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ABSTRACT

We estimate the value employees place on remote work using revealed preferences in a high-stakes, real-world context, focusing on U.S. tech workers. On average, employees are willing to accept a 25% pay cut for partly or fully remote roles. Our estimates are three to five times that of previous studies. We attribute this discrepancy partly to methodological differences, suggesting that existing methods may understate preferences for remote work. Because of the strong preference for remote work, we expected to find a compensating wage differential, with remote positions offering lower compensation than otherwise identical in-person positions. However, using novel data on salaries for tech jobs, we reject that hypothesis. We propose potential explanations for this puzzle, including optimization frictions and worker sorting.

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1 Introduction

Remote working arrangements have become increasingly prevalent in recent years. An estimated 11.8% of full-time employees in the United States work fully-remote, while an additional 29% work partly-remote ("hybrid") (Barrero, Bloom and Davis, 2023). In theory, remote work can be viewed as either a positive or negative amenity: it offers greater scheduling flexibility, enhancing work-life balance, but it may also limit access to face-to-face mentoring and raise concerns about potential career growth penalties. In this article, we present new evidence on employees' preferences for remote work and on the corresponding wage-setting strategies adopted by employers.

We estimate the amenity value of remote work using revealed preference data from Cullen, Pakzad-Hurson and Perez-Truglia (2025), which captures the set of job offers individuals receive and the offers they ultimately accept. The dataset includes a sample of 1,396 workers from the U.S. tech sector. This sector constitutes an interesting context given its highest work-from-home rate (Barrero, Bloom and Davis, 2023) and its status as arguably the highest-paying and most innovative industry. Our findings indicate that, on average, individuals are willing to forgo approximately 25% of total compensation for a job that is otherwise identical but offers partially- or fully-remote work instead of being fully in-person. Our estimate is three to five times that of previous studies, which we partly attribute to methodological differences.

Additionally, we analyze wage-setting differences associated with remote work. Given the strong preference for remote work, a compensating wage differential would be expected, where companies offer a premium for in-person positions. However, our data indicate that the average compensation for in-person roles is, on the contrary, slightly lower than that for otherwise identical remote positions. We propose potential explanations for this puzzling fact, such as optimization frictions and worker sorting.

2 Institutional Context and Data

We use survey data from Cullen, Pakzad-Hurson and Perez-Truglia (2025), collected between May 2023 and December 2024 as part of a field experiment and in collaboration with levels.fyi, a leading platform that provides comprehensive wage data for professionals in the tech sector. The study recruited participants from a sample of workers in the U.S. tech sector. The survey gathers detailed data on the job offers individuals receive and the alternatives they ultimately choose.[1] The survey captures key characteristics of the alternatives, such as total cash compensation, the state where the job is based, and whether the position is remote.

Additionally, we merge the survey responses to complementary datasets to measure other job characteristics. We use data on Glassdoor's employer ratings, which aggregate reviews from current and former employees regarding their overall satisfaction with a company, on a scale from 1 to 5 stars.[2] We use data on employers characteristics such as whether the company belongs to FAANG (Meta (formerly Facebook), Apple, Amazon, Netflix, or Alphabet), whether the company is publicly-traded and the dollar-value of employee benefits.[3] And we use cost-of-living and quality-of-life measures based on job location.[4]

Our relevant sample consists of 1,396 individuals with at least two alternatives, averaging 2.4 alternatives per individual.[5] The average subject in this sample is 32 years old, has 6.7 years of work

[1] At the time of the follow-up survey, for individuals who had not yet officially accepted an offer, the survey elicited the likelihood of accepting each offer. The outcome of interest in our analysis is the offer that was either already chosen or deemed most likely to be chosen.

[2] Glassdoor ratings are missing for 18.6% of observations, mainly due to companies that are too small to appear on Glassdoor. When including this variable, we always control for a separate dummy for missing data.

[3] The benefits data was provided by levels.fyi. It is available mainly for major companies (18.1% of observations). When including this variable, we always control for a separate dummy for missing data.

[4] State-level indices for 2024 from the Council for Community and Economic Research and U.S. News & World Report.

