

The Market of Programming Skills: Market Tightness and Pay Equity

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Abstract

The demand for programming skills has grown dramatically in recent years, driven by the growth of the technology sector and the increasing importance of software in the global economy. As a result, understanding the market for programming skills is critical for policymakers, employers, and workers alike. This paper aims to contribute to this understanding by examining the dynamics of the programming skills market from both the demand and supply sides. Specifically, we use job posting data from Burning Glass Institute and search intensity data from Google Trends to construct a measure of market tightness, which captures the gap between the supply and demand of various programming languages. We then investigate how this measure of market tightness is related to the compensation of programming professionals, and how this relationship varies by gender, age, and other demographic characteristics. Our results shed light on the complex dynamics of the programming skills market and offer insights for policymakers and practitioners seeking to promote economic growth and workforce development.

Keywords: Market Tightness, Compensation, IT Professionals, Online Labor Market

1. Introduction

The demand for computer programming skills has grown rapidly in recent years, making it one of the most sought-after skills in the labor market. This trend is expected to continue, with employment in computer and information technology occupations projected to grow at a much

faster rate than the average for all occupations. For instance, a recent report by the Bureau of Labor Statistics showed that employment in computer and information technology occupations is projected to grow 11% from 2019 to 2029, much faster than the average for all occupations.¹

However, despite the importance of programming skills, little is known about the dynamics of the programming skills market and the impact on compensation. The lack of understanding makes it difficult for policymakers, educators, and employers to make informed decisions regarding workforce development and hiring practices. We aim to fill this gap by exploring both the demand and supply side of the market and investigating the relationship between market tightness and programmer compensation for popular programming languages. By shedding light on the programming skills market, this study seeks to contribute to a better understanding of the labor market and help stakeholders make informed decisions that will ultimately benefit the workforce and the economy as a whole.

To gain insights into the market for programming language skills, we analyzed both the demand and supply side using Burning Glass Institute's technology job posting data and Google Trend's programming language search intensity, respectively. We discovered that the trends of programming language demand and supply do not always align, which prompted us to introduce a measure of market tightness that captures the difference between the two. Our analysis found that Java is in high demand while Python is mostly

¹See "Occupational Outlook Handbook: Computer and Information Technology Occupations." It is published by the Bureau of Labor Statistics, May 2023.

in excess supply. We also examined the average market tightness across US states and found that those with larger populations and higher personal incomes experience a shortage of programmers.

We used programmer-level data, including demographics, programming skills, and compensation, from the Stack Overflow Developer Survey to construct measures of programmer skill in-demandness. These measures provided insights into the overall market shortage of programmers' skills as well as their most sought-after skills. By using these measures, we gained a deeper understanding of the supply and demand dynamics of programming skills and their impact on compensation.

Our investigation into the impact of skill in-demandness on programmer compensation showed that the demand for programmers' skills is positively correlated with their compensation, and highly in-demand skills are associated with higher compensation. Our analysis provided evidence for sorting, as job seekers may prioritize submarkets for their most in-demand skills and then move on to submarkets for skills with lower market tightness. Our results also aligned with prior research on the gender/age wage gap in the labor market, revealing that male workers and senior workers earn higher wages than their female and junior counterparts, respectively, in the programming skills market.

To better understand the factors contributing to the varying effects of market tightness on programmers' compensation, we examined demographics and the distribution of proficient language market tightness. Our analysis showed that female and junior workers tend to have lower wages, and the split-sample analysis revealed that female and junior respondents are more sensitive to changes in skill in-demandness than male and senior respondents, respectively. Additionally, individuals with skills that have more dispersed market tightness have higher compensation, indicating that possessing a diverse range of programming skills is associated with a wage premium. However, knowing programming languages with significantly lower market tightness would decrease compensation, suggesting that job seekers with these skills are more likely to be sorted into different submarkets.

