WORKING PAPER NO. 768

Coworker Influence on Job Choice: Information, Connection, and Industry Switching

Xinyue Lin, Armando Miano, and Sophia Mo

December 2025

University of Naples Federico II **University of Salerno** **Bocconi University, Milan**

CSEF - Centre for Studies in Economics and Finance
DEPARTMENT OF ECONOMICS AND STATISTICS – UNIVERSITY OF NAPLES FEDERICO II
80126 NAPLES - ITALY
Tel. and fax +39 081 675372 – e-mail: csef@unina.it
ISSN: 2240-9696

Working Paper no. 768

Coworker Influence on Job Choice: Information, Connection, and Industry Switching

Xinyue Lin[*], Armando Miano[†], and Sophia Mo[‡]

Abstract

We investigate how coworkers shape job mobility decisions by influencing workers' perceptions of their outside options. Using novel survey data from a representative sample of U.S. wage and salaried workers, we identify two distinct channels through which current and former coworkers affect mobility. First, having more current coworkers with prior experience in an industry enhances both the accuracy of workers' wage beliefs and their perceived probability of receiving a job offer from that industry. Second, having more past coworkers currently employed in a sector raises the perceived likelihood of receiving an offer from that sector. At the firm level, personal connections increase the perceived probability of receiving an offer from that specific firm, as shown in a survey experiment eliciting subjective job-offer probabilities. We incorporate these findings into a job choice model featuring coworker-based learning and referral effects. Relative to standard models that assume perfect information about wages and job opportunities, our framework demonstrates that coworker networks facilitate labor reallocation and mitigate the welfare losses associated with information frictions.

JEL Classification: J01, J62, D91, D83, E71

Keywords: Job Mobility, Job Search, Coworker Networks, Industries, Survey, Subjective Expectations.

Acknowledgments: We gratefully acknowledge support from the Chae Family Research Fund and the Molly and Dominic Ferrante Economics Research Fund. This research is also funded by the European Union - Next Generation EU, in the framework of the GRINS - Growing Resilient, Inclusive and Sustainable Project (GRINS PE00000018 – CUP E63C22002140007). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union and the European Union cannot be held responsible for them.

[*] Harvard University. E-mail: xinyue_lin@g.harvard.edu

[†] University of Naples Federico II, CSEF, and CEPR. E-mail: armando.miano@unina.it

[‡] Harvard University. E-mail: yiningmo@fas.harvard.edu

1 Introduction

Workers spend a substantial portion of their lives alongside their coworkers, sharing experiences, information, and skills that shape their career trajectories. While a rich literature has documented the role of social networks in shaping labor market outcomes (e.g., Granovetter 1973; Calvo-Armengol and Jackson 2004; Bandiera, Barankay and Rasul 2009), less attention has been given to how interactions with coworkers specifically influence job mobility—and through which channels those effects operate. This gap is particularly notable given that the average American spends more time at work than in almost any other social setting, that job-to-job transitions are key drivers of wage growth and career advancement (Topel and Ward 1992; Haltiwanger et al. 2018), and that a great number of public policies aim to promote labor mobility and workplace integration.[1]

Understanding the extent and mechanisms through which coworkers shape job mobility is particularly relevant in today's labor market. These insights are essential for designing effective policies to support mobility, improve labor allocation, and reduce inequality in access to opportunities. In this paper, we leverage novel survey data to study how both current and former coworkers influence workers' job search and mobility decisions. We explore several core questions: Do coworkers affect whether workers switch jobs or industries? Through which channels—informational or referral-based—do these influences operate? Which types of coworkers—past or current—are most influential? Finally, what are the implications for worker welfare and aggregate labor market dynamics when coworker influence is taken into account versus when it is not?

The challenge in addressing these questions lies in the fact that coworkers, wage beliefs, job or industry switching decisions, and job-offering probabilities are all difficult to observe in standard datasets. To overcome this, we designed and administered an online survey to a representative sample of about 3,000 full-time wage and salaried workers in the U.S.[2] The survey responses provide new insights into the extent and nature of coworker influence on job choice, shedding light on when and how coworkers shape mobility decisions. Specifically, we find that having more coworkers previously employed in an industry increases belief accuracy on the wages one could earn in that industry, as well as the perceived probability of receiving an offer if applying to a job in that industry. Having more past coworkers currently employed in an industry also raises the perceived job-offering probability when applying to jobs in that industry. In addition to influencing the perceived job-offering rate, having more past coworkers currently employed in an industry also leads to a higher intention to apply to those industries. Finally, the influence of coworkers on perceived job-offering rates not only applies to the industry choice dimension but also extends to the job choice level. Having connections at a job that one can reach out to is associated with a significant increase in the perceived job-offering

[1] For example, U.S. mobility-supporting policies include retraining programs and tax incentives that facilitate job transitions. Equal employment laws, affirmative action, immigration programs, and workplace safety regulations also promote integration of diverse populations into the workforce.

[2] We do not sample workers in the healthcare industry because the skills of these workers are generally very specific to that industry and less transferable.

rate, holding other job attributes constant.

In the survey, we first investigate how coworkers influence respondents' *future* industry and job choices. We examine the role of current and past coworkers *at the current job* in shaping workers' perceived outside options, including their perceived wages and job-offering rates, and their intentions to switch industry. To begin, we ask each respondent to report the number of current and past coworkers with whom they interact, and whose previous or current industries of employment they know. We then present respondents with five industries, conditioning on their current industry: three industries with the highest transition flows to the respondent's current industry and two with the lowest. We request that respondents list the number of their current coworkers who were previously employed or their previous coworkers who are currently employed in one of these industries. Furthermore, we ask respondents about their beliefs regarding the median wage and their expected starting wage in each of these five industries. We also ask them to indicate whether they would consider applying to a job in each of the five industries and to estimate the likelihood of receiving an offer if they applied to a typical job in those industries.

We find that having more current coworkers who were previously employed in a given industry is associated with more accurate beliefs about the median wage in that industry, even after controlling for how commonly workers move between industries – a proxy for industries' actual similarity or connection. Additionally, having more past coworkers who are currently employed in a particular industry raises respondents' perceived likelihood of receiving a job offer in that industry. This effect holds even after accounting for the typical difficulty of transitioning between the respondents' current industry and the reference industry, as well as the respondents' expected starting wage in the target industry. Quantitatively, having all past coworkers currently employed in a given industry increases the perceived job-offer probability by 11.4 percentage points—roughly a 28% increase relative to the average perceived probability of 40.7%. It also raises the likelihood of expressing an intention to apply to that industry by 33 percentage points, compared to an average application intention of 52%.

Given that the relationship between coworkers and future job-switching intentions reflects stated preferences—which may be subject to reporting or hypothetical bias—we next examine the relationship between individuals' past coworkers from previous jobs and their current job choices, using a realized outcome: their current wage. Controlling for individual characteristics and the difficulty of transitioning between the worker's previous and current industries (for their own occupation), we find that having at least one past coworker who shared their current industry is associated with a 14% higher current wage. Receiving a direct referral from a past coworker is associated with an even larger effect—a 17 log-point increase in wages, which translates to an 18.5% wage premium. Based on the average wage in our sample ($56,785), this corresponds to an increase of approximately $10,500 in annual earnings.

While our previous questions allow us to conclude that individuals associate industries where more of their past coworkers are currently employed with higher job-offering probabilities, we cannot directly quantify the perceived increase in job-offering probabilities due to specific coworker connections. Since we ask about job-switching decisions at the industry level, the effect of coworker connections—which often applies to specific jobs rather than entire industries—remains unclear. To address this gap, we designed a conjoint experiment where each respondent is presented with four pairs of hypothetical job profiles that vary by wage, required skill level, flexibility in work arrangements, and the degree of connection they have through former coworkers.

In this conjoint experiment, respondents are asked to indicate their perceived probability of receiving a job offer for different jobs, which vary in terms of wages, skill requirements, schedule and workplace flexibility, and, crucially, personal connections through previous coworkers. We incorporate these by presenting respondents with realistic scenarios in a fictional job application setting. Our findings reveal a strong positive association between the degree of coworker connection—low, medium, or high—and perceived job-offering probabilities. Specifically, having a high degree of personal connection is perceived to increase job-offering probabilities by 10%, making it the most influential factor in raising perceived job-offering likelihoods among all attributes tested. This association holds across demographic groups, though it is about 5% stronger among active job seekers compared to those who are not currently looking for jobs.

To study the implications of coworkers' influence on search behavior and welfare, we develop a stylized model of job choice that incorporates the influence of coworkers. Departing from standard labor market models that assume workers have full information about wages and job-offer probabilities, we instead allow both perceived wages and job-offer beliefs to depend on the composition of a worker's coworker network. Specifically, we model perceived wages as more accurate in sectors where an individual has more current coworkers with prior experience, and we allow the perceived probability of receiving a job offer to increase with the number of past coworkers currently employed at a firm. These assumptions are directly supported by our reduced-form analysis, and the key parameters governing the strength of coworker influence on wage beliefs and job-offer probabilities are estimated using survey data. This allows us to quantify the relative importance of the two channels—information about wages and referral-based access—and to assess their implications for job mobility and worker welfare through the lens of the model.

Finally, we use the model to study the steady-state welfare implications of coworker influence. We calibrate key model parameters to match observed industry-switching flows and survey-reported beliefs. While the survey allows us to estimate the parameters governing coworker influence on beliefs, we recover switching costs by minimizing the distance between model-implied and empirical flow matrices. We then compare outcomes across scenarios with and without coworker influence, allowing for both perfect and imperfect information about other-sector wages and job-offer probabilities. The results show that coworker influence leads to more equal labor market outcomes, with higher rates of industry switching reducing concentration in high-wage sectors and promoting a more even distribution of workers across industries. Moreover, aggregate welfare is uniformly higher when coworker networks are present, as lower perceived barriers to mobility enable workers to better match with desirable opportunities over time.

Related Literature This paper is related to several strands of literature. First, the literature on job search and mobility provides the foundational framework for understanding workers' employment transitions. Traditional job search models (e.g., Jovanovic 1979; Burdett and Mortensen 1998; Mortensen and Pissarides 1999; Cahuc, Postel-Vinay and Robin 2006) treat job switching as a decision based on wage differentials and match quality. Recent work has expanded this framework to incorporate non-wage job characteristics, providing evidence on workers' valuation of non-wage amenities (e.g., Sullivan and To 2014; He, Neumark and Weng 2021; Sockin 2022). These studies reveal that workers consider multiple dimensions when evaluating employment opportunities. Our contribution to this literature lies in emphasizing the role of non-job-related factors, such as coworkers, which can also significantly influence job-switching decisions.

Second, related to studies on job search transitions, is the literature on how social networks influence labor market decisions. Building on foundational works by Rees (1966), Granovetter (1973), and Montgomery (1991), more recent studies (e.g., Ioannides and Loury 2004; Calvo-Armengol and Jackson 2004; Topa 2001; Dustmann et al. 2016; Caldwell and Harmon 2019) have demonstrated the importance of social ties in job search and labor market outcomes. Glitz (2017) and Lin and Mo (2024) specifically examine the role of coworker networks in job mobility and wages. We extend this line of research by providing a comprehensive analysis of how different types of coworkers—past and present—affect job-switching decisions, and by exploring the specific channels through which this influence operates, such as information sharing and networking opportunities.

Third, our paper contributes to the literature on peer effects in the workplace. Prior research has primarily examined productivity spillovers (e.g., Falk and Ichino 2006; Mas and Moretti 2009; Jackson and Bruegmann 2009; Bandiera, Barankay and Rasul 2009; Azoulay, Graff Zivin and Wang 2010) and compensation-related decisions (e.g., Card et al. 2012), often within laboratory settings or within individual firms. In contrast, relatively few studies draw on representative samples of workers. A notable exception is Cornelissen, Dustmann and Schönberg (2017), which documents peer effects in productivity using administrative data from a representative sample. However, the literature has paid less attention to how coworkers shape job search behavior and mobility decisions across sectors or occupations. Our paper addresses this gap by providing direct survey evidence on peer effects in job mobility, using data from a nationally representative sample of U.S. wage and salaried workers.

Finally, by eliciting workers' expected wages and job opportunities both within and outside their sectors, we contribute to the growing literature on how expectations influence job search behavior. Recent studies (e.g., Conlon et al. 2018; Mueller, Spinnewijn and Topa 2021; Mueller and Spinnewijn 2023; Miano 2023; Jäger et al. 2024) have established that workers' job search decisions involve expectation errors regarding both potential wages and the probability of receiving job offers. We extend this literature by providing direct survey evidence on workers' inaccuracies in perceiving outside options—both in terms of wages and job-offering probabilities—and emphasize that coworker influence can help mitigate these misperceptions.

In summary, our paper makes several key contributions. First, we provide novel survey evidence on how coworkers influence job search and mobility decisions, addressing gaps in the understanding of peer effects in labor markets. Our survey design specifically tackles limitations in existing research by collecting detailed information on both past and present coworker relationships. Second, we distinguish between different mechanisms of coworker influence, including information sharing and social learning. Third, by examining both past and current coworker relationships, we highlight the temporal dynamics of peer effects in career decisions. Finally, we offer new estimates on the effect of coworker connections on job-offer rates and information acquisition. These estimates are derived from both job choice models and a conjoint experiment, enabling us to benchmark coworker influence against other job-related characteristics, such as wages, skill levels, and schedule flexibility. Our findings have important implications for theories of job search and labor market dynamics, underscoring the need to incorporate social influences into traditional models of labor market behavior for more effective policy evaluations.

The rest of the paper proceeds as follows. Section 2 details the procedures for data collection and survey construction. Section 3 documents the relationship between past and current coworker shares and perceived wages and probabilities of receiving an offer. Section 4 explains our conjoint analysis on the importance of coworkers in influencing one's perceived job-offering rate and presents the results. Section 5 presents a conceptual framework on how past and current coworkers can affect workers' job and sectoral choices—and hence welfare—by providing both information and connection opportunities. Section 6 concludes.

2 Survey Design

We administered the survey in the United States between August and September 2024, with a final sample of 2,721 respondents.[3] The survey targeted full-time and salaried workers aged 25 to 60. Self-employed individuals were excluded due to differences in coworker interactions, and healthcare workers were also excluded because of the low transition rate to other sectors due to the specificity of their skills. We designed the survey using Qualtrics, and distribution was handled by the commercial company Bilendi and its partner panels. Quotas were set for gender, age, household income, education, and census region to ensure representativeness of the U.S. employee population aged 25 to 60. Respondents were first screened, and those whose quotas were full were excluded. Respondents were compensated for completing the survey, with an average incentive of $4. The average completion time was 26 minutes, with a median of 20 minutes.[4]

The final sample resembles the target population of full-time wage and salaried workers aged

[3]We filtered out individuals that completed the survey too fast, or that report wages or work hours unreasonably low or high, or coworker numbers unreasonably high.

[4]The distribution of the time taken for completion can be found in Figure B1.

Table 1: Sample Characteristics

	Survey	CPS – March Supplement
Male	0.59	0.60
Age		
25-34 years old	0.27	0.30
35-44 years old	0.31	0.30
45-60 years old	0.42	0.40
Household income		
<$60,000	0.24	0.17
$60,000-$125,000	0.48	0.37
>$125,000	0.28	0.46
4-year college degree or more	0.76	0.46

Note: This table reports summary statistics for the survey, in the first column, and corresponding statistics for the target population in the US, in the second column. Population statistics come from the 2023 March Supplement of the Current Population Survey (2023 CPS ASEC, Flood et al. (2023)). Target population: full-time and salaried workers not in the healthcare sector, between 25 and 60 years old.

25 to 60 in the U.S. Table 1 compares the sample's characteristics with those of the U.S. population, based on the 2023 Current Population Survey Supplement. The survey sample is generally comparable to the CPS, except it oversamples individuals with a college degree and medium incomes ($60,000–$125,000), and undersamples high-income households (over $125,000). To get around the issue of over- or under-sampling of certain categories, we compute survey weights using raking, an iterative proportional fitting, recommended in Stantcheva (2023).[5] We use these weights for all the analysis in the paper. In addition to demographics, we compare the industry composition of survey respondents to the CPS data. Figure B3 shows that industry distribution is comparable to the CPS, except for the absence of healthcare workers and a higher share of "other services." When respondents selected "other services," they were prompted for more details, revealing employers in industries like accommodation, education, and public administration. Finally, the geographical distribution of our sample is similar to the one in CPS. Appendix Figure B2 presents the geographic distribution of respondents by state.

Table 2 presents key labor market statistics for the survey respondents. 15% work more than one job, 69% work in person, 21% work from home for part of the week, and 10% work fully remotely. This indicates that most respondents have some in-person coworker interaction. Regarding job search status, 26% are active job searchers—defined as those actively seeking full-time or part-time employ-

[5] Specifically, we assign equal initial weight to each observation. In each iteration we alternately scale the weights within each category so that the weighted shares match the CPS targets for all categories listed in the Table 1.

ment or due to potential layoffs—and 44% are passive job searchers, open to opportunities but not actively seeking employment.

Table 2: Summary Statics of Employment Characteristics

	Mean	Median	P25	P75	Obs.
Work hours per week	41.96	40.00	40.00	45.00	2721
Gross annual earnings	82,671.08	72,000.00	45,000.00	100,000	2,721
Gross hourly earnings	40.00	32.05	21.26	47.12	2,721
Tenure at current job (in yrs.)	2.29	1.63	0.73	3.29	2,707
Working at multiple jobs	0.15	0.00	0.00	0.00	2,721
Working fully in-person	0.69	1.00	0.00	1.00	2,721
Working remotely some time	0.21	0.00	0.00	0.00	2,721
Active job searcher	0.26	0.00	0.00	1.00	2,721
Passive job searcher	0.44	0.00	0.00	1.00	2,721

Note: Table reports some labor market related summary statistics for the main survey sample. The variables, working at multiple jobs, working fully in person, working remotely some time, active job searcher, and passive job searcher are dummies equal to 1 if the respondent is, respectively, has more than one job, is working fully in person or remotely sometime at his main job, is actively or passively looking for a new job according to the BLS definition of active search methods.

2.1 Survey Overview

We now provide an overview of our survey. The full questionnaire can be found in Appendix A.

Background socioeconomic questions and employment characteristics At the beginning of the survey, we collect demographic information from respondents, including gender, age, race and ethnicity, household income, education, zip code of residence, and current employment status. This information is used for screening purposes and to establish quotas. After the screening questions, we ask about their current job, including when they started, how many hours they work per week, their annual earnings, occupation, employer's industry, whether the job is in-person, remote, or hybrid, and the benefits they receive, if any. Respondents holding more than one job are asked to provide information about their "main" job, defined as the job where they work the most hours per week. We also ask respondents whether they were employed elsewhere or not employed when they found their current job, as workers without a previous job will not be able to answer questions about former coworkers. Additionally, we ask respondents to indicate the number of employees in their current establishment and in all locations of their current firm, as workers in small versus large firms may have different interactions with their co-workers.

Coworkers, Wage Beliefs, and Job-Switching Decisions We dedicate three blocks of the survey to ask about "current coworkers at the current workplace," "past coworkers at the current workplace" and "past coworkers at a previous workplace" Before these blocks, we explain how we define these three types of coworkers to ensure clarity.[6] To test respondents' understanding of these categories, we presented a simple scenario:[7]

"Suppose that Ben and Mary both worked at the same Walmart store in 2022. Ben quit his job at Walmart and started working at Target in January 2023, while Mary continued working at Walmart. For Mary, what type of coworker is Ben?"

Panel (A) of Figure B4 shows the distribution of responses. While 56.2% of participants correctly identified Ben as a "past coworker at the current job," 39.7% mistakenly categorized him as a "past coworker at the previous job." For those who selected the incorrect answer, we provided the correct answer and then asked a follow-up question about what type of coworker Mary is for Ben under the same scenario. Panel (B) of Figure B4 illustrates the distribution of responses for this follow-up question, showing evidence of respondent learning. Of all respondents who answered the first question incorrectly, 68.2% were able to answer the second question correctly. We now explain in more details what each one of the three blocks regarding coworker types entail.

We begin by asking respondents about their current coworkers at their present job. First, we elicit the number of coworkers they regularly interact with, along with how many of these coworkers provide relevant information about their situations, including wages, amenities, and job satisfaction at their previous jobs. Next, we ask respondents to indicate how many of their current coworkers were previously employed in each of five industries—three industries with the highest transition rates into their current industry and two with the lowest. Finally, to test whether having more coworkers enhances one's understanding of the compensation levels in different industries, we ask respondents to estimate the median annual salary of workers with similar characteristics to their own for each of the five industries, and to rate their confidence in these estimates.

Next, we assess whether participants are in touch with their past coworkers at their current job by asking how many coworkers they feel comfortable reaching out to for career-related advice, and how many of these coworkers are aware of their current industry of employment. We then ask respondents to indicate the number of past coworkers they have at their current job who are currently employed in each of the five listed industries.

Finally, with the block "past coworkers at previous job", our goal is to understand how individuals' past coworkers at previous jobs have influenced their current industry and job choices. To achieve this, we asked respondents about the number of past coworkers from their previous job who are currently working in the same industry and job. We also inquired about the number of coworkers who mentioned or recommended their current industry or job, as well as whether any of them directly referred them to their current position.

[6] We asked respondents to categorize individuals who used to work with them at the same office but have since transferred to a different branch or location within the same company as "current coworkers at the current workplace," rather than "past coworkers at the current workplace."

[7] To aid understanding, we provided a graphical illustration depicting the timeline of the scenario, shown in Figure B5.

Future employment To study the influence of current coworkers on job and industry-switching decisions, we use this block to elicit respondents' future employment plans. We begin by asking whether respondents plan to switch jobs or industries within the next year. For those considering switching industries, we present a list of potential industries: three industries that workers in their current industry are most likely to switch into and two industries they are least likely to switch into. We then ask respondents to estimate the probability of receiving a job offer if they applied to each of the five industries. Finally, we ask them to predict their starting wage in each of these industries, along with how confident they are in their wage estimates.