[5] Since data collection is ongoing, we rely on preliminary data from both waves of Cullen, Pakzad-Hurson and Perez-Truglia (2025). The total number of individuals and offers is larger, but some individuals are excluded from the estimation of the conditional logit model because they either have only one alternative or did not accept any of their alternatives.

experience. The average job offers \$239K per year in total compensation.[6] Women make up 16.3% of the sample, slightly lower than other estimates of female representation in the tech industry.[7] Some of the most common position titles include software engineer, product manager and data scientist, and some of the most popular employers include Google, Meta, and Apple. Approximately 18.3% of the offers in the sample are for fully in-person work, while 81.7% are for remote roles.[8]

3 Preferences for Working from Home

We estimate a conditional logit model. We study a set of individuals I. Each individual $i \in I$ chooses one alternative j from a set J_i of i's alternatives that include staying at the current job (for those who are currently employed), each of the offers received from different employers, or the outside option (not being employed). Each individual i chooses the alternative that provides him or her the highest utility: $U_{ij} = V_{ij} + \epsilon_{ij}$, where ϵ_{ij} is the unobservable component of utility, assumed to follow a Gumbel (type I extreme value) distribution. The observable component is $V_{ij} = \mathbf{x}_{ij}\beta$, where x_{ij} is a vector of characteristics of the alternative and β is the vector of coefficients to be estimated via maximum likelihood. It is important to note that our model assumes homogeneous preferences, which leads us to interpret the results as reflecting average preferences. However, in reality, preferences are likely heterogeneous—see Appendix A.1 for further discussion.

The results are presented in Table 1. Column (1) presents the simplest specification, including only two offer characteristics: (log) total compensation and a dummy variable for remote work, which equals 1 for both fully-remote and partly-remote positions.[9]

The coefficient on (log) compensation is positive and statistically significant, indicating that

[6] This total compensation is calculated as the sum of base salary (on average, 68.8% of total compensation), bonus (7.5%) and equity compensation (23.7%).

[7] For example, Deloitte Insights reports that women held approximately 25.0% of technical roles in large U.S. tech companies.

[8] Among the remote roles, 40.7% are fully remote, and 59.3% are partly remote.

[9] The results are broadly similar, but less straightforward to interpret, if total compensation is replaced with its components (base salary, bonus, and equity).

employees are more likely to choose offers with higher compensation. The key coefficient of interest, on the remote work dummy, is also positive and significant, confirming that the average employee views remote work as a valued amenity. The magnitudes of the raw logit coefficients are not directly interpretable. Therefore, Panel (b) presents the willingness to pay for remote work, calculated as the coefficient on the remote work dummy divided by the coefficient on (log) total compensation. The coefficient of 0.296 in column (1) implies that, ceteris paribus, the average individual is willing to forgo 25.6% ($=1\text{-}e^{-0.296}$) of total compensation to have a remote instead of fully in-person position.

Before interpreting this magnitude further, we first present a series of robustness checks. The primary concern is omitted variable bias: unobservable job characteristics may influence utility and be correlated with remote offers. For instance, if more prestigious employers are more likely to offer remote positions and individuals place value on working for such companies, this could introduce a positive bias in the remote work coefficient reported in column (1). Ideally, an experiment randomizing which offers are remote would provide the variation needed for identification. Since this is not feasible, we address omitted variable concerns by incorporating additional job characteristics into the model.

Column (2) incorporates the Glassdoor rating into the model. The positive and large coefficient on this variable shows that workers value employment at higher-rated companies.[10] Most importantly, the willingness to pay for remote work remains nearly unchanged in column (2) compared to column (1). In column (3), we introduce additional control variables, including a dummy for whether the company is publicly listed, a dummy for whether it is a startup, employer-provided benefits, a dummy for current employment at the job, a dummy for whether the location matches the individual's current workplace, and the location's cost of living and quality of life. Comparing the results from column (3) to those in columns (1) and (2) shows that including the additional controls

[10] More precisely, the average individual would be willing to take a pay cut of 20.5% ($=1\text{-}e^{-0.288/1.258}$) in exchange for a one-point increase in the Glassdoor rating.

does not alter the magnitude of the willingness to pay for remote work. In fact, if anything, the willingness to pay increases slightly. The specification in column (4) builds on that in column (3) by adding further controls: 48 dummies for the most common employers and 5 dummies for the most common states.[11] Again, the addition of controls, if anything, slightly increases the estimate on willingness to pay for remote work. While other unobserved characteristics could contribute to omitted-variable bias, the evidence from columns (1) through (4) suggests that this bias may have a limited impact on the conclusions.