Finally, we constructed a metric called programmers' desired skill in-demandness based on the Stack Overflow Developer Survey. This metric indicates how forward-looking a respondent is in terms of market conditions. Our analysis found

that workers with higher current in-demandness are more likely to aspire to work with skills that are in higher demand in the future. Further analysis revealed that female workers tend to consistently target sought-after skills, indicating that they are more sensitive to changes in skill in-demandness.

Our study has important managerial implications. First, it provides valuable insights into the supply and demand dynamics of programming language skills, which can inform educational institutions, policymakers, and employers in designing effective training and education programs to equip the workforce with the skills needed to succeed in the labor market. Second, the research sheds light on the factors that drive the demand for programming language skills, which can help policymakers and educators to anticipate future trends in the labor market and adjust educational and training programs accordingly. Finally, the research can help employers to identify the most in-demand programming languages, and adjust their hiring strategies accordingly to attract the best talent in the market.

The rest of the paper is organized as follows. In the next section, we provide an overview of the literature on the labor market for computer programming skills. We then describe the data sources and measures used in our analysis. The subsequent section presents our analysis of the impact of skill in-demandness on programmer compensation. Finally, we conclude with a discussion of the implications of our findings and future directions for research.

2. Literature Review

Our research makes a significant contribution to the information systems literature on the labor market of IT professionals. First, we add to the study of IT professionals' characteristics and compensation, building upon existing research that has investigated the effects of demographic factors such as gender and age, as well as human capital factors such as education and experience, on IT workers' wages. For example, [6] find that gender and age have similar effects on IT workers' wages in both the United States and Canada, with women and older workers earning less than men and younger workers, respectively. [7] find that foreign IT professionals earn a salary premium compared to those with U.S. citizenship, and that the salary premiums for foreign IT professionals

fluctuate in response to supply shocks created by the annual caps on new H-1B visas. [4] find that programmers in open source software communities receive different economic benefits depending on their roles and activities in the community and their alignment with their paid employment. [5] find that the relative pay gap influences the job mobility patterns of male and female IT professionals differently, with male IT professionals more likely to turnover than turn away between, while female IT professionals are more likely to turn away from IT than turnover when faced with a relative pay gap. [11] investigate how multinational corporations (MNCs) and domestic firms compensate technical and managerial skills of IT professionals within and across geographies and found that MNCs and domestic firms value and compensate IT professionals differently across geographies, depending on their firm-level strategies and capabilities. [10] found that IT workers accept a compensating differential to work with emerging IT systems, and that employers that invest in these systems can, in turn, capture greater value from the wages they pay.

Our study complements the above literature in several ways. First, we analyze how market tightness affects programmer compensation, which has not been explored before. Second, we focus on programmers as a distinct group of IT professionals and examine how their gender and wage influence their pay. Third, we combine the Burning Glass dataset, which provides detailed information on job postings, with a newer and more comprehensive survey dataset than previous studies, which enables us to capture a more complete picture of the determinants of programmer compensation.

Second, we contribute to the literature that focuses on the market tightness of IT workers. Prior research has found that the movement of IT workers among firms is an important mechanism by which IT-related innovations diffuse throughout the economy and enhance productivity growth ([9]). [8] found that big data investment leads to higher wage growth for workers with big data skills, suggesting that these workers capture some of the rents from big data technologies. [3] found that enterprise information systems (EIS) implementation affects professional mobility in two ways: by creating complementarities and by causing disruptions. [2] investigated how search and social interventions for improving professional networking for women in the IT area affect their networking outcomes and career mobility. [1] found that basic IT skills

increase employment probability. However, our study differs from these prior works by focusing on popular programming languages and defining market tightness for each language, then combining other programmers' characteristics to study the impact on programmers' compensation.

3. Data and Measures

3.1. Market Tightness of Programming Languages

To construct our measure of market tightness for the programming languages analyzed in this study, we utilize two datasets. The first dataset is obtained from the Burning Glass Institute and includes monthly data on technology job postings in the United States from 2010 to 2020. For each job posting, we examine the skill requirements in the associated skill files and count the occurrence of programming languages.

