	3.0895	0.0397	0.4787	-0.7680	3.0895	0.0029	0.4596	-0.7680	3.0895	0.2405	0.5697	0.0000	-6.5098
Growth Potential	-0.2208	0.2150	0.0031	0.0322	-0.2208	0.2150	0.0030	0.0323	-0.2208	0.2150	0.0046	0.0318	0.5197	-0.6440
Return on Investment	-0.0823	0.5904	0.0082	0.0601	-0.0823	0.5904	0.0892	0.0612	-0.0823	0.5904	0.0042	0.0524	0.0069	2.7070

Table 4 Descriptive Statistics – Shanghai, female in Shanghai and male in Shanghai

	Shanghai (n= 8690)				Shanghai Sex=1 (n = 7280）				Shanghai Sex=0 (n= 1410)				Male-Female	
Variables	Min	Max	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	P-value	t-stat
Salary	-4.9141	3.2609	0.2568	0.9749	-3.5808	3.2609	0.2660	0.9906	-4.9141	2.7304	0.2093	0.8882	0.0314	2.1529
Sex	0	1	0.8377	0.3687	1	1	1	0	0	0	0	0	-	-
Age	-2.6476	4.0002	0.1804	1.0436	-2.6476	4.0002	0.2511	1.0402	-2.6476	2.9505	-0.1848	0.9832	0.0000	15.091
Total Asset	-4.3413	4.0789	0.1351	1.2828	-4.3413	4.0789	0.1789	1.3007	-4.3413	4.0789	-0.0911	1.1606	0.0000	7.8354
Return on Asset	-5.0829	4.4047	0.0115	0.5315	-0.5083	4.4047	0.0063	0.5270	-5.0829	4.4047	0.0384	0.5537	0.0446	-2.0095
Operating Efficiency	-6.8399	3.1097	0.0498	0.5564	-6.8399	3.1097	0.0418	0.5473	-6.8399	3.1097	-0.0911	0.6000	0.0042	-2.8659
Growth Potential	-1.2679	0.2778	-0.0101	0.1192	-1.2680	0.2778	-0.0089	0.1133	-1.2679	0.2778	-0.0159	0.1456	0.0867	1.7142
Return on Investment	-1.5386	0.5820	-0.0025	0.0975	-1.5486	0.5820	-0.0019	0.0944	-1.5386	0.5820	-0.0039	0.1124	0.2882	1.0625

Table 5 Descriptive Statistics – IT Industry, female in IT and male in IT

	IT (n = 13268)				IT Sex=1 (n = 10817)				IT Sex=0 (n = 2451)				Male-Female	
Variables	Min	Max	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	P-value	t-stat
Salary	-5.7168	3.9780	-0.0000	0.9877	-4.1961	2.9780	0.0275	1.0016	-5.7189	2.4960	-0.1213	0.9145	0.0000	7.1446
Sex	0	1	0.8153	0.3881	1	1	1	0	0	0	0	0	-	-
Age	-3.2308	3.6503	-0.1822	1.0356	-3.2308	3.6503	-0.1044	1.0254	-3.2308	3.4170	-0.5259	1.0104	0.0000	18.5970
Total Asset	-2.4005	5.34238	0.00000	0.8247	-2.4005	5.3424	0.0057	0.8395	-2.4005	4.0450	-0.0252	0.9554	0.0740	1.7870
Return on Asset	-4.3701	17.1380	-0.0042	0.7773	-4.3701	17.1380	-0.0027	0.7610	-4.3701	17.1380	-0.0104	0.8460	0.6791	0.4138
Operating Efficiency	-3.9770	5.8827	0.0142	0.6929	-3.9770	5.8827	0.0193	0.6917	-3.9770	5.8827	-0.0083	0.6975	0.0770	1.7686
Growth Potential	-0.3087	0.7290	-0.0015	0.0458	-0.3087	0.7290	-0.0015	0.0453	-0.2029	0.7290	0.0016	0.0481	0.9725	0.0345
Return on Investment	-0.1464	2.3679	-0.0037	0.0845	-0.1464	2.3679	0.0031	0.0813	-0.1464	2.3679	0.0061	0.0974	0.1646	-1.3901

Table 6 Pearson correlations

Variables	Salary	Age	Total Asset	Return on Asset	Operating Efficiency	Growth Potential	Return on Investment
Salary	1.000						
Age	-0.106***	1.000					
Total Asset	0.234***	0.093***	1.000				
Return on Asset	0.049***	-0.003	0.054***	1.000			
Operating Efficiency	-0.004**	-0.016***	-0.106***	-0.000	1.000		
Growth Potential	0.008***	-0.005**	0.026***	0.000	0.000	1.000	
Return on Investment	-0.007***	-0.005**	-0.003*	0.000	0.000	-0.000	1.000

****** p<0.01, ** p<0.05, * p<0.1***

Table 7 Regression Result

	Whole Sample (1)	BJ/SH (2)	IT (3)
Dependent variable	Salary	Salary	Salary
Sex	0.227***	0.186***	0.230***
BJSH	-	-0.195***	-
Sex*BJSH	-	0.099*	-
IT	-	-	-0.050*
Sex*IT	-	-	-0.031
Age	-0.149***	-0.168***	-0.146***
Total Asset	0.241***	0.205***	0.242***
Return on Asset	0.032***	0.078***	0.032***
Operating	0.017***	0.045**	0.018***
Growth Potential	0.000***	-0.100	0.004
Return on	-0.008***	-0.337***	-0.009***
Constant	0.001***	0.196***	-0.114***
City Dummies	Included	Included	Included
Industry Dummies	Included	Included	Included
Year Dummies	Included	Included	Included
R-squared	0.114	0.093	0.111
Number of obs	232481	16383	232481

****** p<0.01, ** p<0.05, * p<0.1***

Table 8 PCA loadings

Ratios	Return on Asset	Operation Efficiency	Growth Potential	Return on Investment
ROA growth	0.361	-	-	-
Net margin growth	-	-	0.708	-
Opt margin growth	-	-	0.71	-
ROA	0.827	0.111	-	-
ROI	-	-	-	0.998
RO net asset	0.838	-	-	-
Operating margin	0.198	0.871	-	-
Management expense	-0.116	0.888	-	-
Explained cumulative variance	0.196	0.391	0.517	0.642

kw_project

kz2372

12/4/2020

Model 1

```
library(readr)
library(psych)
```

```
## Warning: package 'psych' was built under R version 3.6.2
```

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
fe_lnboth <- read_csv("/Users/kiwi/Desktop/fe_lnboth.csv")
```

```
## Parsed with column specification:
## cols(
##   .default = col_double(),
##   jobtitle = col_character(),
##   id = col_character(),
##   industrycode = col_character(),
##   enddate = col_date(format = ""),
##   industry = col_character(),
##   date = col_date(format = "")
## )

## See spec(...) for full column specifications.
```

```
c7 <- principal(data.frame(fe_lnboth[,34:41]), nfactors = 4, rotate = "varimax", cor=T)
fe_lnboth7 <- fe_lnboth %>% select(fe_lnasset, fe_lnsalary,age, distance)
fe_lnboth7 <- scale(fe_lnboth7)
fe_lnboth7 <- cbind(fe_lnboth7, c7$scores, fe_lnboth[,4], fe_lnboth[,42], fe_lnboth[,43], fe_lnboth[,19
names(fe_lnboth7)[8] <- "ROI"
names(fe_lnboth7)[7] <- "Growth Potential"
names(fe_lnboth7)[6] <- "Operating Efficiency"
names(fe_lnboth7)[5] <- "ROA"
summary(lm(fe_lnsalary~ as.factor(sex)+age+fe_lnasset+ROA+ROI+`Operating Efficiency`+`Growth Potential`
```

```
##
## Call:
## lm(formula = fe_lnsalary ~ as.factor(sex) + age + fe_lnasset +
##     ROA + ROI + `Operating Efficiency` + `Growth Potential` +
##     as.factor(industry) + as.factor(date) + as.factor(city),
##     data = fe_lnboth7)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.5180  -0.6829   0.1376   0.6929   4.4542
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               0.0015387  0.0364651   0.042 0.966341
## as.factor(sex)1           0.2276991  0.0054658  41.659  < 2e-16 ***
## age                      -0.1496070  0.0020261 -73.838  < 2e-16 ***
## fe_lnasset                0.2413818  0.0021421 112.686  < 2e-16 ***
## ROA                       0.0322958  0.0019957  16.183  < 2e-16 ***
## ROI                      -0.0087804  0.0019549  -4.492 7.07e-06 ***
## `Operating Efficiency`    0.0171927  0.0019914   8.633  < 2e-16 ***
## `Growth Potential`        0.0001812  0.0019609   0.092 0.926380
## as.factor(industry)A02    0.0811177  0.0629971   1.288 0.197872
## as.factor(industry)A03   -0.0548423  0.0496809  -1.104 0.269641
## as.factor(industry)A04   -0.1000367  0.0579353  -1.727 0.084223 .
## as.factor(industry)A05   -0.0012902  0.0788642  -0.016 0.986947
## as.factor(industry)B06    0.0278523  0.0413596   0.673 0.500682
## as.factor(industry)B07   -0.1044865  0.0486035  -2.150 0.031574 *
## as.factor(industry)B08    0.0034867  0.0689968   0.051 0.959697
## as.factor(industry)B09   -0.0340432  0.0440070  -0.774 0.439176
## as.factor(industry)B11   -0.1322698  0.0489348  -2.703 0.006873 **
## as.factor(industry)C13   -0.1053128  0.0385896  -2.729 0.006352 **
## as.factor(industry)C14   -0.0981244  0.0401084  -2.446 0.014427 *
## as.factor(industry)C15   -0.0143991  0.0384537  -0.374 0.708069
## as.factor(industry)C17   -0.0803646  0.0384241  -2.092 0.036483 *
## as.factor(industry)C18   -0.1565646  0.0406448  -3.852 0.000117 ***
## as.factor(industry)C19    0.0009167  0.0583104   0.016 0.987457
## as.factor(industry)C20   -0.0689126  0.0519142  -1.327 0.184367
## as.factor(industry)C21   -0.1153800  0.0608046  -1.898 0.057756 .
## as.factor(industry)C22   -0.1357861  0.0418299  -3.246 0.001170 **
## as.factor(industry)C23   -0.1812868  0.0494584  -3.665 0.000247 ***
## as.factor(industry)C24   -0.2677791  0.0502502  -5.329 9.89e-08 ***
## as.factor(industry)C25   -0.0403844  0.0473050  -0.854 0.393271
## as.factor(industry)C26   -0.0753960  0.0353761  -2.131 0.033068 *
## as.factor(industry)C27   -0.0877083  0.0351802  -2.493 0.012664 *
## as.factor(industry)C28   -0.0513610  0.0409951  -1.253 0.210259
## as.factor(industry)C29   -0.1300767  0.0376342  -3.456 0.000548 ***
## as.factor(industry)C30   -0.1281449  0.0366946  -3.492 0.000479 ***
## as.factor(industry)C31   -0.0020238  0.0388521  -0.052 0.958458
## as.factor(industry)C32   -0.0397722  0.0374083  -1.063 0.287696
## as.factor(industry)C33   -0.1331736  0.0376915  -3.533 0.000411 ***
## as.factor(industry)C34   -0.1195444  0.0359773  -3.323 0.000891 ***
## as.factor(industry)C35   -0.1412487  0.0354510  -3.984 6.77e-05 ***
## as.factor(industry)C36   -0.1187125  0.0361157  -3.287 0.001013 **
## as.factor(industry)C37   -0.0623517  0.0379689  -1.642 0.100555
```