For a final robustness check, column (5) is identical to column (3) except that it includes separate dummies for fully-remote and partly-remote work. The coefficients for these two dummies are similar in magnitude. The average employee values fully-remote work slightly more than partly-remote work (raw coefficients of 0.367 versus 0.320), but the difference is statistically insignificant.

Figure 1 demonstrates that the valuation of remote work is substantial, both in dollar terms and relative to other amenities. Specifically, the figure compares the value of remote work to other amenities using the conditional logit estimates from column (3) of Table 1. On average, individuals are willing to forgo 27.8% ($=1-e^{-0.326}$) for a remote position instead of a fully in-person role. In comparison, the corresponding valuations are 21.8% for an employer with a 1-point higher Glassdoor rating, 6.3% for an state with a 1 standard deviation higher standard of living, and 4.4% for a publicly-traded company.

Next, we compare our findings with those of related studies. Some studies have explored variations of a survey question asking how much of a pay cut individuals would accept to work remotely. Barrero, Bloom and Davis (2021) find that the average employee is willing to accept a 7% pay cut to work from home 2–3 days per week. Bartik et al. (2024) report that the median worker would accept a pay cut of around 5% to work remotely.[12] Finally, Mas and Pallais (2017) estimate

[11]For the employer dummies, the omitted category is "other employers," corresponding to 63.3% of observations. For the state dummies, the omitted category is "other states," corresponding to 28.7% of observations.

[12]More precisely, Bartik et al. (2024) report that 40% of respondents would accept a pay cut of 5% or more,

that the average respondent is willing to take a 10% pay cut for remote work, and they confirm similar results using a discrete choice experiment.

Our estimates align directionally with these studies but differ in magnitude.[13] While these studies suggest that the average worker is willing to accept a pay cut between 5% to 10% to work remotely, our estimate is substantially higher, at around 25% (column (1) of Table 1).[14] One plausible source of the discrepancy is the difference in samples, as our study focuses on tech workers. For instance, remote work may function as a luxury good, appealing more to high earners; and tech jobs might be better suited for remote work. This is likely to explain part of the discrepancy, but not all. Using the latest available data from the Survey of Working Arrangements and Attitudes, we find that the average respondent is willing to take a pay cut of 7.0% to work remotely. When looking at a more comparable subsample (respondents in I.T. and with salaries above $150,000), that estimate goes up to 15.8%, but still falls short from our 25% estimate.

The rest of the discrepancy in magnitude between our study and previous studies may stem from methodological differences. Some employees may be unwilling to sacrifice salary to work remotely in hypothetical scenarios, but they may reveal their true preferences when faced with real stakes. For example, when workers are asked how much of a pay cut they would accept to work remotely, they might underreport the true amount due to concerns that employers could use their responses to justify salary reductions.[15]

implying that the median willingness to pay is slightly below 5%.

[13]The positive amenity value is also consistent with evidence that remote work improves job satisfaction and reduces quit rates (e.g., Bloom, Han and Liang, 2024).

[14]Part of the discrepancy may of course stem from measurement error: e.g., while our estimate is highly statistically significant, it is somewhat imprecise, with a 95% confidence interval ranging from 10.5% to 40.7%.

[15]This concern is explicitly discussed in Mas and Pallais (2017); see their footnote 16 for details.

4 Compensating Wage Differential

Given the strong preference for remote work, one might expect a compensating wage differential, with companies offering lower salaries for remote positions compared to in-person ones. To test this hypothesis, we utilize data from levels.fyi, which collects direct user submissions detailing compensation packages. To ensure data quality, levels.fyi employs verification measures such as asking users to upload tax forms or offer letters. Our analysis uses salary submissions from June 2023 to June 2024. This sample is comparable to the survey sample analyzed below, for instance, they work in a similar mix of occupations (e.g., software developer) and companies (e.g., Google). This similarity is expected since survey respondents were recruited from visitors to the levels.fyi website and during a similar time window. The samples are not identical—however, Appendix A.2 shows that the results are similar if we re-weight the observations to make them more comparable.