We include the following programming languages in our analysis: ABAP, Ada, C#, C/C++, COBOL, Dart, Delphi/Pascal, Go, Groovy, Haskell, Java, JavaScript, Julia, Kotlin, Lua, Matlab, Objective-C, Perl, PHP, Python, R, Ruby, Rust, Scala, Swift, TypeScript, VBA, and Visual Basic. This list is consistent with the top programming languages that appeared on the PYPL PopularitY of Programming Language website in 2022.

We then aggregate the occurrence of all programming languages for each month and converted the total number of occurrences into the share of occurrence in job postings. We define the demand share of programming language i at time t $D_{i,t}$ by the fraction of programming language skill i over all programming language skills mentioned in job postings from Burning Glass data at time t .

Figure 1 displays the demand share $D_{i,t}$ for a subset of programming languages from 2010 to 2020. The figure reveals that the demand for Java was highest in 2010 but has decreased steadily over time. In contrast, the demand for Python was the lowest in 2010, but it has been on the rise and caught up with Java around 2020. A similar trend can be observed for JavaScript, which has also experienced an upward trajectory throughout the sample period.

Second, we utilize data from Google Trends to capture the supply side of programming language skills. Specifically, we begin by searching for Google Knowledge Graph IDs for the set of programming languages we use in Burning Glass data. Our

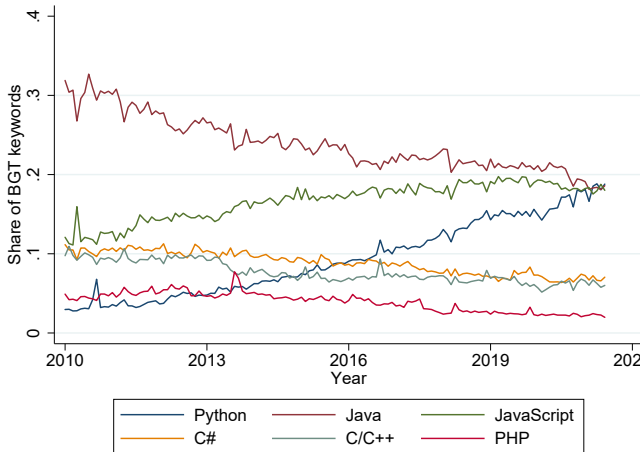


Figure 1. The Demand of Programming Language Skills

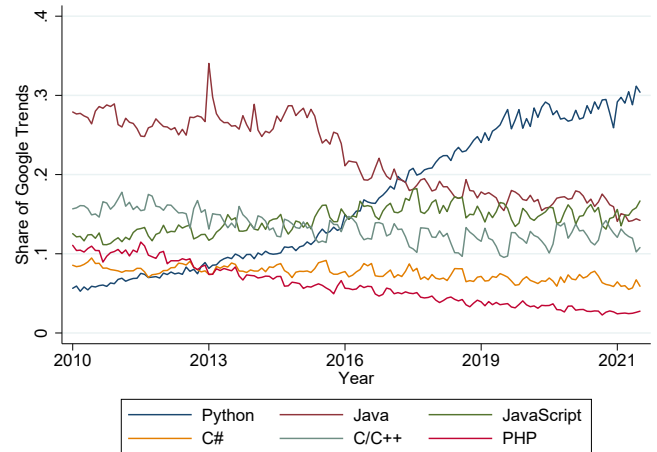


Figure 2. The Supply of Programming Language Skills

approach bears similarities to PYPL Popularity of Programming Language, but differs in that we gather Google searches specifically for the programming languages themselves, rather than for other objects that happen to have the same name. This is made possible by our use of Google Knowledge Graph IDs. We then normalize and convert the search intensity measures for all the programming languages into shares, denoting $S_{i,t}$ as the fraction of programming language skill i over all programming language skills found in Google search intensity at time t (at the monthly level). This provides us with a measure of supply for the focal programming language during that period. As Google Trends tends to show declining trends for almost all keywords, we use shares among programming languages as our primary analysis approach.