```
## as.factor(industry)C38    -0.1542665  0.0352543  -4.376 1.21e-05 ***
## as.factor(industry)C39    -0.2251895  0.0350711  -6.421 1.36e-10 ***
## as.factor(industry)C40    -0.1823152  0.0405901  -4.492 7.07e-06 ***
## as.factor(industry)C41    -0.1703470  0.0411935  -4.135 3.55e-05 ***
## as.factor(industry)C42    -0.3680663  0.0832244  -4.423 9.76e-06 ***
## as.factor(industry)C43    -0.2298755  0.2870139  -0.801 0.423178
## as.factor(industry)D44    -0.0786363  0.0369077  -2.131 0.033122 *
## as.factor(industry)D45    -0.1274486  0.0468081  -2.723 0.006474 **
## as.factor(industry)D46    -0.1583639  0.0462120  -3.427 0.000611 ***
## as.factor(industry)E47    -0.1914472  0.0578651  -3.309 0.000938 ***
## as.factor(industry)E48    -0.1668127  0.0365405  -4.565 4.99e-06 ***
## as.factor(industry)E49     0.0278143  0.1427885   0.195 0.845555
## as.factor(industry)E50    -0.2710396  0.0406935  -6.661 2.73e-11 ***
## as.factor(industry)F51    -0.2060447  0.0378330  -5.446 5.15e-08 ***
## as.factor(industry)F52    -0.1780708  0.0370850  -4.802 1.57e-06 ***
## as.factor(industry)G53    -0.0613268  0.0697110  -0.880 0.379007
## as.factor(industry)G54    -0.1576379  0.0410642  -3.839 0.000124 ***
## as.factor(industry)G55    -0.1813596  0.0427957  -4.238 2.26e-05 ***
## as.factor(industry)G56    -0.2107965  0.0440123  -4.789 1.67e-06 ***
## as.factor(industry)G58    -0.1631442  0.0442751  -3.685 0.000229 ***
## as.factor(industry)G59    -0.2521637  0.0511228  -4.933 8.12e-07 ***
## as.factor(industry)G60    -0.1682996  0.1373160  -1.226 0.220336
## as.factor(industry)H61    -0.2253891  0.0712759  -3.162 0.001566 **
## as.factor(industry)H62    -0.0518672  0.1687177  -0.307 0.758524
## as.factor(industry)I63    -0.1957350  0.0430705  -4.545 5.51e-06 ***
## as.factor(industry)I64    -0.2054975  0.0394009  -5.216 1.83e-07 ***
## as.factor(industry)I65    -0.2331572  0.0356985  -6.531 6.53e-11 ***
## as.factor(industry)J66    -0.1292488  0.0435204  -2.970 0.002980 **
## as.factor(industry)J67    -0.2778486  0.0611702  -4.542 5.57e-06 ***
## as.factor(industry)J68    -0.2359299  0.0631114  -3.738 0.000185 ***
## as.factor(industry)J69    -0.0444315  0.0946747  -0.469 0.638850
## as.factor(industry)K70    -0.2108710  0.0368726  -5.719 1.07e-08 ***
## as.factor(industry)L71    -0.3109828  0.1069353  -2.908 0.003636 **
## as.factor(industry)L72    -0.2411673  0.0426379  -5.656 1.55e-08 ***
## as.factor(industry)M73    -0.2085409  0.1053240  -1.980 0.047705 *
## as.factor(industry)M74    -0.2744663  0.0428211  -6.410 1.46e-10 ***
## as.factor(industry)M75    -0.1929132  0.1067481  -1.807 0.070735 .
## as.factor(industry)N77    -0.2039834  0.0469359  -4.346 1.39e-05 ***
## as.factor(industry)N78    -0.1374016  0.0465129  -2.954 0.003137 **
## as.factor(industry)O79    -0.2304403  0.2086370  -1.105 0.269376
## as.factor(industry)O81    -0.3769359  0.1043984  -3.611 0.000306 ***
## as.factor(industry)P82    -0.3350006  0.1172312  -2.858 0.004269 **
## as.factor(industry)Q83    -0.2064069  0.0637803  -3.236 0.001211 **
## as.factor(industry)R85    -0.1022954  0.0452476  -2.261 0.023773 *
## as.factor(industry)R86    -0.1980428  0.0533822  -3.710 0.000207 ***
## as.factor(industry)R87    -0.1913302  0.0786486  -2.433 0.014987 *
## as.factor(industry)S90    -0.2154926  0.0376695  -5.721 1.06e-08 ***
## as.factor(date)2006-12-31  0.0097571  0.0146435   0.666 0.505214
## as.factor(date)2007-12-31  0.0113572  0.0141621   0.802 0.422587
## as.factor(date)2008-12-31  0.0153749  0.0139972   1.098 0.272020
## as.factor(date)2009-12-31  0.0190908  0.0136793   1.396 0.162837
## as.factor(date)2010-12-31  0.0263603  0.0133981   1.967 0.049130 *
## as.factor(date)2011-12-31  0.0314156  0.0129878   2.419 0.015570 *
## as.factor(date)2012-12-31  0.0310128  0.0127986   2.423 0.015388 *
```

```
## as.factor(date)2013-12-31  0.0321906  0.0125724   2.560 0.010455 *
## as.factor(date)2014-12-31  0.0405368  0.0124681   3.251 0.001149 **
## as.factor(date)2015-12-31  0.0365927  0.0124150   2.947 0.003204 **
## as.factor(date)2016-12-31  0.0416575  0.0121703   3.423 0.000620 ***
## as.factor(date)2017-12-31  0.0484436  0.0120097   4.034 5.49e-05 ***
## as.factor(city)120000     -0.0363087  0.0181001  -2.006 0.044858 *
## as.factor(city)130100     -0.2129950  0.0300003  -7.100 1.25e-12 ***
## as.factor(city)130200     -0.0926315  0.0317667  -2.916 0.003546 **
## as.factor(city)130300     -0.5181728  0.0907332  -5.711 1.12e-08 ***
## as.factor(city)130400     -0.0290587  0.0519632  -0.559 0.576013
## as.factor(city)130500      0.1194733  0.0833787   1.433 0.151888
## as.factor(city)130600     -0.2632112  0.0299220  -8.797  < 2e-16 ***
## as.factor(city)130700     -0.7791306  0.1784383  -4.366 1.26e-05 ***
## as.factor(city)130800      0.2720446  0.0653317   4.164 3.13e-05 ***
## as.factor(city)130900     -0.1344052  0.0653009  -2.058 0.039568 *
## as.factor(city)131000      0.2534430  0.0944106   2.684 0.007265 **
## as.factor(city)131100     -0.6938967  0.0854509  -8.120 4.67e-16 ***
## as.factor(city)140100     -0.3986367  0.0278639 -14.307  < 2e-16 ***
## as.factor(city)140200     -0.5060270  0.0719114  -7.037 1.97e-12 ***
## as.factor(city)140300     -0.2150109  0.0698384  -3.079 0.002079 **
## as.factor(city)140400     -0.7420730  0.0569463 -13.031  < 2e-16 ***
## as.factor(city)140500      0.2330679  0.0766964   3.039 0.002375 **
## as.factor(city)140700     -0.4621231  0.0891635  -5.183 2.19e-07 ***
## as.factor(city)140800     -0.1585291  0.0514496  -3.081 0.002062 **
## as.factor(city)140900     -0.3479297  0.0893947  -3.892 9.94e-05 ***
## as.factor(city)141000     -0.5316541  0.0716470  -7.420 1.17e-13 ***
## as.factor(city)141100     -0.7611649  0.0705679 -10.786  < 2e-16 ***
## as.factor(city)150100      0.1235921  0.0359342   3.439 0.000583 ***
## as.factor(city)150200     -0.3334817  0.0353474  -9.434  < 2e-16 ***
## as.factor(city)150300     -0.3544044  0.0708360  -5.003 5.64e-07 ***
## as.factor(city)150400     -0.5498803  0.1073465  -5.122 3.02e-07 ***
## as.factor(city)150500     -0.0884372  0.1381061  -0.640 0.521941
## as.factor(city)150600     -0.5489812  0.0343824 -15.967  < 2e-16 ***
## as.factor(city)150900     -0.1270582  0.0988271  -1.286 0.198563
## as.factor(city)152900      0.0766482  0.0809897   0.946 0.343949
## as.factor(city)210100     -0.0347588  0.0314915  -1.104 0.269703
## as.factor(city)210200      0.0622946  0.0234575   2.656 0.007916 **
## as.factor(city)210300     -0.2941810  0.0459659  -6.400 1.56e-10 ***
## as.factor(city)210400     -0.4087700  0.0936078  -4.367 1.26e-05 ***
## as.factor(city)210500     -0.7822372  0.0991012  -7.893 2.96e-15 ***
## as.factor(city)210600     -0.3862712  0.0792616  -4.873 1.10e-06 ***
## as.factor(city)210700     -0.3791257  0.1170956  -3.238 0.001205 **
## as.factor(city)210781     -0.2340972  0.1354483  -1.728 0.083933 .
## as.factor(city)210800     -0.1376873  0.0984605  -1.398 0.161994
## as.factor(city)210900     -0.2259856  0.1028116  -2.198 0.027946 *
## as.factor(city)211000     -0.3268548  0.0968143  -3.376 0.000735 ***
## as.factor(city)211100     -0.1850040  0.1251609  -1.478 0.139375
## as.factor(city)211400     -0.5615834  0.0647872  -8.668  < 2e-16 ***
## as.factor(city)220100     -0.0424131  0.0245316  -1.729 0.083825 .
## as.factor(city)220200     -0.3737204  0.0398807  -9.371  < 2e-16 ***
## as.factor(city)220284     -0.1546515  0.0985678  -1.569 0.116652
## as.factor(city)220400      0.0494379  0.2224965   0.222 0.824161
## as.factor(city)220500     -0.7831888  0.0482601 -16.229  < 2e-16 ***
## as.factor(city)222402     -1.0623423  0.1983858  -5.355 8.57e-08 ***
```

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## as.factor(city)222403     -0.5486620  0.0757741  -7.241 4.48e-13 ***
## as.factor(city)230100     -0.2610849  0.0228520 -11.425  < 2e-16 ***
## as.factor(city)230200     -0.0327724  0.0806096  -0.407 0.684333
## as.factor(city)230300     -0.6115080  0.1573953  -3.885 0.000102 ***
## as.factor(city)230600     -0.1088263  0.0861484  -1.263 0.206503
## as.factor(city)230700     -0.7108685  0.1293012  -5.498 3.85e-08 ***
## as.factor(city)230800     -0.5372290  0.1242298  -4.324 1.53e-05 ***
## as.factor(city)230900     -0.1983060  0.1232765  -1.609 0.107699
## as.factor(city)231000     -0.3214144  0.2853513  -1.126 0.260005
## as.factor(city)310000      0.1004526  0.0099885  10.057  < 2e-16 ***
## as.factor(city)320100      0.0255573  0.0154082   1.659 0.097182 .
## as.factor(city)320200     -0.1557009  0.0196197  -7.936 2.10e-15 ***
## as.factor(city)320281     -0.4221329  0.0345622 -12.214  < 2e-16 ***
## as.factor(city)320282      0.0661107  0.1441130   0.459 0.646420
## as.factor(city)320300     -0.0395987  0.0398340  -0.994 0.320178
## as.factor(city)320381     -0.0130419  0.1324480  -0.098 0.921561
## as.factor(city)320400      0.0486320  0.0270892   1.795 0.072615 .
## as.factor(city)320500      0.0106953  0.0165463   0.646 0.518030
## as.factor(city)320581     -0.1004470  0.0718462  -1.398 0.162089
## as.factor(city)320582      0.2226650  0.0416596   5.345 9.06e-08 ***
## as.factor(city)320583      0.2147226  0.1969070   1.090 0.275504
## as.factor(city)320585      0.0291404  0.0908152   0.321 0.748305
## as.factor(city)320600     -0.0557087  0.0223782  -2.489 0.012796 *
## as.factor(city)320682     -0.2467840  0.2661925  -0.927 0.353882
## as.factor(city)320684     -0.1116271  0.0632395  -1.765 0.077540 .
## as.factor(city)320700      0.0391456  0.0365763   1.070 0.284509
## as.factor(city)320800     -0.0088724  0.1359497  -0.065 0.947965
## as.factor(city)320900     -0.0564503  0.0403983  -1.397 0.162312
## as.factor(city)321000     -0.1152206  0.0319219  -3.609 0.000307 ***
## as.factor(city)321081     -0.1973719  0.1092829  -1.806 0.070910 .
## as.factor(city)321100     -0.3968655  0.0363746 -10.911  < 2e-16 ***
## as.factor(city)321181     -0.2896629  0.0822201  -3.523 0.000427 ***
## as.factor(city)321200     -0.4396986  0.0525078  -8.374  < 2e-16 ***
## as.factor(city)321282      0.2410628  0.2436721   0.989 0.322522
## as.factor(city)321300     -0.0688219  0.0559234  -1.231 0.218456
## as.factor(city)330100      0.0304736  0.0135576   2.248 0.024595 *
## as.factor(city)330185      0.0171025  0.0494532   0.346 0.729469
## as.factor(city)330200      0.0108396  0.0174614   0.621 0.534747
## as.factor(city)330281     -0.2855381  0.0871028  -3.278 0.001045 **
## as.factor(city)330282     -0.0985371  0.1192157  -0.827 0.408496
## as.factor(city)330283      0.0472635  0.1064268   0.444 0.656975
## as.factor(city)330300     -0.1401577  0.0352032  -3.981 6.85e-05 ***
## as.factor(city)330382     -0.0573524  0.0998267  -0.575 0.565617
## as.factor(city)330400      0.0305063  0.0264427   1.154 0.248635
## as.factor(city)330481      0.1096818  0.0595910   1.841 0.065685 .
## as.factor(city)330482      0.1086962  0.1095571   0.992 0.321129
## as.factor(city)330483      0.0767902  0.0895526   0.857 0.391176
## as.factor(city)330500     -0.0634982  0.0299190  -2.122 0.033811 *
## as.factor(city)330600     -0.1564626  0.0171818  -9.106  < 2e-16 ***
## as.factor(city)330681     -0.1459465  0.0512475  -2.848 0.004402 **
## as.factor(city)330683     -0.1995283  0.2722501  -0.733 0.463629
## as.factor(city)330700     -0.1851559  0.0299703  -6.178 6.50e-10 ***
## as.factor(city)330782     -0.4155771  0.1136989  -3.655 0.000257 ***
## as.factor(city)330783     -0.1083118  0.0941729  -1.150 0.250089
```

