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Ranking Occupations Using Revealed Preferences*

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Abstract

We apply a novel method from the firm-inequality literature (Sorkin, 2018) to estimate amenity differences between occupations using a revealed-preference argument for occupation switchers. Comparing the results to an alternative stated-preference ranking of occupations based on a job satisfaction survey, we find that they capture a roughly similar ranking, with a rank-correlation of 0.33. However, while the revealed-preference approach attributes half of the gap in earnings between male- and female-dominated occupations to compensating differentials, the stated-preference approach does not. Which ranking is used therefore matters for conclusions about the role of amenities and discrimination for the occupational gender-earnings gap.

Keywords: occupations, amenities, compensating differentials, revealed-preferences, stated-preferences

JEL: C25, J24, J28, J31, J62

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1 Introduction

The last decades have seen a substantial transformation in the occupational composition of the workforce with large shifts in the task-content of workers (Autor and Duggan, 2003), driven by both technological change and a globalization of supply chains (Goos et al., 2014). These changes in the structure of the economy had significant effects on earnings inequality and created both winners and losers (Webb, 2019). However, earnings are not the only aspect of a job which matters for worker welfare.

The quality of working life is determined by many factors. Some occupations are safer, while others may provide greater social recognition or flexibility in working hours. These different aspects of occupations provide amenities and, jointly with earnings, determine overall welfare of workers. Despite our understanding of the differences of occupations in terms of earnings and task contents, we know little about how occupations compare with respect to their non-monetary compensation. In this paper, we implement a new method of estimating occupational amenities drawn from the literature of firm inequality and compare our approach to alternative methods of ranking occupations relying on stated preferences in surveys. We highlight findings that are common to the two methods and suggest explanations for observed discrepancies.

Estimating the value of amenities is challenging. The set of potential amenities relevant to workers' welfare can be exhaustive and amenities are difficult to measure. Moreover, the relationship between observed amenities and pay in a standard hedonic wage regression can be biased due to unobserved productivity differences or the prevalence of a search process, as workers may attain different levels of overall compensation (Hwang et al., 1992, 1998). To address these challenges, we employ a new approach to estimate non-pay values of occupations based on revealed preferences of workers following recent work by Sorkin (2018). The intuition for the approach is simple. When a worker moves to a new occupation, she reveals her preference for the new occupation over the old. Therefore, the offered overall compensation - earnings and amenities - must be at least as high. If earnings of the worker are observed in the old and new occupation, the "revealed-preference" approach allows to estimate the implied value of amenities that best rationalizes the transitions of workers between occupations.

By using this novel approach, our paper provides a new measure of occupational quality to complement a new and growing literature on inequality related to differences in occupational amenities. While other work relies on surveys to measure overall job satisfactions or the prevalence of specific amenities (Maestas et al., 2018; Boar and Lashkari, 2021), our results are residuals of choices that individuals make in the labor market and can capture unobserved components of job quality. Our findings can therefore also be used as a validation for other methods to analyze whether important amenity components are likely missing.

We compare the occupational ranking of our method to a conventional "stated-preference" approach of measuring occupational quality based on a survey. In particular, we use a question about general job satisfaction surveyed in the General Social Surves (GSS) and estimate occupational fixed effect of respondents job satisfaction as an indicator for the overall quality of an occupation[1]. A general short-

[1] A particular sub-sample of the GSS, Quality of Work-Life Module, is used by Boar and Lashkari (2021) to estimate and analyze occupational work quality. Different to our approach, they use 7 specific questions about job characteristics and employ a principal component analysis to reduce the ranking to a single dimension. We choose to compare our ranking to the one resulting from stated general job satisfaction for data constraints. While the general job satisfaction question is included in all survey waves, the Quality of Work-Life module is only available for 2002, 2006, 2010 and 2014, resulting in a relatively small overall sample and often few observations per occupation. For occupations with a large number of workers, the occupation rankings derived from stated job satisfaction and from the principal component analysis are highly correlated.

coming of the "stated-preference" approach is that we cannot determine the value of amenities from a hedonic regression (Hwang et al., 1992), such that we are limited to comparing the non-parametric rank-correlation between the estimated occupation rankings. We find that both methods deliver broadly the same ranking, with a rank-correlation coefficient of 0.33-0.37. However, substantial differences between the two methods remain.

We then provide suggestive evidence that the two methods differ in the degree to which they capture utility-equalizing compensating differentials as opposed to utility-dispersing "Mortensen"-amenities (Mortensen, 2003) which arise from search and matching frictions in the labor market. The former substitute financial compensation and introduce a negative correlation between earnings and amenities, while the latter complement financial compensation and tend to be positively correlated with earnings. We find that the rank-correlation of earnings with the stated-preference ranking is higher than the rank-correlation of earnings with the revealed-preference ranking, suggesting that the latter captures a larger share of compensating differentials.

This distinction matters little in cases where frictions are likely to cause different amenity provisions between occupations. Both methods agree, for example, that occupations with higher education provide more amenities on top of more earnings. Not all workers will become highly educated, which explains why these differences persist. It matters greatly, however, for our understanding of earnings differences between men and women. Consistent with recent findings by Morchio and Moser (2018), our revealed-preference results suggests that occupations with a large share of women provide compensating differentials trough higher amenities albeit lower pay. The stated-preference approach, on the other hand, finds that amenities in these low-paying, female-dominated occupations are essentially the same as in male-dominated occupations, which would suggest that frictions (e.g. discrimination) cause persistent differences in compensation between men and women.