Conjoint experiment on job-offering probabilities Although we ask survey respondents to estimate their job-offering probability for a typical job in a list of five industries different from their own, the role of personal connections through previous coworkers at the firm level remains relatively unclear. To address this, we include a conjoint experiment, asking respondents to assess the probability of receiving a job offer for four pairs of jobs that differ in characteristics such as wage, skill levels, work arrangement flexibility, and the connection they have with incumbent workers. Details regarding the conjoint experiment are outlined in Section 4.

3 Coworkers, Wage Beliefs, and Job-Offering Probabilities

In this section, we describe the sectoral distribution of respondents' current and past coworkers, their beliefs about wages in their own sector and other sectors, as well as their beliefs about job-offering rates.

3.1 Coworker Distribution

We begin by examining the number of current and past coworkers at respondents' current jobs with whom they are familiar or interact regularly. Table C1 shows that workers have extensive interactions and familiarity with their coworkers. On average, respondents in our sample interact with 20 coworkers each month, approximately 20% of whom share details about their past jobs, such as wages, amenities, and job satisfaction levels. Additionally, respondents know the previous industry of employment for an average of 8 current coworkers. Regarding past coworkers at their current jobs, respondents feel comfortable reaching out to an average of 3 individuals, and they are aware of the current industry of employment for about 4 coworkers.

Do respondents accurately perceive the previous and current industries of employment of their coworkers, both before these coworkers entered and after they left the reference firm? To investigate this question, we examine the relationship between respondents' perceived inflows and outflows at their current firms and the actual cross-sector flows observed in the CPS. In Panels (A) and (B) of Figure C1, we plot responses to questions on coworker movements across industries. Panel (A) shows respondents' estimates of how many current coworkers were last employed in a specific industry against the actual inflow from that industry into the respondent's industry. Panel (B) plots respondents' estimates of how many past coworkers are currently employed in each industry against the actual outflow from the respondent's industry into each other industry. These plots demonstrate a positive correlation between perceived and actual industry-level transitions, suggesting that respondents' estimates of coworker movements are generally reliable.

Finally, we explore whether it is necessary to distinguish between different types of coworkers by examining the relationship between past and current coworkers. If both types of coworkers simply reflect the difficulty of transitioning across industries, then distinguishing between them might be redundant. Moreover, the coworker network effects we study rely on deviations from the law of large numbers, meaning there is some variation in coworker shares across firms. Panel (C) of Figure C1 examines the relationship between inflows to an establishment from an outside industry and outflows from the establishment to that industry. We study this by residualizing the number of past coworkers currently employed in each industry based on the number of current coworkers last employed in that industry and controlling for respondent fixed effects. The results in Panel (C) indicate substantial variation in the residualized number of past coworkers across industries, supporting our distinction between different types of coworker connections.

3.2 Wage Beliefs

How accurate are workers' beliefs about wages across industries? To answer this question we conduct two analyses using the answers collected for both respondents' beliefs on the median wage in a sector and their beliefs on their personal starting wage if they switch into a sector. First, we compare workers' beliefs about the median wage in each of the listed industries with the actual median wage for those industries, obtained from the CPS. Next, we compare workers' beliefs about their potential starting wage in each of the destination industries with the wage we predict they could have earned.[8] We also examine the difference in wage beliefs by worker characteristics, including gender, income, and job search status.

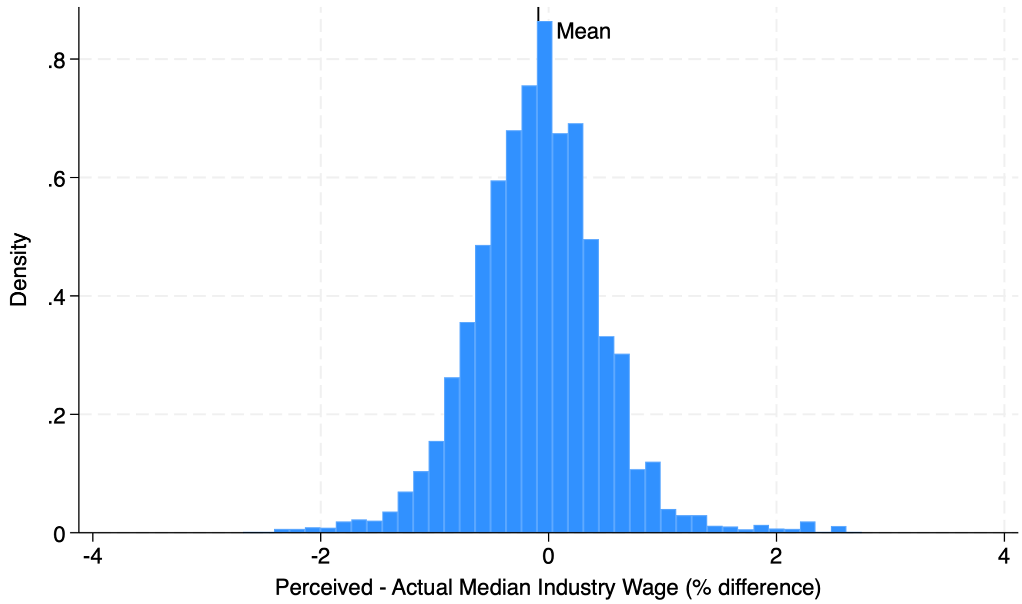
Figure 1 shows the distribution of the difference between the logged perceived median wage and the logged actual median wage by industry. Although the distribution centers around zero, there is substantial heterogeneity in the prediction error. The 25th and 75th percentiles of the logged prediction error for the median industry wage are -0.42 and 0.22, respectively, which correspond to perceived median wages that are 66% and 125% of the actual median wages.

Figure C2 presents binscatter plots from regressions of survey participants' logged predicted median wage against the logged actual median wage.

$$\log(PredictedMedianWage)_{is} = \alpha_0^{median} + \alpha_1^{median}\log(ActualMedianWage)_s + \gamma_i + \epsilon_{is} \quad (1)$$

[8] The predicted wage is derived using a Mincer-style earnings regression (Mincer 1958). Specifically, for each individual in the CPS, we regress their wage on age, squared age, an indicator for college attendance, state, industry (at the two-digit NAICS code level), and occupation. We then use the estimated coefficients from this regression to predict the wage for each respondent in our survey based on their personal characteristics.

Figure 1: Misperception: Median Industry Wage



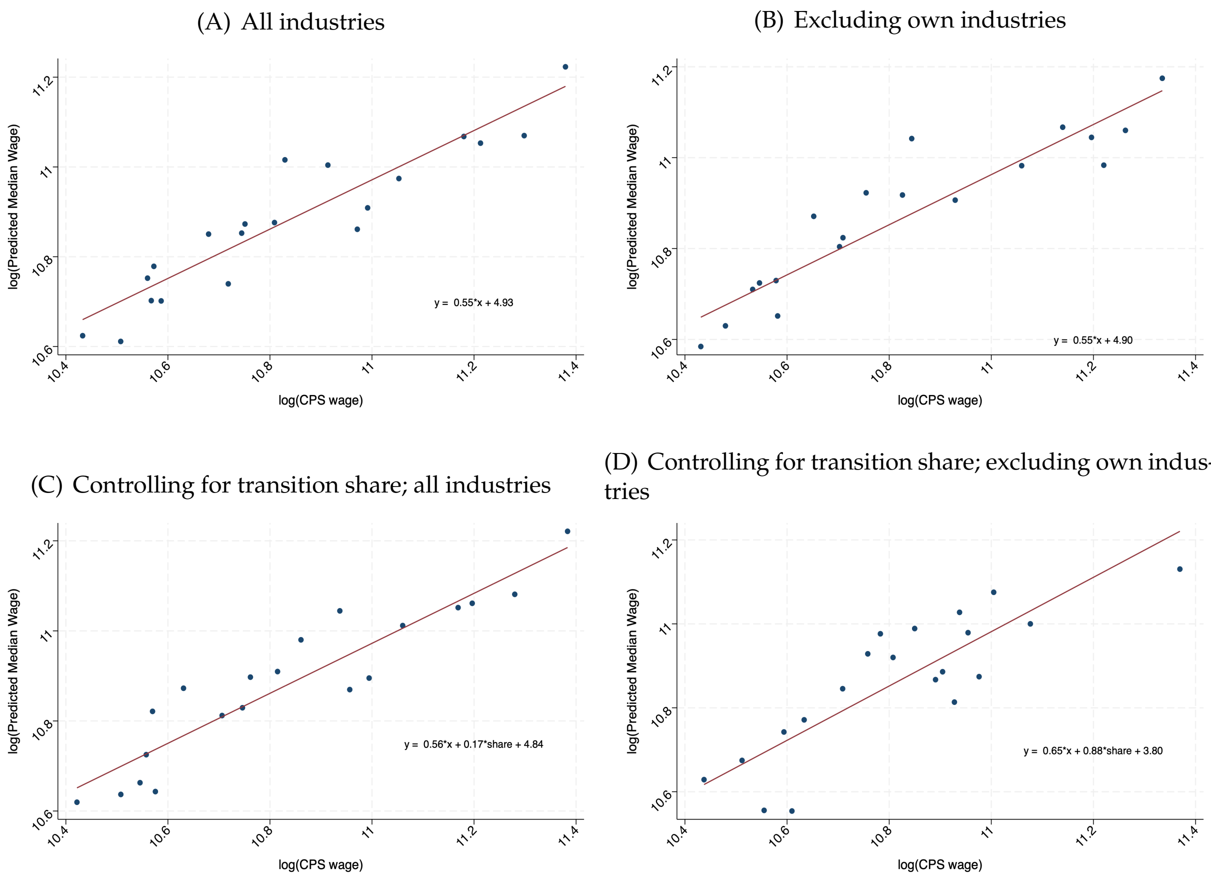
Note: Figure plots the distribution of respondents' misperception of the median wage industries other than their own. Misperception is defined as the difference between the answers respondents' put down for the median wage in the industries minus the median industry wage as reported in CPS.

where i indexes the individual and s indexes the industry that the respondent is being asked about. We include individual fixed effects to isolate each participant's tendency to over- or under-estimate wages across all industries. On average, individuals have a reasonable sense of median salaries across sectors, with notably more accurate predictions for their own sector. This conclusion holds when we additionally control for the "similarity" between origin and destination industries—measured by job-to-job transition shares—or when we exclude individual fixed effects to allow for variation in average prediction levels across individuals.

Although perceived median wages are highly correlated with actual median wages, the slope of the regression is 0.55. This implies that, on average, a 10% higher actual median wage in an industry is associated with only a 5.5 percentage point increase in perceived wages. The slope suggests substantial underestimation of wage levels in higher-paying sectors (and overestimation in lower-paying ones). When controlling for job-to-job transition shares and excluding respondents' own industries, the slope remains stable. More details are shown in Figure 2. This relationship is robust to controlling for respondents' occupation at the 2-digit SOC code level, as seen in Figure C3.

Apart from the median wage in an industry, respondents' beliefs about their own starting wages are positively correlated with wage predictions derived from data. Figure C4 shows binscatter plots from a regression of survey participants' log-predicted starting wages against the log-predicted wage in a reference industry, estimated using a Mincer-style regression on CPS data. On average, respondents' expected starting wages in various industries are positively correlated with the predictions

Figure 2: Predicted vs. Actual Median Wage



Note: Figure plots respondents' predicted median wage against the actual median wage by industry reported in CPS. Panel (A) and (B) include individual fixed effects. Panel (C) and (D) include individual fixed effects and control for the transition share from the listed sector to the participants' own sector. Sample consists of 2,721 individuals, each answering for a list of five industries, including three that are the most similar to their current industry (including their current industry) and three that are the most different from their current industry.

based on CPS data. This holds even after accounting for transition difficulty between the respondent's current industry and the industry in question by including the transition share between each industry pair as a control variable, and the slope increases to being close to one. Nevertheless, there is still lower variation among perceived personal starting wages compared to the actual wages observed in the data.

3.2.1 Heterogeneity in Wage Beliefs

How does the perception of wages in other sectors vary with individual characteristics? Understanding heterogeneity in misperceptions is important for identifying which groups may face greater barriers to efficient job transitions. We now examine whether these misperceptions in the median wage of other industries differ by gender, income level, and job search status. The results are displayed in Table C2.

We find that the slope coefficient, α_1^{median}, which captures the responsiveness of perceived sectoral wages to actual wages, is smaller for males compared to females, and smaller for active job seekers compared to those with a lower willingness to switch jobs within the next year. In contrast, the intercepts, α_0^{median}, are larger for both males and job seekers. This pattern indicates that, conditional on their own level of wage beliefs, males and job seekers are less responsive to true cross-sector wage variation. Moreover, both groups tend to overestimate wages in lower-paying sectors, consistent with the higher intercepts.[9] Unlike heterogeneity by gender and job search status, we find that both slope and intercept are relatively stable across income groups.

The Relationship with Coworker Shares While perceived and actual sectoral wages are positively correlated, the estimated coefficient remains well below one, indicating that individuals do not fully internalize available wage information. This suggests that people may rely on incomplete or selective sources when forming beliefs. One plausible source of sector-specific information is their coworkers, who may transmit wage knowledge through daily interactions or shared experiences. We then investigate whether having more coworkers is associated with lower prediction error in the following regression:

$$AbsolutePredictionError_{is} = \alpha_0^{pred} + \alpha_1^{pred} CoworkerShare_{is} + \boldsymbol{\beta}^{pred} \boldsymbol{X}'_{is} + \gamma_i + v_{is}^{pred} \tag{2}$$

We define $AbsolutePredictionError_{is}$ as the absolute value of either the difference between the values or the logged values of individuals' perceived median wage in an industry and the actual me-

[9] One possible interpretation is that job seekers face greater uncertainty and possess less accurate or more optimistic wage beliefs, especially in unfamiliar sectors. For the gender difference, it may reflect differences in labor market experience or the types of jobs and sectors men and women are typically exposed to. If women are more concentrated in a narrower range of sectors or have more stable sectoral trajectories, they may form more accurate beliefs about cross-sector wage differences. Alternatively, the observed gap may reflect differences in the way men and women gather or use wage information during job search.

dian wages observed in the CPS.[10] $CoworkerShare_{is}$ represents the proportion of individual i's current coworkers who were last employed in industry s. To control for individual tendencies toward optimism or pessimism about job prospects, we include individual fixed effects. Furthermore, factors such as the difficulty of transitions between industry pairs, which may influence respondents' perceived wages in other industries, could also vary with their shares of current coworkers last employed in an industry. To address this potential correlation thoroughly, we include a set of controls, $\boldsymbol{X}_{is}$, either separately or in combination across different specifications. First, we control for the proportion of individuals transitioning from the respondent's current industry to the industry in question. Second, we incorporate the perceived probabilities of job offers from individuals for themselves if they were to apply to the reference sector. Third, we control for occupational group fixed effects at the 2-digit SOC level. Fourth, to check whether past coworkers or current coworkers exert more influences on workers' wage prediction errors, we include both the share of current coworkers who were previously employed in the reference sector and the share of past coworkers at the current job who are currently employed in that sector as regressors. Finally, we look into the differential impacts of coworkers on positive vs. negative wage prediction errors, by including an indicator variations *PositiveError* that indicates overestimation of the median wage in an industry, as well as an interaction between the indicator variable and the *CoworkerShare*.

Table 3 shows that a higher share of current coworkers who previously worked in an industry is associated with smaller errors when respondents predict that industry's median wage. In Column (1), moving from zero to all such coworkers reduces the prediction error by \$7,466. This estimate remains similar in magnitude and statistically significant after adding controls for the perceived probability of receiving a job offer in that industry and occupation fixed effects. In Column (4), we include the share of past coworkers who moved into the industry (*PastCoworkerShare*) and find a statistically insignificant coefficient. Column (5) tests for asymmetric effects by interacting *CoworkerShare* with an indicator for overestimation (*PositiveError*). Although overestimators err by a larger amount on average, the interaction term is statistically insignificant, suggesting no evidence of differential impact of coworker exposure on optimistic versus pessimistic respondents.

Table C3 defines *AbsolutePredictionError* as the difference between the logged values of individuals' perceived median wage in an industry and the actual median wage observed in CPS. Across specifications that add respondents' perceived offer probability for the industry, occupation-group fixed effects, the share of past coworkers currently employed in the industry, and an indicator for wage overestimation (with its interaction with coworker share), the coefficient on *CoworkerShare* is stable at -0.05 to -0.06. Quantitatively, a 10 percentage point increase in *CoworkerShare* is associated with roughly a 0.5–0.6 percentage point improvement in accuracy.

With respect to starting wage, Table C4 shows that having more coworkers last employed in an industry reduces the gap between the predicted starting wage from observations in the CPS and the

[10] We also select our sample to exclude answers that fall above the level that is being top-coded by CPS or the ones that fall below the federal minimum wage.

Table 3: Impact of Current Coworkers' Past Industries on Prediction Errors in Median Wages

	Wage Error	Wage Error	Wage Error	Wage Error	Wage Error
CoworkerShare	-7,465.85*	-7,174.27*	-7,327.36*	-8,051.10*	-7,528.77*
	(4,214.11)	(4,222.24)	(4,246.77)	(4,148.59)	(3,931.96)
OutTransition	-513.22**	-493.11**	-469.18**	-478.10**	-741.63***
	(236.07)	(240.00)	(239.09)	(238.96)	(248.93)
PerceivedProb		-18.79	-19.76	-22.60	0.22
		(28.69)	(28.80)	(28.44)	(29.33)
PastCoworkerShare				4,215.96	
				(4,676.20)	
PositiveError					10,312.55***
					(2,874.40)
PositiveError $\times$ *CoworkerShare*					1,874.86
					(5,628.42)
Occupation FE	No	No	Yes	Yes	Yes
Mean of Dep. Var	25,434.43	25,450.92	25,415.73	25,415.73	25,415.73
R^2	0.24	0.24	0.24	0.24	0.25

Note: Table displays the coefficient estimates for equation (2). Columns (1) - (2) define *PredictionError* using the absolute value of the difference between respondents' predicted median wage in another industry and the actual median wage observed in CPS. Columns (3) - (4) define *PredictionError* using the absolute value of the difference between logged predicted median wage and logged actual wage for the same industry in CPS.

perceived own starting wage indicated by each respondent, with the caveat that the estimate is no longer statistically significant.[11]

3.3 Job-Offering Probabilities

Other than perceived wages for a given sector, perceived job-offering probabilities are also important for determining workers' job-switching decisions, as they factor into the option value of potentially switching jobs in the future. Before embarking on our primary goal is to examine the role of coworkers in influencing perceived job-offering probabilities, we first assess how accurate these perceptions are on average. Unlike industry-level wages, there is no directly observable moment in the data corresponding to the actual job-offering rate. Therefore, we compare perceived job-offering probabilities with realized flows between the respondent's origin industry and the industry for which they are predicting the job-offering rate.

Admittedly, transition flows between industry pairs may capture factors beyond job-offering probabilities, such as transition difficulties due to skill or labor demand differentials between industries. However, given the absence of data on actual job-offering probabilities, using in- and out-transition flows between industry pairs as a proxy is a practical approach. These transition flows

[11]Since our predicted starting wage is obtained using a Mincer-style regression with observables, there may be some noise in imputation, leading to the statistical insignificance.

capture the frequency of successful moves between industries, which indirectly reflects job-offering rates. Since individuals can only switch industries if they receive job offers, these flows provide a reasonable benchmark for evaluating perceived job-offering probabilities.

Figure C6 shows the distribution of perceived job-offering rates in other industries, pooling responses across all industries and participants. The distribution is relatively uniform, with notable peaks at around 0%, 50%, and 100%, indicating that respondents often group job opportunities into broad categories. Figure C7 plots the perceived probability of receiving a job offer in an industry against the actual transition flows into or out of that industry, controlling for individual fixed effects. Overall, respondents predict higher job-offering probabilities for industries that experience higher inflows into their current industry or outflows from it, as well as for industries that workers in their current industry tend to transition into.

Additionally, for each 1 percentage point increase in the outflow transition rate, respondents predict a 1.09 percentage point increase in the job-offering probability. Conversely, they predict a 0.86 percentage point increase in job-offering probability for industries with higher inflows. This pattern aligns with the idea that higher outflow transition rates signal that the target industry is easier to move into, leading respondents to predict higher job-offering rates for industries that are perceived as easier to transition into.

The Relationship with Coworker Shares We look into whether having more coworkers are associated with higher perceived job-offering probabilities, by examining the following specification:

$$PerceivedProb_{is} = \alpha_0^{offer} + \alpha_1^{offer} PastCoworkerShare_{is} + \alpha_2^{offer} CoworkerShare_{is} + \boldsymbol{\beta}^{offer} \boldsymbol{X}'_{is} + \gamma_i + v_{is}^{offer} \tag{3}$$

When applying for jobs, workers tend to reach out to both their connections from the past and from the present to enhance the probabilities that they receive an offer. We therefore include both the past and the current coworker shares in the specification. More specifically, $PastCoworkerShare_{is}$ represents the share of individual i's past coworkers at the current job who are currently employed in industry s, and $CoworkerShare_{is}$ represents the share of individual i's current coworkers who were previously employed in sector s. Similar to our specification on perceived wages, we control for individual fixed effects to account for an individual's tendency to be overly optimistic or pessimistic about their job prospects in general. Factors such as the transition difficulty between industry pairs, which may influence perceived job-offering probabilities, could also correlate with the share of past coworkers currently employed in a given industry. To address this issue as comprehensively as possible, we include a set of controls, $\boldsymbol{X}_{is}$. These controls are included either separately or in combination across different specifications. First, we control for the fraction of individuals transitioning from the respondent's current industry to the industry they were asked about. Second, we include individuals' perceived starting wage for themselves if they were to transition into the reference sector. Third, we control for individuals' occupational group fixed effects.