Figure 2 depicts the supply shares $S_{i,t}$ of the programming languages included in the sample from 2010 to 2020. As illustrated in the figure, the supply for Java was the highest in 2010 but gradually decreased over the years. In contrast, the supply for Python was the lowest in 2010 but steadily increased over time, surpassing Java’s supply around 2017.

Figures 1 and 2 reveal that the trends in demand and supply of programming languages do not always align. For example, the supply of Python appears to be increasing at a faster pace than its demand. To quantify the mismatch between the demand and supply, we introduce the concept of *market tightness*

for programming language i at time t , defined as:

$$\theta_{i,t} = \frac{D_{i,t}}{S_{i,t}}$$

The market tightness measure captures the ratio of demand to supply for each programming language and time period. A higher market tightness indicates a greater level of competition among employers for workers with that programming language skill, while a lower market tightness suggests a relatively larger supply of workers compared to the demand.

Figure 3 displays the smoothed time series of market tightness for Python and Java over the sample period. While demand and supply trends do not always align, we observe that the market tightness for Python is consistently below one, indicating that supply tends to outstrip demand. In contrast, Java’s market tightness is above one for most of the sample period, except between 2013 and 2016. This suggests that Java’s demand is relatively high compared to its supply.

Average market tightness across states To explore the potential factors that influence the market tightness of programming skills, we calculate the average market tightness measure across US states. For each programming language skill i , time t , and state j , we compute the demand share $D_{i,t,j}$ as the fraction of job postings mentioning skill i over all programming language skills in state j and time t , using Burning Glass data. Similarly, we calculate the supply share $S_{i,t,j}$ as the fraction of Google

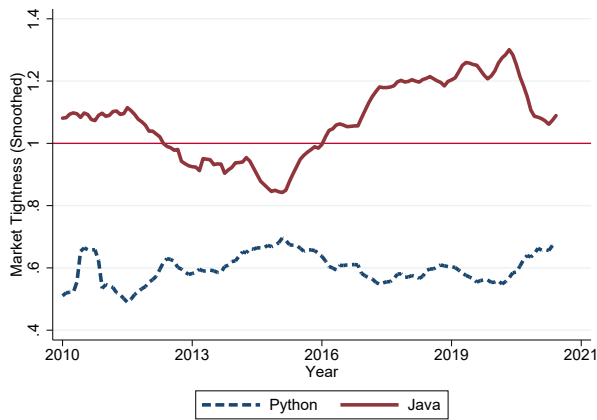


Figure 3. Market Tightness of Programming Language Skills

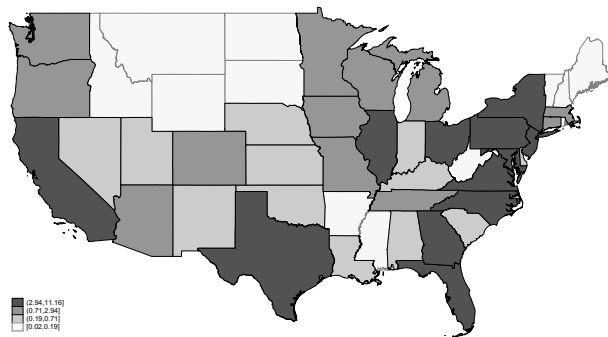


Figure 4. Average Market Tightness across states

search intensity for skill i over all programming language skills in state j and time t . We then average the demand and supply shares across all programming language skills and time periods to obtain the average demand share \bar{D}_j and supply share \bar{S}_j of programming languages in each state j . Finally, we compute the average market tightness of programming language skills across states by taking the ratio of the average demand share to the average supply share, denoted as $\bar{\theta}_j$.

Figure 4 presents the average market tightness of programming skills across states, with darker colors indicating higher market tightness and greater competition among employers for workers with programming skills. Based on the map, the top states experiencing a shortage of programmers are California, Texas, and Virginia, while the top states with excess programmer supply are Wyoming, North Dakota, and Vermont. In general, we find that states experiencing a shortage of programmers are those with larger populations and higher personal incomes.