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## as.factor(city)330800      -0.4303101  0.0633036  -6.798 1.07e-11 ***
## as.factor(city)330881      -0.2998662  0.1379054  -2.174 0.029674 *
## as.factor(city)330900      -0.3222700  0.0980128  -3.288 0.001009 **
## as.factor(city)331000       0.0801272  0.0198378   4.039 5.37e-05 ***
## as.factor(city)331081       0.0248414  0.0779275   0.319 0.749897
## as.factor(city)331082       0.0232649  0.0570367   0.408 0.683352
## as.factor(city)331100      -0.0346197  0.0607384  -0.570 0.568692
## as.factor(city)340100      -0.1053696  0.0198190  -5.317 1.06e-07 ***
## as.factor(city)340181      -0.2703772  0.0560601  -4.823 1.42e-06 ***
## as.factor(city)340200      -0.2798422  0.0310202  -9.021  < 2e-16 ***
## as.factor(city)340300      -0.1079548  0.0419976  -2.570 0.010156 *
## as.factor(city)340400       0.0427363  0.1015930   0.421 0.674003
## as.factor(city)340500      -0.2825826  0.0365169  -7.738 1.01e-14 ***
## as.factor(city)340600       0.0224844  0.0522858   0.430 0.667175
## as.factor(city)340700      -0.4751688  0.0410561 -11.574  < 2e-16 ***
## as.factor(city)340800      -0.6069070  0.0663830  -9.143  < 2e-16 ***
## as.factor(city)341000      -0.4551229  0.0785334  -5.795 6.83e-09 ***
## as.factor(city)341100      -0.1188309  0.0512365  -2.319 0.020382 *
## as.factor(city)341200      -0.3972780  0.0857530  -4.633 3.61e-06 ***
## as.factor(city)341500       0.0459350  0.0645812   0.711 0.476914
## as.factor(city)341600       0.1588134  0.1022060   1.554 0.120220
## as.factor(city)341800      -0.2172131  0.0572600  -3.793 0.000149 ***
## as.factor(city)341881      -0.1462742  0.1298636  -1.126 0.260011
## as.factor(city)350100      -0.1870238  0.0227105  -8.235  < 2e-16 ***
## as.factor(city)350181       0.4141741  0.0634226   6.530 6.57e-11 ***
## as.factor(city)350200      -0.0328945  0.0199836  -1.646 0.099749 .
## as.factor(city)350300      -0.2737791  0.1206545  -2.269 0.023262 *
## as.factor(city)350400      -0.4420869  0.0503807  -8.775  < 2e-16 ***
## as.factor(city)350500      -0.2515886  0.0354538  -7.096 1.29e-12 ***
## as.factor(city)350582      -0.1053788  0.0596112  -1.768 0.077101 .
## as.factor(city)350583      -0.4840388  0.0953365  -5.077 3.83e-07 ***
## as.factor(city)350600      -0.1313775  0.0502379  -2.615 0.008920 **
## as.factor(city)350700       0.0499772  0.0487175   1.026 0.304959
## as.factor(city)350800       0.1391835  0.0413216   3.368 0.000756 ***
## as.factor(city)350900      -0.2774051  0.0792460  -3.501 0.000464 ***
## as.factor(city)360100      -0.0245104  0.0229995  -1.066 0.286563
## as.factor(city)360200      -0.4733035  0.0532093  -8.895  < 2e-16 ***
## as.factor(city)360300      -1.0227989  0.1269473  -8.057 7.86e-16 ***
## as.factor(city)360500      -0.3391542  0.0615060  -5.514 3.51e-08 ***
## as.factor(city)360600      -0.2635821  0.1046779  -2.518 0.011802 *
## as.factor(city)360681      -0.1707450  0.0609975  -2.799 0.005123 **
## as.factor(city)360700       0.2715232  0.0781522   3.474 0.000512 ***
## as.factor(city)360900      -0.6755085  0.0565142 -11.953  < 2e-16 ***
## as.factor(city)361000      -0.0274796  0.1156183  -0.238 0.812133
## as.factor(city)361100      -0.2090399  0.0670805  -3.116 0.001832 **
## as.factor(city)370100      -0.1717054  0.0241528  -7.109 1.17e-12 ***
## as.factor(city)370200      -0.2685406  0.0224484 -11.963  < 2e-16 ***
## as.factor(city)370281      -0.0815766  0.2725567  -0.299 0.764710
## as.factor(city)370300      -0.1005258  0.0226801  -4.432 9.33e-06 ***
## as.factor(city)370400      -0.5302446  0.2224318  -2.384 0.017133 *
## as.factor(city)370500      -0.4538497  0.0476287  -9.529  < 2e-16 ***
## as.factor(city)370600      -0.2054602  0.0229026  -8.971  < 2e-16 ***
## as.factor(city)370681      -0.4731618  0.0601595  -7.865 3.70e-15 ***
## as.factor(city)370682      -0.1480377  0.1651472  -0.896 0.370041
```

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## as.factor(city)370683      -0.2392733  0.1548822  -1.545 0.122378    
## as.factor(city)370700      -0.3017243  0.0290028 -10.403  < 2e-16 ***
## as.factor(city)370782      -0.5004039  0.0982734  -5.092 3.55e-07 ***
## as.factor(city)370783      -0.0198578  0.0544798  -0.364 0.715486    
## as.factor(city)370786      -0.2849603  0.1431200  -1.991 0.046476 *  
## as.factor(city)370800      -0.5360404  0.0317786 -16.868  < 2e-16 ***
## as.factor(city)370900      -0.3103726  0.0626320  -4.955 7.22e-07 ***
## as.factor(city)371000      -0.0660570  0.0422204  -1.565 0.117684    
## as.factor(city)371082      -0.6959501  0.0861391  -8.079 6.54e-16 ***
## as.factor(city)371100      -0.3633184  0.0825004  -4.404 1.06e-05 ***
## as.factor(city)371200       0.0231146  0.1077488   0.215 0.830140    
## as.factor(city)371300      -0.3389901  0.0440467  -7.696 1.41e-14 ***
## as.factor(city)371400      -0.4898620  0.1251886  -3.913 9.12e-05 ***
## as.factor(city)371482      -0.0642579  0.0588317  -1.092 0.274732    
## as.factor(city)371500      -0.0841398  0.0408452  -2.060 0.039403 *  
## as.factor(city)371600      -0.2430381  0.0436134  -5.573 2.51e-08 ***
## as.factor(city)371700      -0.0671152  0.1424902  -0.471 0.637630    
## as.factor(city)410100      -0.2594462  0.0227926 -11.383  < 2e-16 ***
## as.factor(city)410200      -0.3757556  0.0993332  -3.783 0.000155 ***
## as.factor(city)410300      -0.1984214  0.0358005  -5.542 2.99e-08 ***
## as.factor(city)410400      -0.3188427  0.0545392  -5.846 5.04e-09 ***
## as.factor(city)410500      -0.6372761  0.0667574  -9.546  < 2e-16 ***
## as.factor(city)410581      -0.3592860  0.0889269  -4.040 5.34e-05 ***
## as.factor(city)410700      -0.2450130  0.0644943  -3.799 0.000145 ***
## as.factor(city)410800      -0.2103449  0.0353073  -5.958 2.56e-09 ***
## as.factor(city)410900       0.2187850  0.0702767   3.113 0.001851 ** 
## as.factor(city)411000      -0.3718265  0.0471869  -7.880 3.29e-15 ***
## as.factor(city)411082      -0.5040566  0.0752416  -6.699 2.10e-11 ***
## as.factor(city)411100      -0.0226215  0.0537297  -0.421 0.673738    
## as.factor(city)411281      -0.4923110  0.1175700  -4.187 2.82e-05 ***
## as.factor(city)411300      -0.2833341  0.0720837  -3.931 8.47e-05 ***
## as.factor(city)411481       0.3217613  0.0654772   4.914 8.93e-07 ***
## as.factor(city)411500      -0.2840171  0.0537484  -5.284 1.26e-07 ***
## as.factor(city)411600      -0.4922793  0.1643508  -2.995 0.002742 ** 
## as.factor(city)411681       0.0100096  0.0911058   0.110 0.912514    
## as.factor(city)411700      -0.6670758  0.0904876  -7.372 1.69e-13 ***
## as.factor(city)419001      -0.4439265  0.0660686  -6.719 1.83e-11 ***
## as.factor(city)420100      -0.1326101  0.0167604  -7.912 2.54e-15 ***
## as.factor(city)420200       0.1020481  0.0458178   2.227 0.025931 *  
## as.factor(city)420300      -0.7095444  0.1458163  -4.866 1.14e-06 ***
## as.factor(city)420500      -0.1530887  0.0347657  -4.403 1.07e-05 ***
## as.factor(city)420582      -0.4590724  0.0734735  -6.248 4.16e-10 ***
## as.factor(city)420600      -0.3229215  0.0342008  -9.442  < 2e-16 ***
## as.factor(city)420700       0.2997551  0.1547215   1.937 0.052700 .  
## as.factor(city)420800      -0.4008191  0.0478984  -8.368  < 2e-16 ***
## as.factor(city)420900      -0.6660740  0.0939765  -7.088 1.37e-12 ***
## as.factor(city)420981      -0.0662472  0.1264613  -0.524 0.600381    
## as.factor(city)420984      -0.3649201  0.0741946  -4.918 8.73e-07 ***
## as.factor(city)421000      -0.1067715  0.0320446  -3.332 0.000862 ***
## as.factor(city)421182      -0.1494825  0.0688495  -2.171 0.029921 *  
## as.factor(city)421300       0.0847756  0.2624485   0.323 0.746682    
## as.factor(city)429004      -0.1304199  0.2230908  -0.585 0.558814    
## as.factor(city)429005      -0.2411774  0.0833074  -2.895 0.003792 ** 
## as.factor(city)430100      -0.0561828  0.0173803  -3.233 0.001227 ** 
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## as.factor(city)430181      -0.4420268  0.1311012  -3.372 0.000747 ***
## as.factor(city)430200      -0.5150890  0.0332024 -15.514  < 2e-16 ***
## as.factor(city)430300      -0.2629135  0.0452630  -5.809 6.31e-09 ***
## as.factor(city)430400      -0.0212622  0.0977547  -0.218 0.827814
## as.factor(city)430600      -0.0821826  0.0395278  -2.079 0.037608 *
## as.factor(city)430700      -0.0924917  0.0762785  -1.213 0.225302
## as.factor(city)430900      -0.4101198  0.0815524  -5.029 4.94e-07 ***
## as.factor(city)430981      -0.0593869  0.1055749  -0.563 0.573769
## as.factor(city)431000      -0.3372018  0.0684436  -4.927 8.37e-07 ***
## as.factor(city)431100       0.0596377  0.0780177   0.764 0.444622
## as.factor(city)431200      -0.0249162  0.1097687  -0.227 0.820433
## as.factor(city)433101       0.2109967  0.0737431   2.861 0.004220 **
## as.factor(city)440100       0.0672879  0.0148074   4.544 5.52e-06 ***
## as.factor(city)440200      -0.5145908  0.0450333 -11.427  < 2e-16 ***
## as.factor(city)440300       0.1847114  0.0102771  17.973  < 2e-16 ***
## as.factor(city)440400       0.0049941  0.0226771   0.220 0.825693
## as.factor(city)440500      -0.0552765  0.0269590  -2.050 0.040328 *
## as.factor(city)440600       0.1553944  0.0207974   7.472 7.94e-14 ***
## as.factor(city)440700      -0.1136870  0.0428069  -2.656 0.007912 **
## as.factor(city)440783       0.0959255  0.2730906   0.351 0.725394
## as.factor(city)440785      -0.1018333  0.1756124  -0.580 0.561999
## as.factor(city)440800       0.1950490  0.0789159   2.472 0.013451 *
## as.factor(city)440900       0.2922551  0.0760330   3.844 0.000121 ***
## as.factor(city)441200       0.0297751  0.0430010   0.692 0.488669
## as.factor(city)441300      -0.0677946  0.0476722  -1.422 0.154999
## as.factor(city)441400       0.1372455  0.0358404   3.829 0.000129 ***
## as.factor(city)441481      -0.1495834  0.0920989  -1.624 0.104343
## as.factor(city)441700      -0.3787584  0.2727509  -1.389 0.164937
## as.factor(city)441900      -0.0426501  0.0353575  -1.206 0.227722
## as.factor(city)442000      -0.0378654  0.0275689  -1.373 0.169604
## as.factor(city)445100      -0.2332586  0.0725044  -3.217 0.001295 **
## as.factor(city)445200      -0.5849316  0.0418847 -13.965  < 2e-16 ***
## as.factor(city)445281      -0.0530175  0.1187301  -0.447 0.655209
## as.factor(city)445300       0.4569345  0.1145769   3.988 6.66e-05 ***
## as.factor(city)450100      -0.1704627  0.0368573  -4.625 3.75e-06 ***
## as.factor(city)450200       0.0138920  0.0413759   0.336 0.737060
## as.factor(city)450300      -0.0751943  0.0432385  -1.739 0.082026 .
## as.factor(city)450400      -0.0636974  0.0590930  -1.078 0.281071
## as.factor(city)450500      -0.3416061  0.0555524  -6.149 7.80e-10 ***
## as.factor(city)450800       0.0927415  0.0957171   0.969 0.332590
## as.factor(city)450900      -0.2638338  0.0940198  -2.806 0.005014 **
## as.factor(city)451100      -0.2382514  0.0773942  -3.078 0.002081 **
## as.factor(city)451200      -0.4722033  0.0935756  -5.046 4.51e-07 ***
## as.factor(city)460100      -0.2445181  0.0245118  -9.976  < 2e-16 ***
## as.factor(city)460200      -0.1711687  0.1128054  -1.517 0.129172
## as.factor(city)469023      -0.3841180  0.1567910  -2.450 0.014291 *
## as.factor(city)469026       0.0279592  0.2431477   0.115 0.908454
## as.factor(city)5e+05       -0.2388357  0.0169644 -14.079  < 2e-16 ***
## as.factor(city)510100      -0.2302068  0.0153884 -14.960  < 2e-16 ***
## as.factor(city)510300      -0.2772347  0.0465981  -5.949 2.69e-09 ***
## as.factor(city)510400      -0.5154212  0.0979447  -5.262 1.42e-07 ***
## as.factor(city)510500      -0.0617437  0.0539029  -1.145 0.252019
## as.factor(city)510600      -0.0570890  0.0515939  -1.107 0.268508
## as.factor(city)510682      -0.1375856  0.2289029  -0.601 0.547797
```

```
## as.factor(city)510700     -0.4170936  0.0323642 -12.888  < 2e-16 ***
## as.factor(city)510900     -0.3116309  0.0384576  -8.103 5.38e-16 ***
## as.factor(city)511000     -0.2480986  0.1889254  -1.313 0.189114
## as.factor(city)511100      0.0570925  0.0796172   0.717 0.473321
## as.factor(city)511181     -0.0219348  0.0981793  -0.223 0.823212
## as.factor(city)511300     -0.4188127  0.1973694  -2.122 0.033841 *
## as.factor(city)511400      0.1561497  0.1286349   1.214 0.224788
## as.factor(city)511500     -0.4507339  0.0512731  -8.791  < 2e-16 ***
## as.factor(city)511800      0.2097216  0.0840381   2.496 0.012577 *
## as.factor(city)512081      0.0695617  0.1784737   0.390 0.696715
## as.factor(city)513401      0.3328380  0.2227388   1.494 0.135099
## as.factor(city)520100     -0.1213008  0.0228619  -5.306 1.12e-07 ***
## as.factor(city)520200     -0.1061215  0.1106777  -0.959 0.337643
## as.factor(city)520300     -0.4530992  0.0431151 -10.509  < 2e-16 ***
## as.factor(city)520400     -0.2035548  0.0662853  -3.071 0.002134 **
## as.factor(city)522700     -0.5452331  0.0800405  -6.812 9.65e-12 ***
## as.factor(city)530100     -0.3081239  0.0218748 -14.086  < 2e-16 ***
## as.factor(city)530300     -0.2125137  0.0529896  -4.010 6.06e-05 ***
## as.factor(city)530400     -0.3475598  0.2439028  -1.425 0.154160
## as.factor(city)530500     -0.0981533  0.0788098  -1.245 0.212969
## as.factor(city)530600     -0.3236013  0.1109124  -2.918 0.003527 **
## as.factor(city)530800     -0.2839224  0.2668455  -1.064 0.287332
## as.factor(city)532600      0.4044347  0.1356505   2.981 0.002869 **
## as.factor(city)540100     -0.2681068  0.0353973  -7.574 3.63e-14 ***
## as.factor(city)540400      0.0508978  0.0852975   0.597 0.550702
## as.factor(city)542200     -0.2016045  0.1045982  -1.927 0.053929 .
## as.factor(city)610100     -0.3089354  0.0222638 -13.876  < 2e-16 ***
## as.factor(city)610200     -0.0392513  0.2239986  -0.175 0.860899
## as.factor(city)610300     -0.5437633  0.0426156 -12.760  < 2e-16 ***
## as.factor(city)610400     -0.7224500  0.0793088  -9.109  < 2e-16 ***
## as.factor(city)610581     -0.8763915  0.1913535  -4.580 4.65e-06 ***
## as.factor(city)610700     -0.0860577  0.0947383  -0.908 0.363682
## as.factor(city)620100     -0.4325128  0.0274938 -15.731  < 2e-16 ***
## as.factor(city)620200      0.0422245  0.0827051   0.511 0.609672
## as.factor(city)620400     -0.1035595  0.1212511  -0.854 0.393055
## as.factor(city)620500      0.3817023  0.0824874   4.627 3.70e-06 ***
## as.factor(city)620600     -0.9532143  0.1792041  -5.319 1.04e-07 ***
## as.factor(city)620900     -0.4403526  0.0863898  -5.097 3.45e-07 ***
## as.factor(city)621200     -0.8711005  0.0908816  -9.585  < 2e-16 ***
## as.factor(city)630100     -0.4423068  0.0359363 -12.308  < 2e-16 ***
## as.factor(city)630200     -0.0953675  0.1823499  -0.523 0.600980
## as.factor(city)632801     -0.3736321  0.0741486  -5.039 4.68e-07 ***
## as.factor(city)640100     -0.2260745  0.0453962  -4.980 6.36e-07 ***
## as.factor(city)640181     -0.5292712  0.0807110  -6.558 5.48e-11 ***
## as.factor(city)640200     -0.3711157  0.0696444  -5.329 9.90e-08 ***
## as.factor(city)640300     -0.5781370  0.0867020  -6.668 2.60e-11 ***
## as.factor(city)640500     -0.4173091  0.1865158  -2.237 0.025262 *
## as.factor(city)650100     -0.2354011  0.0206810 -11.383  < 2e-16 ***
## as.factor(city)650200     -0.2803328  0.0800286  -3.503 0.000460 ***
## as.factor(city)652300     -0.3206142  0.1246266  -2.573 0.010094 *
## as.factor(city)652301     -0.1357827  0.0476046  -2.852 0.004341 **
## as.factor(city)652701     -0.6630642  0.1329339  -4.988 6.11e-07 ***
## as.factor(city)652800     -0.7911726  0.0780828 -10.132  < 2e-16 ***
## as.factor(city)652901     -0.2425225  0.1135919  -2.135 0.032759 *
```

```
## as.factor(city)654000     -0.2077913  0.0735177  -2.826 0.004708 **
## as.factor(city)659001     -0.2798966  0.0543336  -5.151 2.59e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9421 on 232060 degrees of freedom
##   (104 observations deleted due to missingness)
## Multiple R-squared:  0.1138, Adjusted R-squared:  0.1122
## F-statistic: 70.93 on 420 and 232060 DF,  p-value: < 2.2e-16
```