The rest of the paper is structured as follows. Section 2 describes the two datasets used in this paper: the Current Population Survey for occupation switchers and a job satisfaction survey from the General Social Survey. We further describe our approach to estimate occupational earnings fixed effects and stated job satisfactions. Section 3 introduces the frictional model of occupational choice which underlies our revealed-preference approach. Section 4 presents our revealed-preference ranking of occupations and provides intuition for the partialling-out of earnings from occupation values. It then compares the revealed- and stated-preference rankings graphically and in terms of rank-correlation. Section 5 explores the reasons for differences between the two estimated rankings. Section 6 concludes and caveats the weaknesses of our results.

2 Data

We use monthly economic survey data from the Current Population Survey (CPS) as provided by IPUMS (Flood et al., 2021). The survey consists of a rotating sample of representative households containing around 60,000 individuals, who are interviewed on a multitude of socio-economic and demographic characteristics. Interviews are conducted monthly for a period of 4 months, followed by a break of 8 months and another period of monthly interviews over 4 months. Survey participants are asked about their weekly earnings and hours twice before they drop out of the active sample – in their 4^{th} survey month, just before the survey pause, and in their 8^{th} survey month. These two observations per individual are called the "outgoing rotation group" and are exactly 12 months apart. We focus on these two

observations per individual to construct our data set of occupation switchers. Income in the CPS is top-coded at levels that vary over the years. In order to have a more precise measure of earnings changes, we drop 4950 observations with top-coded income from our final sample of occupation switchers. We further restrict our sample to the years 1984 to 2002, since occupations in the CPS thereafter undergo a recategorization following new Census occupation codes[2]. We normalize earnings to 1999-$ values and work with log-earnings throughout the paper.

We want to use a large, representative sample of the population that is at the same time strongly attached to the labor market. We therefore restrict our data to workers between the age of 30 and 55. We exclude young workers since it may take a substantial amount of time before workers find their "true calling"[3] and occupational choices of young workers therefore are more likely to represent idiosyncratic preferences. It further reduces the risk that our estimates are driven by "career ladders", in which workers spend time in one occupation in order to gain experience to move to their desired profession. For example, many workers are employed as paralegals before or while attending law school to become attorneys. Young workers also pose the problem that they are more likely to enter and exit the labor force, for example because of schooling decisions. We further exclude older workers in order to mitigate concerns that workers change careers in anticipation of retirement or may drop out of the labor market due to early retirement.

In order to compare our estimates with another available measure of occupational quality, we use the General Social Survey (GSS) conducted approximately every two years from 1974 to 2021. The GSS surveys general job satisfaction by asking the question "On the whole, how satisfied are you with the work you do–would you say you are very satisfied, moderately satisfied, a little dissatisfied, or very dissatisfied?", to which respondents pick one of the 4 ordinal levels. We focus our attention on an indicator of whether the respondent has indicated the highest level of job satisfaction. We do this for two reasons: first, a large share of respondents (48.5%) select this option, rendering variation in the lower categories less useful. Second, it is easier and more straightforward to interpret an ordinal variable in this way, as numeric differences between the levels of reported satisfaction have no meaning.

Apart from job satisfaction, the survey asks a variety of questions regarding hours worked, demographics, occupation, as well as annual income[4]. We construct a measure of occupational quality by taking the estimates of occupational fixed effects from a regression of our job-satisfaction indicator on demographics, hours, income and occupation (see table A.5 in the appendix). The GSS is a smaller sample than the CPS and many smaller occupations have limited data points. To increase precision of our estimates, we restrict our analysis to 171 occupations with at least 30 observations in the GSS. Overall, these occupations capture 86 % of employment in the CPS data.

Table 1 provides an overview of our sample. Among all observations, 31.5 % of individuals report a change in occupation between one year and the next. While the number may appear large, it is driven in part by moves between closely related occupations[5]. Unfortunately, there is no information whether

[2] We count 352 unique occupations before and 450 after 2002.

[3] We do not want our results to be affected by early-career search for such idiosyncratic match quality. For example, Gervais et al. (2016) show that learning about personal occupational fit of young workers explains the observed differences in unemployment rates between young and and old workers.

[4] We omit the earliest survey waves in 1972 and 1973 since income and hours have not been surveyed then.

[5] vom Lehn et al. (2022) study the bias from longitudinal occupation questions in the CPS and find the true occupational mobility to be around 5-7% annually. For example, around 1100 occupation changes are recorded in each direction between "Elementary and Middle School Teachers" and "Secondary School Teachers". Since we have no method to determine these occupation changes in our data, we work with the biased recorded occupation switches. If the flows are not systematically mismeasured, this should have a limited effect on our ranking.

employees changed employer as well. The restrictions also impose some differences on key demographics. In the restricted sample, the share of college and high-school educated workers is larger, reflecting in part the decision to drop younger employees. Moreover, the share of women is slightly lower.

To compare our different estimates of occupational value to the typical earnings of each occupation, we run a regression of log-earnings on demographics, education and fixed-effects on year, occupation and one-digit industry codes (see table A.4 in the appendix). We use the estimated occupational fixed effects to proxy for different earnings potential of occupations.

Table 1: Summary statistics of occupation changers from the Current Population Survey (CPS) outgoing rotation group between 1984 and 2002.