3.2. Programmer Characteristics and Skill In-demandness

We gather data on programmer characteristics from the Stack Overflow Developer Survey, conducted annually from 2010 to 2020. This survey includes questions on individual demographics, programming skills, compensation, and other related topics. The number of respondents varies over the years, ranging from around 3,000 in 2011 to approximately 65,000 in 2020. About half of the respondents are from the United States, and the rest are from other parts of the world. To focus our analysis, we only include respondents from the United States with complete information on their demographic characteristics, such as age, gender, and self-reported compensation.

Skill in-demandness We construct a measure of programmers' skill in-demandness using the survey respondents' reported programming language proficiency. For each programmer with a set of programming language skills I , we compute the average of the market tightness $\theta_{i,t}$ across all $i \in I$ and t to obtain programmer i 's mean in-demandness. The mean in-demandness of a programmer measures the market shortage of the programmer's overall programming language skills. We also compute the maximum of the market tightness $\theta_{i,t}$ across all $i \in I$ to obtain the programmer's maximum in-demandness. The maximum in-demandness of a programmer measures the demand for the programmer's most sought-after skill.

Figure 5 presents the distribution of the programmers' mean in-demandness. The measure ranges from 0 to 4, with higher values indicating higher demand for the programmer's language skills. Our analysis shows that a large fraction of programmers have an in-demandness of around 1, indicating that their skills are in moderate demand. However, a significant fraction of programmers have high-demand skills, as shown by an in-demandness measure above 2.

Table 1 presents the summary statistics for our regression sample, including the in-demandness measures. As shown in Figure 5, these measures exhibit significant variation across the sample. The average log compensation for our sample is 11.56, corresponding to approximately \$105,000. The average log age is 3.47, equivalent to around 32 years old. Among the respondents in our sample, 83% are identified as male, and 7% are identified as

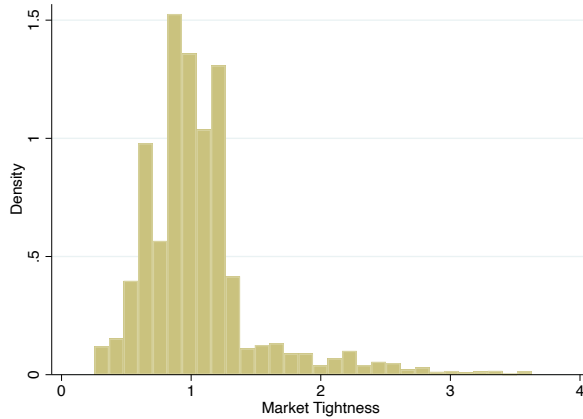


Figure 5. Skill In-demandness For Survey Respondents

female.

4. The Impact of Skill In-demandness on Programmer Compensation

In this section, we aim to investigate the relationship between programmers' skill in-demandness and their compensation. To do so, we estimate the following regression equation:

$$\text{Log(Wage)}_{n,t} = \beta \text{In-demandness}_{n,t} + \gamma X_{n,t} + \phi_t + \varepsilon_{n,t},$$

where n represents the survey respondents, t represents the survey year, $\text{log(Compensation)}_{n,t}$ is the natural logarithm of the salary for survey respondent n in year t , $\text{In-demandness}_{n,t}$ is survey respondent n 's skill in-demandness in year t , $X_{n,t}$ is a vector of individual demographic variables such as age and gender, and ϕ_t is the year fixed effect. Note that our regression sample is cross-sectional since we cannot link survey respondents across years. The coefficient of interest is denoted by β , which captures the correlation between survey respondents' skill in-demandness and their wages.

Table 2 presents our analysis of the relationship between programmer in-demandness and compensation using mean and max in-demandness measures. In column (1), we report the simple correlation between programmers' skill in-demandness and their compensation. We find that the estimated coefficient is positive and statistically significant, which confirms our economic intuition that programmers' wages increase as the demand for their skills increase relative to the supply.