Model 2

```
#Descriptivedata for bjsh
## bj
library("readr")
library(readxl)
library("dplyr")
all = read_excel("/Users/kiwi/Desktop/bjsh.xls")
bj = all[all$bjsh == 1,] ## all bj data
bjm = bj[bj$sex == 1,] ## all bj male
bjfm = bj[bj$sex == 0 ,] ## all bj female
summary(bj)
```

```
##    fe_lnasset       fe_lnsalary           age                ROA
##  Min.   :-3.9567   Min.   :-4.1733   Min.   :-2.9975   Min.   :-0.96546
##  1st Qu.:-0.4215   1st Qu.:-0.5023   1st Qu.:-0.4317   1st Qu.:-0.23050
##  Median : 0.5166   Median : 0.4229   Median : 0.1515   Median :-0.03136
##  Mean   : 0.5252   Mean   : 0.2249   Mean   : 0.1836   Mean   : 0.04380
##  3rd Qu.: 1.2228   3rd Qu.: 0.9346   3rd Qu.: 0.7346   3rd Qu.: 0.18591
##  Max.   : 3.5691   Max.   : 3.2881   Max.   : 4.1168   Max.   : 4.56456
##  Operating Efficiency Growth Potential          ROI                 sex
##  Min.   :-0.76803     Min.   :-0.2207755    Min.   :-0.082307   Min.   :0.0000
##  1st Qu.:-0.22610     1st Qu.:-0.0073193    1st Qu.:-0.004042   1st Qu.:1.0000
##  Median :-0.06389     Median : 0.0008961    Median : 0.003411   Median :1.0000
##  Mean   : 0.03974     Mean   : 0.0030645    Mean   : 0.008244   Mean   :0.8568
##  3rd Qu.: 0.15798     3rd Qu.: 0.0112181    3rd Qu.: 0.011463   3rd Qu.:1.0000
##  Max.   : 3.08946     Max.   : 0.2150124    Max.   : 0.590433   Max.   :1.0000
##       bjsh
##  Min.   :1
##  1st Qu.:1
##  Median :1
##  Mean   :1
##  3rd Qu.:1
##  Max.   :1
```

```
sd(bj$fe_lnasset)
```

```
## [1] 1.206391
```

```r
sd(bj$fe_lnsalary)
```

```
## [1] 0.9463329
```

```r
sd(bj$sex)
```

```
## [1] 0.3503474
```

```r
sd(bj$age)
```

```
## [1] 1.012545
```

```r
sd(bj$ROA)
```

```
## [1] 0.5826817
```

```r
sd(bj$`Operating Efficiency`)
```

```
## [1] 0.478695
```

```r
sd(bj$`Growth Potential`)
```

```
## [1] 0.03222413
```

```r
sd(bj$ROI)
```

```
## [1] 0.06006161
```

```r
summary(bjm)
```

```
##    fe_lnasset        fe_lnsalary            age                 ROA
##  Min.   :-3.9567   Min.   :-3.7338   Min.   :-2.9975   Min.   :-0.96546
##  1st Qu.:-0.4053   1st Qu.:-0.4797   1st Qu.:-0.4317   1st Qu.:-0.22776
##  Median : 0.5743   Median : 0.4578   Median : 0.1515   Median :-0.03986
##  Mean   : 0.5767   Mean   : 0.2510   Mean   : 0.2353   Mean   : 0.03598
##  3rd Qu.: 1.2825   3rd Qu.: 0.9600   3rd Qu.: 0.7346   3rd Qu.: 0.15958
##  Max.   : 3.5691   Max.   : 3.2881   Max.   : 4.1168   Max.   : 4.56456
##  Operating Efficiency Growth Potential          ROI                   sex
##  Min.   :-0.76803     Min.   :-0.2207755   Min.   :-0.082307   Min.   :1
##  1st Qu.:-0.22826     1st Qu.:-0.0073193   1st Qu.:-0.003022   1st Qu.:1
##  Median :-0.07316     Median : 0.0008002   Median : 0.003512   Median :1
##  Mean   : 0.02289     Mean   : 0.0029688   Mean   : 0.008922   Mean   :1
##  3rd Qu.: 0.13962     3rd Qu.: 0.0108099   3rd Qu.: 0.011524   3rd Qu.:1
##  Max.   : 3.08946     Max.   : 0.2150124   Max.   : 0.590433   Max.   :1
##       bjsh
##  Min.   :1
##  1st Qu.:1
##  Median :1
##  Mean   :1
##  3rd Qu.:1
##  Max.   :1
```

```r
summary(bjfm)
```

```
##    fe_lnasset       fe_lnsalary            age                ROA
##  Min.   :-3.9567   Min.   :-4.17326   Min.   :-2.5310   Min.   :-0.96546
##  1st Qu.:-0.6295   1st Qu.:-0.67834   1st Qu.:-0.8982   1st Qu.:-0.24767
##  Median : 0.2173   Median : 0.16887   Median :-0.1984   Median : 0.03189
##  Mean   : 0.2174   Mean   : 0.06856   Mean   :-0.1255   Mean   : 0.09056
##  3rd Qu.: 0.8745   3rd Qu.: 0.77058   3rd Qu.: 0.5013   3rd Qu.: 0.30534
##  Max.   : 3.5691   Max.   : 1.92532   Max.   : 3.4170   Max.   : 4.56456
##  Operating Efficiency Growth Potential         ROI                  sex
##  Min.   :-0.768034    Min.   :-0.220776   Min.   :-0.082307   Min.   :0
##  1st Qu.:-0.204547    1st Qu.:-0.007570   1st Qu.:-0.008813   1st Qu.:0
##  Median : 0.006062    Median : 0.001618   Median : 0.001319   Median :0
##  Mean   : 0.140532    Mean   : 0.003636   Mean   : 0.004184   Mean   :0
##  3rd Qu.: 0.295039    3rd Qu.: 0.013498   3rd Qu.: 0.011424   3rd Qu.:0
##  Max.   : 3.089465    Max.   : 0.215012   Max.   : 0.590433   Max.   :0
##       bjsh
##  Min.   :1
##  1st Qu.:1
##  Median :1
##  Mean   :1
##  3rd Qu.:1
##  Max.   :1
```

```r
sd(bjm$fe_lnasset)
```

```
## [1] 1.220024
```

```r
sd(bjm$fe_lnsalary)
```

```
## [1] 0.9495177
```

```r
sd(bjm$sex)
```

```
## [1] 0
```

```r
sd(bjm$age)
```

```
## [1] 0.9901188
```

```r
sd(bjm$ROA)
```

```
## [1] 0.5808504
```

```r
sd(bjm$`Operating Efficiency`)
```

```
## [1] 0.4596267
```

```r
sd(bjm$`Growth Potential`)
```

```
## [1] 0.03230117
```

```r
sd(bjm$ROI)
```

```
## [1] 0.06122206
```

```r
sd(bjfm$fe_lnasset)
```

```
## [1] 1.071476
```

```r
sd(bjfm$fe_lnsalxary)
```

```
## Warning: Unknown or uninitialised column: 'fe_lnsalxary'.
```

```
## [1] NA
```

```r
sd(bjfm$sex)
```

```
## [1] 0
```

```r
sd(bjfm$age)
```

```
## [1] 1.087818
```

```r
sd(bjfm$ROA)
```

```
## [1] 0.5916292
```

```r
sd(bjfm$`Operating Efficiency`)
```

```
## [1] 0.5697207
```

```r
sd(bjfm$`Growth Potential`)
```

```
## [1] 0.03176797
```

```r
sd(bjfm$ROI)
```

```
## [1] 0.05243101
```

```r
t.test(bjm$fe_lnasset, bjfm$fe_lnasset)
```

```
##
##  Welch Two Sample t-test
##
## data:  bjm$fe_lnasset and bjfm$fe_lnasset
## t = 10.089, df = 1617.4, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.2893881 0.4290568
## sample estimates:
## mean of x mean of y
## 0.5766574 0.2174350
```

```r
t.test(bjm$fe_lnsalary, bjfm$fe_lnsalary)
```

```
##
##  Welch Two Sample t-test
##
## data:  bjm$fe_lnsalary and bjfm$fe_lnsalary
## t = 6.11, df = 1527.9, p-value = 1.262e-09
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.1238637 0.2409971
## sample estimates:
##  mean of x  mean of y
## 0.25099467 0.06856428
```

```r
t.test(bjm$age, bjfm$age)
```

```
##
##  Welch Two Sample t-test
##
## data:  bjm$age and bjfm$age
## t = 10.32, df = 1422.6, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.2922509 0.4294281
## sample estimates:
##  mean of x  mean of y
##  0.2353322 -0.1255073
```

```r
t.test(bjm$ROA, bjfm$ROA)
```

```
##
##  Welch Two Sample t-test
##
## data:  bjm$ROA and bjfm$ROA
## t = -2.8422, df = 1478.1, p-value = 0.004542
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.09225494 -0.01691264
## sample estimates:
##  mean of x  mean of y
## 0.03598068 0.09056447
```

```r
t.test(bjm$`Operating Efficiency`, bjfm$`Operating Efficiency`)
```

```
##
##  Welch Two Sample t-test
##
## data:  bjm$`Operating Efficiency` and bjfm$`Operating Efficiency`
## t = -6.5098, df = 1351, p-value = 1.058e-10
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.15309651 -0.08219272
## sample estimates:
##  mean of x  mean of y
## 0.02288756 0.14053218
```

```r
t.test(bjm$`Growth Potential`, bjfm$`Growth Potential`)
```

```
##
##  Welch Two Sample t-test
##
## data:  bjm$`Growth Potential` and bjfm$`Growth Potential`
## t = -0.64402, df = 1507, p-value = 0.5197
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.002700359  0.001365462
## sample estimates:
##   mean of x   mean of y
## 0.002968847 0.003636296
```

```r
t.test(bjm$ROI, bjfm$ROI)
```

```
##
##  Welch Two Sample t-test
##
## data:  bjm$ROI and bjfm$ROI
## t = 2.707, df = 1645.9, p-value = 0.006859
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.001305016 0.008170769
## sample estimates:
##   mean of x   mean of y
## 0.008922297 0.004184404
```

```r
##Descriptive Data for bjsh
##sh
sh = all[all$bjsh == 0,] ## all sh data
shm = sh[sh$sex == 1,] ## all sh male
shfm = sh[sh$sex == 0 ,] ## all sh female
summary(sh)
```

```
##    fe_lnasset        fe_lnsalary           age                 ROA
##  Min.   :-4.3413   Min.   :-4.9141   Min.   :-2.6476   Min.   :-5.08288
```

```