Table 4 presents the results for specification (14). According to the first column, having more past coworkers currently employed in an industry and more current coworkers who were last employed in an industry both increase the perceived job-offering probability for a job in that industry. This relationship remains positive and significant even when controlling for the average transition difficulty to that industry, the perceived logged starting wage in that industry, and the occupational group fixed effects. Quantitatively, according the fourth column, increasing the share of past coworkers who move to an industry from 0 to 1 will increase the perceived probability of receiving an offer from that industry by 11.65 percentage points, and increasing the share of current coworkers who were last employed in the industry from 0 to 1 will increase the perceived probability by 24.75 percentage points.

Table 4: Impact of Past Coworkers' Current Industries on Perceived Job Offering Rates

	Offer Probability	Offer Probability	Offer Probability	Offer Probability
$PastCoworkerShare$	13.98^{***}	11.41^{***}	11.85^{***}	11.65^{***}
	(2.32)	(2.26)	(2.55)	(2.57)
$CoworkerShare$	27.94^{***}	24.04^{***}	24.55^{***}	24.75^{***}
	(2.42)	(2.40)	(2.64)	(2.64)
$OutTransition$		0.96^{***}	1.03^{***}	1.03^{***}
		(0.07)	(0.08)	(0.08)
$\log(StartWage)$			-1.13	-1.13
			(1.09)	(1.09)
Occupation FE	No	No	No	Yes
Mean of Dep. Var	40.76	40.76	40.87	40.91
R^2	0.55	0.58	0.56	0.56

Note: Table displays the coefficient estimates for equation (14). *PastCoworkerShare* is defined as the share of past coworkers who have left the respondent's current job and move to a certain industry, out of all past coworkers at the current job who the respondent knows the industry where they are currently employed. *CoworkerShare* is defined as the share of current coworkers for the respondent that come from a certain industry, out of the coworkers who the respondent knows the industry where they were previously employed. Column (2) controls for the out transition probability in percentage from the individual's own industry to the industry they were asked about. Column (3) controls for the respondent's logged starting wage that they believe they could have earned by moving into the industry. Column (4) additionally controls for the occupational group fixed effects.

3.4 Job-Switching Intentions

Section 3.3 explores the relationship between individuals' perceived job-offering probabilities and their coworkers. However, another key question in studying industry transitions, which remains unexplored, is whether individuals intend to apply to these industries in the first place. We now examine the relationship between individuals' intention to apply to a job in another industry and their coworker composition. For each respondent, we elicit the probability that they are voluntarily looking for a new job at a new different employer. For respondents who indicated a nonzero probability of voluntarily switching to another employer, we asked whether they would consider switching to a job outside of their own current industry. For those who answered "yes" to potentially switching to a job in a different industry, they were then asked to answer 'yes' or 'no' for a list of five industries other than their own, indicating whether they would consider applying for a job in each.

We define the outcome variable $LookforJobIndustry$, an indicator variable which equals one if the respondent is willing to look for a job in a certain industry, and estimate the following regression at the individual level and for each potential destination industry:

$$LookforJobIndustry_{is} = \alpha_0^{ind} + \alpha_1^{ind} PastCoworkerShare_{is} + \alpha_2^{ind} CoworkerShare_{is} + \boldsymbol{\beta}^{ind} \boldsymbol{X}_{is}' + \gamma_i + v_{is}^{ind} \tag{4}$$

Analogous to the regression examining coworker influences on wage perception, $PastCoworkerShare_{is}$ represents the share of individual i's past coworkers who are currently employed in industry s, and $CoworkerShare_{is}$ is the share of current coworkers previously employed in industry s. We control for individual fixed effects to account for individual tendencies toward optimism or pessimism regarding job prospects. Additionally, we control for the out-transition probability from the individual's current industry to a potential destination industry and the perceived logged starting wage in that industry to capture both the transition difficulty and the attractiveness of a job in industry s.

Table 5 presents the results for specification (4). If the share of past coworkers currently employed in an industry increases from 0 to 1, the intention to apply for a job in that industry increases by 33 percentage points. This relationship remains positive and significant even when controlling for average transition difficulty to that industry, by including the out-transition rate and the logged perceived starting wage, and when controlling for occupation fixed effects. Importantly, the coefficient estimate for $PastCoworkerShare$ remains positive and significant, only 4 percentage points lower than in the specification that excludes both the perceived wage and out-transition probabilities. Current coworkers also influence workers' intentions but to a lesser extent: if the share of current coworkers previously employed in an industry increases from 0 to 1, the intention to apply for a job in that industry increases by 20 percentage points. This coefficient shrinks and loses statistical significance when controlling for the other variables and occupation fixed effects.

Other factors influencing job-switching decisions Other than their intention to search and their perceived outside options, we elicit participants' answers to questions about the general reasons why they chose their current job, as well as the factors they consider most important when deciding which industry other than their own to switch to. Participants were asked to choose three options from a list of job attributes.[12]

[12] The options listed include: wage and benefits; probability of receiving an offer; costs (ease) of application; match of your own skills and qualifications; career growth prospects; networking and connection opportunities; job security, prestige, and work-life balance; convenient location; flexibility in work hours or ability to work from home; company culture and friendly work environment; other (please specify).

Table 5: Impact of Past and Current Coworkers on Intention to Apply

	Switch Industry	Switch Industry	Switch Industry	Switch Industry
PastCoworkerShare	0.34***	0.33***	0.30***	0.30***
	(0.06)	(0.06)	(0.07)	(0.07)
CoworkerShare	0.20***	0.19**	0.14*	0.15*
	(0.07)	(0.07)	(0.08)	(0.08)
OutTransition		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
$\log(StartingWage)$			0.14***	0.14***
			(0.05)	(0.05)
Occupation FE	No	No	No	Yes
Mean of Dep. Var	0.52	0.52	0.52	0.52
R^2	0.25	0.25	0.24	0.23

Note: Table displays the coefficient estimates for equation (4). *PastCoworkerShare* is defined as the share of past coworkers who have left the respondent's current job and move to a certain industry, out of all past coworkers at the current job who the respondent knows the industry where they are currently employed. *CoworkerShare* is defined as the share of current coworkers for the respondent that were previously employed in a certain industry, out of the coworkers who the respondent knows the industry where they were previously employed. Column (2) controls for the out transition probability in percentage from the individual's own industry to the industry they were asked about. Column (3) controls for the respondent's logged starting wage that they believe they could have earned by moving into the industry. Column (4) additionally controls for the occupational group fixed effects.

In Figure C8, we show the distribution of respondents choosing each of the provided categories. Seventy-four percent of the participants chose "wage" as one of the three reasons why they chose their current job, while 83% of the respondents selected "wage" as one of their major considerations for choosing the next industry. Other reasons that were most frequently selected were "job security, prestige, and work-life balance" and "career growth prospects."

Overall, participants consider the same factors when they chose their current job and when making future decisions about which industry to switch into next. The only exceptions are that respondents place more importance on the flexibility of work arrangements for the industries they are planning to move into compared to when they chose their current job. They also place slightly less importance on the extent of skill match when considering future options.

To sum up, the analysis of workers' job-switching decisions emphasizes the importance of wages in influencing these choices and consequently highlights the role of coworkers. By enhancing workers' accuracy of wage beliefs associated with their outside options, coworkers can propel individuals to select into industries that better align with their considerations.

3.5 Past Coworkers and Current Employment Outcomes

The previous analysis on coworkers at current jobs and one's future employment decisions may be influenced by stated preference bias, where discrepancies between what individuals report in surveys and what they actually do can arise. This bias is well-documented in economics, stemming from factors like hypothetical scenarios in surveys, social desirability, or the lack of real economic consequences.[13] To address this concern, we examine one set of revealed preferences: the influence of past coworkers at previous firms on individuals' current job choices. In Table C6, we report summary statistics related to the number of past coworkers at previous jobs who may have potentially impacted respondents' current job choices. On average, respondents remain in contact with 4.24 past coworkers from prior jobs, with 16.75 coworkers having mentioned their current industry and 4.02 specifying their current firm. Although these summary statistics cannot isolate the exact mechanisms through which coworkers exert influence, the number of coworkers sharing information about their current industry and firm strongly suggests the importance of coworker networks. Notably, 30% of respondents have heard from past coworkers about their current industry or firm, and 20% have received a referral from a past coworker. These patterns demonstrate that coworkers play a significant role in shaping realized choices, both in terms of industry and firm.

What is the relationship between workers' wages at their current jobs and their past coworkers? To explore answers to this question, we study the specification that regresses the respondents' current logged wages on indicator variables for whether the respondent has at least one past coworkers at her past job that worked in the current industry, mentioned to her the current industry, or referred her to the current job:

$$\ln(wage)_i = \alpha_0^{wage} + \alpha_1^{wage} \mathbb{1}(coworker)_i + \boldsymbol{\beta}^{wage} \boldsymbol{X}_i' + v_{is}^{wage} \tag{5}$$

We control for a comprehensive set of variables that may influence individual i's wage, including personal characteristics such as age, gender, tenure at the current job, education level, and state of work. Additionally, we include occupation-by-previous-industry-by-current-industry fixed effects to capture the transition difficulty for individuals with specific skill sets moving from their previous industry of employment to their current industry. Given that our occupation codes are categorized at the six-digit SOC level, these fixed effects should provide a reasonably detailed representation of skill variation.

Table 6 shows that even after controlling for a comprehensive set of fixed effects to absorb the difficulty in transition between one's last and current industry that is specific to her occupation, together with her personal characteristics, having at least one past coworker at past job that mentioned the current industry of employment in some way to the respondent is associated with a 14 p.p. increase in her current wage. The effect is similar for referral: having at least one past coworker at past job that referred the respondent to her current job is associated with a 17 p.p. in her current wage.

[13] For example, see Ben-Akiva, Morikawa and Shiroishi 1992, Cummings, Harrison and Rutström 1995, List and Gallet 2001, Harrison and Rutström 2008.

Table 6: Impact of Past Coworkers on Wage at Current Job

	(1)	(2)	(3)	(4)	(5)	(6)
Past coworkers work in current industry	0.16***	0.07				
	(0.05)	(0.09)				
Past coworkers mention current industry			0.22***	0.14*		
			(0.07)	(0.08)		
Past coworker referral					0.10	0.17*
					(0.08)	(0.10)
Controls	No	Yes	No	Yes	No	Yes
Mean of Dep. Var	10.94	10.97	10.92	10.97	10.92	10.97
R^2	0.00	0.24	0.01	0.24	0.00	0.24

Note: Table displays the coefficient estimates for equation (5). Columns (1) - (2) define *coworker* as having at least one past coworker who has been employed in the reference individual's current industry. Columns (3) - (4) define *coworker* as having at least one past coworker who has mentioned to the individual her current industry of employment. Columns (5) - (6) define *coworker* as having at least one past coworker who referred the reference individual to their current position. Columns (1), (3), and (5) do not include other controls. Columns (2), (4), and (6) control for the share of workers that transition from the reference individual's previous industry to their current industry.

4 The Importance of Coworkers in Influencing Perceived Job-Offering Probabilities

Section 3.3 delineates the correlation between the percentage of coworkers in a sector and the perceived probabilities of job offer once applied to a job in that sector. However, it remains unclear how important coworkers are compared to other characteristics that impact the probabilities of receiving an offer. To quantify the effect of coworker connections on job-offer probabilities, we designed a conjoint experiment for survey respondents aimed at assessing their beliefs regarding job offers within their current sector. The introductory text prompts respondents to imagine seeking a new job in their current sector and applying to two different companies. They are then asked to evaluate short descriptions of these positions and select the one they believe is more likely to result in a job offer.

Specifically, respondents are presented with the following instructions: "We are going to show you four pairs of jobs. These jobs are identical in all aspects except for the characteristics presented in the tables you will see. We will ask you to indicate how likely you believe you are to receive a job offer if you apply to each of the jobs presented. Remember, a job offer is not necessarily a job you will accept. Please respond without considering whether the job is ideal for you. You will be able to select a percentage chance of receiving a job offer for each job by moving the sliders below the tables, where 0 on the far left means you believe it is absolutely impossible you will receive an offer, and 100 on the far right means you are certain to receive an offer."After reading the instructions, respondents are shown a table comparing the two jobs, each with sliders ranging from 0 to 100, allowing them to indicate their perceived probability of receiving an offer for each job separately. Figure B6 contains a screenshot of one example of the conjoint experiment according to how it was presented to survey respondents.

To avoid overwhelming respondents with too many variables, we follow Folke and Rickne (2022) by limiting the comparison to four key job attributes: monthly wage, skill level required, schedule flexibility (including the option to work from home), and personal connections with other workers. Other than these attributes, the jobs are identical.

We introduce randomization by varying both the order of the rows and the values of the job attributes in each description.[14] The personal connection attribute is presented through vignettes outlining different levels of coworker connections, with four possible conditions: (i) Null condition: "You do not know any other current employees at the job you are applying for." (ii) Slightly positive condition: "You know at least one employee at the job you are applying for but have not reached out for any discussion of the job." (iii) More positive condition: "You know and have reached out to at least one employee at the job. They have a good opinion of you but are unable to assist with your application in any concrete way." (iv) Active effort condition: "You know and have reached out to at least one employee at the job, and they are actively helping you with your application (e.g., providing a referral or advocating on your behalf)." This last condition is oversampled to have a 33% probability of occurrence, while the other three conditions each have a 22% probability.

Quantifying personal connections can be challenging, so we use vignettes to illustrate different scenarios in which personal connections may influence job-offer probabilities. The vignettes for positive coworker connections include the following scenarios: (i) Referral agreement: "You had a coffee chat with a previous colleague currently employed at the target firm, and they have agreed to provide a referral." (ii) Networking support: "You had a coffee chat with a previous colleague at the target firm. While they cannot provide a referral themselves, they have agreed to ask their other connections at the firm to do so." (iii) Informal mention: "You had a coffee chat with a previous colleague at the target firm. While they cannot formally refer you, they will informally mention you to recruiters."

4.1 Calculating the perceived impact of connection on job offering probability

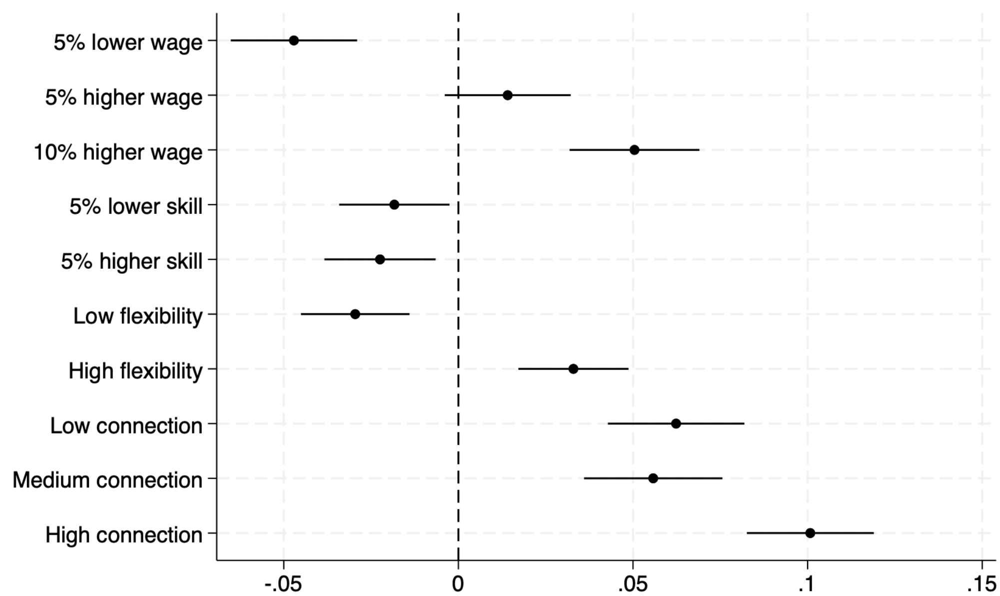
Following existing survey studies with conjoint analysis (Hainmueller, Hopkins and Yamamoto 2014, Folke and Rickne 2022), we measure the importance of connection through coworkers on individuals' perceived probabilities of receiving a job offer. We create a dummy variable $ChooseJob_{ijt}$ to indicate whether individual i believes she is more likely to receive an offer from job j in table t. We regress this indicator variable on one dummy for each value of each job trait:

$$ChooseJob_{ijt} = \alpha + \beta_{connection} Connection_{ijt} + \boldsymbol{\beta}_x \mathbf{X}'_{ijt} + \gamma^k_{table} table^k_{ijt} + e_{ijt} \tag{6}$$

[14] The values for the first three job traits are randomly selected from predefined lists with equal probabilities. For example, wage options include: "5% less than your current wage," "approximately the same as your current wage," "5% more than your current wage," or "10% more than your current wage." Skill requirements are presented as: "5% lower than your current job," "approximately the same as your current job," or "5% higher than your current job." Schedule flexibility options include: "entirely flexible and able to work from home," "flexible hours but unable to work from home," or "no personal influence over work hours and unable to work from home."

where we omit one dummy for each value of each job trait. $Connection_{ijt}$ is equal to 1 if one of the three "active effort" of establishing personal connection vignettes is shown. To simplify notation, we put the other categories of personal connection, as well as other job traits, including wages, job flexibility, and skills required in the **X** vector. In case that the order in which a job is shown matters for respondents' selection, we also control for a dummy variable $table^k_{ijt}$, which is equal to 1 if the table is the k-th one being shown to the respondents. The coefficients γ^k_{table} are all close to 0 and statistically insignificant, showing that individuals tend to make consistent choices regardless of the order in which they are being shown the different pairs of jobs.

Figure 3: Estimates of the Importance of Job Features in influencing Job-Offering Rate



Note: 95% confidence intervals are adjusted for clustering by respondent. Each respondent provided responses to four experiments on job-offering probabilities. The dependent variable is equal to 1 if the respondent selects a higher probability of receiving an offer from a job, compared to other job in the table. N = 2,920.

We pool the three "high connection" scenarios into a single dummy variable, $Connection_{ijt}$. The coefficient $\beta_{connection}$ on this variable shows the percentage point difference in the proportion of people who associates a job with higher job-offering rate compared to the reference category, "no connection." For the wage characteristic, we set the reference category to "approximately the same as your current wage." Interestingly, individuals on average think that the probability they will receive an offer from a job *increases* with the compensation level of that job. The coefficient estimates for "5% less", "5% more" and "10% more" are $-0.04, 0.01, 0.05$, respectively.[15] The fact that respondents tend to associate higher-wage jobs with high job-offering rate despite that such positions are typically more competitive and our reminder on how having a job offer doesn't indicate acceptance of the job may be due to several reasons. First, optimism bias may lead respondents to overestimate their chances of securing high-

[15] The t-stats associated with the three categories are -4.87, 1.58, and 5.15, respectively.

paying positions, driven by confidence in their own qualifications. Additionally, wage levels may serve as a signal of job desirability, making respondents believe that companies offering higher wages are more eager to fill roles, despite increased competition. Finally, workers may be overqualified for lower-paid positions. In our study, we do not attempt to delve into the exact reasons why respondents associate higher-wage jobs with higher job-offering probabilities.

Figure 3 presents the full set of estimates on the importance of job attributes in influencing perceived job-offering probabilities among all respondents. On average, respondents believe that having connections plays a significant and positive role in increasing their likelihood of receiving a job offer. In fact, respondents perceive a strong connection to be the most important factor in improving their chances of getting an offer. Having someone who is willing to make an effort—whether through a direct referral or by communicating with the hiring team—is seen as increasing a candidate's chances by 10%. Even without active outreach, simply having at least one former coworker at the firm where the individual is applying is perceived to raise the probability of receiving an offer by 5-6%, which is higher than the perceived importance of any other job attribute unrelated to connection in bringing up the job-offering rate.

We examine heterogeneity in perceived job-offering probabilities across workers with different characteristics. First, we run specification (6) separately for male and female workers. Second, we explore heterogeneity by age. As shown in Figure C10, job-offering probabilities do not vary significantly by gender or wage, with a few exceptions. Female workers tend to associate jobs requiring higher skill levels than their current position with lower job-offering probabilities, and they perceive having a high degree of connection as slightly more beneficial in securing an offer.[16] Finally, we account for wage level differences by classifying workers into low (annual wage of \$0–\$49,999), middle (\$50,000–\$99,999), and high wage (\$100,000 or more) groups. Although wage groups generally do not strongly influence perceptions of how job attributes affect job-offering rates, high-wage workers tend not to associate high wages with higher job-offering rates—consistent with the idea that high-wage jobs are more competitive and feature lower offer rates. However, even among high-wage workers, having a connection is still considered the most important factor in improving job-offering probabilities. This mitigates concerns that respondents confuse job-offering probability with their likelihood of accepting a job.[17]

Since we ask about the specific job-offering probabilities associated with each one of the two jobs in a table, we can examine as a robustness check an additional specification that is otherwise identical to equation (6) but includes the perceived job-offering probability, $JobOfferProbability_{ijt}$ for individual i's perceived probability that she will receive an offer from job j in table t, as the dependent

[16]The point estimate for the "high connection" category is higher for females than males, though the 95% confidence intervals overlap.

[17]Despite overlapping confidence intervals across wage groups, the point estimate for the "high connection" category is about 50 percentage points higher than the baseline estimate, underscoring the importance of connections in job-offering probabilities, even among those least likely to misinterpret the survey question.

variable:

$$JobOfferProbability_{ijt} = \alpha + \beta_{connection} Connection_{ijt} + \boldsymbol{\beta}_x \boldsymbol{X}'_{ijt} + \gamma^k_{table} table^k_{ijt} + e_{ijt} \tag{7}$$

Figure C9 plots the estimates from this specification. The coefficient estimates for the personal connection categories are still positive and significant. Respondents on average perceive that having high connection will increase their job by 3.9% on average. We further discuss the reliability of our estimates in the conjoint experiment in Appendix C.2.