	All	All (occ. change)	Restricted
# of observations	2577087	614750	138446
# of top-coded observations	27389	0	0
# unique occupations	354	353	172
Share: occupation change	0.314	1.0	1.0
Share: $<$ HS	0.197	0.148	0.085
Share: HS, some college	0.272	0.368	0.369
Share: college	0.33	0.484	0.546
Share: female	0.523	0.486	0.516
Age	37.64	38.851	41.087
	(22.626)	(13.841)	(7.092)
Hours	38.217	37.808	39.982
	(11.525)	(10.918)	(8.501)
Real earnings (1999 $)	585.02	532.822	641.546
	(426.709)	(366.547)	(374.128)

Notes. Standard deviations are in parentheses. The first column shows the full sample of employed respondents, while the second column restricts to workers with an occupation change from one year to the next. The third column restricts the sample to workers aged 30 to 55 and excludes observations with top-coded earnings as well as occupations with less than 30 observations in the General Social Survey (GSS).

3 Model

We build an occupational-choice model with search frictions to infer the amenity values of occupations from occupational changes. We depart from the canonical model of occupational sorting – the Roy model of comparative advantages (Roy (1951), see French and Taber (2011) for a summary) – by mod-

eling occupational sorting as the result of search frictions in the labor market. While typical models of occupational sorting assume that workers choose a utility-maxing occupation among the set of all occupations based on comparative advantages (Keane and Wolpin, 1997), we specify workers' occupational choice decisions as sequential pairwise comparisons between occupations. Through the lens of our model, observing that a worker quits his job as a waiter to become a bartender is only informative about this worker's preference ordering between the two occupations and does not reveal his utility-maximizing choice among the set of all occupations.

We motivate this departure by the substantial costs associated with a switch to a new occupation: a worker needs to learn about and invest into new opportunities by searching for a job, acquiring new skills and expanding her network.[6] Our formulation of occupational choice as a frictional process follows a well-established tradition in the job search literature (Burdett and Mortensen, 1998) and is inspired by previous papers that seek to inference workers' preferences over employers from job-to-job flows (Sorkin, 2018; Taber and Vejlin, 2020; Lehmann, 2022). A desirable feature of our approach is that it delivers a unique ordering of occupation values and only relies on observing workers' transitions between occupations and their wages at these occupations.

We consider a labor market with a discrete set of workers I and occupations O. Workers are ex-ante identical and attach common value V_o to being employed in an occupation $o \in O$. An occupation's common value can be decomposed additively into a non-financial component a_o and a financial component $\beta\overline{w}_o$

$$V_o = a_o + \beta\overline{w}_o \tag{1}$$

The non-financial component captures all characteristics of an occupation that do not relate to income such as e.g. the working environment, future job opportunities, or flexible working hours. The financial component is assumed to be proportional to average log earnings $\overline{w}_o$ in occupation o. We are interested in identifying the occupation values $\{V_o\}_{o\in O}$, their non-financial components $\{a_o\}_{o\in O}$, and the parameter mapping log earnings into utility units β.

If workers completely agreed on the ranking of occupations, we would not observe bi-directional flows between occupations. To generate countervailing flows, we introduce two sources of heterogeneity for occupation value in the model: within-occupation earnings dispersion and idiosyncratic preference shocks over occupations. Concretely, we let worker i's value for occupation o at time t take the form

$$V_{i,o,t} = a_0 + \beta w_{i,o,t} + \zeta_{i,o,t} \tag{2}$$

where $w_{i,o,t}$ is realized log earnings and $\zeta_{i,o,t}$ is a non-pecuniary taste shock. We take a partial equilibrium approach and do not model the source of within-occupation wage dispersion. We leave the earnings offer distribution unrestricted and allow for systematic earnings offer differences across occupations. However, we impose that workers are ex-ante identical and draw earnings from the same distribution in each occupation. We assume that the taste shocks $\zeta_{i,o,t}$ are Gumbel-distributed with variance normalized to 1 and that they are independent from the wage shocks. We also impose that the taste shocks are uncorrelated over time and across occupations. Taste shocks allow idiosyncratic preferences to play

[6] While we recognize that this approach is highly stylized, the converse assumption – that workers consider all occupations – might not be more realistic.

a role in occupational choice and are necessary to rationalize the bi-directional flows observed after conditioning on workers' earnings in their past and current occupations.

Workers sort into occupations to maximize utility, but they face search frictions in the process. We abstract from unemployment and assume that workers hold a single occupation. In each period t, each worker considers switching occupations with probability λ. Conditional on considering an occupation switch, a worker draws an occupation p from the pool of occupations O. We let f_p be occupation p's consideration rate, i.e. the probability that a worker draws occupation p among the set of occupations, with $\sum_{p \in O} f_p = 1$. Conditional on considering an occupational switch to occupation p in period t, a worker draws new taste shocks $(\zeta_{i,o,t}, \zeta_{i,p,t})$ and earnings $(w_{i,o,t}, w_{i,p,t})$ for her current occupation o and occupation p. Worker i then switches from occupation o to occupation p if this provides her with a higher occupation value, that is if the following condition is satisfied:

$$V_{i,p,t} = V_p + \beta w_{i,p,t} + \zeta_{i,p,t} \geq V_o + \beta w_{i,o,t} + \zeta_{i,o,t} = V_{i,o,t}. \tag{3}$$

If a worker does not consider an occupation switch, which occurs with probability $1 - \lambda$, she remains in occupation o in the next period and does not draw new earnings and preference shocks, i.e. we let $w_{i,o,t+1} = w_{i,o,t}$ and $\zeta_{i,o,t+1} = \zeta_{i,o,t}$ in this case.