The key for this exercise is to compare salaries in positions that are in-person versus remote but otherwise identical. We split individuals into groups, where each group is a combination of company (e.g., Google), company-specific position title (e.g., Level-3 Software Engineer in Back-End API Development), location (e.g., Bay Area) and experience level (e.g., 0–3 years).[16] We keep groups in which there are at least five observations and at least one of them is remote and one is in-person, resulting in a final sample of 4,352 unique groups. As shown in Appendix A.3, and consistent with the high-skill nature of the position (Cullen, Li and Perez-Truglia, 2025), there is quite a bit of salary dispersion: some employees are paid significantly more than others even though they work for the same company, in the same position, location and experience level.

Within each group, we can compare the average salary for in-person positions to the average salary of the (otherwise identical) remote positions. Figure 2 presents a histogram of those differences.[17]

[16] Following's levels.fyi categorization, we consider three experience levels: Entry Level (0–1 years), Middle (2–6 years) and Senior (7 or more years).

[17] To minimize the potential influence of outliers, in all the results we winsorize observations at ±50% of the group

According to compensating wage differential hypothesis, we expect remote positions to be paid about 25% less than otherwise identical remote positions. However, the results deviate substantially from this prediction. If anything, we find a statistically significant (p-value<0.001) difference in the opposite direction, and small in magnitude: remote positions are, on average, paid 1.1% *more* than otherwise identical in-person positions.

We propose several potential explanations for this puzzle. One possibility is optimization frictions: since remote work is a relatively new phenomenon, companies may still be adapting and have yet to optimize their wage-setting practices. Worker sorting could also play a role. If remote positions are limited, and employers systematically aim to attract the most talented employees by offering remote work opportunities (in addition to higher pay), this could exert a force against the compensating wage differential.

Another possible explanation is that, due to fairness concerns or legal constraints (Gentile Passaro, Kojima and Pakzad-Hurson, 2024), companies may avoid paying different salaries to employees in the same position, regardless of whether they work remotely or in-person. However, this explanation is unlikely, as it predicts pay compression, whereas substantial pay dispersion is observed. Equilibrium forces on the employer side could also provide an explanation. If companies believe remote positions are more productive than in-person positions, this would exert a force against compensating differentials. However, if employers consistently perceived remote positions as more productive, we may expect them to cease offering in-person positions altogether.

5 Conclusions

We presented evidence on how participants in a real-world labor market value remote work arrangements. This study contributes to a small but growing body of literature focused on measuring

average.

employee preferences for remote work (Mas and Pallais, 2017; Barrero, Bloom and Davis, 2021; Bartik et al., 2024). We contribute in two main ways. In terms of methodology, we infer the willingness to pay for remote work via revealed-preferences, in a real-world context with high-stakes. This improves over the existing approach of unincentivized or hypothetical questions. Indeed, our preferred interpretation is that the existing non-incentivized methods may significantly underestimate the true willingness to pay for remote work. Second, we contribute with a puzzling observation: despite the high willingness to pay for remote work, we do not find a compensating wage differential between remote and in-person jobs. While we discuss some potential explanations for this puzzle, we leave its investigation as an avenue for future research.