5 A Stylized Model on Coworkers and Job Choices

Our empirical results underscore the influence of current and past coworkers on individuals' perceptions of wages and job-offer probabilities in other sectors. However, several important questions remain: What are the implications of coworker influence for workers' search behavior and welfare? And what are the consequences of ignoring these effects?

Motivated by these findings, we develop a partial-equilibrium sector choice model that incorporates beliefs about search costs and job-offer rates, both shaped by coworker networks. In the model, workers are assumed to have perfect information about wages in their current sector but only imperfect information about wages in other sectors. They must therefore rely on current coworkers—particularly those who recently transitioned from other sectors—for information. We use the model to study the implication on welfare calculation when we consider the coworker mechanism versus when we ignore its presence.

We then test the assumptions and predictions of our conceptual model by examining the relationship between perceived wages and job-offering rates, and the presence of current and past coworkers. After validating the model's assumptions, we quantify the relevant variables and apply the conceptual framework to assess the relative importance of different channels through which coworker influence operates. Finally, we calculate the welfare implications of accounting for coworker influence compared to scenarios where it is excluded.

5.1 Setup

The model focuses on employed workers. Time is infinite and discrete. An agent can supply one unit of labor to $n = 1, ..., N$ sectors. Agents receive the competitive market wage w^n_t if employed in firm j and industry n at time t. We consider the partial equilibrium for a sequence of wages, $\{w^n_t\}$, that follow any exogenous stochastic process, in each industry.

Denote the number of workers in industry n at the beginning of period t by L^n_t. At the end of each period, workers choose which firm and sector combination they want to move to based on adjustment costs, their perceived wages differentials, idiosyncratic taste shocks, and the job offering rate. Denote the fraction of workers that reallocate from industry n to k $\mu^{n,k}_t$. If a worker moves from n to k, she incurs an adjustment cost $\kappa^{n,k}$, which is the same for all workers in all periods and is publicly known.

The adjustment costs can be thought of as the cost for skill upgrading to move from the origin sector to the destination sector, and only applies if the worker receives the job offer in the destination sector.

In addition to the adjustment costs, workers are subject to idiosyncratic taste shocks $\nu\epsilon_t^n$ each period. The idiosyncratic taste shocks are independently and identically distributed across individuals, and drawn from a Type-I Extreme-Value (Gumbel) Distribution with zero mean and scaled by a parameter ν.

We assume that workers in the same industry all have the same beliefs. The belief of workers in industry n at the end of period t about the wage in industry k at time $t' \geq t$ is characterized by the following equation:

$$\mathbb{E}_t^n \ln w_{t'}^k = \begin{cases} \phi^{\frac{\mu^{k,n}L^k}{L^n}} \ln w_{t'}^k + (1 - \phi^{\frac{\mu^{k,n}L^k}{L^n}}) \ln w_{t'}^n & k \neq n \\ \mathbb{E}_t \ln w_{t'}^k & k = n \end{cases} \tag{8}$$

Equation (8) assumes that agents' form beliefs of wages in other sectors as a weighted average of the correct industry wage and her own industry wage.[18] The weight of the correct beliefs that workers in an industry n have for their beliefs of industry k rely on the share of workers in n that worked in industry k in the steady state. The parameter ϕ measures the important of coworkers on having the correct belief.

When workers in sector n apply for jobs in sector k, they expect to receive an offer with probability $\Gamma^{n,k}$, which depends on their social connections:

$$\Gamma^{n,k} = \mathcal{F}(\mu^{n,k})$$

where $\mathcal{F}$ is such that $\Gamma^{n,k} \in [0, 1]$, and $\Gamma^{n,n} = 1$. If they do not receive an offer, they must remain in the same sector for the next period. Nonetheless, the adjustment costs, $\kappa^{n,k}$, are sunk and incurred regardless of whether they switch sectors.

Crucially, $\Gamma^{n,k}$ reflects only workers' perceived likelihood of receiving an offer, shaping their decision to apply for jobs in a different industry. It does not, however, place any real constraint on their ability to make the move. We make the additional assumption that $\Gamma^{n,k}$ follows the specific form:

$$\log\left(\frac{\Gamma^{n,k}}{1 - \Gamma^{n,k}}\right) = \psi_0 + \psi_1 \mu^{n,k} + \psi_2 \log(w_t^k) \tag{9}$$

where the job-offering probability is dependent on both the transition difficulty, as represented by the outflow from the origin to the destination industry, as well as the destination industry wage.

[18] We assume that beliefs of other industries' wages depend on own wages because agents could use their own compensation level to infer the temporary shocks hitting the entire economy. In addition, recent works such as Jäger et al. (2022) have shown that workers' beliefs of outside options are correlated with their own wage.

Therefore, the value of an agent in sector n at time t is assumed to be given by:

$$V_t^n = \ln w_t^n + \max_k \left\{ \left(\mathbb{E}_t^n [\Gamma^{n,k} \beta V_{t+1}^k + (1 - \Gamma^{n,k}) \beta V_{t+1}^n - \kappa^{n,k}] \right) + \nu \epsilon_t^k \right\}$$

Taking the expectation of V_t^n with respect to the vector ϵ, we can obtain the expected value of being employed in sector n:

$$\mathbb{E}_t^n [V_t^n] = \mathbb{E}_t^n \ln w_t^n + \mathbb{E}_\epsilon \left[\max_k \left\{ \mathbb{E}_t^n [\Gamma^{n,k} \beta V_{t+1}^k + (1 - \Gamma^{n,k}) \beta V_{t+1}^n - \kappa^{n,k}] + \nu \epsilon_t^k \right\} \right]$$

Note that the superscript n for the expectation operator indicates that the expected value of being in a sector depends on the workers' current sector. The coworker composition in industry n affects both the beliefs on wages and the job offering rate.

Proposition 1. *The estimation equation can be written as:*

$$\begin{aligned} \ln \mu_t^{n,m} - \ln \mu_t^{n,n} = & \frac{\beta}{\nu} \Gamma^{n,m} \mathbb{E}_t^n [\ln w_{t+1}^m - \ln w_{t+1}^n] \\ & - \beta \Gamma^{n,m} \mathbb{E}_t^n \ln \mu_{t+1}^{m,m} + \beta (\Gamma^{n,m} - 1) \mathbb{E}_t^n \ln \mu_{t+1}^{n,n} + \beta \mathbb{E}_t^n \ln \mu_{t+1}^{n,m} \\ & - \frac{1 - \beta}{\nu} \Gamma^{n,m} \kappa^{n,m} \end{aligned} \tag{10}$$

Proof. See Appendix D.2. □

Welfare Implication The welfare of workers in sector n at time t is

$$W_t^n = \ln w_t^n + \sum_k \mu_t(n,k) \mathbb{E}_t [(\beta W_{t+1}^k - \kappa^{n,k})]$$

At the steady state, we can calculate welfare associated with each sector by solving for the equation:

$$W^n = \ln w^n + \sum_k \mu(n,k) (\beta W^k - \kappa^{n,k})$$

which, in matrix representation, can be written as:

$$\begin{aligned} \vec{W} &= \ln \vec{w} + \beta \boldsymbol{\mu} \vec{W} - (\boldsymbol{\mu} \odot \boldsymbol{\kappa}) \mathbf{1} \\ &= (\mathbb{I} - \beta \boldsymbol{\mu})^{-1} \left(\ln \vec{w} - (\boldsymbol{\mu} \odot \boldsymbol{\kappa}) \mathbf{1} \right) \end{aligned} \tag{11}$$

which reflects the present discounted value of wages net of transition costs, aggregated over an infinite horizon.

5.2 Model Assumptions and Parameters

After motivating the model using reduced-form evidence, in this section we test its functional form assumptions and calibrate key parameters—particularly those governing the influence of coworkers on perceived wages and job-offer probabilities.

Coworker and Wage Beliefs In Section 5.1, we present a framework to analyze the role of current and past coworkers in shaping individuals' perceptions of external job opportunities, which ultimately influence their job choice decisions. We propose that coworker influence operates through two channels. First, current coworkers provide information about their previous sectors of employment, improving the accuracy of perceived wages in those sectors. Second, past coworkers create connection opportunities at their current place of employment, increasing the likelihood of receiving job offers at the current firm. These two key assumptions regarding coworker influence can be directly tested using our survey. Additionally, the survey results enable us to calibrate the parameters that govern the extent to which coworkers affect perceived wages and job-offering probabilities.

Equation (8) assumes that workers' beliefs about the wage in a destination sector are a function of both their own-sector wage and the actual destination-sector wage. To test this assumption and estimate the weight parameter governing the importance of coworkers in improving wage accuracy, we regress the logged prediction error—-defined as the difference between the expected industry wage and actual mean level of wages in an industry obtained from CPS—-on the share of coworkers who were last employed in that sector, interacted with the logged difference between the destination industry wage and the own industry wage:

$$\log(PredictionError)_{ijs} = \phi CoworkerShare_{ijs} \times \log(WageDiff)_{ijs} + \gamma_i + \epsilon_{ijs} \quad (12)$$

where $CoworkerShare_{ijst}$ is the share of current coworkers for respondent i–who is currently employed in sector j'–who were last employed in sector s before starting their current position. To account for the fact that individuals may be systematically biased when asked about the perceived wages in other industries, we include the individual fixed effects, γ_i.

The results for specification (12) are presented in Table 7. We test the robustness of this assumption by using three different definitions for the denominator of the coworker share variable. First, we use respondents' answers to the question, "For how many of your current coworkers do you know the industry where they were working before joining your employer?" Second, we use responses to the question, "Among all the coworkers you interact with at your current job, approximately how many have mentioned the compensation they received at their previous job?" Finally, we explore an alternative specification by approximating the total number of coworkers as the sum of individuals' answers across the five listed industries.

The coefficient estimates for all definitions of coworker share are positive and significant, supporting our assumption that individuals place greater weight on their own industry's wage when predicting wages in other industries, particularly when they have more coworkers from those industries. Our preferred specification is shown in column (1), where we proxy for the share of coworkers last employed in an industry using respondents' estimates of the number of current coworkers from that industry, divided by the total number of coworkers for whom they know the previous industries. Based on this specification, we set $\phi = 0.57$ as the baseline value for the remainder of the analysis.

Table 7: Impact of Current Coworkers' Past Industries on Wage Beliefs

	(1)	(2)	(3)
$CoworkerShare \times \log(WageDiff)$	0.57***	0.61***	0.72***
	(0.03)	(0.02)	(0.07)
Mean of Dep. Var	-0.36	-0.36	-0.36
R^2	0.60	0.63	0.61

Note: Table displays the coefficient estimates, ϕ, for equation (12). Column (1) defines coworker share as the number of current coworkers last employed in an industry over the total number of current coworkers of which the respondents know their last industry of employment. Column (2) defines coworker share as the number of current coworkers last employed in an industry over the total number of current coworkers who mentioned their wage associated with their last job during their interactions with the reference individual. Column (3) defines coworker share as the number of current coworkers last employed in an industry over the sum of all current coworkers last employed in one of the three closest or two farthest industries (the industries we asked about in the survey).

Equation (8) assumes a symmetric contribution of both the origin-industry wage and the destination-industry wage to the prediction error. To further test this assumption, we estimate an additional specification that allows for differential weighting of the own-industry and other-industry wages:

$$\begin{aligned} \log(PredictionError)_{ijs} =& \phi_1 CoworkerShare_{ijs} \times \log(DestWage)_{ijs} + \\ & \phi_2 CoworkerShare_{ijs} \times \log(OrigWage)_{ijs} + \gamma_i + \epsilon_{ijs} \end{aligned} \tag{13}$$

The results are presented in Table C5. Across all definitions of coworker share, the estimates for ϕ_1 and ϕ_2 are comparable, confirming our modeling assumption that individuals form beliefs about other-industry wages using a weighted average of their own-industry wage and the other-industry wage. The weight applied to each depends on the share of coworkers coming from the reference industry.

Coworkers and Beliefs on Job Offering Probabilities Similar to how we test the assumption on coworker share and wage beliefs, we test our assumption in the conceptual framework that perceived job offering probabilities in an industry are an increasing function of the share of past coworkers currently employed in that industry, and obtain the estimates for ψ_0 and ψ_1 in equation (14) using our survey data. More specifically, we conduct a fractional outcome logistic regression:

$$\log\left(\frac{PerceivedProb_{is}}{1 - PerceivedProb_{is}}\right) = \psi_0 + \psi_1 PastCoworkerShare_{is} + \psi_2 \ln(StartWage_{is}) + \psi_3 MeanShare_i \tag{14}$$

where same as above, $PerceivedProb_{is}$ represents the perceived probability of receiving an offer for individual i in industry s. We divide the probabilities selected by the respondents by 100 to ensure that the outcome variable falls within the interval $[0, 1]$. $PastCoworkerShare_{is}$ is the share of past coworkers currently employed in the industry s. We control for the logged predicted starting wage.[19] Furthermore, we include in the specification the mean share of coworkers an individual put down across all industries listed to control for unobserved heterogeneity in individual propensity to underestimate or overestimate their number of coworkers at all industries. Table 8 shows the results from evaluating equation (14). We set $\psi_1 = 0.89$, and $\psi_2 = 0.07$ according to column (1).[20]

Table 8: Impact of Past Coworkers' Current Industries on Perceived Job-Offering Probabilities

	(1)	(2)	(3)
$PastCoworkerShare$	0.89***	0.70***	1.21***
	(0.08)	(0.08)	(0.09)
$\log(StartingWage)$	0.07***	0.07***	0.07***
	(0.02)	(0.02)	(0.03)
Mean of Dep. Var	0.40	0.40	0.42

Note: Table displays the coefficient estimates, ψ_0, ψ_1, ψ_2, for equation (14). Column (1) defines coworker share as the number of current coworkers last employed in an industry over the total number of current coworkers of which the respondents know their last industry of employment. Column (2) defines coworker share as the number of current coworkers last employed in an industry over the total number of current coworkers who mentioned their wage associated with their last job during their interactions with the reference individual. Column (3) defines coworker share as the number of current coworkers last employed in an industry over the sum of all current coworkers last employed in one of the three closest or two farthest industries (the industries we asked about in the survey).

5.3 Welfare Implication

With the results in reduced form that confirm the importance of past and current coworkers in influencing wage and job offer rate beliefs, we shift our focus back to the stylized model to derive implications for labor distribution and welfare. We solve the steady-state model and calibrate the standard parameters by setting the discount factor $\beta = 0.96$ and the industry-switching elasticity to $\nu = 2$. Furthermore, we make the simplifying assumption that transition costs are constant across

[19] Similar to the results from the Conjoint experiment, a higher perceived starting wages is associated with an increase in the perceived probability of receiving a job offer in an industry.

[20] And we set ψ_0 such that the average of perceived job-offering probabilities across industries match with the one we observe in the survey data

sector pairs, so $\kappa^{n,k} = \kappa, \forall n, k$. Using the values of ϕ and ψ obtained above, we solve for the $\kappa's$ that minimize the distance between the industry labor distribution in the data and the one indicated by the model. In the model without coworker influence—whether workers are assumed to have perfect or imperfect information about wages and job-offering probabilities—the estimated transition cost parameter κ is slightly higher. This reflects the model's need to impose greater frictions in order to match the observed levels of industry switching. Without the informational or referral advantages provided by coworkers, transitions must be mechanically suppressed through higher costs. In contrast, when coworker effects are present, some of the observed lower levels of mobility can be attributed to the lack of existence of those networks, allowing the model to rationalize the data with a lower κ. [21]

To evaluate the impact of coworkers, we compare our steady-state model results to the case without coworker network, by assuming two scenarios. First, we assume that individuals do not have accurate beliefs on median wages, according to the results by estimating equation (1). Second, we evaluate another scenario where individuals have perfect information on other-industry wages. In both scenarios, we also assume away the influence of coworkers on job-offering probabilities. Instead of letting Γ be dependent on the share of coworkers who leave from the origin sector and enter the destination sector, we re-estimate equation (14) using only sectoral wage and the mean of each individuals' perceived job-offering probabilities across industries as the independent variables.[22] We then re-estimate the κ to minimize the distance between the model-implied transition matrices and the one observed in the CPS data.

Table 9 shows that the fraction of industry stayers in the stylized model when we assume coworker influences is much lower compared to when we assume no coworker influence at the steady state. As a result, the labor distribution is relative equalized between industries, compared to the case without coworker influence when labor concentrates in high-paying industries. Analogously, Figure 4 shows that the steady-state welfare is also relatively equalized across industries, and uniformly higher in the case with coworker influences than when assuming no impact from coworkers, with either perfect or imperfect information on wages. The inequality level is much lower in the model under coworker influences, as demonstrated in the Lorenz curve of welfare in Figure 5.

When coworker influence is active, individuals benefit from lower effective transition costs due to information spillovers and referral effects. These mechanisms effectively reduce the perceived or actual κ they face when switching industries, even if the structural cost is held constant in the model. With easier mobility, individuals can reallocate more readily in response to differences in wages, shocks, or mismatches, allowing the economy to better align talent with opportunity. This dynamic leads to a more fluid allocation of labor, reducing welfare losses from misallocation and

[21] In the model with coworker influences on wages and job-offering probabilities, κ is estimated to be 8.12. In the model without coworker influence but perfect information on wages and 100% job-offering probabilities, κ is estimated to be 10.82. In the model without coworker influence and imperfect information on both wages and job-offering probabilities, κ is estimated to be 10.90.

[22] And we re-calibrate ψ_0 such that the mean of job offering probabilities across sectors correspond to the mean we observe in the survey data.

yielding higher average welfare.

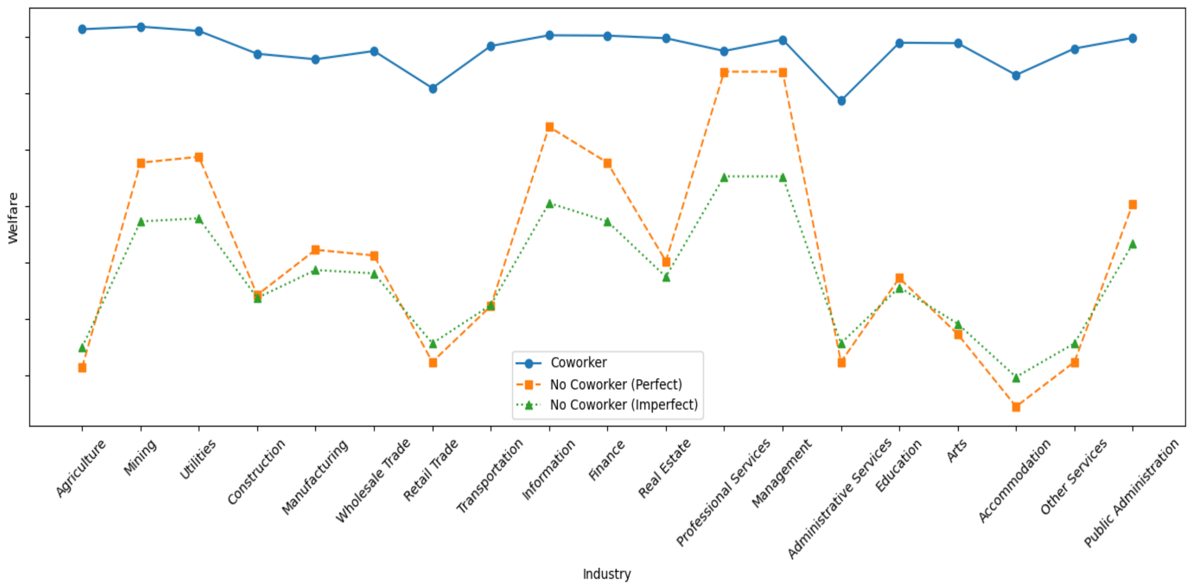
In contrast, when coworker influence is shut off, individuals either lack accurate beliefs or receive no referral support, which increases the barriers to switching sectors. To reconcile the same observed low mobility rates, the model compensates by assigning a higher κ, thereby penalizing transitions more heavily. This discourages reallocation even when it is welfare-improving, leading to an uneven distribution of labor: workers remain concentrated in a subset of high-paying industries, while others remain underpopulated despite offering competitive adjusted wages. As a result, the steady-state allocation is more distorted, and welfare is both lower on average and more unequally distributed. Coworker networks, in this sense, serve as a decentralized coordination mechanism that enhances the efficiency and equity of labor market outcomes.