##  1st Qu.:-0.7947   1st Qu.:-0.5109   1st Qu.:-0.5483   1st Qu.:-0.24605
##  Median :-0.1556   Median : 0.4208   Median : 0.1515   Median :-0.05003
##  Mean   : 0.1351   Mean   : 0.2568   Mean   : 0.1804   Mean   : 0.01152
##  3rd Qu.: 0.8333   3rd Qu.: 0.9805   3rd Qu.: 0.8512   3rd Qu.: 0.23719
##  Max.   : 4.0789   Max.   : 3.2609   Max.   : 4.0002   Max.   : 4.40467
##  Operating Efficiency Growth Potential          ROI                 sex
##  Min.   :-6.839886    Min.   :-1.2679018   Min.   :-1.538561   Min.   :0.0000
##  1st Qu.:-0.175519    1st Qu.:-0.0096694   1st Qu.:-0.007378   1st Qu.:1.0000
##  Median :-0.005918    Median :-0.0003158   Median : 0.004038   Median :1.0000
##  Mean   : 0.049756    Mean   :-0.0100628   Mean   :-0.002494   Mean   :0.8377
##  3rd Qu.: 0.234525    3rd Qu.: 0.0091586   3rd Qu.: 0.012179   3rd Qu.:1.0000
##  Max.   : 3.109707    Max.   : 0.2777850   Max.   : 0.582005   Max.   :1.0000
##       bjsh
##  Min.   :0
##  1st Qu.:0
##  Median :0
##  Mean   :0
##  3rd Qu.:0
##  Max.   :0
```

```r
sd(sh$fe_lnasset)
```

```
## [1] 1.282812
```

```r
sd(sh$fe_lnsalary)
```

```
## [1] 0.9749116
```

```r
sd(sh$sex)
```

```
## [1] 0.3687062
```

```r
sd(sh$age)
```

```
## [1] 1.043562
```

```r
sd(sh$ROA)
```

```
## [1] 0.5314989
```

```r
sd(sh$`Operating Efficiency`)
```

```
## [1] 0.5564425
```

```r
sd(sh$`Growth Potential`)
```

```
## [1] 0.1191598
```

```r
sd(sh$ROI)
```

```
## [1] 0.09753483
```

```r
summary(shm)
```

```
##    fe_lnasset       fe_lnsalary           age                ROA
##  Min.   :-4.3413   Min.   :-3.5808   Min.   :-2.6476   Min.   :-5.08288
##  1st Qu.:-0.7746   1st Qu.:-0.5380   1st Qu.:-0.4317   1st Qu.:-0.24605
##  Median :-0.1324   Median : 0.4388   Median : 0.2681   Median :-0.05003
##  Mean   : 0.1789   Mean   : 0.2660   Mean   : 0.2511   Mean   : 0.00631
##  3rd Qu.: 0.9670   3rd Qu.: 1.0146   3rd Qu.: 0.9679   3rd Qu.: 0.23483
##  Max.   : 4.0789   Max.   : 3.2609   Max.   : 4.0002   Max.   : 4.40467
##  Operating Efficiency Growth Potential          ROI                   sex
##  Min.   :-6.839886    Min.   :-1.2679018   Min.   :-1.538561   Min.   :1
##  1st Qu.:-0.182288    1st Qu.:-0.0096694   1st Qu.:-0.007344   1st Qu.:1
##  Median :-0.007484    Median :-0.0002744   Median : 0.004054   Median :1
##  Mean   : 0.041750    Mean   :-0.0089228   Mean   :-0.001943   Mean   :1
##  3rd Qu.: 0.216800    3rd Qu.: 0.0088710   3rd Qu.: 0.012131   3rd Qu.:1
##  Max.   : 3.109707    Max.   : 0.2777850   Max.   : 0.582005   Max.   :1
##       bjsh
##  Min.   :0
##  1st Qu.:0
##  Median :0
##  Mean   :0
##  3rd Qu.:0
##  Max.   :0
```

```r
sd(shm$fe_lnasset)
```

```
## [1] 1.300693
```

```r
sd(shm$fe_lnsalary)
```

```
## [1] 0.9906192
```

```r
sd(shm$sex)
```

```
## [1] 0
```

```r
sd(shm$age)
```

```
## [1] 1.040192
```

```r
sd(shm$ROA)
```

```
## [1] 0.52698
```

```r
sd(shm$`Operating Efficiency`)
```

```
## [1] 0.5472819
```

```r
sd(shm$`Growth Potential`)
```

```
## [1] 0.1133066
```

```r
sd(shm$ROI)
```

```
## [1] 0.09438094
```

```r
summary(shfm)
```

```
##    fe_lnasset        fe_lnsalary           age                ROA
##  Min.   :-4.34133   Min.   :-4.9141   Min.   :-2.6476   Min.   :-5.08288
##  1st Qu.:-0.89601   1st Qu.:-0.3839   1st Qu.:-0.8982   1st Qu.:-0.24967
##  Median :-0.33440   Median : 0.3204   Median :-0.1984   Median :-0.05231
##  Mean   :-0.09113   Mean   : 0.2093   Mean   :-0.1848   Mean   : 0.03843
##  3rd Qu.: 0.44262   3rd Qu.: 0.8431   3rd Qu.: 0.5013   3rd Qu.: 0.24821
##  Max.   : 4.07885   Max.   : 2.7304   Max.   : 2.9505   Max.   : 4.40467
##  Operating Efficiency Growth Potential          ROI                  sex
##  Min.   :-6.839886    Min.   :-1.2679018   Min.   :-1.538561   Min.   :0
##  1st Qu.:-0.155945    1st Qu.:-0.0097670   1st Qu.:-0.007903   1st Qu.:0
##  Median : 0.001735    Median :-0.0006273   Median : 0.003913   Median :0
##  Mean   : 0.091097    Mean   :-0.0159483   Mean   :-0.005334   Mean   :0
##  3rd Qu.: 0.279136    3rd Qu.: 0.0097005   3rd Qu.: 0.012324   3rd Qu.:0
##  Max.   : 3.109707    Max.   : 0.2777850   Max.   : 0.582005   Max.   :0
##       bjsh
##  Min.   :0
##  1st Qu.:0
##  Median :0
##  Mean   :0
##  3rd Qu.:0
##  Max.   :0
```

```r
sd(shfm$fe_lnasset)
```

```
## [1] 1.160596
```

```r
sd(shfm$fe_lnsalary)
```

```
## [1] 0.8882195
```

```r
sd(shfm$sex)
```

```
## [1] 0
```

```r
sd(shfm$age)
```

```
## [1] 0.9832586
```

```r
sd(shfm$ROA)
```

```
## [1] 0.5536574
```

```r
sd(shfm$`Operating Efficiency`)
```

```
## [1] 0.6000329
```

```r
sd(shfm$`Growth Potential`)
```

```
## [1] 0.1455925
```

```r
sd(shfm$ROI)
```

```
## [1] 0.1124148
```

```r
t.test(shm$fe_lnasset, shfm$fe_lnasset)
```

```
##
##  Welch Two Sample t-test
##
## data:  shm$fe_lnasset and shfm$fe_lnasset
## t = 7.8354, df = 2153.2, p-value = 7.28e-15
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.2024479 0.3376163
## sample estimates:
##   mean of x   mean of y
##  0.17889704 -0.09113505
```

```r
t.test(shm$fe_lnsalary,shfm$fe_lnsalary)
```

```
##
##  Welch Two Sample t-test
##
## data:  shm$fe_lnsalary and shfm$fe_lnsalary
## t = 2.1529, df = 2145.6, p-value = 0.03143
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.005055701 0.108404298
## sample estimates:
## mean of x mean of y
##  0.266029  0.209299
```

```r
t.test(shm$age, shfm$age)
```

```
##
##  Welch Two Sample t-test
##
## data:  shm$age and shfm$age
## t = 15.091, df = 2067.2, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.3792372 0.4925277
## sample estimates:
##  mean of x  mean of y
##  0.2511041 -0.1847783
```

```r
t.test(shm$ROA, shfm$ROA)
```

```
##
##  Welch Two Sample t-test
##
## data:  shm$ROA and shfm$ROA
## t = -2.0095, df = 1935.3, p-value = 0.04463
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.0634745640 -0.0007718407
## sample estimates:
##   mean of x   mean of y
## 0.006309666 0.038432869
```

```r
t.test(shm$`Operating Efficiency`, shfm$`Operating Efficiency`)
```

```
##
##  Welch Two Sample t-test
##
## data:  shm$`Operating Efficiency` and shfm$`Operating Efficiency`
## t = -2.8659, df = 1890.1, p-value = 0.004204
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.08311767 -0.01557768
## sample estimates:
##  mean of x  mean of y
## 0.04174952 0.09109720
```

```r
t.test(shm$`Growth Potential`, shfm$`Growth Potential`)
```

```
##
##  Welch Two Sample t-test
##
## data:  shm$`Growth Potential` and shfm$`Growth Potential`
## t = 1.7142, df = 1754.3, p-value = 0.08667
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
```

```
##  -0.001012845  0.015063719
## sample estimates:
##    mean of x    mean of y
## -0.008922841 -0.015948278
```

```r
t.test(shm$ROI, shfm$ROI)
```

```
##
##  Welch Two Sample t-test
##
## data:  shm$ROI and shfm$ROI
## t = 1.0625, df = 1813.4, p-value = 0.2882
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.002868587  0.009650461
## sample estimates:
##    mean of x    mean of y
## -0.001943293 -0.005334230
```

```r
##bjsh difference
summary(lm(fe_lnsalary~ as.factor(sex)++as.factor(bjsh) + as.factor(sex):as.factor(bjsh) + age+fe_lnass
```

```
##
## Call:
## lm(formula = fe_lnsalary ~ as.factor(sex) + +as.factor(bjsh) +
##     as.factor(sex):as.factor(bjsh) + age + fe_lnasset + ROA +
##     `Operating Efficiency` + `Growth Potential` + ROI, data = all)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.8743 -0.6655  0.1472  0.6584  3.1168
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     0.186399   0.024502   7.608 2.95e-14 ***
## as.factor(sex)1                 0.081299   0.026867   3.026 0.002482 **
## as.factor(bjsh)1               -0.195026   0.036928  -5.281 1.30e-07 ***
## age                            -0.167976   0.007077 -23.737  < 2e-16 ***
## fe_lnasset                      0.204537   0.005962  34.306  < 2e-16 ***
## ROA                             0.078417   0.013255   5.916 3.36e-09 ***
## `Operating Efficiency`          0.044895   0.014300   3.140 0.001695 **
## `Growth Potential`             -0.100289   0.081602  -1.229 0.219087
## ROI                            -0.337232   0.088380  -3.816 0.000136 ***
## as.factor(sex)1:as.factor(bjsh)1  0.099362   0.040005   2.484 0.013010 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9159 on 16373 degrees of freedom
## Multiple R-squared:  0.09348,    Adjusted R-squared:  0.09298
## F-statistic: 187.6 on 9 and 16373 DF,  p-value: < 2.2e-16
```