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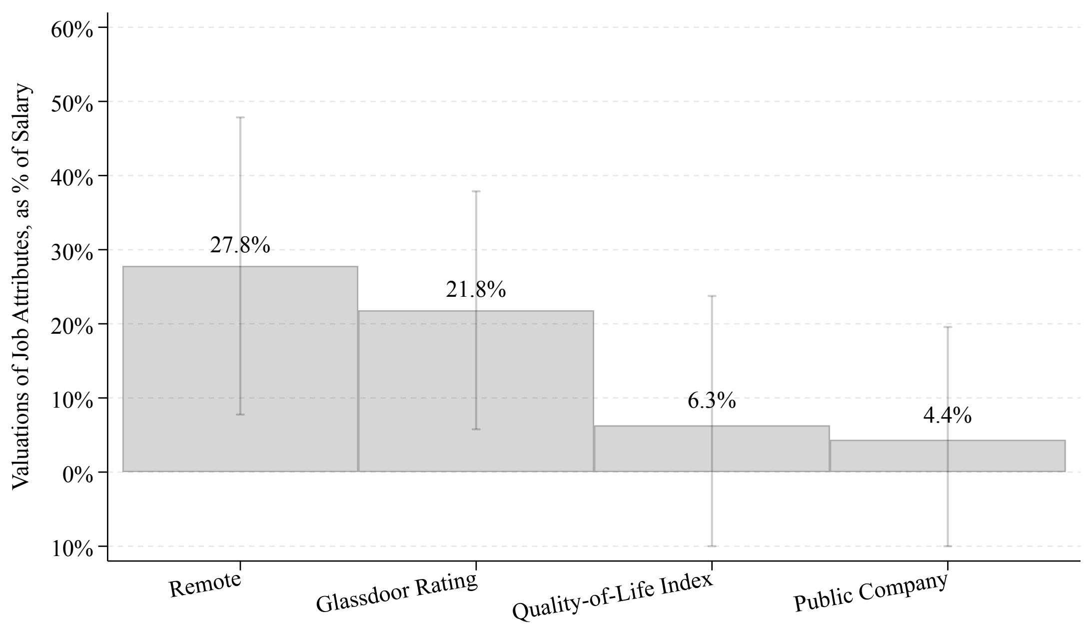
Table 1 Results from the Conditional Logit Model

	(1)	(2)	(3)	(4)	(5)
Panel (a): Raw Coefficients					
Log(Total Compensation)$^{(i)}$	1.239***	1.258***	1.068***	1.045***	1.071***
	(0.130)	(0.132)	(0.133)	(0.141)	(0.133)
Remote (=1)$^{(ii)}$	0.367***	0.345***	0.348**	0.368**	
	(0.122)	(0.122)	(0.143)	(0.149)	
Glassdoor Rating$^{(iii)}$		0.288***	0.263**	0.255**	0.272**
		(0.105)	(0.109)	(0.128)	(0.109)
Fully Remote (=1)					0.367**
					(0.147)
Partly Remote (=1)					0.320**
					(0.134)
Panel (b): WTP					
Remote ((ii)/(i))	0.296***	0.274***	0.326**	0.352**	
	(0.104)	(0.102)	(0.142)	(0.152)	
Basic Controls			✓	✓	✓
Additional Controls				✓	
Individuals	1,396	1,396	1,396	1,396	1,396
Observations	3,351	3,351	3,351	3,351	3,351

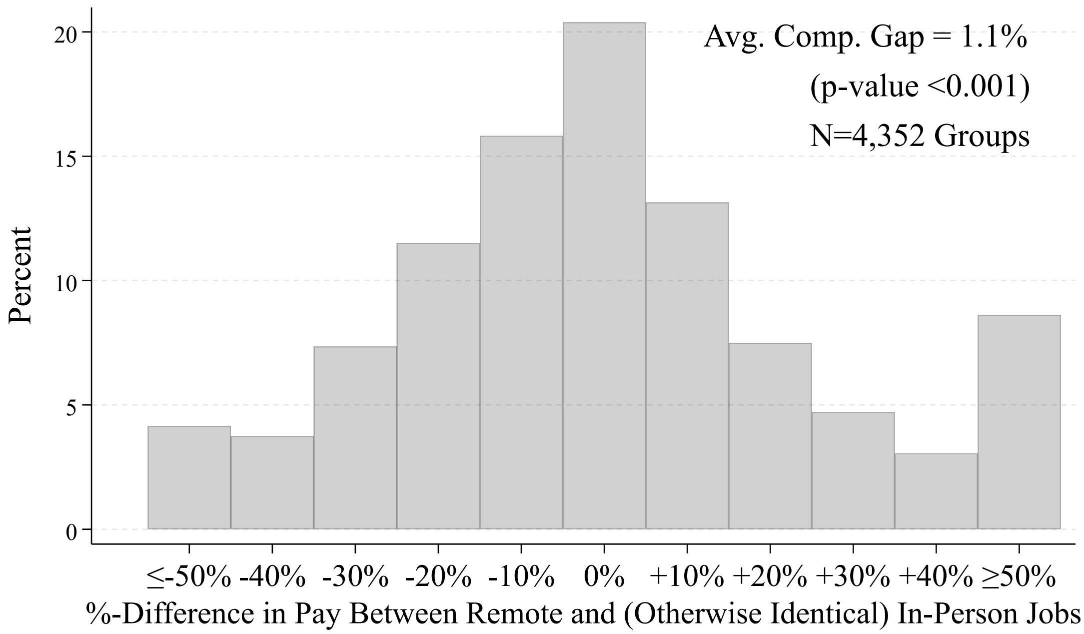
Notes: Significant at *10%, **5%, ***1%. Conditional logit model results analyzing job offer choices. Each column represents a different specification. Basic controls include dummies for publicly-listed and startup companies, dollar value of employer-provided benefits, dummies for current employer and state, and the state's cost of living and quality of life. Additional controls add 48 dummies for top employers and 5 for top states. Standard errors are clustered at the individual level.