Because occupation amenities are unobserved, we need to infer them from occupational choices. If we knew which workers considered a switch from occupation o to occupation p (or vice versa), we could use their decisions to change occupations or not to estimate a_o and a_p. Indeed, given the workers' idiosyncratic occupation values (2) and the i.i.d. Gumbel-distribution assumptions, a worker i prefers occupation o to p conditional on earnings realizations $(w_{i,o,t}, w_{i,p,t})$ with probability

$$\begin{aligned} Pr(V_{i,p,t} \geq V_{i,o,t} | w_{i,o,t}, w_{i,p,t}) =& \frac{\exp(a_p + \beta w_{i,p,t})}{\exp(a_o + \beta w_{i,o,t}) + \exp(a_p + \beta w_{i,p,t})} \\ =& \frac{1}{1 + \exp(a_o - a_p + \beta(w_{i,o,t} - w_{i,p,t}))} \end{aligned} \tag{4}$$

However, while we observe workers who change occupations in the data, i.e. those workers who prefer their new occupation draws over their current occupations, we do not observe those workers who prefer to remain in their current occupations.

To circumvent this problem, we can make assumptions about the sampling of occupations for occupational change consideration. To see this, let n_{ot} be the number of individuals holding occupation o at time t. The expected number of workers switching from occupation o to occupation p at time t is

$$S_{opt} = n_{ot} \lambda f_p Pr(V_{i,p,t} \geq V_{i,o,t}). \tag{5}$$

At the same time, the expected number of workers who consider and reject a move from occupation o to occupation p is

$$R_{opt} = n_{ot} \lambda f_p Pr(V_{i,p,t} < V_{i,o,t}). \tag{6}$$

Combining these two equations, we obtain a relationship between the expected number of workers

rejecting a move from occupation p to o and the expected flow from occupation o to p.

$$R_{pot} = \frac{n_{pt}}{n_{ot}} \frac{f_o}{f_p} M_{opt} \tag{7}$$

We can use this expression to state the probability that individuals prefer occupation p over o in pairwise comparisons at time t as a function of the observed bi-directional switches between o and p and their respective occupation consideration rates only.

$$\begin{aligned} Pr(V_{i,p,t} \geq V_{i,o,t}) &= \frac{M_{opt} + R_{pot}}{M_{opt} + R_{pot} + M_{pot} + R_{opt}} \\ &= \frac{\frac{1}{n_{ot} f_p} M_{opt}}{\frac{1}{n_{ot} f_p} M_{opt} + \frac{1}{n_{pt} f_o} M_{pot}} \end{aligned} \tag{8}$$

Hence, if we knew the ratio of occupation consideration rates f_p / f_o for all pairs of occupations $(o, p) \in O^2$, we could construct an estimate of the probability that an occupation p is preferred over another occupation o purely from the observed flows between these occupations.

These derivations have interesting implications for the identification of the value of occupation amenities. For ease of exposition, the derivations in the previous paragraph were made for the unconditional choice probability $Pr(V_{i,p,t} \geq V_{i,o,t})$. However, an analogous argument applies to the conditional probability $Pr(V_{i,p,t} \geq V_{i,o,t} | w_{i,o,t}, w_{i,p,t})$. Under our model assumptions, we can therefore estimate the relative values of amenities in each occupation $\{a_o\}_{o \in O}$ by estimating equation (4) via Logit with appropriate weights $1/n_{ot} f_p$ for each observational switch from o to p in the data. Because we can only identify differences in amenity values across occupations, we normalize amenity values to have mean 0 among all occupations when taking our model to the data.

Jointly estimating the amenity values has two advantages over doing it separately for each pair of occupations. First, it allows to identify the amenity values for occupations between which we do not observe any switches or only unidirectional switches but who belong to the same connected set of occupations. Second, it delivers unique amenity values for each occupation. By contrast, estimating relative occupation values by pairwise comparisons may lead to an inconsistent ranking of occupations.

In this section, we have provided a sufficient set of assumptions to estimate the values of occupation amenities if the relative rates at which workers consider switches between two occupations are known. One could try to approximate the offer consideration rates $\{f_o\}_{o \in O}$ using job advertisement data. In fact, we could even think of situations in which these offer consideration rates depend on the current occupation such that we should write $f_{o,p}$ instead of f_p.

When applying our method to data from the United States in this project, we will take a leap of faith and assume that workers sample occupation at random within the stock of occupations, i.e. proportional to occupation size.

$$f_{o,t} = \frac{n_{o,t}}{N} \tag{9}$$

This assumption ensures that the number of workers considering a move from occupation o to occupation p ($n_{o,t} \lambda f_p$) is the same as the number of workers considering the opposite occupational transition in expectation. We can then estimate occupation amenities and the conversion parameter β by using each

individual occupation switch in the data as an observation.

4 Results

4.1 Understanding the revealed-preference ranking

In this section, we show the results of a revealed-preference approach to ranking occupations as detailed above and subsequently highlight to what extent the ranking coincides with an alternative measure of of occupational quality derived from a job satisfaction survey.

First, we run a logistic regression as suggested by equation (4) to estimate the occupational value based on the revealed preferences of occupational switchers. In a baseline estimation, we do not include any further explanatory control variables - in this case, the assigned occupation values have no cardinal interpretation apart from the fact that they best rationalize the pattern of observed flows if every transition was made under a discrete choice model. It corresponds to equation (4) under the restriction that β is set to zero. The difference in the estimated values of two occupations then corresponds to the the log-odds ratio of choosing one occupation over the other if both options were simultaneously available to the worker. If workers value earnings –such that the true β is not 0– the estimated occupation values under this specification reflect both the financial and non-financial attributes of occupations.