Model 3

```r
#Descriptive Data for it industry
## it
industry = read_csv("/Users/kiwi/Desktop/fe_lnboth7_scale.csv")
```

```
## Parsed with column specification:
## cols(
##   fe_lnsalary = col_double(),
##   sex = col_double(),
##   age = col_double(),
##   fe_lnasset = col_double(),
##   ROA = col_double(),
##   `Operating Efficiency` = col_double(),
##   `Growth Potential` = col_double(),
##   ROI = col_double(),
##   industry = col_character(),
##   it = col_double(),
##   city = col_double()
## )
```

```r
it = industry[industry$it == 1,]
nit = industry[industry$it ==0,]
inm = it[it$sex == 1,]
infm = it[it$sex == 0,]
summary(it)
```

```
##   fe_lnsalary          sex               age            fe_lnasset
##  Min.   :-5.7168   Min.   :0.0000   Min.   :-3.2308   Min.   :-2.40048
##  1st Qu.:-0.7778   1st Qu.:1.0000   1st Qu.:-0.8982   1st Qu.:-0.52640
##  Median : 0.1862   Median :1.0000   Median :-0.3151   Median :-0.04371
##  Mean   : 0.0000   Mean   :0.8153   Mean   :-0.1822   Mean   : 0.00000
##  3rd Qu.: 0.7521   3rd Qu.:1.0000   3rd Qu.: 0.3847   3rd Qu.: 0.53414
##  Max.   : 2.9780   Max.   :1.0000   Max.   : 3.6503   Max.   : 5.34238
##       ROA              Operating Efficiency Growth Potential
##  Min.   :-4.370106   Min.   :-3.97695     Min.   :-0.3087076
##  1st Qu.:-0.223419   1st Qu.:-0.45317     1st Qu.:-0.0104561
##  Median :-0.041958   Median :-0.07408     Median : 0.0006919
##  Mean   :-0.004151   Mean   : 0.01421     Mean   :-0.0015436
##  3rd Qu.: 0.151219   3rd Qu.: 0.34771     3rd Qu.: 0.0114828
##  Max.   :17.137956   Max.   : 5.88269     Max.   : 0.7290344
##       ROI              industry               it         city
##  Min.   :-0.146410   Length:13268       Min.   :1   Min.   :110000
##  1st Qu.:-0.004935   Class :character   1st Qu.:1   1st Qu.:110000
##  Median : 0.003492   Mode  :character   Median :1   Median :320100
##  Mean   : 0.003656                      Mean   :1   Mean   :290336
##  3rd Qu.: 0.010367                      3rd Qu.:1   3rd Qu.:430100
##  Max.   : 2.367903                      Max.   :1   Max.   :610100
```

```r
sd(it$fe_lnsalary)
```

```
## [1] 0.987736
```

```r
sd(it$sex)
```

```
## [1] 0.3880931
```

```r
sd(it$age)
```

```
## [1] 1.035612
```

```r
sd(it$fe_lnasset)
```

```
## [1] 0.824702
```

```r
sd(it$ROA)
```

```
## [1] 0.7773504
```

```r
sd(it$`Operating Efficiency`)
```

```
## [1] 0.6928526
```

```r
sd(it$`Growth Potential`)
```

```
## [1] 0.04584956
```

```r
sd(it$ROI)
```

```
## [1] 0.08447985
```

```r
summary(inm)
```

```
##   fe_lnsalary            sex         age              fe_lnasset
##  Min.   :-4.19609   Min.   :1   Min.   :-3.2308   Min.   :-2.400475
##  1st Qu.:-0.77780   1st Qu.:1   1st Qu.:-0.7816   1st Qu.:-0.530445
##  Median : 0.24276   Median :1   Median :-0.1984   Median :-0.034548
##  Mean   : 0.02749   Mean   :1   Mean   :-0.1044   Mean   : 0.005698
##  3rd Qu.: 0.78648   3rd Qu.:1   3rd Qu.: 0.5013   3rd Qu.: 0.546158
##  Max.   : 2.97800   Max.   :1   Max.   : 3.6503   Max.   : 5.342378
##       ROA           Operating Efficiency Growth Potential
##  Min.   :-4.37011   Min.   :-3.97695     Min.   :-0.3087076
##  1st Qu.:-0.22048   1st Qu.:-0.43651     1st Qu.:-0.0103275
##  Median :-0.03739   Median :-0.06519     Median : 0.0007328
##  Mean   :-0.00273   Mean   : 0.01930     Mean   :-0.0015368
##  3rd Qu.: 0.15269   3rd Qu.: 0.34165     3rd Qu.: 0.0115082
##  Max.   :17.13796   Max.   : 5.88269     Max.   : 0.7290344
##       ROI              industry                it          city
##  Min.   :-0.146410   Length:10817       Min.   :1   Min.   :110000
##  1st Qu.:-0.005277   Class :character   1st Qu.:1   1st Qu.:110000
##  Median : 0.003254   Mode  :character   Median :1   Median :320100
##  Mean   : 0.003112                      Mean   :1   Mean   :290666
##  3rd Qu.: 0.010200                      3rd Qu.:1   3rd Qu.:430100
##  Max.   : 2.367903                      Max.   :1   Max.   :610100
```

```r
sd(inm$fe_lnsalary)
```

```
## [1] 1.001591
```

```r
sd(inm$sex)
```

```
## [1] 0
```

```r
sd(inm$age)
```

```
## [1] 1.025416
```

```r
sd(inm$fe_lnasset)
```

```
## [1] 0.8395351
```

```r
sd(inm$ROA)
```

```
## [1] 0.7609646
```

```r
sd(inm$`Operating Efficiency`)
```

```
## [1] 0.6917433
```

```r
sd(inm$`Growth Potential`)
```

```
## [1] 0.04532813
```

```r
sd(inm$ROI)
```

```
## [1] 0.08125868
```

```r
summary(infm)
```

```
##   fe_lnsalary          sex         age              fe_lnasset
##  Min.   :-5.7168   Min.   :0   Min.   :-3.23075   Min.   :-2.40048
##  1st Qu.:-0.7778   1st Qu.:0   1st Qu.:-1.24808   1st Qu.:-0.50836
##  Median :-0.0118   Median :0   Median :-0.66494   Median :-0.05428
##  Mean   :-0.1213   Mean   :0   Mean   :-0.52585   Mean   :-0.02515
##  3rd Qu.: 0.5360   3rd Qu.:0   3rd Qu.: 0.03483   3rd Qu.: 0.46489
##  Max.   : 2.4960   Max.   :0   Max.   : 3.41704   Max.   : 4.04499
##       ROA           Operating Efficiency Growth Potential
##  Min.   :-4.37011   Min.   :-3.976954    Min.   :-0.2028571
##  1st Qu.:-0.23468   1st Qu.:-0.477018    1st Qu.:-0.0111513
##  Median :-0.05111   Median :-0.122515    Median :-0.0004445
##  Mean   :-0.01042   Mean   :-0.008251    Mean   :-0.0015736
##  3rd Qu.: 0.13168   3rd Qu.: 0.362910    3rd Qu.: 0.0106558
```

```
##  Max.   :17.13796   Max.   : 5.882691    Max.   : 0.7290344
##       ROI               industry               it          city
##  Min.   :-0.146410   Length:2451        Min.   :1   Min.   :110000
##  1st Qu.:-0.003273   Class :character   1st Qu.:1   1st Qu.:110000
##  Median : 0.004259   Mode  :character   Median :1   Median :320100
##  Mean   : 0.006055                      Mean   :1   Mean   :288878
##  3rd Qu.: 0.010854                      3rd Qu.:1   3rd Qu.:430100
##  Max.   : 2.367903                      Max.   :1   Max.   :610100
```

```r
sd(infm$fe_lnsalary)
```

```
## [1] 0.9144834
```

```r
sd(infm$sex)
```

```
## [1] 0
```

```r
sd(infm$age)
```

```
## [1] 1.01035
```

```r
sd(infm$fe_lnasset)
```

```
## [1] 0.7554166
```

```r
sd(infm$ROA)
```

```
## [1] 0.8460204
```

```r
sd(infm$`Operating Efficiency`)
```

```
## [1] 0.6974252
```

```r
sd(infm$`Growth Potential`)
```

```
## [1] 0.04809285
```

```r
sd(infm$ROI)
```

```
## [1] 0.09741447
```

```r
t.test(inm$fe_lnsalary, infm$fe_lnsalary)
```

```
##
##  Welch Two Sample t-test
##
## data:  inm$fe_lnsalary and infm$fe_lnsalary
```

```
## t = 7.1446, df = 3897.6, p-value = 1.072e-12
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.1079900 0.1896723
## sample estimates:
##   mean of x   mean of y
##  0.02749358 -0.12133759
```

```
t.test(inm$age, infm$age)
```

```
##
##  Welch Two Sample t-test
##
## data:  inm$age and infm$age
## t = 18.597, df = 3681.7, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.3770599 0.4659334
## sample estimates:
##  mean of x  mean of y
## -0.1043541 -0.5258507
```

```
t.test(inm$fe_lnasset, infm$fe_lnasset)
```

```
##
##  Welch Two Sample t-test
##
## data:  inm$fe_lnasset and infm$fe_lnasset
## t = 1.787, df = 3943.2, p-value = 0.07401
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.002995806  0.064691553
## sample estimates:
##    mean of x    mean of y
##  0.005698119 -0.025149754
```

```
t.test(inm$ROA, infm$ROA)
```

```
##
##  Welch Two Sample t-test
##
## data:  inm$ROA and infm$ROA
## t = 0.41379, df = 3404.7, p-value = 0.6791
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.02875511  0.04413898
## sample estimates:
##    mean of x    mean of y
## -0.002729687 -0.010421624
```

```r
t.test(inm$`Operating Efficiency`, infm$`Operating Efficiency`)
```

```
##
##  Welch Two Sample t-test
##
## data:  inm$`Operating Efficiency` and infm$`Operating Efficiency`
## t = 1.7686, df = 3623.2, p-value = 0.07704
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.00299099  0.05809570
## sample estimates:
##    mean of x    mean of y
##  0.019300868 -0.008251487
```

```r
t.test(inm$`Growth Potential`, infm$`Growth Potential`)
```

```
##
##  Welch Two Sample t-test
##
## data:  inm$`Growth Potential` and infm$`Growth Potential`
## t = 0.034514, df = 3503.4, p-value = 0.9725
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.002050770  0.002124264
## sample estimates:
##    mean of x    mean of y
## -0.001536803 -0.001573551
```

```r
t.test(inm$ROI, infm$ROI)
```

```
##
##  Welch Two Sample t-test
##
## data:  inm$ROI and infm$ROI
## t = -1.3901, df = 3265.1, p-value = 0.1646
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.007093910  0.001208076
## sample estimates:
##   mean of x   mean of y
## 0.003111926 0.006054843
```

```r
##it difference
options(max.print=1000000)
summary(lm(fe_lnsalary~ as.factor(sex)+as.factor(it) + as.factor(sex):as.factor(it) + age+fe_lnasset + R
```

```
##
## Call:
## lm(formula = fe_lnsalary ~ as.factor(sex) + as.factor(it) + as.factor(sex):as.factor(it) +
##     age + fe_lnasset + ROA + `Operating Efficiency` + `Growth Potential` +
##     ROI + as.factor(city), data = industry)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.5451  -0.6839   0.1384   0.6949   4.5795
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    -0.1144912  0.0081538 -14.041  < 2e-16 ***
## as.factor(sex)1                 0.2295868  0.0056276  40.796  < 2e-16 ***
## as.factor(it)1                 -0.0496123  0.0199114  -2.492 0.012716 *
## age                            -0.1457044  0.0020054 -72.657  < 2e-16 ***
## fe_lnasset                      0.2421045  0.0021388 113.194  < 2e-16 ***
## ROA                             0.0322909  0.0019865  16.255  < 2e-16 ***
## `Operating Efficiency`          0.0176196  0.0019915   8.847  < 2e-16 ***
## `Growth Potential`              0.0003599  0.0019630   0.183 0.854548
## ROI                            -0.0085228  0.0019575  -4.354 1.34e-05 ***
## as.factor(city)120000          -0.0425207  0.0172541  -2.464 0.013725 *
## as.factor(city)130100          -0.1618031  0.0297065  -5.447 5.14e-08 ***
## as.factor(city)130200          -0.0755151  0.0311987  -2.420 0.015502 *
## as.factor(city)130300          -0.5133570  0.0906345  -5.664 1.48e-08 ***
## as.factor(city)130400          -0.0025090  0.0511044  -0.049 0.960843
## as.factor(city)130500           0.2887533  0.0803093   3.596 0.000324 ***
## as.factor(city)130600          -0.2437429  0.0294391  -8.280  < 2e-16 ***
## as.factor(city)130700          -0.7801418  0.1784446  -4.372 1.23e-05 ***
## as.factor(city)130800           0.3745512  0.0643731   5.818 5.95e-09 ***
## as.factor(city)130900          -0.0773413  0.0634164  -1.220 0.222626
## as.factor(city)131000           0.2153525  0.0937032   2.298 0.021549 *
## as.factor(city)131100          -0.5641700  0.0837237  -6.738 1.60e-11 ***
## as.factor(city)140100          -0.3278306  0.0272274 -12.040  < 2e-16 ***
## as.factor(city)140200          -0.4202998  0.0625692  -6.717 1.85e-11 ***
## as.factor(city)140300          -0.0551077  0.0670536  -0.822 0.411165
## as.factor(city)140400          -0.6133130  0.0552444 -11.102  < 2e-16 ***
## as.factor(city)140500           0.4019072  0.0733411   5.480 4.26e-08 ***
## as.factor(city)140700          -0.3216670  0.0878628  -3.661 0.000251 ***
## as.factor(city)140800          -0.0924154  0.0511018  -1.808 0.070536 .
## as.factor(city)140900          -0.2725115  0.0890740  -3.059 0.002218 **
## as.factor(city)141000          -0.4335007  0.0652971  -6.639 3.17e-11 ***
## as.factor(city)141100          -0.6339704  0.0684337  -9.264  < 2e-16 ***
## as.factor(city)150100           0.1644068  0.0352994   4.658 3.20e-06 ***
## as.factor(city)150200          -0.2496741  0.0345670  -7.223 5.10e-13 ***
## as.factor(city)150300          -0.3119473  0.0704945  -4.425 9.64e-06 ***
## as.factor(city)150400          -0.4203862  0.1050733  -4.001 6.31e-05 ***
## as.factor(city)150500           0.0983002  0.1363856   0.721 0.471063
## as.factor(city)150600          -0.4701009  0.0337870 -13.914  < 2e-16 ***
## as.factor(city)150900          -0.0612566  0.0986364  -0.621 0.534577
## as.factor(city)152900           0.1379512  0.0805949   1.712 0.086960 .
## as.factor(city)210100          -0.0225890  0.0312821  -0.722 0.470229
## as.factor(city)210200           0.0733439  0.0214506   3.419 0.000628 ***
## as.factor(city)210300          -0.2445634  0.0455085  -5.374 7.71e-08 ***
## as.factor(city)210400          -0.2590339  0.0919263  -2.818 0.004835 **
## as.factor(city)210500          -0.6341670  0.0975436  -6.501 7.98e-11 ***
## as.factor(city)210600          -0.3705008  0.0786439  -4.711 2.47e-06 ***
## as.factor(city)210700          -0.3225802  0.1163455  -2.773 0.005561 **
## as.factor(city)210781          -0.2903784  0.1324224  -2.193 0.028321 *
```