Figure 1 Valuation of Job Attributes



Notes: The figure shows how much of a pay cut the average individual is willing to take in exchange for a specific job amenity. For example, the first bar shows that the average individual is willing to forgo 27.8% of total compensation for a remote position instead of a fully in-person role. The other bars represent the corresponding valuations for working for an employer with a 1-point higher Glassdoor rating, in a state with a 1 standard deviation higher standard of living, and for a publicly-traded company. Results based on a selection of coefficients from the conditional logit model estimated in column (3) of Table 1. 95% Confidence Intervals reported in brackets, based on standard errors clustered at the individual level.

Figure 2 Difference in Average Compensation between Remote and In-Person Jobs



Notes: Within each group (defined by employees at the same company, in the same position, location, and experience level) we calculate the difference in average total compensation between remote and in-person positions, as a percentage of the in-person average. Results are based on salary submissions provided by levels.fyi, covering the period from June 2023 to June 2024.

A Additional Results

A.1 Heterogeneity Analysis

In Table 1, we documented that the average employees has a strong preference for remote positions over in-person positions. That model assumes that preferences are homogenous, but in reality they are probably heterogeneous. Ideally, we would identify preference heterogeneity non-parametrically by estimating a mixed logit model. However, the available variation is insufficient for such an analysis. Instead, we provide some basic heterogeneity analysis. Columns (1) and (2) of Table A.1 replicate the specification of column (3) of Table 1, but are estimated separately for workers with at least six years of experience (column (1)) and those with less than six years (column (2)).[18] Highlighting the potential role of heterogeneity, the results suggest that more experienced workers place a significantly greater value on remote work, with a coefficient of 0.527 compared to 0.180 for less experienced workers. One possible interpretation of this evidence is that junior workers may find remote positions less appealing, perhaps because they value face-to-face mentoring and are concerned about potential promotion penalties (Cullen and Perez-Truglia, 2023; Emanuel, Harrington and Pallais, 2023). However, this difference should be interpreted with caution, as it is imprecisely estimated and statistically insignificant (p-value = 0.244).

A.2 Comparison between Samples

The analysis from Section 3 is based on survey data from Cullen, Pakzad-Hurson and Perez-Truglia (2025) (henceforth, the "survey sample"), while the analysis from Section 4 is based on salary submission data provided by levels.fyi (henceforth, the "levels.fyi sample"). Here we provide a comparison of observable individual characteristics across the two samples. The results

[18] We selected this threshold to balance the two subsamples as evenly as possible in terms of size.

are presented in Table A.2. Each row corresponds to a different observable characteristic, such as total compensation and whether the position is remote. For each characteristic, column (1) shows the average in the survey sample, while column (2) shows the corresponding average in the levels.fyi sample.[19] The two samples are quite similar along some dimensions such as average total compensation ($239K in the survey sample vs. $204K in the levels.fyi sample), the share of female individuals (16.32% vs. 19.26%), the share of positions at FAANG companies (11.55% vs. 15.75%), the share of product managers (4.89% vs. 6.51%) or the share of data scientists (6.86% vs. 5.73%). This similarity is unsurprising, as the survey respondents were recruited from visitors to the levels.fyi website within a similar time frame. However, there are some notable differences: remote positions are noticeably more common in the survey sample (81.71% vs. 42.91%), and software engineers are less common in the survey sample (35.90% vs. 60.11%).