Table 9: Fraction of Industry Stayers & Labor Distribution

Industries	Coworker Influence		Perfect Info		Imperfect Info	
	Stayer	Dist	Stayer	Dist	Stayer	Dist
Agriculture, Forestry, Fishing and Hunting	0.34	0.05	0.28	0.04	0.30	0.04
Mining, Quarrying, and Oil and Gas Extraction	0.34	0.05	0.37	0.06	0.35	0.06
Utilities	0.34	0.05	0.37	0.06	0.35	0.06
Construction	0.34	0.05	0.32	0.05	0.32	0.05
Manufacturing	0.34	0.05	0.34	0.05	0.33	0.05
Wholesale Trade	0.34	0.05	0.34	0.05	0.33	0.05
Retail Trade	0.34	0.05	0.29	0.04	0.30	0.05
Transportation and Warehousing	0.34	0.05	0.31	0.04	0.32	0.06
Information	0.34	0.05	0.38	0.07	0.36	0.06
Finance and Insurance	0.34	0.05	0.37	0.06	0.35	0.05
Real Estate and Rental and Leasing	0.34	0.05	0.33	0.05	0.33	0.06
Professional, Scientific, and Technical Services	0.34	0.05	0.40	0.07	0.36	0.06
Management of Companies and Enterprises	0.34	0.05	0.40	0.07	0.36	0.05
Administrative and Support and Waste Management and Remediation Services	0.34	0.05	0.29	0.04	0.30	0.05
Educational Services	0.34	0.05	0.33	0.05	0.33	0.05
Arts, Entertainment, and Recreation	0.34	0.05	0.30	0.04	0.31	0.045
Accommodation and Food Services	0.34	0.05	0.26	0.04	0.29	0.04
Other Services (except Public Administration)	0.34	0.05	0.29	0.04	0.30	0.05
Public Administration	0.34	0.05	0.36	0.06	0.34	0.06

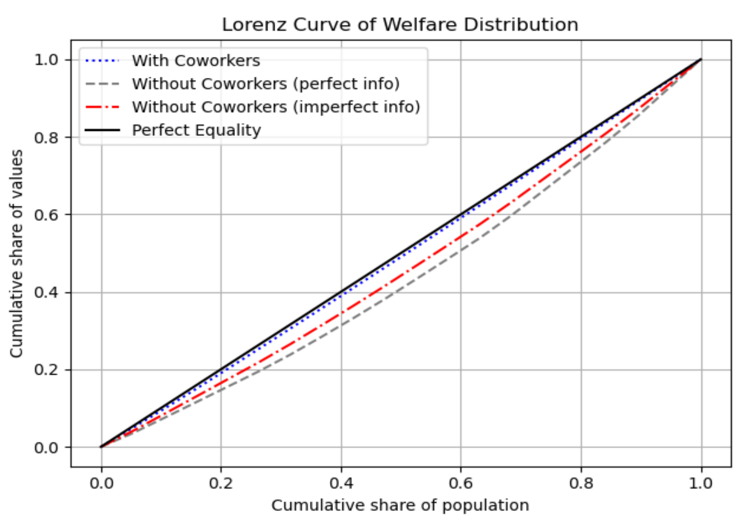
Note: Table shows fraction of stayers in industries, as well as the labor distribution in each industry, with vs. without coworker influence.

Figure 4: Estimated Welfare by Industry



Note: Figure shows welfare in industries with vs. without coworker influence. The blue solid line assumes that coworkers have some impact on workers' perceived wages or job offering probabilities. The orange dashed line assumes that workers are perfectly aware of the wages in the other sectors. The green dotted line assumes that workers do not have perfect information on wages or job-offering probabilities, and that coworkers do no influence their perceptions.

Figure 5: Lorenz Curve of Welfare Distribution



Note: Figure plots the Lorenz curve for welfare for the case with vs. without coworker influences. The solid black line shows the case with perfect equality. The dotted blue line plots the case with coworker influence on perceptions of both wages and job-offering probabilities. The dashed gray line plots the case without coworker influence, where individuals have imperfect information on wages and job-offering probabilities. The dash-dotted red line plots the case without coworker influence, where individuals know wages perfectly and assume that they will receive a job offer with probability 1 after applying.

6 Conclusion

Using novel survey data on their current and past coworkers, perceived outside options in other industries, and job-switching intentions, we analyze how workers form beliefs about their outside employment options. Workers' beliefs about wages and hiring probabilities in other industries correlate with actual industry compensation and transition difficulties. Both current and past coworkers influence these beliefs: having more current coworkers previously employed in another industry improves the accuracy of beliefs about that industry's median and entry-level wages. On the other hand, having more past coworkers currently employed in an industry increases perceived hiring probabilities and intentions to switch to that industry. These network effects extend to firm-level perceived outside options—a hypothetical job experiment shows that having more past coworkers at a specific firm increases perceived hiring probabilities at that firm, holding job attributes constant. Using our stylized model calibrated to industry flows and our survey data, we show that the fraction of individuals staying at their jobs is much lower when we consider coworker influences versus when we assume no coworker influence. The aggregate welfare and level of equality are higher under coworker influence.

Our paper opens up several avenues for future research. First, future studies could explore the heterogeneity of coworker influences based on worker attributes, such as skills, experience, and tenure. Second, given the growing interest in the effects of remote work (Bloom et al. 2015, Dingel and Neiman 2020, Tønnessen, Dhir and Flåten 2021, Yang et al. 2022, Hackney et al. 2022, Barrero, Bloom and Davis 2023), it will be valuable to examine whether remote work weakens the impact of coworker influence on job choice by reducing in-person interactions or, conversely, expands the network's reach. More broadly, studying how firm management practices influence the extent and effectiveness of coworker networks could yield valuable insights. Third, future research could investigate the mechanisms by which coworkers impact other labor market outcomes, including self-employment decisions, earnings losses after involuntary unemployment, geographic mobility, and job satisfaction. Finally, incorporating the coworker channel into evaluations of labor market policies and regulations—such as wage transparency laws, non-compete agreements, occupational licensing, and diversity or immigration policies—would be an important step forward.

References

Azoulay, Pierre, Joshua S Graff Zivin, and Jialan Wang. 2010. "Superstar extinction." *The Quarterly Journal of Economics*, 125(2): 549–589.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul. 2009. "Social connections and incentives in the workplace: Evidence from personnel data." *Econometrica*, 77(4): 1047–1094.

Barrero, José María, Nicholas Bloom, and Steven J Davis. 2023. "The evolution of work from home." *Journal of Economic Perspectives*, 37(4): 23–49.

Ben-Akiva, Moshe, Takayuki Morikawa, and Fumiaki Shiroishi. 1992. "Analysis of the reliability of preference ranking data." *Journal of business research*, 24(2): 149–164.

Bloom, Nicholas, James Liang, John Roberts, and Zhichun Jenny Ying. 2015. "Does working from home work? Evidence from a Chinese experiment." *The Quarterly journal of economics*, 130(1): 165–218.

Burdett, Kenneth, and Dale T Mortensen. 1998. "Wage differentials, employer size, and unemployment." *International Economic Review*, 257–273.

Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin. 2006. "Wage bargaining with on-the-job search: Theory and evidence." *Econometrica*, 74(2): 323–364.

Caldwell, Sydnee, and Nikolaj Harmon. 2019. "Outside options, bargaining, and wages: Evidence from coworker networks." *Unpublished manuscript, Univ. Copenhagen*, 203–207.

Calvo-Armengol, Antoni, and Matthew O Jackson. 2004. "The effects of social networks on employment and inequality." *American economic review*, 94(3): 426–454.

Card, David, Alexandre Mas, Enrico Moretti, and Emmanuel Saez. 2012. "Inequality at work: The effect of peer salaries on job satisfaction." *American Economic Review*, 102(6): 2981–3003.

Conlon, John J, Laura Pilossoph, Matthew Wiswall, and Basit Zafar. 2018. "Labor market search with imperfect information and learning." National Bureau of Economic Research.

Cornelissen, Thomas, Christian Dustmann, and Uta Schönberg. 2017. "Peer effects in the workplace." *American Economic Review*, 107(2): 425–456.

Cummings, Ronald G, Glenn W Harrison, and E Elisabet Rutström. 1995. "Homegrown values and hypothetical surveys: is the dichotomous choice approach incentive-compatible?" *The American Economic Review*, 85(1): 260–266.

Dingel, Jonathan, and Brent Neiman. 2020. "How Many Jobs Can be Done at Home?"

Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker. 2016. "Referral-based job search networks." *The Review of Economic Studies*, 83(2): 514–546.

Falk, Armin, and Andrea Ichino. 2006. "Clean evidence on peer effects." *Journal of labor economics*, 24(1): 39–57.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, et al. 2023. "Integrated Public Use Microdata Series, Current Population Survey: Version 11.0 [dataset]."

Folke, Olle, and Johanna Rickne. 2022. "Sexual harassment and gender inequality in the labor market." *The Quarterly Journal of Economics*, 137(4): 2163–2212.

Glitz, Albrecht. 2017. "Coworker networks in the labour market." *Labour Economics*, 44: 218–230.

Granovetter, Mark S. 1973. "The strength of weak ties." *American journal of sociology*, 78(6): 1360–1380.

Hackney, Amy, Marcus Yung, Kumara G Somasundram, Behdin Nowrouzi-Kia, Jodi Oakman, and Amin Yazdani. 2022. "Working in the digital economy: A systematic review of the impact of work from home arrangements on personal and organizational performance and productivity." *Plos one*, 17(10): e0274728.

Hainmueller, Jens, Daniel J Hopkins, and Teppei Yamamoto. 2014. "Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments." *Political analysis*, 22(1): 1–30.

Haltiwanger, John C, Henry R Hyatt, Lisa B Kahn, and Erika McEntarfer. 2018. "Cyclical job ladders by firm size and firm wage." *American Economic Journal: Macroeconomics*, 10(2): 52–85.

Harrison, Glenn W, and E Elisabet Rutström. 2008. "Experimental evidence on the existence of hypothetical bias in value elicitation methods." *Handbook of experimental economics results*, 1: 752–767.

He, Haoran, David Neumark, and Qian Weng. 2021. "Do workers value flexible jobs? A field experiment." *Journal of Labor Economics*, 39(3): 709–738.

Ioannides, Yannis M, and Linda Datcher Loury. 2004. "Job information networks, neighborhood effects, and inequality." *Journal of economic literature*, 42(4): 1056–1093.

Jackson, C Kirabo, and Elias Bruegmann. 2009. "Teaching students and teaching each other: The importance of peer learning for teachers." *American Economic Journal: Applied Economics*, 1(4): 85–108.

Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer. 2022. "Worker Beliefs About Outside Options." National Bureau of Economic Research.

Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer. 2024. "Worker beliefs about outside options." *The Quarterly Journal of Economics*, qjae001.

Jovanovic, Boyan. 1979. "Job matching and the theory of turnover." *Journal of political economy*, 87(5, Part 1): 972–990.

Lin, Xinyue, and Sophia Mo. 2024. "Does Mobility Beget Mobility? Coworker Networks and the Sectoral Reallocation of Labor." Working Paper.

List, John A, and Craig A Gallet. 2001. "What experimental protocol influence disparities between actual and hypothetical stated values?" *Environmental and resource economics*, 20: 241–254.

Mas, Alexandre, and Amanda Pallais. 2020. "Alternative work arrangements." *Annual Review of Economics*, 12(1): 631–658.

Mas, Alexandre, and Enrico Moretti. 2009. "Peers at work." *American Economic Review*, 99(1): 112–145.

Miano, Armando. 2023. "Search Costs, Outside Options, and On-the-Job Search." *Job market paper, Harvard University*.

Mincer, Jacob. 1958. "Investment in human capital and personal income distribution." *Journal of political economy*, 66(4): 281–302.

Montgomery, James D. 1991. "Social networks and labor-market outcomes: Toward an economic analysis." *The American economic review*, 81(5): 1408–1418.

Mortensen, Dale T, and Christopher A Pissarides. 1999. "New developments in models of search in the labor market." *Handbook of labor economics*, 3: 2567–2627.

Mueller, Andreas I, and Johannes Spinnewijn. 2023. "Expectations data, labor market, and job search." *Handbook of Economic Expectations*, 677–713.

Mueller, Andreas I, Johannes Spinnewijn, and Giorgio Topa. 2021. "Job seekers' perceptions and employment prospects: Heterogeneity, duration dependence, and bias." *American Economic Review*, 111(1): 324–363.

Rees, Albert. 1966. "Information networks in labor markets." *The American Economic Review*, 56(1/2): 559–566.

Sockin, Jason. 2022. "Show Me the Amenity: Are Higher-Paying Firms Better All Around?"

Stantcheva, Stefanie. 2023. "How to run surveys: A guide to creating your own identifying variation and revealing the invisible." *Annual Review of Economics*, 15(1): 205–234.

Sullivan, Paul, and Ted To. 2014. "Search and nonwage job characteristics." *Journal of Human Resources*, 49(2): 472–507.

Tønnessen, Øystein, Amandeep Dhir, and Bjørn-Tore Flåten. 2021. "Digital knowledge sharing and creative performance: Work from home during the COVID-19 pandemic." *Technological Forecasting and Social Change*, 170: 120866.

Topa, Giorgio. 2001. "Social interactions, local spillovers and unemployment." *The Review of Economic Studies*, 68(2): 261–295.

Topel, Robert H, and Michael P Ward. 1992. "Job mobility and the careers of young men." *The Quarterly Journal of Economics*, 107(2): 439–479.

Yang, Longqi, David Holtz, Sonia Jaffe, Siddharth Suri, Shilpi Sinha, Jeffrey Weston, Connor Joyce, Neha Shah, Kevin Sherman, Brent Hecht, et al. 2022. "The effects of remote work on collaboration among information workers." *Nature human behaviour*, 6(1): 43–54.

Appendix

A Survey Design

A.1 Full Survey: link here

A.1.1 Screening and Quotas

1. Do you currently live in the United States?
2. How do you identify your gender?
3. How old are you?
4. In which state is your primary residence (the place where you usually live)?
5. What is the highest level of education you have completed?
6. What was the TOTAL income of your household, before any taxes or deductions, in 2023?
7. What is your current employment status?
8. How many jobs do you have (excluding volunteer or other unpaid work)?
9. What kind of industry is your employer in? If you have more than one job, please consider the employer for whom you work the most hours per week. Please select the most appropriate industry from the dropdown menu. You can find a brief description of each industry below.

A.2 Attention Check

1. This is a question to check that you are paying attention and reading the questions carefully. Please select both "1" and "4" to move to the next page of the survey.

A.3 Personal Characteristics

1. Are you working for a temporary employment agency, a firm that connects businesses to workers for temporary or contract work?
2. Do you consider yourself of Hispanic, Latino or Spanish origin?
3. Which of the following best describes your race?
4. What is the ZIP code of your primary residence (the place where you usually live)?

A.4 Employment Characteristics

1. What was the month and year that you started working at your main job?
2. What is your occupation at your main job? Some examples of occupation titles include electrical engineer, stock clerk, waiter/waitress, typist...

   Please type your occupation in the box below and select one of the suggested options. Try to be specific. For instance, write "preschool teacher" or "high school teacher" rather than just "teacher".

   If none of the options correspond to your occupation, try adding more detail or rephrasing.

3. How many hours per week do you USUALLY work at your main job? Please include overtime hours.
4. How much do you earn before taxes and other deductions at your main job in a year? Please include any bonuses, overtime pay, tips or commissions.
5. Roughly speaking, what are your annual earnings, before taxes and other deductions, at your main job? Please include any bonuses, overtime pay, tips or commissions.
6. Is your job primarily in-person, remote, or a hybrid of both?
7. How many hours per week do you usually work IN PERSON?
8. How many people work for your main employer at your usual place of work?
9. Counting all locations where your employer operates, what is your best guess for the total number of persons who work for your main employer?
10. Are you currently looking for a new job?
11. Were you employed somewhere else when you were hired for your main job?
12. Which of the following statements best describes your situation when you were hired for your main job? [I was employed when I got hired and quit my previous job; I was employed when I got hired but was about to lose my previous job; I was employed when I got hired but a temporary or seasonal job ended; I was employed when I got hired and kept my previous job; I was employed in a temporary job that was converted into a permanent job; Other (please specify)]
13. Why did you apply to your main job? Choose the three most important reasons from the ones listed below.

A.5 Past Employment

1. What kind of industry was your employer at your previous job in? Please select the relevant industry from the dropdown menu below. Industries are defined as in the previous question.

A.6 Types of coworkers - Explainer

1. Now we would like to ask you some questions about your current and past co-workers. We are going to mention three different types of coworkers. Please take some time to read the definitions below for each type, so you can answer the following question referring to the correct type of co-workers. Thanks a lot!

   1. Current coworkers at the current job: These are the coworkers that you have at your current employer and are still employed there. Please also include coworkers who are working for your employer in different offices/locations/branches.

   2. Past coworkers at the current job: These are the coworkers that worked with you at your current employer at some point in the past, but who have then left to work at other employers. Please do not consider those coworkers who transferred to different offices, but still work for your employer. Instead, consider those coworkers as belonging to category 1, "current coworkers at the current job."

3. Past coworkers at the previous job: These are the coworkers that worked with you at your previous employer (the employer where you worked before the current one). Please consider all those coworkers who worked for your previous employer while you were there, regardless of whether they have since then switched to other jobs.

2. To test your understanding of our definitions of the three types of coworkers, please answer the question below:

   Suppose that Ben and Mary both worked at the same Walmart store in 2022. Ben quit his job at Walmart and started working at a Target store in January 2023, while Mary continued working at Walmart. For Mary, what type of coworker is Ben? Please see the image below for a graphical depiction.

3. (If answered previous question wrong) Now think again about Ben and Mary. Remember that Ben and Mary both worked at the same Walmart store in 2022. Ben quit his job at Walmart and started working at a Target store in January 2023, while Mary continued working at Walmart. For Ben, what type of coworker is Mary? See the image below for a graphical depiction.

A.7 Current Coworkers at Current Job

1. Among all those who work at your current employer, approximately how many coworkers do you interact with at least once every month? Include those that you interact with for either work purpose or non-work purpose. These workers do not have to be working in the same team as you do.
2. Among all the coworkers that you interact with at your current job, approximately how many have mentioned the compensation they received at their previous job? Please count all those who mention the compensation at their previous job in a broad sense; they do not need to talk in specific details of their wages.
3. Among all the coworkers that you interact with at your current job, approximately how many have mentioned the non-wage benefits and amenities at their previous job?
4. Among all the coworkers that you interact with at your current job, approximately how many have mentioned how satisfied they were with their previous job? You can count all those who mention their feelings about their previous job in a broad sense.
5. For how many of all your current coworkers do you know the industry where they were working before starting working for your employer?
6. Among the coworkers whose previous jobs you know, how many of them worked in each of the listed industries for their last job? [Show to respondents the five sectors they are the most likely to transition into based on their current sector of employment]
7. In each of the listed industries, what do you believe is the median annual salary for individuals with the same characteristics as you, including age, gender, education, location, etc., before taxes and other deductions, and including extras like bonuses, overtime pay, tips, or commissions? [Show to respondents the five sectors they are the most likely to transition into based on their current sector of employment]
8. How certain are you of your answers to the previous question?

A.8 Past Coworkers at Current Job

1. In this section, we would like to ask you about your past coworkers at your current job, that is, coworkers who have worked with you at your current employer at some point in the past, but now work for another employer.

2. How many of your past coworkers who now work for another employer do you feel comfortable reaching out to for a career-related advice?

3. For how many of all your past coworkers at the current job do you know the industry where they are currently employed?

4. To the best of your knowledge, how many of your past coworkers who have changed job now work at employers in each one of these industries? [Show to respondents the five sectors they are the most likely to transition into based on their current sector of employment]

A.9 Past Coworkers at Past Job

1. How many people worked for your previous employer at your usual place of work, during your time of employment there?

2. Counting all locations where your previous employer operates, what is your best guess for the total number of persons who worked for your previous employer, during your time of employment there?

3. How many of your past coworkers at your previous job had also worked in your current industry of employment in the past, before working for your previous employer?

4. Did any of your past coworkers at your previous job mention to you any employer within the industry of your current employment?

5. How many of your past coworkers at your previous job have also worked at your current employer in the past?

6. Did any of your past coworkers at your previous job mention to you the company where you are currently employed?

7. Did any of them refer you to the position?

8. How many of your past coworkers at your previous job do you still maintain regular contact with? Please include those you feel comfortable reaching out to for networking and referrals.

A.10 Future Employment

1. Over the next year, what is the percent chance that you will voluntarily look for a new job at a different employer?

   Please move the slider to select a percentage from 0 to 100, where 0 means that there is no chance you will look for a new job and 100 means that it is absolutely certain that you will look for a new job. Please note that if you plan to switch position or branch within the same company, this does not count as looking for new jobs.

2. Would you consider switching to a job in another industry?

3. When considering which industry you'd like to switch into next, what are the factors that matter for your decisions? Please, select the three most important ones that influence your industry-switching decisions:

4. Would you consider looking for a job in each of the industries listed below? [Show to respondents the five sectors they are the most likely to transition into based on their current sector of employment]

5. What is the percent chance that you will receive a job offer if you apply to work for another employer within your current industry right now? Remember that a job offer is not necessarily a job you will accept.

6. In your opinion, what is the percent chance that you will receive a job offer if you apply to each one of the industries listed below? Remember that a job offer is not necessarily a job you will accept. Please move the sliders to select a percentage, where 0 on the far left means that it absolutely impossible that you will receive an offer and 100 on the far right means that you will receive an offer for sure. [Show to respondents the five sectors they are the most likely to transition into based on their current sector of employment excluding own sector]

7. What do you anticipate would be your annual starting salary if you were to switch to another employer within your current industry right now? Please include bonuses, overtime pay, tips, or commissions you expect.

8. For each of the listed industries, what do you anticipate would be your annual starting salary if you were to switch to that industry right now? Please include bonuses, overtime pay, tips, or commissions you expect. [Show to respondents the five sectors they are the most likely to transition into based on their current sector of employment]

9. How certain are you about your answers for the previous question?

A.11 Conjoint Experiment

Details are outlined in Section 4.

A.12 Additional Personal Characteristics

1. Are you currently married or living with a partner?

2. During the last year, how many months in total did you spend without a job?

A.13 Verification of Occupation and Industry

1. The next question addresses the following problem again. In surveys like this one, there are sometimes participants who don't read the questions carefully and just "click" through the questionnaire quickly. As a result, there are many random answers that falsify the results of the study. That's why we ask you to write your occupation at your main job below again, as you wrote it at the beginning of the survey.

2. Please select again the industry of your main employer from the list below, as you selected it at the beginning of the survey.