In columns (2) and (3), we add year-fixed effects and other control variables to control for unobserved heterogeneity across surveys and individual demographics. The coefficients remain positive and statistically significant, with a magnitude of 0.057 in column (3), suggesting that, a one standard deviation increase in mean in-demandness is associated with a 3.7% ($=0.65 \times 0.057$) increase in compensation.

However, using the mean in-demandness measure assumes that all skills are equally valuable in the market and does not consider the possibility of segmentation in the labor market. For example, job seekers may prioritize the submarkets for their most in-demand skills and then move on to submarkets for skills with lower market tightness. Therefore, in columns (4) to (6) of our analysis, we use the maximum in-demandness measure, which captures the demand for a programmer's most sought-after skill.

The coefficients using the maximum in-demandness measure remain positive and statistically significant, with a magnitude of 0.037 in column (6). This suggests that a one standard deviation increase in maximum in-demandness is associated with a 5.3% ($=1.44 \times 0.037$) increase in compensation, which is greater than the effect of the mean in-demandness. This finding suggests that, holding everything else constant, having a highly in-demand skill can have a significant impact on compensation. In untabulated tables, our analysis found that the coefficients for minimum market tightness were small in magnitude and statistically insignificant, providing further evidence of sorting.

Our findings underscore the significance of programmers' in-demandness in determining their compensation and emphasize the value of specialized skills in the labor market. Furthermore, our results align with prior research on the gender/age wage gap in the labor market, revealing that male workers earn higher wages than their female counterparts and that senior workers earn more than junior ones in the market of programming skills.

4.1. Heterogeneous Effects of In-demandness on Compensation

We now investigate the factors that may contribute to the heterogeneous effects of programmers' market tightness on compensation. Specifically, we study two types of factors: (1) how these effects vary with the demographics of

| Variable | Observation | Mean | Std.Dev. | P25 | P50 | P75 |
|-------------------------|-------------|-------|----------|-------|-------|-------|
| | count | mean | sd | p25 | p50 | p75 |
| Market Tightness (Mean) | 55036 | 1.09 | 0.65 | 0.81 | 0.96 | 1.22 |
| Market Tightness (Max) | 55036 | 1.55 | 1.44 | 1.08 | 1.22 | 1.28 |
| Log Compensation | 55036 | 11.56 | 0.83 | 11.21 | 11.56 | 11.85 |
| Log(Age) | 55036 | 3.47 | 0.26 | 3.30 | 3.40 | 3.66 |
| Log(Age) ² | 55036 | 12.08 | 1.81 | 10.86 | 11.57 | 13.42 |
| Male | 55036 | 0.83 | 0.37 | 1.00 | 1.00 | 1.00 |
| Female | 55036 | 0.07 | 0.26 | 0.00 | 0.00 | 0.00 |

Table 1. Summary Statistics

| Variables | Log(Wage) | | | | | |
|-----------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Market Tightness | 0.082*** (0.022) | 0.078*** (0.019) | 0.057*** (0.012) | 0.051*** (0.012) | 0.042*** (0.009) | 0.037*** (0.008) |
| Log(Age) | | | 6.343 (4.003) | | | 6.362 (3.996) |
| Log(Age) ² | | | -0.791 (0.552) | | | -0.793 (0.551) |
| Male | | | 0.078*** (0.021) | | | 0.081*** (0.020) |
| Female | | | -0.072** (0.024) | | | -0.065** (0.023) |
| Year FE | No | Yes | Yes | No | Yes | Yes |
| Observation | 55,036 | 55,036 | 55,036 | 55,036 | 55,036 | 55,036 |
| R ² | 0.004 | 0.105 | 0.181 | 0.008 | 0.107 | 0.183 |

Table 2. The Effect of In-demandness on Compensation

survey respondents and (2) how they vary with distribution of proficient language market tightness.