```
## as.factor(city)210800          -0.1611359  0.0970713  -1.660 0.096921 .
## as.factor(city)210900          -0.2012968  0.1019741  -1.974 0.048383 *
## as.factor(city)211000          -0.2475968  0.0965353  -2.565 0.010323 *
## as.factor(city)211100          -0.0773437  0.1210047  -0.639 0.522707
## as.factor(city)211400          -0.4652002  0.0639895  -7.270 3.61e-13 ***
## as.factor(city)220100          -0.0175979  0.0237149  -0.742 0.458051
## as.factor(city)220200          -0.3752260  0.0395670  -9.483  < 2e-16 ***
## as.factor(city)220284          -0.0615995  0.0975487  -0.631 0.527731
## as.factor(city)220400           0.0771712  0.2224958   0.347 0.728709
## as.factor(city)220500          -0.7264977  0.0476587 -15.244  < 2e-16 ***
## as.factor(city)222402          -1.1384337  0.1970201  -5.778 7.56e-09 ***
## as.factor(city)222403          -0.4930801  0.0754714  -6.533 6.45e-11 ***
## as.factor(city)230100          -0.2366484  0.0223095 -10.607  < 2e-16 ***
## as.factor(city)230200          -0.0332458  0.0794582  -0.418 0.675651
## as.factor(city)230300          -0.5405682  0.1573935  -3.435 0.000594 ***
## as.factor(city)230600          -0.0349555  0.0858018  -0.407 0.683716
## as.factor(city)230700          -0.7252144  0.1274242  -5.691 1.26e-08 ***
## as.factor(city)230800          -0.5440343  0.1240763  -4.385 1.16e-05 ***
## as.factor(city)230900          -0.0827338  0.1190597  -0.695 0.487123
## as.factor(city)231000          -0.3404594  0.2845778  -1.196 0.231555
## as.factor(city)310000           0.0958233  0.0095943   9.987  < 2e-16 ***
## as.factor(city)320100           0.0135083  0.0149566   0.903 0.366437
## as.factor(city)320200          -0.1472143  0.0192857  -7.633 2.30e-14 ***
## as.factor(city)320281          -0.3859818  0.0338718 -11.395  < 2e-16 ***
## as.factor(city)320282           0.0705961  0.1440548   0.490 0.624089
## as.factor(city)320300           0.0074786  0.0393451   0.190 0.849249
## as.factor(city)320381           0.0701376  0.1323212   0.530 0.596074
## as.factor(city)320400           0.0592441  0.0266686   2.221 0.026319 *
## as.factor(city)320500          -0.0121640  0.0159866  -0.761 0.446723
## as.factor(city)320581          -0.0720307  0.0716401  -1.005 0.314680
## as.factor(city)320582           0.2350363  0.0410959   5.719 1.07e-08 ***
## as.factor(city)320583           0.2694357  0.1968713   1.369 0.171129
## as.factor(city)320585           0.0931469  0.0902275   1.032 0.301906
## as.factor(city)320600          -0.0597852  0.0219298  -2.726 0.006407 **
## as.factor(city)320682          -0.1983298  0.2617800  -0.758 0.448679
## as.factor(city)320684          -0.1175970  0.0628391  -1.871 0.061291 .
## as.factor(city)320700           0.0707054  0.0361019   1.958 0.050173 .
## as.factor(city)320800           0.1324710  0.1349652   0.982 0.326338
## as.factor(city)320900          -0.0531430  0.0399457  -1.330 0.183394
## as.factor(city)321000          -0.0760978  0.0315645  -2.411 0.015916 *
## as.factor(city)321081          -0.1144791  0.1070469  -1.069 0.284877
## as.factor(city)321100          -0.3987831  0.0359786 -11.084  < 2e-16 ***
## as.factor(city)321181          -0.2494299  0.0791843  -3.150 0.001633 **
## as.factor(city)321200          -0.3827712  0.0515533  -7.425 1.13e-13 ***
## as.factor(city)321282           0.2834311  0.2437226   1.163 0.244861
## as.factor(city)321300           0.0056462  0.0550618   0.103 0.918326
## as.factor(city)330100           0.0252196  0.0131019   1.925 0.054246 .
## as.factor(city)330185           0.0441599  0.0493078   0.896 0.370469
## as.factor(city)330200          -0.0008038  0.0167593  -0.048 0.961747
## as.factor(city)330281          -0.3368128  0.0867586  -3.882 0.000104 ***
## as.factor(city)330282          -0.0832405  0.1190649  -0.699 0.484478
## as.factor(city)330283           0.0018404  0.1064075   0.017 0.986201
## as.factor(city)330300          -0.1210214  0.0343125  -3.527 0.000420 ***
## as.factor(city)330382          -0.0508396  0.0997414  -0.510 0.610253
```

```
## as.factor(city)330400            0.0569881  0.0256885   2.218 0.026527 *
## as.factor(city)330481            0.1086648  0.0594932   1.827 0.067775 .
## as.factor(city)330482            0.1253858  0.1070509   1.171 0.241490
## as.factor(city)330483            0.1255010  0.0890068   1.410 0.158536
## as.factor(city)330500           -0.0062804  0.0293189  -0.214 0.830384
## as.factor(city)330600           -0.1404500  0.0167376  -8.391  < 2e-16 ***
## as.factor(city)330681           -0.1121423  0.0504602  -2.222 0.026258 *
## as.factor(city)330683           -0.1252059  0.2724951  -0.459 0.645890
## as.factor(city)330700           -0.1591111  0.0295982  -5.376 7.64e-08 ***
## as.factor(city)330782           -0.3991290  0.1129789  -3.533 0.000411 ***
## as.factor(city)330783           -0.1439695  0.0941221  -1.530 0.126116
## as.factor(city)330800           -0.3754875  0.0629759  -5.962 2.49e-09 ***
## as.factor(city)330881           -0.2206655  0.1377927  -1.601 0.109283
## as.factor(city)330900           -0.2772981  0.0965286  -2.873 0.004070 **
## as.factor(city)331000            0.1039191  0.0194780   5.335 9.55e-08 ***
## as.factor(city)331081            0.0979609  0.0765924   1.279 0.200902
## as.factor(city)331082            0.0676967  0.0565102   1.198 0.230936
## as.factor(city)331100           -0.0275094  0.0587784  -0.468 0.639772
## as.factor(city)340100           -0.0978194  0.0193840  -5.046 4.51e-07 ***
## as.factor(city)340181           -0.1907738  0.0531673  -3.588 0.000333 ***
## as.factor(city)340200           -0.2447882  0.0306668  -7.982 1.44e-15 ***
## as.factor(city)340300           -0.1020397  0.0414199  -2.464 0.013758 *
## as.factor(city)340400            0.2160670  0.0991393   2.179 0.029301 *
## as.factor(city)340500           -0.2333127  0.0355899  -6.556 5.55e-11 ***
## as.factor(city)340600            0.1017306  0.0515447   1.974 0.048424 *
## as.factor(city)340700           -0.4571831  0.0407159 -11.229  < 2e-16 ***
## as.factor(city)340800           -0.5618724  0.0656004  -8.565  < 2e-16 ***
## as.factor(city)341000           -0.4808232  0.0773519  -6.216 5.11e-10 ***
## as.factor(city)341100           -0.0759202  0.0508321  -1.494 0.135295
## as.factor(city)341200           -0.2677803  0.0840335  -3.187 0.001440 **
## as.factor(city)341500           -0.0563312  0.0616572  -0.914 0.360918
## as.factor(city)341600            0.2913964  0.1008124   2.890 0.003847 **
## as.factor(city)341800           -0.1640587  0.0569031  -2.883 0.003938 **
## as.factor(city)341881           -0.0808153  0.1297862  -0.623 0.533495
## as.factor(city)350100           -0.2076694  0.0223319  -9.299  < 2e-16 ***
## as.factor(city)350181            0.4291153  0.0623210   6.886 5.77e-12 ***
## as.factor(city)350200           -0.0401109  0.0196296  -2.043 0.041015 *
## as.factor(city)350300           -0.2010934  0.1200231  -1.675 0.093846 .
## as.factor(city)350400           -0.3075885  0.0418451  -7.351 1.98e-13 ***
## as.factor(city)350500           -0.1883666  0.0347382  -5.422 5.88e-08 ***
## as.factor(city)350582           -0.1165931  0.0572988  -2.035 0.041869 *
## as.factor(city)350583           -0.4726384  0.0950757  -4.971 6.66e-07 ***
## as.factor(city)350600           -0.0948953  0.0498619  -1.903 0.057021 .
## as.factor(city)350700            0.0942360  0.0480856   1.960 0.050025 .
## as.factor(city)350800            0.1781539  0.0398706   4.468 7.89e-06 ***
## as.factor(city)350900           -0.2039962  0.0784948  -2.599 0.009354 **
## as.factor(city)360100            0.0086403  0.0225075   0.384 0.701063
## as.factor(city)360200           -0.4114421  0.0529222  -7.774 7.61e-15 ***
## as.factor(city)360300           -0.9069711  0.1263060  -7.181 6.95e-13 ***
## as.factor(city)360500           -0.2516229  0.0607890  -4.139 3.49e-05 ***
## as.factor(city)360600           -0.2944848  0.1025678  -2.871 0.004091 **
## as.factor(city)360681           -0.0672968  0.0592176  -1.136 0.255777
## as.factor(city)360700            0.3421866  0.0773519   4.424 9.70e-06 ***
## as.factor(city)360900           -0.6722835  0.0562419 -11.953  < 2e-16 ***
```

```
## as.factor(city)361000           0.0375568  0.1154961   0.325 0.745046    
## as.factor(city)361100          -0.2077706  0.0651499  -3.189 0.001427 ** 
## as.factor(city)370100          -0.1442923  0.0236818  -6.093 1.11e-09 ***
## as.factor(city)370200          -0.2399256  0.0219286 -10.941  < 2e-16 ***
## as.factor(city)370281          -0.0493332  0.2724702  -0.181 0.856322    
## as.factor(city)370300          -0.0674129  0.0217707  -3.096 0.001958 ** 
## as.factor(city)370400          -0.4412656  0.2225367  -1.983 0.047381 *  
## as.factor(city)370500          -0.4213483  0.0463109  -9.098  < 2e-16 ***
## as.factor(city)370600          -0.1551598  0.0224622  -6.908 4.94e-12 ***
## as.factor(city)370681          -0.3855504  0.0592368  -6.509 7.60e-11 ***
## as.factor(city)370682          -0.0954209  0.1644024  -0.580 0.561638    
## as.factor(city)370683          -0.0862182  0.1512513  -0.570 0.568656    
## as.factor(city)370700          -0.2754558  0.0285218  -9.658  < 2e-16 ***
## as.factor(city)370782          -0.4809188  0.0981349  -4.901 9.56e-07 ***
## as.factor(city)370783          -0.0157282  0.0490070  -0.321 0.748258    
## as.factor(city)370786          -0.2572798  0.1424512  -1.806 0.070905 .  
## as.factor(city)370800          -0.4784344  0.0307873 -15.540  < 2e-16 ***
## as.factor(city)370900          -0.2914399  0.0625156  -4.662 3.14e-06 ***
## as.factor(city)371000          -0.0742577  0.0419136  -1.772 0.076448 .  