3. Please feel free to give us any feedback or impression regarding this survey.

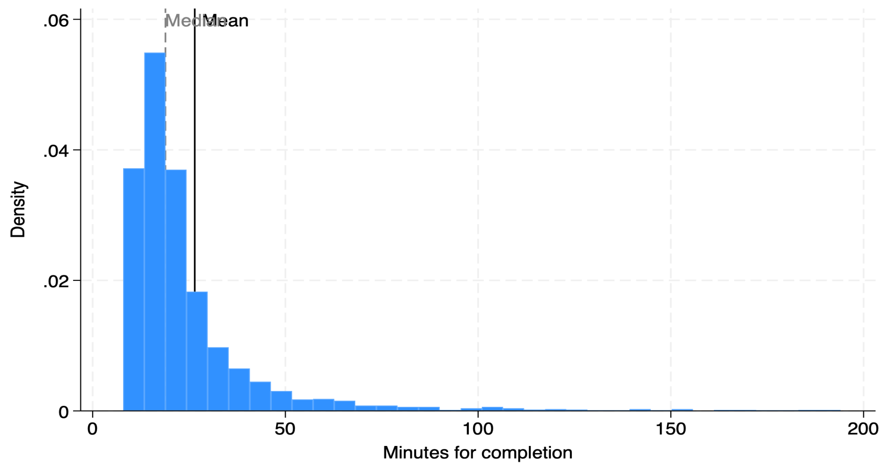
B Occupation Classifications

Although our paper focuses primarily on industry switching as opposed to occupation switching, we aim to college accurate information on workers' occupations to best proxy for their skills and obtain a good sence of their outside options. Therefore, we adopt the occupational classification method outlined in Miano (2023), aiming to assign respondents to a 6-digit Standard Occupational Classification (SOC) group. Initially, respondents are shown a prompt, as seen in Figure A-4, asking them to describe their occupation in their own words using a text box. As they begin typing, a drop-down menu with suggested occupation titles appears, from which respondents are instructed to choose. If none of the options match their occupation, they are encouraged to modify their input.

To generate these suggestions, we begin with the "alternate occupation titles" compiled by ONET. These titles provide more accessible, everyday terminology for occupations compared to the official SOC titles. We perform a light cleanup of the original ONET list by removing overly broad titles (e.g., "Supervisor") and overly narrow ones (e.g., "Visiting Teacher"). We then use the O*NET mapping of alternate titles to 6-digit SOC codes to assign an occupation code based on the respondent's selection. Some alternate titles map directly to a single SOC code (e.g., "Accountant" corresponds to "Accountants and Auditors," SOC code 13-2011), while others correspond to multiple codes. For instance, "Secretary" could refer to "Legal Secretary," "Medical Secretary," or "Secretary, except medical and legal," which are distinct groups. When respondents select a title that corresponds to multiple SOC codes, they are prompted with a follow-up question.

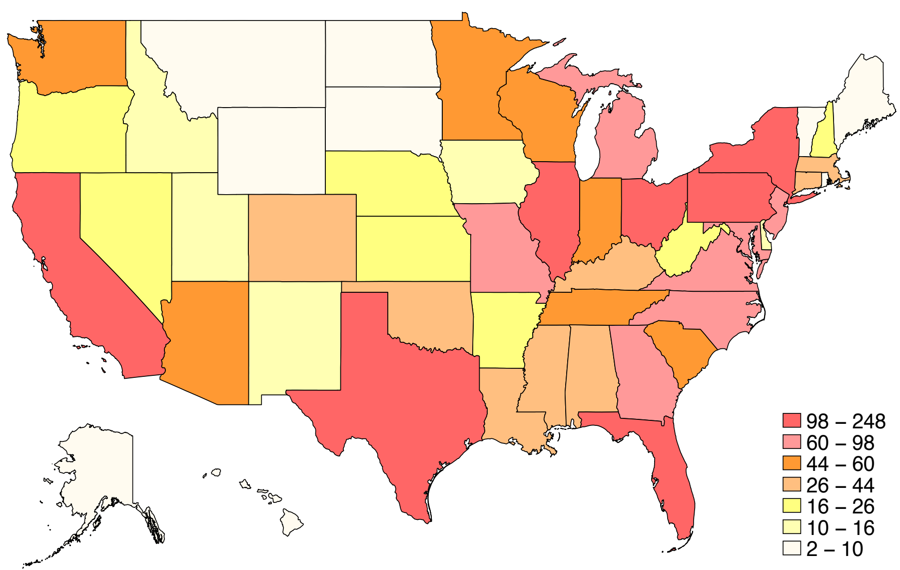
B.1 Sample Quality

Figure B1: Distribution of Time for Survey Completion



Note: Figure shows the distribution of the time respondents spent on the survey (truncated at 200 minutes). The mean duration is 26 minutes, the median 19, and the 25th and 75th percentiles are 14 and 27.

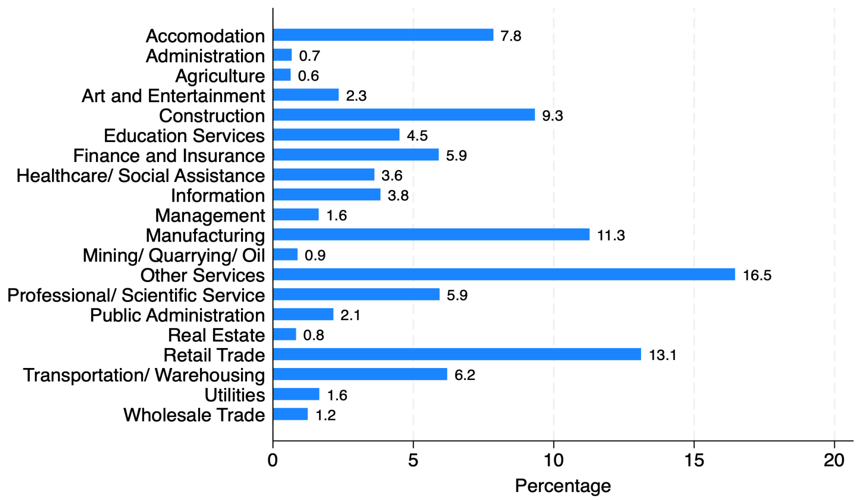
Figure B2: Geographic Distribution of Respondents in Sample



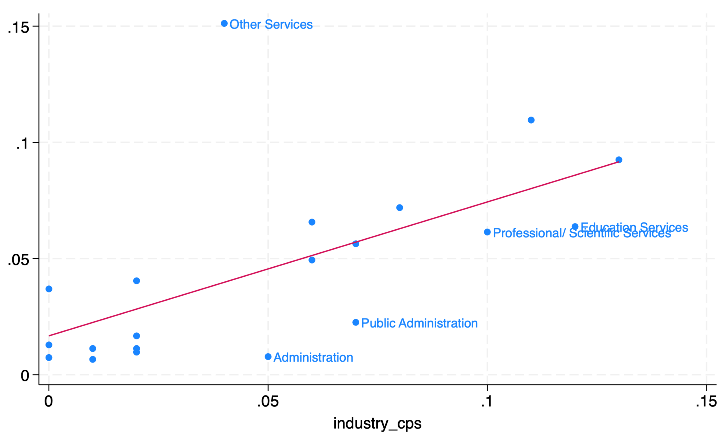
Note: Figure plots the number of respondents for the main survey sample by state.

Figure B3: Distribution of Sector

(A) Share of Respondents by Sector



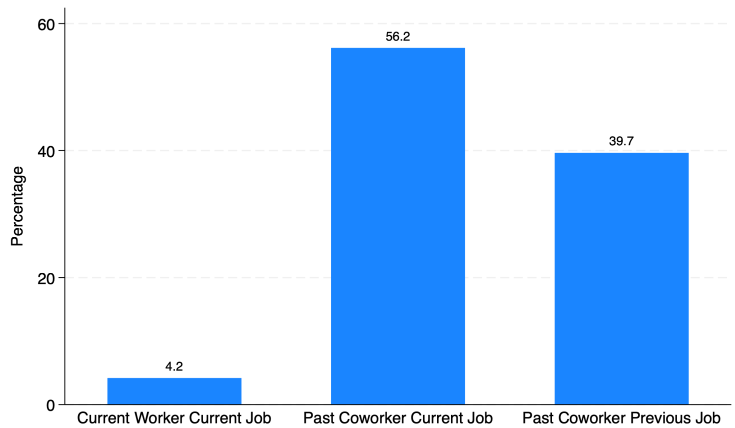
(B) Share of Respondents by Sector in Survey vs. in CPS



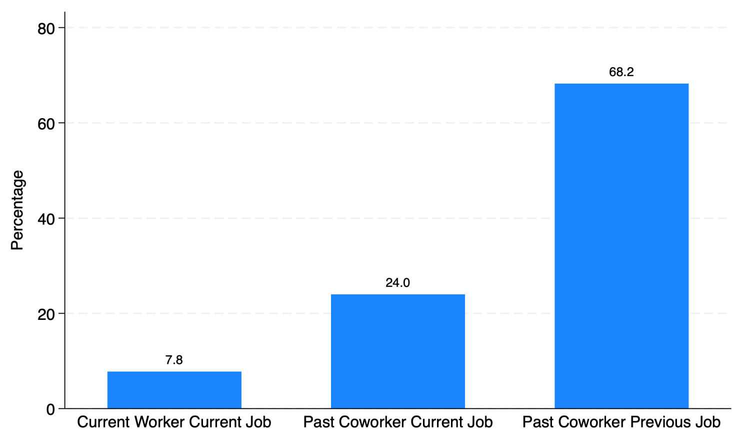
Note: Panel (A) plots the share of respondents in the main survey sample by 2-digit NAICS sector. Panel (B) plots the share of respondents by 2-digit NAICS sector in CPS data against the share of respondents by 2-digit NAICS sector in the main survey sample (on the y axis). The sectors that feature a higher difference in their shares between the survey and the CPS sample are labeled.

Figure B4: Distribution of Answers for the Coworker Type Question

(A) First Question



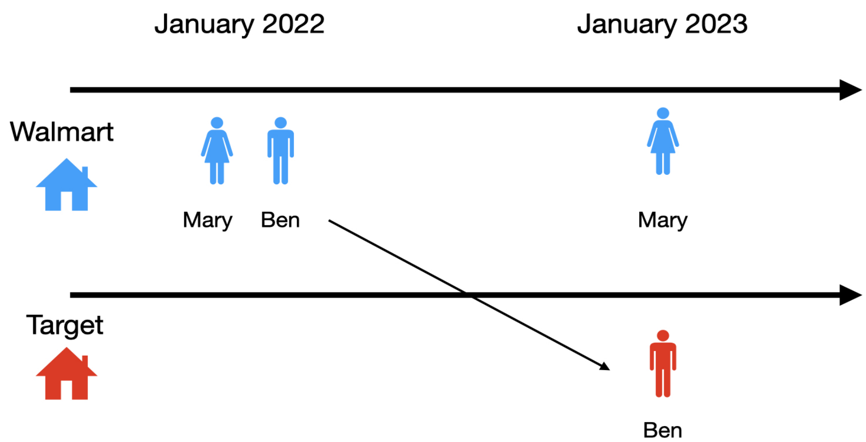
(B) Second Question



Note: Figure shows the percentage of respondents selecting into each category for the questions testing understanding of different types of coworkers. For those who answered the first question wrongly, a follow-up question is shown. The answer to the first question is "Past coworker at current job" and the answer to the second question is "past coworker at previous job." N = 2,721 for the question, and 1,177 for the second question.

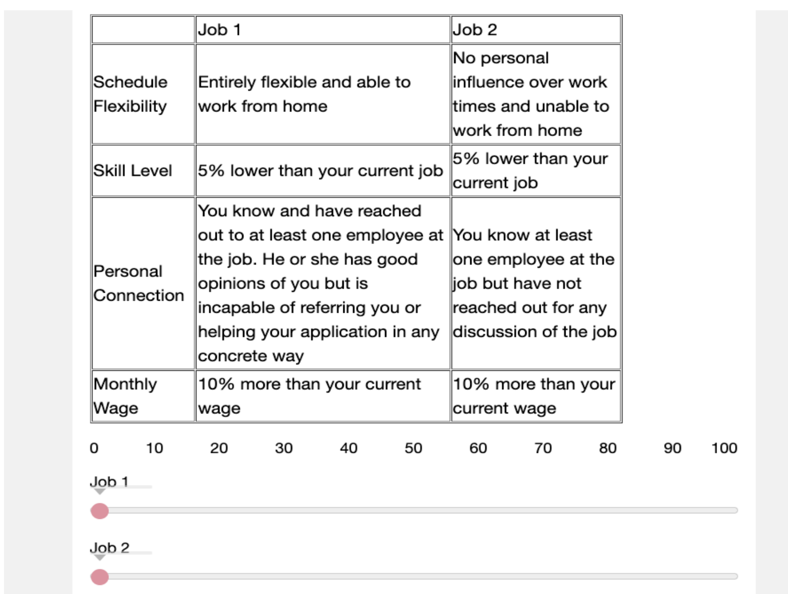
B.2 Survey Design

Figure B5: Illustrative Graph for Coworker Types



Note: Figure show what the conjoint experiment on job-offering probabilities looks like for survey respondents. The features for Job 1 and 2 are randomly generated.

Figure B6: Conjoint Experiment



	Job 1	Job 2
Schedule Flexibility	Entirely flexible and able to work from home	No personal influence over work times and unable to work from home
Skill Level	5% lower than your current job	5% lower than your current job
Personal Connection	You know and have reached out to at least one employee at the job. He or she has good opinions of you but is incapable of referring you or helping your application in any concrete way	You know at least one employee at the job but have not reached out for any discussion of the job
Monthly Wage	10% more than your current wage	10% more than your current wage

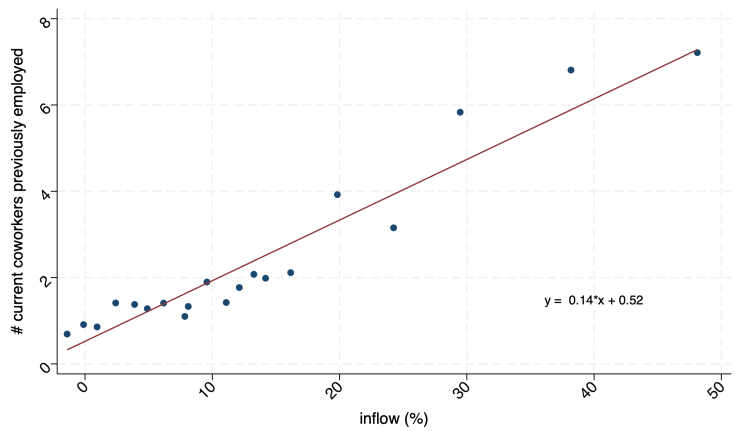
Note: Figure show what the conjoint experiment on job-offering probabilities looks like for survey respondents. The features for Job 1 and 2 are randomly generated.

C Additional Results

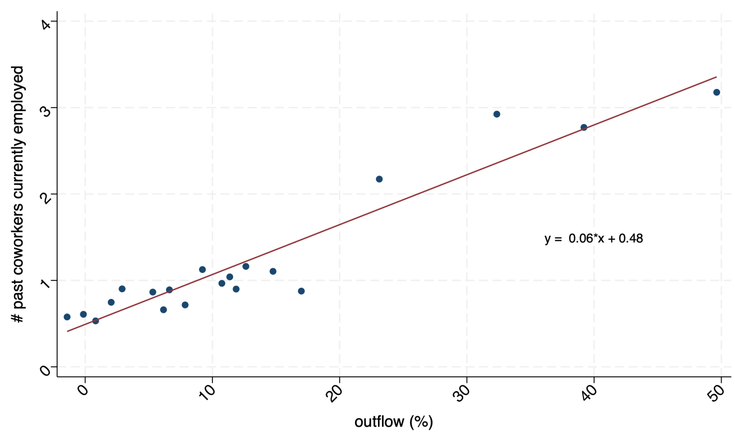
C.1 Additional Figures and Tables

Figure C1: Number of Coworkers

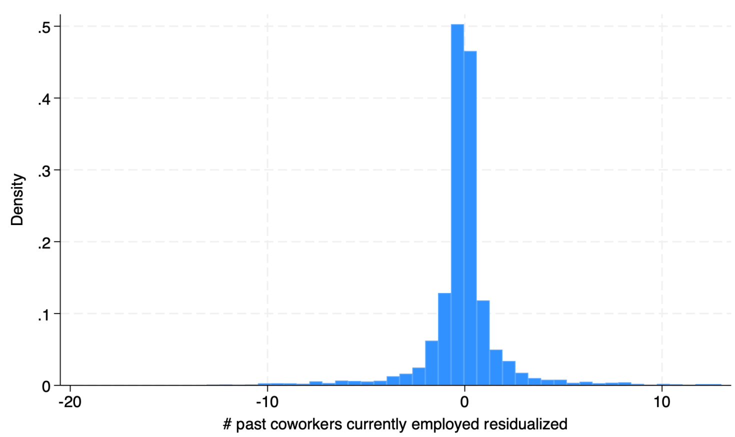
(A) Current Coworkers' Past Industries



(B) Past Coworkers' Current Industries



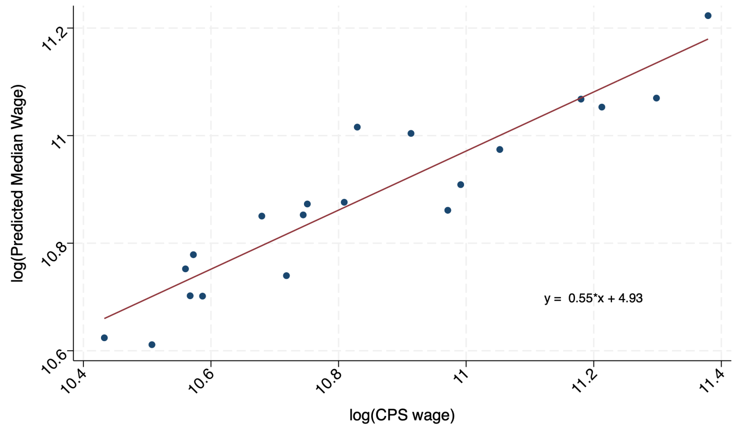
(C) Variation in Residualized Past Coworkers' current Industries



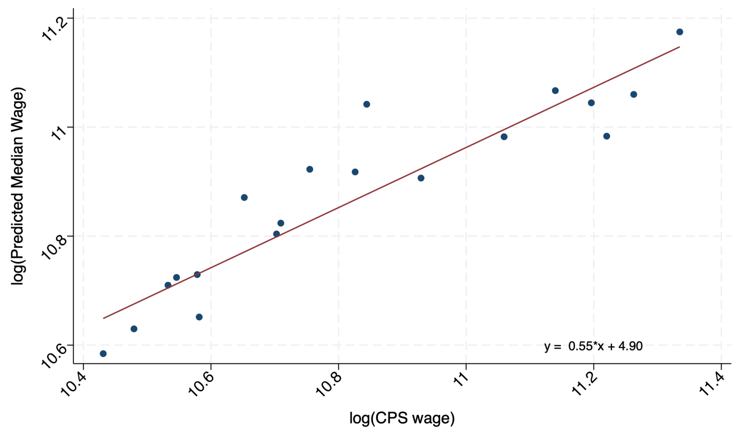
Note: Panel (A) is a binscatter plot of respondents' reported number of current coworkers last employed in an industry against the flow from that industry to her current industry of employment. Panel (B) is a binscatter plot of respondents' reported number of past coworkers currently employed in an industry against the outflow from her current sector of employment to that industry. Panel (C) is a histogram of the residualized number of past coworkers currently employed in each industry, obtained by regressing the number of past coworkers currently employed in an industry on the number of current coworkers previously employed in an industry and respondent fixed effect. Data is winsorized at the 99th percentile.

Figure C2: Predicted vs. Actual Median Wage (Own Sector vs. Other Sector)

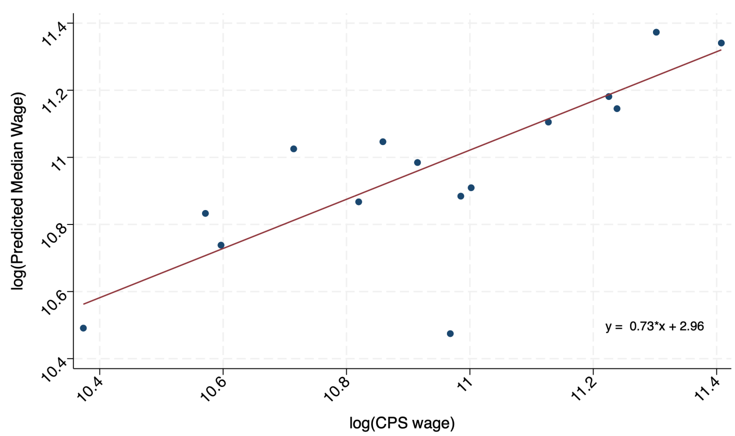
(A) All industries



(B) Other industries



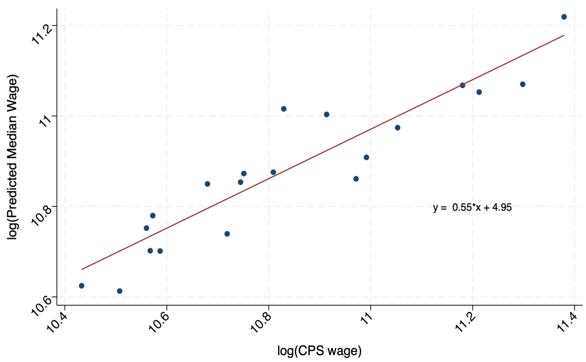
(C) Own industries



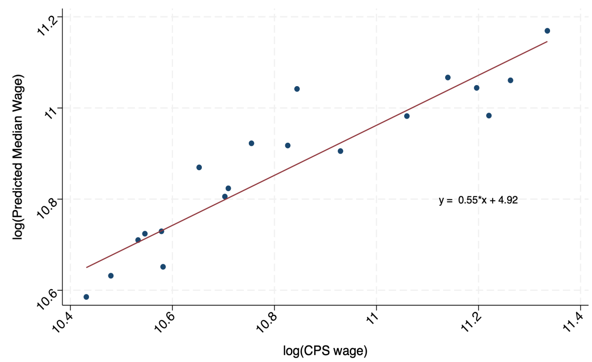
Note: Figure plots respondents' predicted median wage against the actual median wage by industry reported in CPS. Panel (A) pools across all industries. Panel (B) includes only estimates for industries other than their own. Panel (C) includes estimates for only their current industries. Sample consists of 2,721 individuals, each answering for a list of five industries, including three that are the most similar to their current industry (including their current industry) and three that are the most different from their current industry.