Demographics and Wage Gap In our benchmark analysis, we find evidence that female and younger workers tend to have lower wages, consistent with the literature on the gender/age wage gap in the labor market. When the labor market becomes tighter, we would expect the wages of lower-paid workers to grow faster, resulting in a reduction in the gender/age wage gap. As a result, we hypothesize that female and junior workers may be more responsive to changes in the market tightness of their proficient programming languages (i.e., in-demandness) than male and senior workers. Our analysis of the heterogeneous effects of respondent demographics supports this intuition.

We conducted a split-sample analysis to investigate whether there are differences in the response of survey respondents to changes in skill in-demandness based on their gender and age. The results are presented in Table 3, which

shows the coefficients of the interaction terms between market tightness and gender/age variables on compensation. As shown in columns (1) to (3), female respondents exhibit the highest coefficient, followed by other gender respondents, while male respondents have the smallest coefficient. The results in columns (4) and (5) reveal that junior respondents are more sensitive to changes in skill in-demandness than senior respondents. It is noteworthy that we define respondents with ages above the median as senior workers and those below the median as junior workers. In sum, our findings suggest that female respondents and junior respondents are more sensitive to changes in skill in-demandness than their male and senior counterparts, respectively.

Proficient Language Market Tightness Distribution We now investigate how the effects vary with the distribution of proficient language market tightness. Specifically, we analyze the impact of the number of proficient programming languages, the dispersion of the market tightness

| Variables | Log(Wage) | | | | |
|------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| | Gender | | | Age | |
| | Male | Female | Other | Junior | Senior |
| | (1) | (2) | (3) | (4) | (5) |
| Market Tightness | 0.036*** (0.008) | 0.045*** (0.008) | 0.040*** (0.012) | 0.041*** (0.008) | 0.033*** (0.007) |
| Control | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observation | 45,919 | 4,018 | 5,099 | 28,879 | 26,157 |
| R ² | 0.184 | 0.108 | 0.223 | 0.202 | 0.088 |

Table 3. Heterogeneous Effect: Cross-Section on Individual Characteristics

of the proficient programming languages, and the interquartile range of the market tightness of the proficient programming languages on compensation.

In Column (1), we first explore the effect of the number of programming languages on compensation. We find that, contrary to expectations, the number of programming languages is not significantly associated with individual compensation (baseline effect). Moreover, conditional on the maximum in-demandness, knowing more programming languages does not increase compensation through the labor market channel (interaction effect).

In Columns (2) and (3), we investigate the effect of the dispersion of the proficient programming languages' market tightness on compensation. Our results show that individuals with skills that have more dispersed market tightness have higher compensation, indicating that there is a wage premium associated with possessing a diverse range of programming skills (baseline effect). However, when we examine the interaction effect between the maximum in-demandness and the interquartile differences of market tightness of the proficient programming languages, we find that knowing programming languages with significantly lower market tightness would decrease the compensation, suggesting that such job seekers are more likely to be sorted into different submarkets.

Overall, these findings highlight the importance of considering the distribution of market tightness of the proficient programming languages and the potential segmentation of the labor market in understanding the relationship between programmers' skills and their compensation.

4.2. Forward-looking Programmers

In the Stack Overflow Developer Survey, respondents were asked to report what

| Variables | Log(Wage) | | |
|--|---------------------|---------------------|----------------------|
| | (1) | (2) | (3) |
| Market Tightness | 0.038*** (0.010) | 0.025** (0.008) | 0.031*** (0.007) |
| Market Tightness × # of Language | -0.001 (0.001) | | |
| Market Tightness × Dispersion of tightness | | -0.004** (0.001) | |
| Market Tightness × Range of tightness | | | -0.003*** (0.001) |
| # of Language | 0.004 (0.006) | | |
| Dispersion of tightness | | 0.065*** (0.020) | |
| Range of tightness | | | 0.039** (0.012) |
| Control | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observation | 55,036 | 55,036 | 55,036 |
| R ² | 0.183 | 0.183 | 0.183 |