To make the results of Section 4 more directly comparable to those of Section 3, Figure A.2 reproduces Figure 2, but reweighting the observations to match the average characteristics of the survey sample. The reweighted results are similar to the unweighted ones.

A.3 Pay Dispersion

Figure A.1 presents a histogram of the difference between an individual's total compensation and the corresponding group average (i.e., the average among all other salary submissions for the same company, position, location, and experience level). For example, an observation of +5% indicates that an individual earns 5% more than the average pay of others in their group. The key takeaway from this figure is the substantial dispersion in pay, even within the same company, position, location, and experience level.

[19] In the survey sample, we calculate the average of the characteristic across all alternatives for each individual. In the levels.fyi sample, providing gender information is optional, resulting in missing responses for 67.1% of observations. We report the average based on all non-missing observations.

Table A.1 Heterogeneity Analysis from the Conditional Logit Model

	(1)	(2)
Panel (a): Raw Coefficients		
Log(Total Compensation)$^{(i)}$	1.008***	1.138***
	(0.192)	(0.187)
Remote (=1)$^{(ii)}$	0.531**	0.205
	(0.224)	(0.190)
Glassdoor Rating$^{(iii)}$	0.200	0.357**
	(0.154)	(0.158)
Panel (b): WTP		
Remote ((ii)/(i))	0.527**	0.180
	(0.243)	(0.172)
Sample	Higher-Exp.	Lower-Exp.
Basic Controls	✓	✓
Additional Controls		
Individuals	613	783
Observations	1,514	1,837

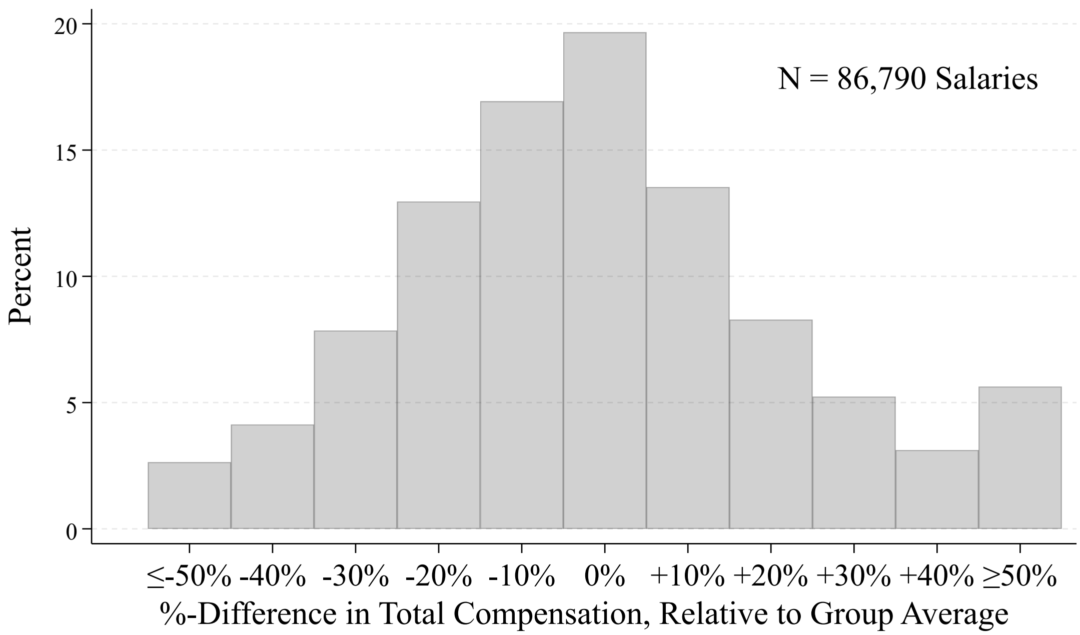
Notes: Significant at *10%, **5%, ***1%. Conditional logit model results analyzing job offer choices. This table reports the same model from column (3) of Table 1, except that splitting the sample by individuals with at least six years of experience (column (1)) versus those with less than six years (column (2)). Standard errors clustered at individual level.