Figure C3: Predicted vs. Actual Median Wage (Controlling for Occupations)

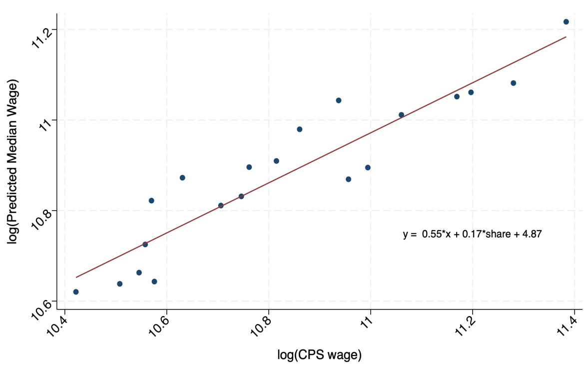
(A) All industries



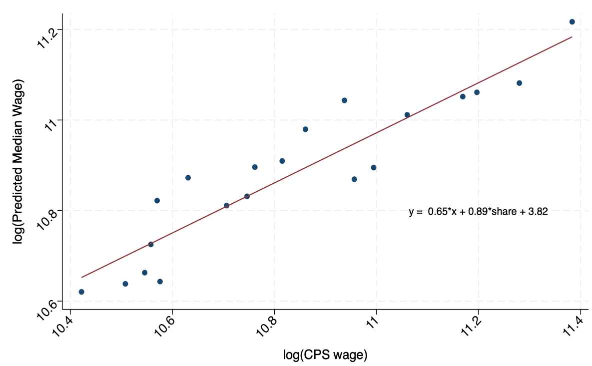
(B) Excluding own industries



(C) Controlling for transition share; all industries



(D) Controlling for transition share; excluding own industries

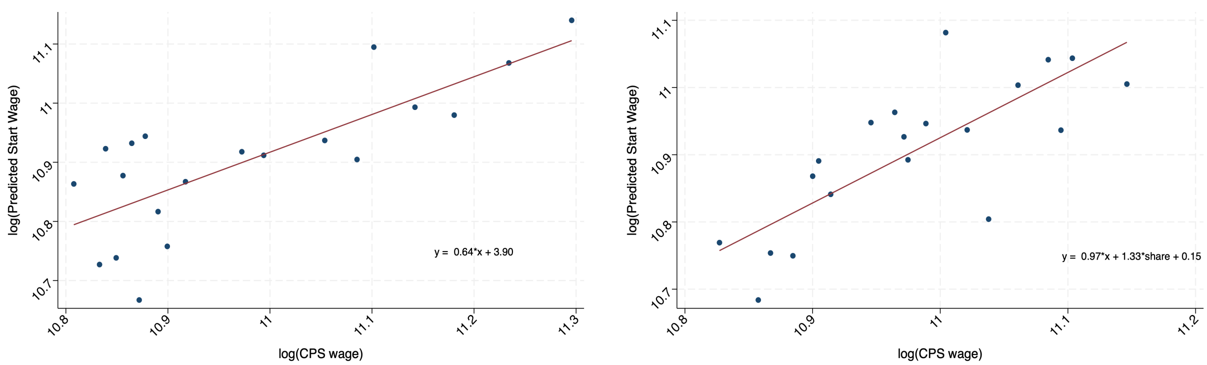


Note: Figure plots respondents' predicted median wage against the actual median wage by industry reported in CPS, controlling for individuals' occupation at the 2-digit SOC level. Panel (A) and (B) include individual fixed effects. Panel (C) and (D) include individual fixed effects and control for the transition share from the listed sector to the participants' own sector. Sample consists of 2,721 individuals, each answering for a list of five industries, including three that are the most similar to their current industry (including their current industry) and three that are the most different from their current industry.

Figure C4: Predicted vs. Actual Personal Wage

(A) All industries

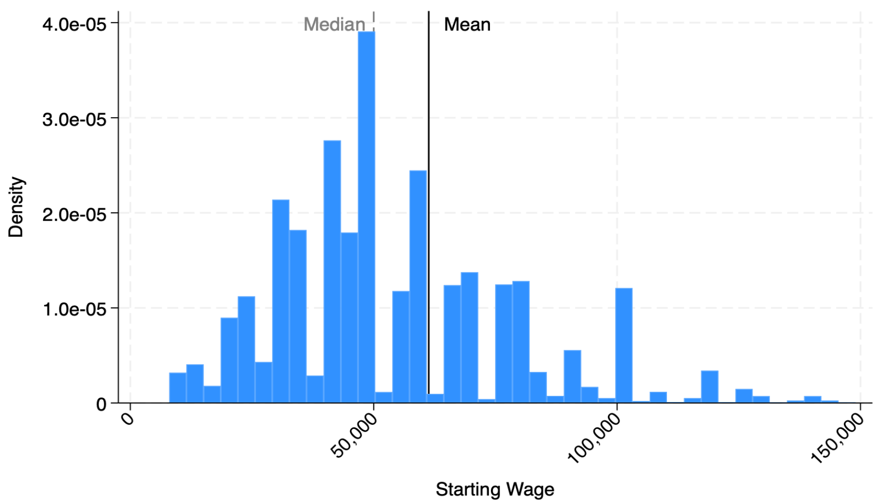
(B) Controlling for transition share; all industries



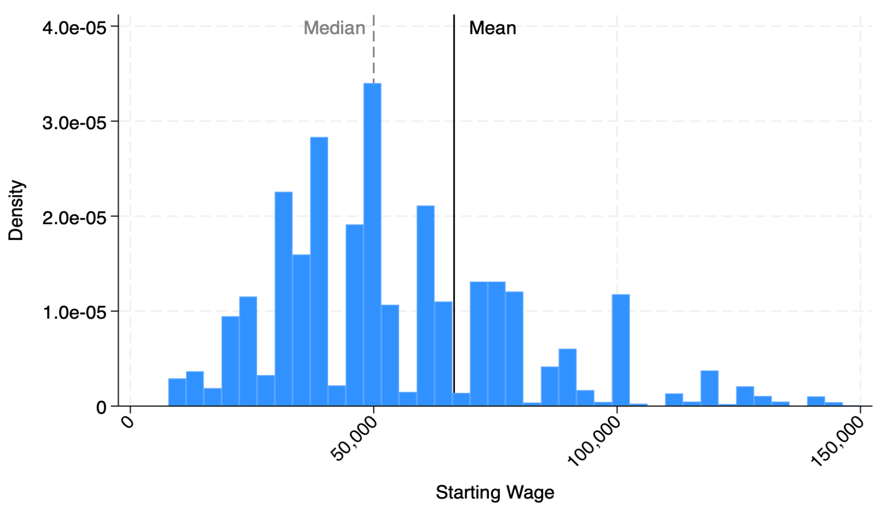
Note: Figure plots respondents' predicted own wage against the wage predicted by personal characteristics using data from by industry reported in CPS. Panel (A) includes individual fixed effects and do not control for the transition shares between industry pairs. Panel (B) includes individual fixed effects and control for the transition share from the listed sector to the participants' own sector. Sample consists of 2,721 individuals, each answering for a list of five industries, including three that are the most similar to their current industry (including their current industry) and three that are the most different from their current industry.

Figure C5: Distribution of Perceived Median and Starting Wages

(A) Perceived Median Wage

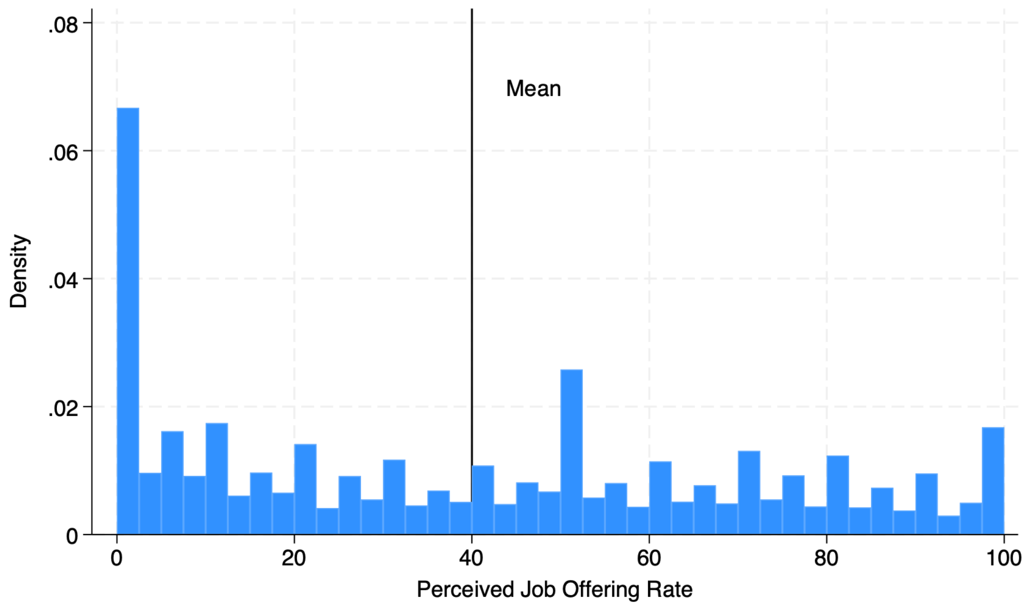


(B) Perceived Personal Starting Wage



Note: Panel (A) plots the distribution of perceived median wages, pulled across all industries and respondents. Panel (B) plots the distribution of perceived personal starting wages.

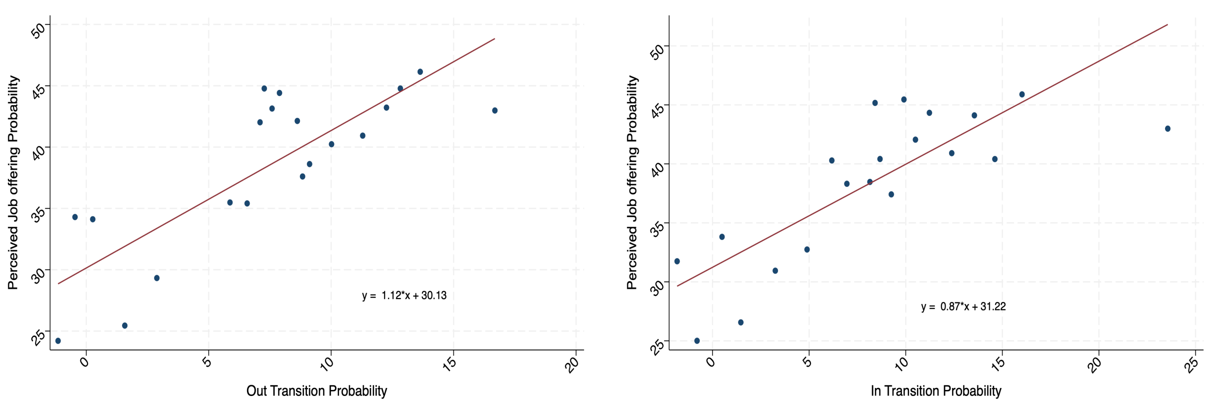
Figure C6: Distribution of Perceived Job-offering Probabilities



Note: Figure plots the distribution of respondents' perceived job-offering rate in other industries.

Figure C7: Perceived Job Offering Probability vs. Flow

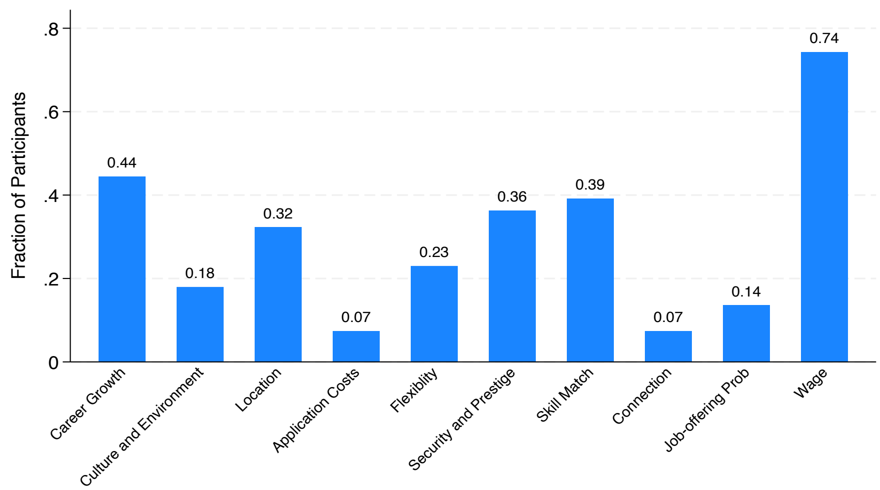
(A) Out Transition (B) In Transition



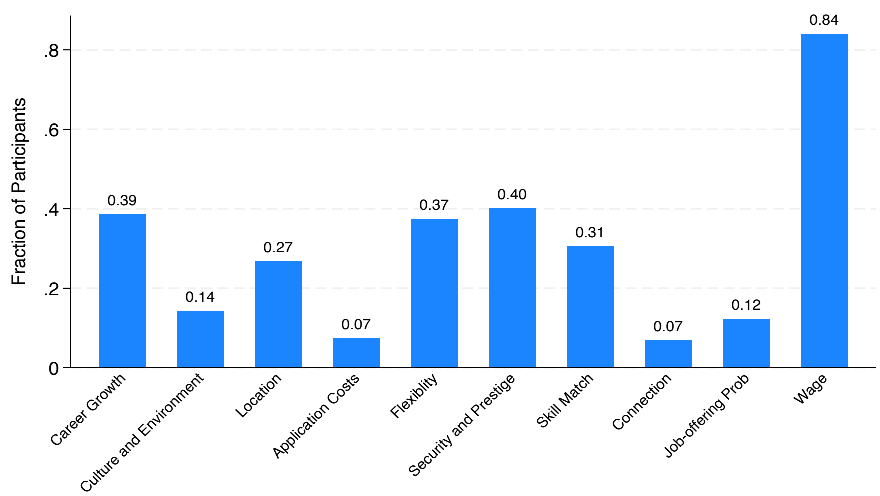
Note: Figure plots respondents' predicted job-offering rate in an industry against the actual transition probability. Panel (A) plots the perceived job-offering probability against the transition from their current industry to another industry. Panel (B) plots the perceived job-offering probability against the transition from another industry into their current industry.

Figure C8: Factors Influencing Job- and Sector Switching Decisions

(A) Reasons for Choosing the Current Job

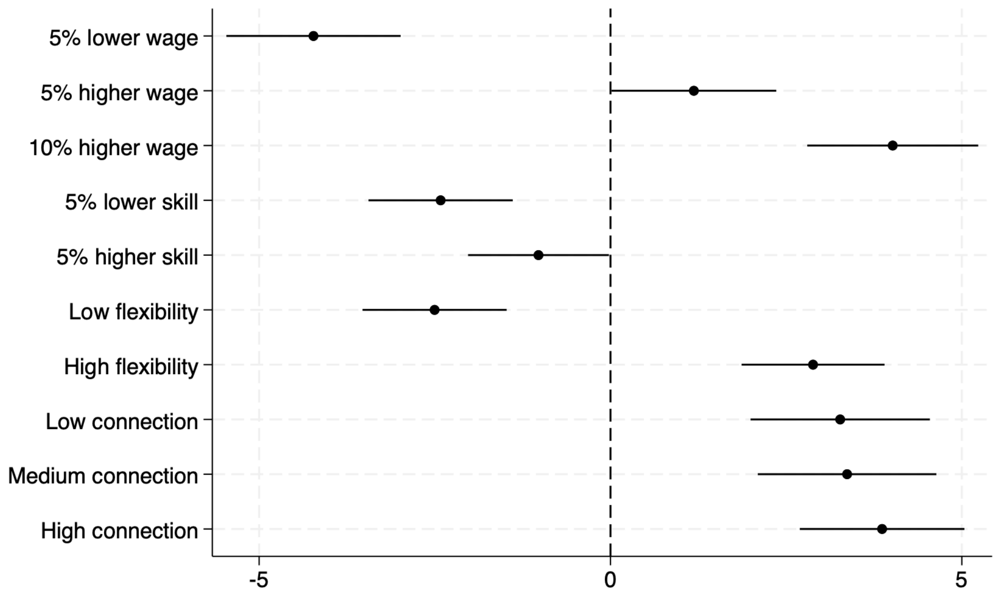


(B) Reasons for Choosing the Next Industry



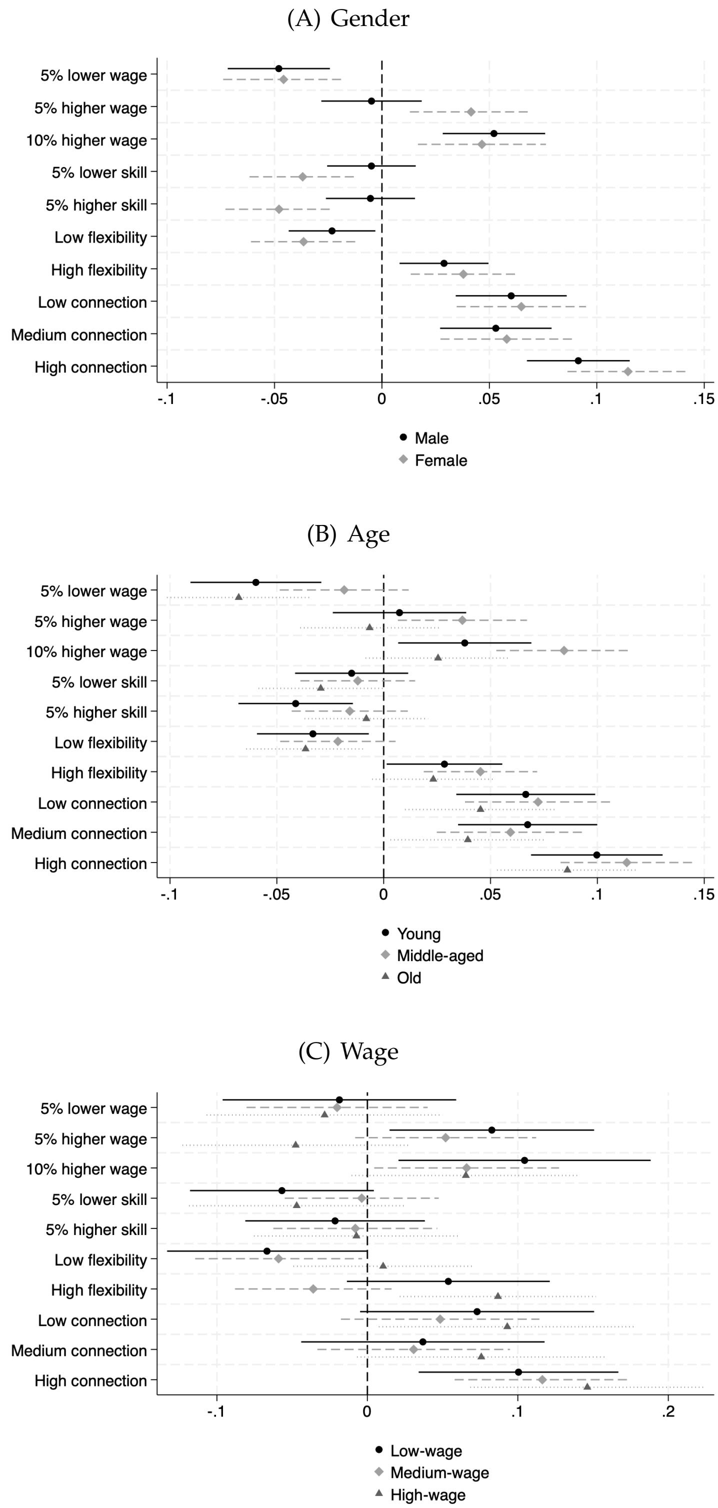
Note: Panel (A) plots the share of respondents choosing each reason for the question, "Why did you apply to your main job?" Panel (B) plots the share of respondents choosing each reason for the question, "When considering which industry you'd like to switch into next, what are the factors that matter for your decisions?" Each respondent selected three reasons, and some respondents chose the category "Other" which is excluded here.

Figure C9: Estimates of the Importance of Job Features in influencing Job-Offering Rate



Note: 95% confidence intervals are adjusted for clustering by respondent. Each respondent provided responses to four experiments on job-offering probabilities. The dependent variable is the respondent's perceived probability of receiving an offer. N = 2,920.

Figure C10: Estimates of the Importance of Job Features in influencing Job-Offering Rate



Note: 95% confidence intervals are adjusted for clustering by respondent. Each respondent provided responses to four experiments on job-offering probabilities. The dependent variable is the respondent's perceived probability of receiving an offer. Panel (A) plots separately for male vs. female. Panel (B) plots separately for young, middle-aged, and old workers. Panel (C) plots separately for low-wage, medium-wage, and high-wage workers. N = 2,920.

Table C1: Summary Statistics of Current Coworkers and Past Coworkers at Current Jobs

	Mean	Median	P25	P75	Obs.
Current coworkers with interaction	19.76	12.00	5.00	25.00	2,721
Current coworkers mention wages	4.11	1.00	0.00	4.00	2,721
Current coworkers mention amenities	3.78	0.00	0.00	3.00	2,720
Current coworkers mention satisfaction	4.61	1.00	0.00	5.00	2,721
Current coworkers know past industry	8.07	4.00	1.00	10.00	2,721
Past coworkers able to reach out to	3.43	1.00	0.00	4.00	2,721
Past coworkers know current industry	4.23	2.00	0.00	4.00	2,721

Note: Table reports the summary statistics regarding current and past coworkers at the current jobs. The first row indicates the number of current coworkers the respondents are interacting with every month. The second to fourth rows indicate the number of current coworkers that mention the wages, amenities, and their levels of satisfaction with their previous jobs. The fifth row indicates the number of current coworkers for whom the respondents are aware of their previous industry of employment. The sixth row indicates the number of past coworkers that left the respondents' current employers and to whom the respondents feel comfortable enough to reach out. The last row indicates the number of past coworkers that left the respondents' current employers and for whom the respondents know their current industry of employment.