Figure 1a plots the estimates against the earnings fixed-effects that we derived above. The positive relationship in the plot demonstrates that a ranking based on flows alone partly reflects differences in the pay between occupations. Our model and further estimates suggest, however, that the variation in occupational value on the vertical axis for occupations with a similar earnings fixed-effect hints at the fact that workers value some occupations differently than others irrespective of pay. For example, the estimates suggest that workers prefer to work as "Teacher Assistants" over "Waiters" as well as "Doctors" over "Engineers". Moreover, taking into account the revealed-preference argument through the flow approach may also matter tremendously when comparing occupations with different pay. For instance, "Childcare Workers" find themselves at the lowest rung of the occupational earnings distribution, yet are ranked higher than waiters based on the flow-approach.

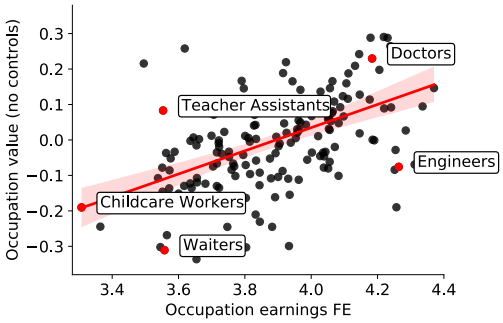
The advantage of our approach compared to the seminal work of Sorkin (2018) is that we can control for further idiosyncratic factors that change for the worker upon making a transition[7]. In our case, the most important factors are earnings and working hours before and after the transition. Intuitively, workers will be more likely to change occupations if it resulted in increased earnings and/or less time at the office. Table 2 shows parameter estimates from our model, controlling for different factors. We use the fixed-effects of the model in column 3, the occupational value which is unexplained by working hours or differences in earnings, and refer to it as the revealed-preference non-financial value of an occupation. Controlling for differences in earnings before and after the occupation transition has the further important advantage that it allows us to scale the estimated occupational values into dollar-units and therefore transform differences in estimated values into interpretable differences in log earnings.

The effect of these measures can be seen in figure 1b. Once we control for earnings differences in our estimation of occupational values, the relationship between average earnings in an occupation

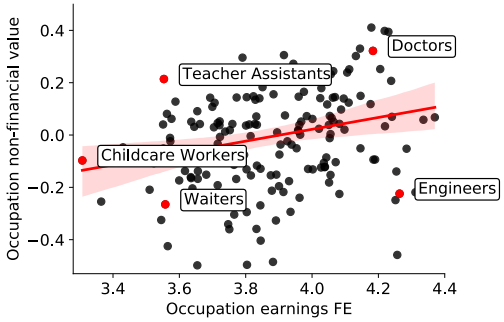
[7] The key difference is that Sorkin (2018) builds a model of worker flows between firms and derives simple moment conditions for the firm values, a computational simplification which allows him to further endogenize the separation risk and unemployment value in the model. In contrast, we estimate the values through maximum-likelihood, which allows us to partial out confounding factors but would make it computationally prohibitive to further complicate the model.

Figure 1: Relation between earnings and occupational quality

(a) Occupation earnings effects vs. Total value (no controls)



(b) Occupation earnings effects vs. Revealed-preference non-financial value



and the estimated residual occupation value weakens. This new ranking of occupations captures only unobserved characteristics that determine worker flow. On these values, the ranking of occupations can differ fundamentally from a ranking based on earnings. "Childcare Workers", for example, is one of the lowest-paying occupation but ranks similarly in terms of revealed-preference amenities to "Engineers", one of the highest-paying occupations. Using our estimate of β of 0.584, we can now interpret the cardinal differences in occupational values between "Childcare Workers" and "Engineers". While both occupations provide similar earnings, workers value the difference in the occupational value between "Doctors" and "Engineers" to the same extent as a difference in log-earnings of 0.55 (see figure 1b).[8]

4.2 Comparison between revealed-preference and stated-preference ranking

A natural question to ask is whether the method we propose yields a similar ranking of occupations as alternative sources of worker preferences. As an example, we use a question in the General Social Survey (GSS) concerning job satisfaction to elicit an alternative stated-preference ranking of occupations according to non-monetary benefits.

Relying on a survey to understand worker preferences over occupations poses separate issues. Most importantly, workers have been asked about general job satisfaction, which may or may not include satisfaction with the financial compensation which they currently receive. The best that we can do in this case is to control for self-reported income brackets in a regression. Similarly, we control for demographic information such as age, gender and race in order to control for systematic differences in reported job satisfaction between respondents. Table A.5 in the appendix reports estimates. The right column includes occupational fixed effects while the model on the left does not. Comparing the two models hints at the fact that the occupational composition of respondents may be important. For example, women show higher job satisfaction in the model without occupation fixed effects than after controlling for occupations.

Another drawback of the survey-based method is that we cannot convert the reported values into

[8]The precise names of the highlighted occupations in the 2010-occupational dictionary used by the CPS are as follows: "1460: Mechanical Engineers", "2540: Teacher Assistants", "3060: Physicians and Surgeons", "4110: Waiters and Waitresses" and "4600: Childcare Workers".