Table A.2 Comparison between the Two Samples

	(1) Survey Sample	(2) Levels.fyi
Total Compensation ($100,000)	2.39	2.04
	(0.03)	(0.00)
Remote (%)	81.71	42.91
	(0.67)	(0.12)
Female (%)	16.32	19.26
	(0.64)	(0.16)
FAANG Companies (%)	11.55	15.75
	(0.55)	(0.09)
Software Engineer (%)	35.90	60.11
	(0.83)	(0.12)
Product Manager (%)	4.89	6.51
	(0.37)	(0.06)
Data Scientist (%)	6.86	5.73
	(0.44)	(0.05)
Observations	1,396	86,790

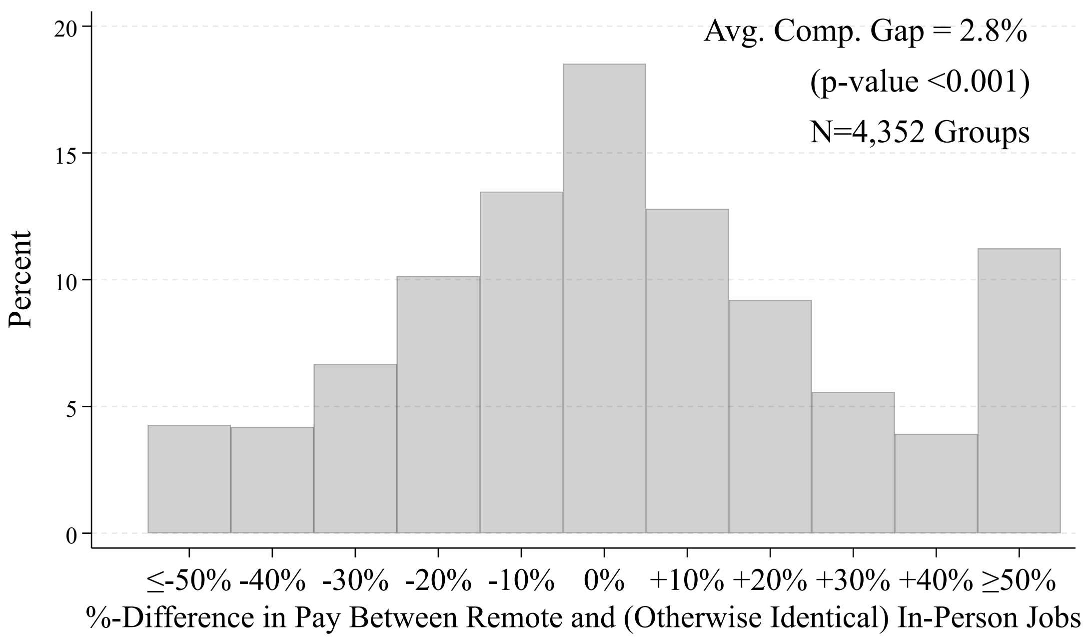
Notes: The table reports the average characteristics between our survey sample (column (1)) and the salary submission data provided by levels.fyi (Column (2)), with standard errors in parentheses. *Total Compensation* is in yearly basis and equal to the sum of base salary, bonus and equity compensation. *Remote* denotes the share of positions that are remote. *Female* is the share of female respondents. *FAANG* is the share of positions in Meta (formerly Facebook), Apple, Amazon, Netflix, or Alphabet. *Software Engineer*, *Product Manager* and *Data Scientist* correspond to the share of jobs with the corresponding position titles.

Figure A.1 Within-Group Pay Dispersion



Notes: The histogram presents the percentage difference between an individual's total yearly compensation and the mean compensation of other salary submissions from same company, with the same company-specific position, in the same location, and with the same experience level.

Figure A.2 Difference in Average Compensation between Remote and In-Person Jobs (Reweighted)



Notes: Figure A.2 reproduces Figure 2, but reweighting the observations to match the average characteristics of the survey sample. The histogram presents the percentage difference between an individual's total yearly compensation and the average of other salary submissions at the same company, with the same position, in the same location, and with the same experience level. Results are based on salary submissions provided by levels.fyi, covering the period from June 2023 to June 2024.