Table C2: Perceived and Actual Wages by Worker Characteristics

	(1)	(2)	(3)	(4)
	Panel (A): Gender and Search Status			
	Male	Female	Job Seekers	Job Stayers
log(Predicted Median Wage)	0.50***	0.62***	0.49***	0.60***
	(0.04)	(0.05)	(0.05)	(0.04)
Constant	5.45***	4.16***	5.58***	4.43***
	(0.40)	(0.52)	(0.50)	(0.41)
Mean of Dep. Var	10.91	10.82	10.87	10.88
R^2	0.57	0.50	0.56	0.53
	Panel (B): Income Groups			
log(Predicted Median Wage)	0.50***	0.54***	0.57***	
	(0.05)	(0.04)	(0.05)	
Constant	5.05***	5.01***	4.85***	
	(0.49)	(0.41)	(0.55)	
Mean of Dep. Var	10.50	10.83	11.02	
R^2	0.53	0.42	0.54	

Notes: Table displays the coefficient estimates from regressing logged predicted median wage on logged actual median wage in the CPS data, while controlling for respondent fixed effect. Standard errors are clustered by the industry elicited. The dependent variable in all regressions is the probability of switching to a certain destination sector. In Panel (A), first and second columns use the samples of males and females only. Third and Fourth columns use the samples of job seekers and non-seekers only. Job seekers are defined as individual who think of themselves as having higher than 40 percent of chance of looking for a job in a company different from the ones that they are currently employed at within the next year. Panel (B) displays the estimates obtained separately for different income groups, with columns (1) - (3) being low income, middle income, and high income, respectively.

Table C3: Impact of Current Coworkers' Past Industries on Prediction Errors in Logged Median Wages

	Wage Error	Wage Error	Wage Error	Wage Error	Wage Error
CoworkerShare	-0.05	-0.06*	-0.06*	-0.06*	-0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
OutTransition	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PerceivedProb		0.00	0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)	(0.00)
PastCoworkerShare				0.02	
				(0.04)	
PositiveError					0.00
					(0.02)
PositiveError $\times$ *CoworkerShare*					-0.01
					(0.04)
Occupation FE	No	No	Yes	Yes	Yes
Mean of Dep. Var	0.40	0.40	0.40	0.40	0.40
R^2	0.35	0.35	0.35	0.35	0.35

Note: Table displays the coefficient estimates for equation (2). The outcome variable for all columns is the absolute value of the logged difference between respondents' predicted median wage in another industry and the actual median wage observed in CPS. The second to column adds the control for the respondent's perceived probability of receiving an offer in that industry. The third additionally controls for occupational group fixed effects. The fourth column controls for the share of coworkers at the last job that are currently employed at the reference industry. The last column studies the asymmetric effect of current coworkers on errors in wage prediction, separately for respondents who overestimate and underestimate wages, by including an indicator variable *PositiveError* for overestimation, and including its interaction with the current coworker shares.

Table C4: Impact of Current Coworkers' Past Industries on Prediction Errors in Starting Wages

	Wage Error	Wage Error	Wage Error	Wage Error	Wage Error
CoworkerShare	-3,203.75	-3,724.97	-3,557.09	-2,883.35	-8,157.85*
	(3,370.58)	(3,441.64)	(3,475.12)	(3,572.57)	(4,672.58)
OutTransition	-546.58**	-604.54**	-599.55**	-593.69**	-559.93**
	(244.74)	(255.78)	(257.38)	(256.46)	(265.07)
PerceivedProb		43.33	43.42	45.23	40.66
		(41.01)	(41.42)	(41.85)	(41.73)
PastCoworkerShare				-3,564.25	
				(4,105.47)	
PositiveError					-4,570.62*
					(2,484.47)
PositiveError $\times$ *CoworkerShare*					7,667.84
					(5,541.70)
Occupation FE	No	No	Yes	Yes	Yes
Mean of Dep. Var	33,499.49	33,508.45	33,364.08	33,364.08	33,364.08
R^2	0.43	0.43	0.43	0.43	0.43

Note: Table displays the coefficient estimates for equation (2). The outcome variable for all columns is the absolute value of the difference between the respondents' predicted starting wage for themselves in another industry and the starting wage for them predicted by CPS data, obtained using a Mincer-style regression with individual characteristics. The second to column adds the control for the respondent's perceived probability of receiving an offer in that industry. The third additionally controls for occupational group fixed effects. The fourth column controls for the share of coworkers at the last job that are currently employed at the reference industry. The last column studies the asymmetric effect of current coworkers on errors in wage prediction, separately for respondents who overestimate and underestimate wages, by including an indicator variable *PositiveError* for overestimation, and including its interaction with the current coworker shares.

Table C5: Impact of Current Coworkers' Past Industries on Wage Beliefs

	(1)	(2)	(3)
$CoworkerShare \times \log(DestWage)$	0.54***	0.60***	0.54***
	(0.03)	(0.02)	(0.08)
$CoworkerShare \times \log(OrigWage)$	-0.55***	-0.60***	-0.55***
	(0.03)	(0.02)	(0.08)
Mean of Dep. Var	-0.36	-0.36	-0.36
R^2	0.60	0.63	0.62

Note: Table displays the coefficient estimates, ϕ, for equation (13). Column (1) defines coworker share as the number of current coworkers last employed in an industry over the total number of current coworkers of which the respondents know their last industry of employment. Column (2) defines coworker share as the number of current coworkers last employed in an industry over the total number of current coworkers who mentioned their wage associated with their last job during their interactions with the reference individual. Column (3) defines coworker share as the number of current coworkers last employed in an industry over the sum of all current coworkers last employed in one of the three closest or two farthest industries (the industries we asked about in the survey).

Table C6: Summary Statistics of Past Coworkers at Past Jobs

	Mean	Median	P25	P75	Obs.
Past coworkers in contact	4.24	1.00	0.00	3.00	2,467
Past coworkers employed in current industry	16.75	2.00	0.00	9.00	2,465
Past coworkers employed in current firm	4.02	0.00	0.00	2.00	2,468
Past coworkers mentioned current industry	0.30	0.00	0.00	1.00	2,492
Past coworkers mentioned current firm	0.30	0.00	0.00	1.00	2,493
Past coworkers referral	0.20	0.00	0.00	0.00	2,493

Note: Table reports some summary statistics related to the past coworkers at the previous job. The variables, past coworkers mentioned current industry, past coworkers mentioned current firm, past coworkers referral are dummies equal to 1 if the respondent has at least one past coworker at their previous job that, respectively, mentioned to them their current industry of employment, mentioned to them their current firm of industry, and provided them with a referral for the current position.

C.2 Reliability of the Estimates from our Survey

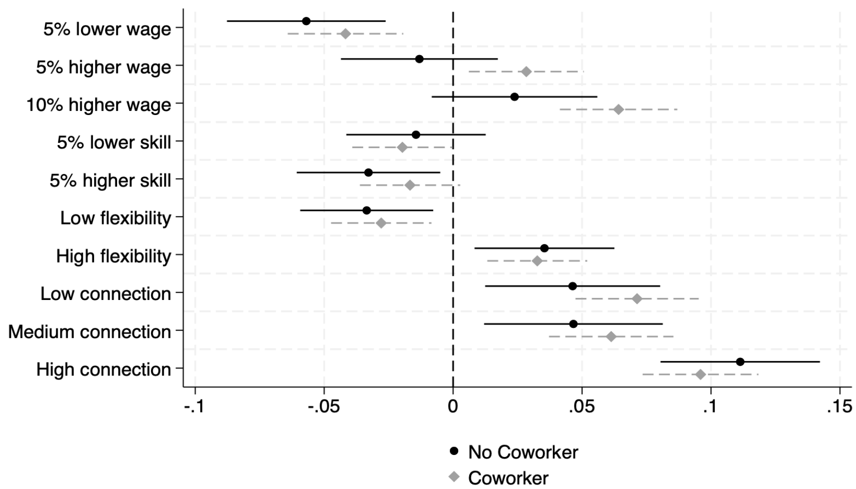
Our conjoint analysis results are consistent across workers with varying personal and employment characteristics. However, the measures derived from the conjoint experiment may be subject to hypothetical bias. Survey experiments can yield less reliable data when respondents face choices that are unrealistic or unfamiliar to them (Mas and Pallais (2020)). We addressed this by using plain language in the vignettes to present concrete scenarios where coworker connections could influence job-offering rates, which should help respondents better understand and relate to the situations, thus mitigating this concern. To further address this form of bias, we conducted some more direct tests by splitting the sample into groups based on their expected familiarity with coworker relationships. We anticipate higher familiarity with referral mechanisms or other implicit connection-induced job-offering advantages among respondents who are more in touch with their past coworkers, as well as those who are actively seeking new job opportunities or who are working in person.

A few survey questions enable us to categorize respondents based on their interactions with past coworkers and their personal experiences. Specifically, we divide workers into binary groups using four different criteria. First, we classify workers as either "in touch with coworkers" or "not in touch with coworkers" based on whether they report a number higher than 1 for the question: "How many of your past coworkers who now work for another employer do you feel comfortable reaching out to for career-related advice?" To enhance robustness, we repeat the classification using responses to a similar question. The results, shown in Figure C11, reveal that the importance respondents place on connections is consistent across these subsamples, contradicting the notion that hypothetical bias drives our findings. The estimates for low, medium, and high connections are comparable between workers who are in contact or comfortable reaching out to their previous coworkers and those who are not. Moreover, respondents that work in person place a lower importance on the "high flexibility in work schedule" category, providing evidence for that workers who tend to associate jobs that are similar to their current ones higher probabilities of receiving an offer.

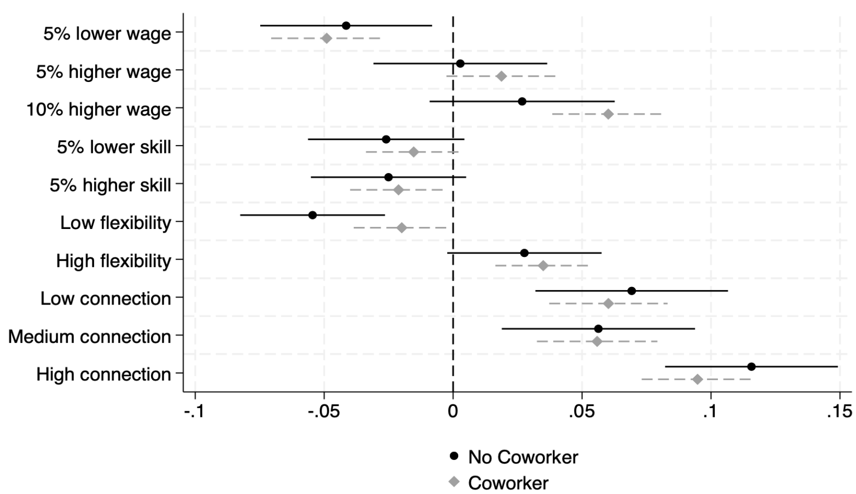
In addition, we classify workers into groups based on their labor market experiences and situations. Workers who interact more with their coworkers at their current workplace may have a more accurate perception of the benefits personal connections can provide. In addition, remote workers may be more reliant on their connections in searching for new jobs because of the lack of opportunity to engage with other individuals in other workplace-related platforms. Thus, we categorize workers by whether their main job is currently remote/hybrid or in-person. Moreover, job seekers may provide more accurate estimates, given their direct involvement in the job search process. We therefore classify workers into those who are not searching for a job and those actively looking for a new job—whether to replace their primary or secondary jobs or to prepare for potential layoffs. Figure C12 shows that the 95% confidence intervals for the connection categories overlap across subsamples of in-person vs. remote/hybrid workers and job seekers vs. non-job seekers, indicating consistency in the perceived importance of connections across these groups. Moreover, the importance workers with flexible work arrangements place on the “high-flexibility" category is high, while the importance workers with in-person jobs place on the “high-flexibility" category is low, suggesting that workers are likely to associate higher job-offering rates with job features similar to their own.

Figure C11: Estimates of the Importance of Job Features in influencing Job-Offering Rate

(A) Coworkers for Reaching Out



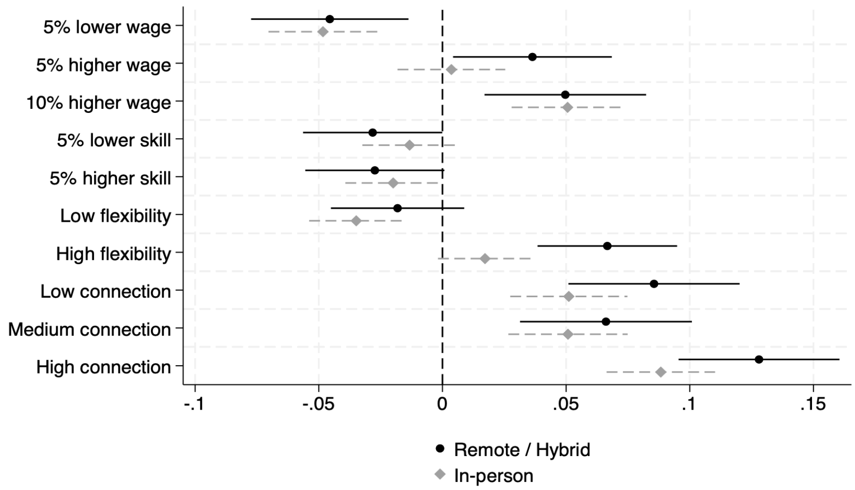
(B) Coworkers in Contact



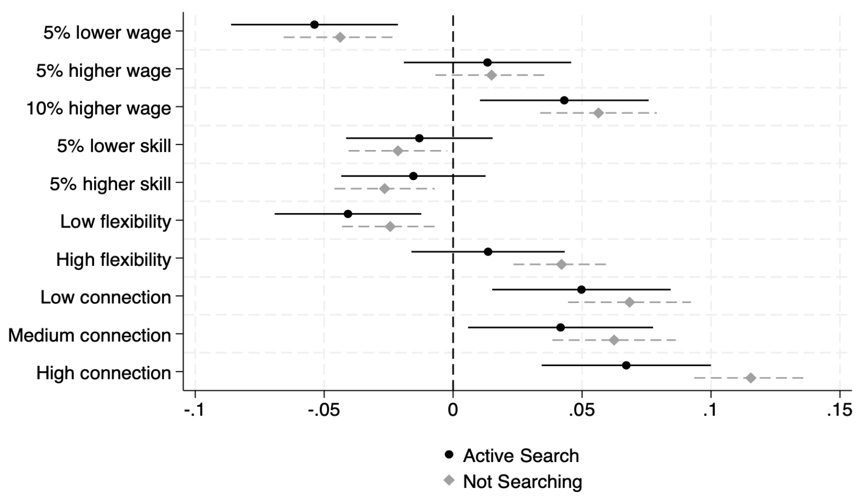
Note: 95% confidence intervals are adjusted for clustering by respondent. Each respondent provided responses to four experiments on job-offering probabilities. The dependent variable is the respondent's perceived probability of receiving an offer. Panel (A) plots separately for those who have at least one previous coworker with whom they are comfortable reaching out vs. those who do not. Panel (B) plots separately for those who have at least one previous coworker with whom they are in regular contact vs. those who do not. N = 2,920.

Figure C12: Estimates of the Importance of Job Features in influencing Job-Offering Rate

(A) Remote Work



(B) Searching for Job



Note: 95% confidence intervals are adjusted for clustering by respondent. Each respondent provided responses to four experiments on job-offering probabilities. The dependent variable is the respondent's perceived probability of receiving an offer. Panel (A) plots separately for those working a remote or a hybrid job vs. those who work in person. Panel (B) plots separately for workers who are searching for a job vs. those who are not. N = 2,920.

D Model Appendix

D.1 Model Derivation

Recall that the Bellman equation is:

$$V_t^n = \ln w_t^n + \max_k \left\{ \mathbb{E}_t^n \left[\Gamma^{n,k} \beta V_{t+1}^k + (1-\Gamma^{n,k}) \beta V_{t+1}^n - \kappa^{n,k} \right] + \nu \epsilon_t^k \right\}$$

We can write the sector-choice probabilities from origin sector k to destination sector m from the perspective of workers in sector k as:

$$\begin{aligned}
&\mu_t^n(k,m) \\
=&\Pr\left(\mathbb{E}_t^n \left[\Gamma^{k,m} \beta V_{t+1}^m + \left(1-\Gamma^{k,m}\right) \beta V_{t+1}^k - \kappa^{k,m} \right] + \nu \epsilon_t^m \right. \\
\geq& \left. \mathbb{E}_t^n \left[\Gamma^{k,j} \beta V_{t+1}^j + \left(1-\Gamma^{k,j}\right) \beta V_{t+1}^j - \kappa^{k,j} \right] + \nu \epsilon_t^j, \quad \forall j \neq m \right) \\
=&\Pr\left(\nu \left(\epsilon_t^m - \epsilon_t^j \right) \geq \mathbb{E}_t^n \left[\Gamma^{k,j} \beta V_{t+1}^j - \Gamma^{k,m} \beta V_{t+1}^m - \left(\kappa^{k,j} - \kappa^{k,m} \right) \right], \quad \forall j \neq k \right) \\
=&\Pr\left(\epsilon_t^j \leq \epsilon_t^m - \frac{1}{\nu} \mathbb{E}_t^n \left[\Gamma^{k,j} \beta V_{t+1}^j - \Gamma^{k,m} \beta V_{t+1}^m - \left(\kappa^{k,j} - \kappa^{k,m} \right) \right], \quad \forall j \neq k \right) \\
=&\frac{\exp\left(\mathbb{E}_t^n [\Gamma^{k,m} \beta V_{t+1}^m + (1-\Gamma^{k,m}) \beta V_{t+1}^k - \kappa^{k,m}] \right)^{\frac{1}{\nu}}}{\sum_j \exp\left(\mathbb{E}_t^n [\Gamma^{k,j} \beta V_{t+1}^j + (1-\Gamma^{k,j}) \beta V_{t+1}^k - \kappa^{k,j}] \right)^{\frac{1}{\nu}}}
\end{aligned}$$

where the last line uses the property of the Gumbel distribution.

In addition, using the property of the Gumbel distribution, we can also write the expected utility of being employed in sector n:

$$\mathbb{E}_t^n [V_t^k] = \mathbb{E}_t^n [\ln w_t^k] + \nu \ln \left(\sum_j \exp \left(\frac{1}{\nu} \mathbb{E}_t^n \left[\Gamma^{k,j} \beta V_{t+1}^j + \left(1-\Gamma^{k,j}\right) \beta V_{t+1}^j - \kappa^{k,j} \right] \right) \right)$$

D.2 Estimation Equation

The belief on flows coincides with the actual flow, $\mu_t(n,m)$, when $n = k$, i.e., $\mu_t(n,m) = \hat{\mu}_t^n(n,m)$. Therefore,

$$\mu_t(n,m) = \hat{\mu}_t^n(n,m) = \frac{\exp\left(\mathbb{E}_t^n [\Gamma^{n,m} \beta V_{t+1}^m + (1-\Gamma^{n,m}) \beta V_{t+1}^n - \kappa^{n,m}] \right)^{\frac{1}{\nu}}}{\sum_j \exp\left(\mathbb{E}_t^n [\Gamma^{n,j} \beta V_{t+1}^j + (1-\Gamma^{n,j}) \beta V_{t+1}^n - \kappa^{n,j}] \right)^{\frac{1}{\nu}}} \tag{D.2}$$

Based on equation (D.2), we can obtain the following equation:

$$\ln \frac{\mu_t(n,m)}{\mu_t(n,n)} = \frac{1}{\nu} \mathbb{E}_t^n [\Gamma^{n,m} \beta (V_{t+1}^m - V_{t+1}^n) - \kappa^{n,m}] \tag{D.3}$$

Moreover, the extreme value algebra also yields the following equation:

$$\mathbb{E}_t^n[V_t^n] = \ln w_t^n + \beta \mathbb{E}_t^n[V_{t+1}^n] - \nu \ln \mu_t^{n,n} \tag{D.4}$$

And more generally we have

$$\mathbb{E}_t^n[V_{t+1}^m] = \mathbb{E}_t^n \mathbb{E}_{t+1}^n[V_{t+1}^m] = \mathbb{E}_t^n \ln w_{t+1}^m + \beta \mathbb{E}_t^n[V_{t+2}^m] - \nu \mathbb{E}_t^n \ln \mu_{t+1}^{m,m} \tag{D.5}$$

Combining equations (D.3), (D.4), and (D.5), we arrive at the estimation equation (10).

D.3 Solving the model at steady state

We solve for the distribution and flows of labor and welfare in the steady state, in the following steps:

- For a given value of the adjustment cost, κ, we can calculate the implied flows, $\mu^{n,m}$, for every pair of origin and destination sectors, according to equation (10).
- Estimate the value of κ by minimizing the distance between the model-implied and the actual flows from the CPS data.
- Given the labor flow matrix, we can calculate welfare according to equation (11).
- Compare to the case with no coworker influence by repeating the previous steps, but assuming that workers either have perfect knowledge on the other destination sectors, or by assuming imperfect knowledge but no influence from coworkers.

D.4 Parameter Values

Table C7: Parameter Values

Parameter	Value	Moment	Source
β	0.95	Discount factor	Standard
ν	2	Job-switching elasticity	Standard
ϕ	0.57	Coworker influence on wage	Equation (12)
ψ_0	2.45	Job offering probability (mean)	Equation (14)
ψ_1	0.89	Coworker influence on job offering probability	Equation (14)
ψ_2	0.07	Wage influence on job offering probability	Equation (14)
κ	8.12	Adjustment cost	GMM

Notes: The model is calibrated at yearly frequency.