Table 2: Estimates

	(1)	(2)	(3)
Parameter estimates			
Δ log real earnings		0.522	0.584
Δ hours			-0.009
Rank Correlation with			
Job Satisfaction - fixed effect	0.382 (0.0)	0.338 (0.0)	0.329 (0.0)
Job Satisfaction - average	0.454 (0.0)	0.38 (0.0)	0.373 (0.0)
Earnings - fixed effect	0.524 (0.0)	0.256 (0.001)	0.255 (0.001)

Notes. The top part of the table shows the estimates for the parameters of the revealed-preference model of occupational choice. The bottom part of the table shows Spearman's rank correlation coefficient between the estimated revealed-preference ranking and alternative occupation rankings based on the GSS or earnings. P-values for the rank-correlation coefficient are reported in paranthesis. We restrict occpations to those with more than 30 observations in the GSS.

monetary units without making strong assumptions on preferences. To compare the rankings of both methods, we report their visual relationships in figures 2a - 2d to display the degree by which these methods deliver similar rankings and to compare the relative position of the occupations that we highlighted above. Figures 2b and 2d compare the revealed-preference ranking with and without controls to the average job satisfaction in each occupation. Figures 2a and 2b, on the other hand, use the stated-preference ranking derived from the occupation job satisfaction fixed effects, such that differences in the levels of job satisfaction between different demographics and income brackets are accounted for. The ranking on our highlighted occupations roughly aligns between both methods, especially in our main ranking in panels 2b and 2d which control for earnings changes in the revealed-preference approach.

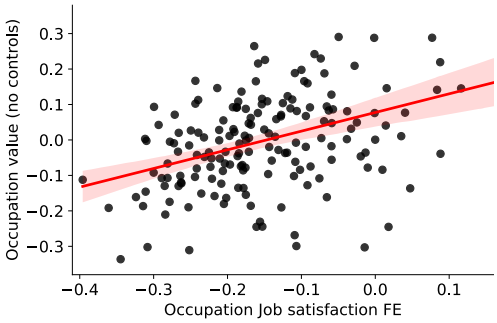
Relying purely on visual comparisons between our methods may be misleading, however. To gain a better understanding of the quantitative strength of the relationship between the different rankings, we report Spearman's rank correlation coefficient (or Spearman's ρ) in the bottom part of table 2. Spearman's ρ is defined as the regular Pearson correlation coefficient between the ranks of two values and is highly appropriate when the relationship of interest is monotonic but not necessarily linear. The rank-correlation is positive and significant at the 5-% threshold for all our specifications, indicating that the underlying rankings are weakly similar to each other. The rank-correlation between the revealed-preference ranking from column (3) and the occupational job satisfaction fixed effect is 0.329, which summarizes the monotone relationship visualized in figure 2b.[9]

Earnings clearly matter for self-reported satisfaction - the highest earners are 4.2 percentage points more likely to be "Very satisfied" than the lowest earners in the General Social Survey (table A.5). But our results indicate that accounting for income differences also changes the relationship between the dif-

[9]For comparison, we also report the rank correlation between our estimates with the earnings fixed effect, which corresponds to measures of the monotonic relationship in figure 1. As suspected, the rankings are highly correlated when differences in earnings are not factored into the model of occupation choice in column (1). Once earnings differences are allowed to matter for occupation decisions, the rank correlation drops significantly from 0.52 to 0.25-0.26.

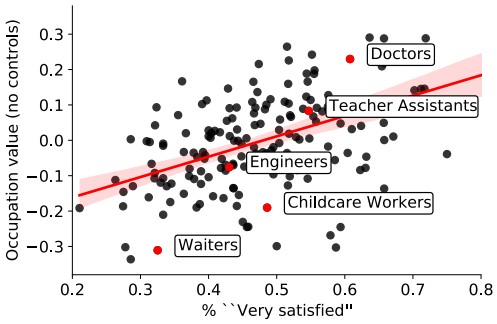
Figure 2: Relationship between reported Job satisfaction and occupational quality

(a) Job satisfaction (fixed effect) vs. estimated value (no controls)

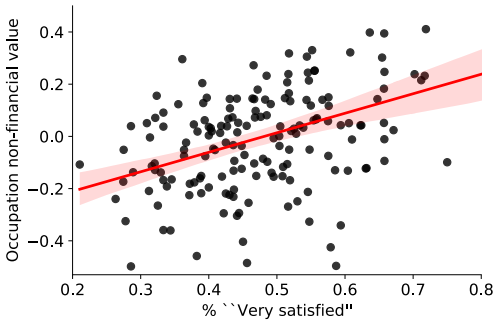


(b) Job satisfaction (fixed effect) vs. Non-financial value

(c) Job satisfaction (average) vs. Total value (no controls)



(d) Job satisfaction (average) effects vs. Non-financial value



ferent ranking methods. For example, "Childcare Workers" report higher job satisfaction in the GSS than "Engineers" but rank lower in the revealed-preference ranking. After accounting for the fact that occupational switches to become an engineer usually carry a high financial reward, the revealed-preference ranking reverts back and aligns with the job-satisfaction ranking. The same pattern does not apply, however, to the strength of the relationship between the rankings at large. When measured via Spearman's ρ, the rankings are less similar when earnings is controlled for in either the job-satisfaction ranking or the revealed-preference ranking. One interpretation of these results is that earnings have a similar effect on both self-reported job satisfaction and occupation career decisions, while the converse is not true about non-financial amenities. How workers self-report job satisfaction and how they decide on the labor market are oftentimes two different things.