Table 4. Heterogeneous Effect: Cross-Section on Individual Skills

programming skills they would like to work with in the upcoming year. From the programming skills provided by the respondents, we define the *desired in-demandness* of a respondent as the maximum market tightness of the programming skills they aspire to work with in the future. The desired in-demandness indicates the extent to which a respondent is forward-looking in terms of market conditions. We investigate the relationship between respondents' current in-demandness and their desired in-demandness. The results presented in Table 5 suggest that workers with higher current in-demandness are more likely to aspire to work with skills that are in higher demand in the future.

| Variables | Desired In-demandness | | |
|-----------------------|-----------------------|---------------------|---------------------|
| | (1) | (2) | (3) |
| Log(Wage) | 0.009 (0.016) | 0.003 (0.008) | 0.005 (0.008) |
| Max In-demandness | 0.497*** (0.022) | 0.493*** (0.024) | 0.493*** (0.024) |
| Log(Age) | | | -0.447 (0.302) |
| Log(Age) ² | | | 0.064 (0.042) |
| Male | | | -0.026* (0.012) |
| Female | | | 0.005 (0.019) |
| Year FE | No | Yes | Yes |
| Observation | 44,737 | 44,737 | 44,737 |
| R ² | 0.188 | 0.201 | 0.201 |

Table 5. The effect of current on Desired In-demandness

We conducted further analysis to investigate whether the correlation between current and desired in-demandness is affected by gender or age. The results, as presented in Table 6, suggest that the correlation between current and desired in-demandness is higher for female workers than for male workers. This finding implies that female workers tend to consistently target sought-after skills, which is consistent with our previous result that female workers are more sensitive to changes in skill in-demandness.

| Variables | Desired In-demandness | | | | |
|-----------------------|-----------------------|---------------------|---------------------|---------------------|---------------------|
| | Gender | | | Age | |
| | Male | Female | Other | Junior | Senior |
| | (1) | (2) | (3) | (4) | (5) |
| Log(Wage) | 0.010 (0.011) | -0.042 (0.028) | -0.004 (0.041) | -0.002 (0.008) | 0.017 (0.017) |
| Max In-demandness | 0.497*** (0.023) | 0.538*** (0.073) | 0.356*** (0.046) | 0.496*** (0.014) | 0.490*** (0.036) |
| Log(Age) | -0.820** (0.237) | -0.869 (1.230) | 0.560 (0.417) | -0.079 (0.119) | -2.790* (1.296) |
| Log(Age) ² | 0.117** (0.033) | 0.114 (0.181) | -0.056 (0.076) | 0.008 (0.018) | 0.384* (0.169) |
| Male | | | | 0.019 (0.061) | -0.094 (0.096) |
| Female | | | | 0.054 (0.062) | -0.070 (0.074) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observation | 39,380 | 3,469 | 1,888 | 24,114 | 20,623 |
| R ² | 0.196 | 0.212 | 0.261 | 0.185 | 0.220 |

Table 6. The heterogeneous effect of current on Desired In-demandness

5. Conclusion

In conclusion, our study provides valuable insights into the dynamics of the programming skills market and their impact on compensation. By exploring both the demand and supply side of the market and investigating the relationship between market tightness and programmer compensation for popular programming languages, we contribute to a better understanding of the labor market for computer programming skills. Our findings can inform policymakers, educators, and employers in designing effective training and education programs to equip the workforce with the skills needed to succeed in the labor market.

Our investigation into the impact of skill in-demandness on programmer compensation showed that the demand for programmers' skills is positively correlated with their compensation, and highly in-demand skills are associated with higher compensation. Our analysis also revealed that male workers and senior workers earn higher wages than their female and junior counterparts,

respectively, in the programming skills market. Furthermore, individuals with skills that have more dispersed market tightness have higher compensation, indicating that possessing a diverse range of programming skills is associated with a wage premium.

Overall, our study sheds light on the programming skills market and contributes to a better understanding of the labor market. However, there are limitations to our study, including the use of self-reported data and the exclusion of some important factors that could affect programmer compensation. Future research could consider these limitations and further investigate the relationship between market tightness and programmer compensation.

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