## as.factor(city)371082          -0.6534498  0.0751288  -8.698  < 2e-16 ***
## as.factor(city)371100          -0.3914943  0.0803160  -4.874 1.09e-06 ***
## as.factor(city)371200           0.1152652  0.1071068   1.076 0.281852    
## as.factor(city)371300          -0.3087632  0.0436199  -7.078 1.46e-12 ***
## as.factor(city)371400          -0.4421307  0.1240838  -3.563 0.000366 ***
## as.factor(city)371482          -0.0262956  0.0582455  -0.451 0.651658    
## as.factor(city)371500          -0.0346382  0.0404938  -0.855 0.392332    
## as.factor(city)371600          -0.1848637  0.0433186  -4.268 1.98e-05 ***
## as.factor(city)371700           0.0072541  0.1423990   0.051 0.959372    
## as.factor(city)410100          -0.2182770  0.0223082  -9.785  < 2e-16 ***
## as.factor(city)410200          -0.3523947  0.0986055  -3.574 0.000352 ***
## as.factor(city)410300          -0.1852347  0.0355298  -5.214 1.85e-07 ***
## as.factor(city)410400          -0.2427298  0.0537428  -4.517 6.29e-06 ***
## as.factor(city)410500          -0.5445143  0.0653184  -8.336  < 2e-16 ***
## as.factor(city)410581          -0.3502947  0.0886252  -3.953 7.73e-05 ***
## as.factor(city)410700          -0.1663111  0.0628426  -2.646 0.008134 ** 
## as.factor(city)410800          -0.1453656  0.0348207  -4.175 2.98e-05 ***
## as.factor(city)410900           0.2369551  0.0691535   3.427 0.000611 ***
## as.factor(city)411000          -0.3155237  0.0439025  -7.187 6.65e-13 ***
## as.factor(city)411082          -0.4903485  0.0742151  -6.607 3.93e-11 ***
## as.factor(city)411100           0.0056438  0.0517115   0.109 0.913091    
## as.factor(city)411281          -0.3159273  0.1154828  -2.736 0.006225 ** 
## as.factor(city)411300          -0.2058168  0.0704503  -2.921 0.003484 ** 
## as.factor(city)411481           0.4208758  0.0638321   6.593 4.31e-11 ***
## as.factor(city)411500          -0.2164732  0.0523160  -4.138 3.51e-05 ***
## as.factor(city)411600          -0.4233721  0.1643899  -2.575 0.010013 *  
## as.factor(city)411681           0.0461172  0.0887801   0.519 0.603445    
## as.factor(city)411700          -0.6202012  0.0902225  -6.874 6.25e-12 ***
## as.factor(city)419001          -0.3575864  0.0653193  -5.474 4.39e-08 ***
## as.factor(city)420100          -0.1389268  0.0164799  -8.430  < 2e-16 ***
## as.factor(city)420200           0.1098709  0.0451254   2.435 0.014901 *  
## as.factor(city)420300          -0.6941589  0.1457544  -4.763 1.91e-06 ***
## as.factor(city)420500          -0.1053184  0.0339681  -3.101 0.001932 ** 
## as.factor(city)420582          -0.4547485  0.0726973  -6.255 3.97e-10 ***
## as.factor(city)420600          -0.3012525  0.0338272  -8.906  < 2e-16 ***
```

```
## as.factor(city)420700           0.2907480  0.1532185   1.898 0.057750 .
## as.factor(city)420800          -0.3705356  0.0474490  -7.809 5.78e-15 ***
## as.factor(city)420900          -0.6026215  0.0936701  -6.433 1.25e-10 ***
## as.factor(city)420981           0.0147858  0.1263089   0.117 0.906812
## as.factor(city)420984          -0.4304712  0.0731114  -5.888 3.92e-09 ***
## as.factor(city)421000          -0.1033632  0.0316601  -3.265 0.001096 **
## as.factor(city)421182          -0.1001980  0.0684533  -1.464 0.143266
## as.factor(city)421300           0.0773183  0.2617969   0.295 0.767737
## as.factor(city)429004          -0.0954163  0.2225006  -0.429 0.668043
## as.factor(city)429005          -0.1793808  0.0830378  -2.160 0.030756 *
## as.factor(city)430100          -0.0401619  0.0169144  -2.374 0.017577 *
## as.factor(city)430181          -0.3742181  0.1310227  -2.856 0.004289 **
## as.factor(city)430200          -0.4712707  0.0326481 -14.435  < 2e-16 ***
## as.factor(city)430300          -0.2393031  0.0446827  -5.356 8.54e-08 ***
## as.factor(city)430400           0.0301627  0.0976126   0.309 0.757319
## as.factor(city)430600          -0.0448806  0.0382785  -1.172 0.241007
## as.factor(city)430700          -0.0235588  0.0702742  -0.335 0.737443
## as.factor(city)430900          -0.3727260  0.0806356  -4.622 3.80e-06 ***
## as.factor(city)430981           0.0303748  0.1044549   0.291 0.771210
## as.factor(city)431000          -0.2585680  0.0674446  -3.834 0.000126 ***
## as.factor(city)431100           0.1323522  0.0776142   1.705 0.088148 .
## as.factor(city)431200           0.0832019  0.1064225   0.782 0.434329
## as.factor(city)433101           0.3410387  0.0716936   4.757 1.97e-06 ***
## as.factor(city)440100           0.0686715  0.0144804   4.742 2.11e-06 ***
## as.factor(city)440200          -0.4676027  0.0441320 -10.596  < 2e-16 ***
## as.factor(city)440300           0.1518230  0.0099414  15.272  < 2e-16 ***
## as.factor(city)440400          -0.0037937  0.0223515  -0.170 0.865224
## as.factor(city)440500          -0.0800661  0.0255133  -3.138 0.001700 **
## as.factor(city)440600           0.1602893  0.0202604   7.911 2.55e-15 ***
## as.factor(city)440700          -0.0921380  0.0421266  -2.187 0.028731 *
## as.factor(city)440783           0.1874207  0.2724648   0.688 0.491535
## as.factor(city)440785          -0.0679197  0.1753577  -0.387 0.698519
## as.factor(city)440800           0.2280926  0.0753896   3.026 0.002482 **
## as.factor(city)440900           0.3691201  0.0721414   5.117 3.11e-07 ***
## as.factor(city)441200           0.0150741  0.0425157   0.355 0.722924
## as.factor(city)441300          -0.1342256  0.0473963  -2.832 0.004626 **
## as.factor(city)441400           0.1584115  0.0353350   4.483 7.36e-06 ***
## as.factor(city)441481          -0.1824270  0.0919312  -1.984 0.047214 *
## as.factor(city)441700          -0.3403791  0.2725832  -1.249 0.211770
## as.factor(city)441900          -0.0323377  0.0351468  -0.920 0.357533
## as.factor(city)442000          -0.0499263  0.0272097  -1.835 0.066526 .
## as.factor(city)445100          -0.2268011  0.0721091  -3.145 0.001660 **
## as.factor(city)445200          -0.5423791  0.0416399 -13.025  < 2e-16 ***
## as.factor(city)445281          -0.1667121  0.1146228  -1.454 0.145826
## as.factor(city)445300           0.5455712  0.1121823   4.863 1.16e-06 ***
## as.factor(city)450100          -0.1266594  0.0357853  -3.539 0.000401 ***
## as.factor(city)450200           0.0730631  0.0408478   1.789 0.073670 .
## as.factor(city)450300          -0.0794075  0.0415577  -1.911 0.056034 .
## as.factor(city)450400          -0.0502703  0.0587899  -0.855 0.392505
## as.factor(city)450500          -0.3026195  0.0548026  -5.522 3.36e-08 ***
## as.factor(city)450800           0.1100101  0.0946077   1.163 0.244911
## as.factor(city)450900          -0.2450286  0.0927898  -2.641 0.008274 **
## as.factor(city)451100          -0.1677484  0.0761465  -2.203 0.027598 *
## as.factor(city)451200          -0.4127455  0.0932383  -4.427 9.57e-06 ***
```

```
## as.factor(city)460100          -0.2124598  0.0237959  -8.928  < 2e-16 ***
## as.factor(city)460200          -0.1427078  0.1121993  -1.272 0.203405    
## as.factor(city)469023          -0.4298228  0.1552700  -2.768 0.005637 ** 
## as.factor(city)469026           0.1924769  0.2359758   0.816 0.414693    
## as.factor(city)5e+05           -0.1933281  0.0164672 -11.740  < 2e-16 ***
## as.factor(city)510100          -0.2127661  0.0149835 -14.200  < 2e-16 ***
## as.factor(city)510300          -0.2507734  0.0460405  -5.447 5.13e-08 ***
## as.factor(city)510400          -0.3769027  0.0914835  -4.120 3.79e-05 ***
## as.factor(city)510500           0.0506501  0.0524545   0.966 0.334245    
## as.factor(city)510600           0.0011208  0.0511553   0.022 0.982520    
## as.factor(city)510682          -0.1319956  0.2289781  -0.576 0.564308    
## as.factor(city)510700          -0.4303810  0.0318953 -13.494  < 2e-16 ***
## as.factor(city)510900          -0.2389767  0.0379301  -6.300 2.97e-10 ***
## as.factor(city)511000          -0.2072301  0.1888596  -1.097 0.272524    
## as.factor(city)511100           0.1077055  0.0792468   1.359 0.174112    
## as.factor(city)511181          -0.0637784  0.0960592  -0.664 0.506723    
## as.factor(city)511300          -0.3926871  0.1969524  -1.994 0.046173 *  
## as.factor(city)511400           0.1826526  0.1285889   1.420 0.155481    
## as.factor(city)511500          -0.3853120  0.0505247  -7.626 2.43e-14 ***
## as.factor(city)511800           0.2853239  0.0836835   3.410 0.000651 ***
## as.factor(city)512081           0.1556669  0.1784881   0.872 0.383132    
## as.factor(city)513401           0.4180074  0.2225490   1.878 0.060345 .  
## as.factor(city)520100          -0.1090304  0.0225480  -4.835 1.33e-06 ***
## as.factor(city)520200           0.0737201  0.1084658   0.680 0.496719    
## as.factor(city)520300          -0.4009450  0.0421133  -9.521  < 2e-16 ***
## as.factor(city)520400          -0.1380587  0.0660901  -2.089 0.036714 *  
## as.factor(city)522700          -0.4815295  0.0797505  -6.038 1.56e-09 ***
## as.factor(city)530100          -0.2579486  0.0211134 -12.217  < 2e-16 ***
## as.factor(city)530300          -0.1074825  0.0503952  -2.133 0.032943 *  
## as.factor(city)530400          -0.3157918  0.2437153  -1.296 0.195066    
## as.factor(city)530500          -0.0944091  0.0780290  -1.210 0.226309    
## as.factor(city)530600          -0.2675902  0.1106821  -2.418 0.015622 *  
## as.factor(city)530800          -0.0755172  0.2617847  -0.288 0.772987    
## as.factor(city)532600           0.4844393  0.1350534   3.587 0.000335 ***
## as.factor(city)540100          -0.2102228  0.0342371  -6.140 8.25e-10 ***
## as.factor(city)540400           0.1156322  0.0850383   1.360 0.173905    
## as.factor(city)542200          -0.1349560  0.1044334  -1.292 0.196265    
## as.factor(city)610100          -0.2852468  0.0217624 -13.107  < 2e-16 ***
## as.factor(city)610200          -0.2453728  0.2111027  -1.162 0.245099    
## as.factor(city)610300          -0.5297958  0.0419476 -12.630  < 2e-16 ***
## as.factor(city)610400          -0.6605175  0.0789577  -8.365  < 2e-16 ***
## as.factor(city)610581          -0.7612629  0.1888260  -4.032 5.54e-05 ***
## as.factor(city)610700          -0.1586971  0.0946325  -1.677 0.093547 .  
## as.factor(city)620100          -0.3882462  0.0269672 -14.397  < 2e-16 ***
## as.factor(city)620200           0.1599812  0.0820851   1.949 0.051301 .  
## as.factor(city)620400          -0.0457977  0.1209908  -0.379 0.705043    
## as.factor(city)620500           0.3577929  0.0820919   4.358 1.31e-05 ***
## as.factor(city)620600          -0.8178462  0.1785407  -4.581 4.64e-06 ***
## as.factor(city)620900          -0.4211715  0.0857206  -4.913 8.96e-07 ***
## as.factor(city)621200          -0.8002073  0.0906346  -8.829  < 2e-16 ***
## as.factor(city)630100          -0.3688418  0.0350912 -10.511  < 2e-16 ***
## as.factor(city)630200           0.0502501  0.1817300   0.277 0.782157    
## as.factor(city)632801          -0.3221969  0.0738149  -4.365 1.27e-05 ***
## as.factor(city)640100          -0.2018246  0.0449099  -4.494 6.99e-06 ***
```

```
## as.factor(city)640181          -0.4639718  0.0789134  -5.880 4.12e-09 ***
## as.factor(city)640200          -0.2890840  0.0689811  -4.191 2.78e-05 ***
## as.factor(city)640300          -0.5723977  0.0860723  -6.650 2.93e-11 ***
## as.factor(city)640500          -0.4076230  0.1851772  -2.201 0.027719 *
## as.factor(city)650100          -0.2162927  0.0204218 -10.591  < 2e-16 ***
## as.factor(city)650200          -0.2065020  0.0758533  -2.722 0.006482 **
## as.factor(city)652300          -0.2595475  0.1230619  -2.109 0.034939 *
## as.factor(city)652301          -0.1280399  0.0469775  -2.726 0.006420 **
## as.factor(city)652701          -0.5101487  0.1286247  -3.966 7.31e-05 ***
## as.factor(city)652800          -0.7335684  0.0756072  -9.702  < 2e-16 ***
## as.factor(city)652901          -0.2269548  0.1129678  -2.009 0.044536 *
## as.factor(city)654000          -0.0792969  0.0714804  -1.109 0.267280
## as.factor(city)659001          -0.1973532  0.0533385  -3.700 0.000216 ***
## as.factor(sex)1:as.factor(it)1 -0.0310961  0.0218439  -1.424 0.154576
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9435 on 232150 degrees of freedom
## Multiple R-squared:  0.1107, Adjusted R-squared:  0.1095
## F-statistic: 87.61 on 330 and 232150 DF,  p-value: < 2.2e-16
```