5 What drives the differences?

On the face of it, the relationship between the rankings is weak given the fact that both are supposed to measure non-financial occupational compensation. In the following, we will highlight a particular pattern in the result estimates where the rankings disagree to provide suggestive evidence of a systematic

difference in both methods.

Table 3: Correlation matrix between Earnings, Stated-preference and Revealed-preference rankings

Ranking based on	Earnings	Stated-pref.	Revealed-pref.
Earnings	1.0	0.369	0.245
Stated-pref.		1.0	0.33
Revealed-pref.			1.0

The Earnings ranking is based on the occupational fixed effects of earnings from table A.4. The Stated-preference ranking is based on the occupational fixed effects of job-satisfaction based on table A.5. The Revealed-preference ranking is based on the estimates from model (3) in table 2.

Amenities in the labor market can take two forms. Compensating differentials, on the one hand, describe utility-equalizing amenities that workers receive in order to be compensated for lower pay. Compensating differentials in addition to the monetary compensation of occupations would leave workers indifferent between alternative occupations. Empirically, one expects to find a negative relationship between compensating differentials and pay. On the other hand, persistent utility-dispersing amenity differences may arise if workers differ in unobserved ability (Hwang et al., 1992) or as part of a search process that limits the free allocation of workers (Hwang et al., 1998). These forces commonly introduce a positive correlation between amenities and earnings. For a lack of better term, we will follow the notation in Sorkin (2018) and refer to the latter type as "Mortensen"-amenities (Mortensen, 2003).

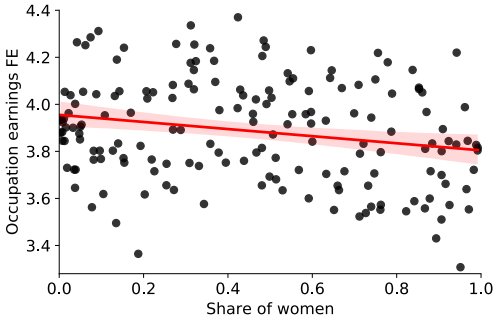
To understand which type of amenities drives the estimates of each method, we compute the rank-correlation with the earnings-fixed effect in table 3. We find that the rank-correlation between earnings and the stated-preference approach is significantly higher than the rank-correlation between earnings and the revealed-preference approach, which suggests that the latter captures compensating differentials while the former is more related to utility-dispersing "Mortensen"-amenities. Note, however, that we do not claim that the difference between compensating differentials and "Mortensen"-amenities is clearly identified and thus our results here are merely suggestive[10]. To highlight how these concepts of amenity dispersion affect our methods and interpretations of results, we provide two examples - one in which the rankings agree and another in which they disagree.

For the first example, we compute the share of women in each occupation as observed in the CPS data over our time frame from 1984 to 2002. Figure 3a displays a well-known fact about female labor market earnings. Not only do women earn less ($\sim$ 19% in our earnings regression in table A.4), but occupations with a higher share of women also pay less even after conditioning on demographics. Morchio and Moser (2018) use a similar approach to ours and find that compensating differentials explain a significant proportion of these differences in the context of firm amenities. Our findings from the revealed-preference approach are consistent with these results, as occupations with a higher share of women are estimated to have a higher non-financial value which offset parts of the earnings-loss of female-dominated occupations (3b). While the difference in earnings between occupations with the lowest and highest share of women amounts to approximately 0.22 units of log-earnings the additional

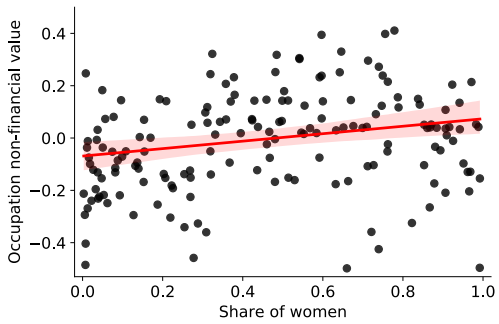
[10] Another potential source of disparities between the two methods is underlying differences in data quality. While the GSS has low overall sample size and is subject to idiosyncratic differences in the interpretation of survey questions, the CPS has a well-known problem in correctly classifying occupation changes (vom Lehn et al., 2022).

Figure 3: Financial and non-financial compensation in occupations with different gender composition

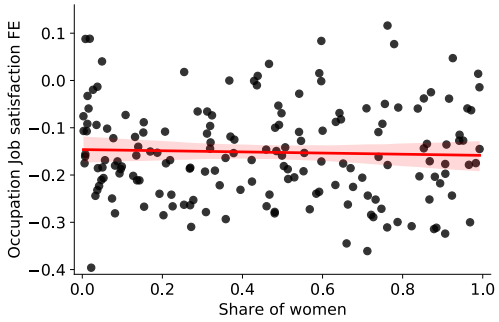
(a) Share of female workers vs. Earnings Fixed Effect



(b) Share of female workers vs. Non-financial value



(c) Share of female workers vs. Job satisfaction



non-financial value compensates for 0.11 units of log-earnings or half of the difference (see A.7). The same result does not appear from the stated-preference approach in figure 3c. The stated job satisfaction after controlling for demographics and income of occupations is largely unrelated with the share of women in these occupations, which suggests that the observed earnings-difference maps one-to-one to persistent utility dispersion between these occupations. The results from the stated-preference approach therefore point towards frictions (e.g. discrimination, social pressure) to explain these differences.

To give a suggestive example of "Mortensen"-amenities, we look at occupations relative to the share of college-educated workers in each occupation. Occupations with a high share of college-educated workers also provide higher earnings - even after accounting for the general education premium of $\sim$ 33% for college-educated workers over workers without a high-school degree in the earnings regression. Occupations with the highest share of college-educated workers command additional premium of $\sim$ 0.6 units of log-earnings (figure 4a). Trough the revealed-preference approach, this difference in compensation is is further increased by 0.4 log-earnings by the estimated value of the non-financial component of pay (figure 4c). This is consistent with a story of amenities of the "Mortensen" kind, in which search frictions or unobserved differences in productivity drive a positive correlation with financial and non-financial compensation and prevent the equalization of utility across workers. Interestingly, the same pattern now also appears in the ranking based on the stated-preference approach. After control-

ling for income and demographics, workers in occupations with the largest share of college-educated workers are about 15 percentage points more likely to indicate that they are very satisfied with their job. Contrary to the example above, the stated-preference approach seems to capture the relevant amenities, too.

The results above suggest that the revealed-preference approach remains consistent in a setting of compensating differentials as well as in amenities based on frictions, whereas the stated-preference approach fails to account for compensating differentials. For this interpretation to hold, workers must fail to incorporate some welfare-relevant job attributes when stating their job satisfaction. This pattern could arise, for example, if workers only considered job characteristics related to their experience at work when stating their satisfaction, but discarded those job characteristics that matter through their interaction with non-work activities, such as the flexibility to leave work early. By ignoring some of the trade-offs solved when choosing their occupations, workers would then state different preferences over occupations than what their occupation choices reveal. However, these conclusions are suggestive and should be taken with a grain of salt. In the first example, the question arises to what extend men and women differ in the preferences that they exhibit for occupational quality. Morchio and Moser (2018), for example, show that such preference heterogeneity in the revealed-preference approach matters greatly to account for differences in earnings and compensating differentials. Due to the data limitations - the sample size in many occupations would be small if restricted to only men or women - we are limited to impose a common ranking between both sexes.

The second example, on the other hand, suggests that there is utility dispersion between workers which could be rationalized by a frictional process of the allocation process. While the choice of occupations comes with many frictions due to educational and skill requirements, our approach here relies on two strong assumptions that abstracts from these elements: purely random search and homogeneous workers. It would require more data and a less parsimonious model of occupational choice to better understand the role of search frictions on the estimated non-financial values.

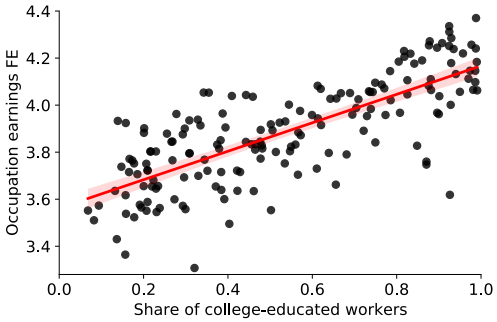
6 Conclusion

In this paper, we applied a new method from the literature of firm amenities and compensating differentials to estimate a revealed-preference ranking of occupations based on observed flows between occupations over time. In order to compare our ranking to an alternative measure of occupational quality, we use survey data of workers in the United States capturing a similar time frame as our sample of occupation switchers and compute a stated-preference ranking based on reported job satisfaction. The two approaches broadly deliver a similar ranking of occupations. In particular, the coefficient of rank correlation between the methods varies between 0.33 and 0.37, which indicates that the two rankings capture a weakly similar monotonic relationship. We find suggestive evidence that the revealed-preference approach captures compensating differentials which the stated-preference approach does not find. We gave an example - the occupational gender-earnings gap - where the differences matter for the interpretation of findings. In a second example - amenity dispersion between occupations with higher educational demands - both methods deliver the same conclusion.

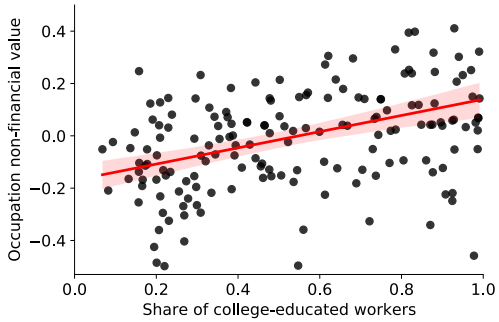
A main short-coming of the revealed-preference method as we have applied it here is that we are not able to distinguish occupational flows caused by changing skill demand over time. For instance, the rise of non-routine cognitive and associated fall of routine-manual work may give rise to reallocation

Figure 4: Financial and non-financial compensation in occupations with different skill level

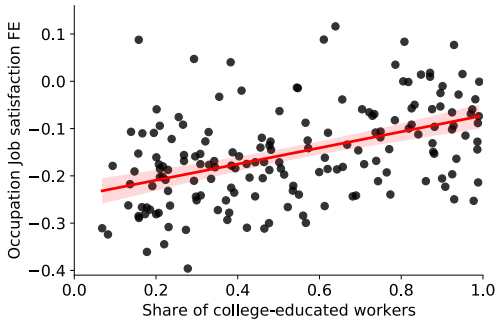
(a) Share of college-educated workers vs. Earnings Fixed Effect



(b) Share of college-educated workers vs. Non-financial value



(c) Share of college-educated workers vs. Job satisfaction



between occupations that is driven by demand for specific skills. Staying at the old occupation may no longer be in the choice set, contradicting the underlying assumption of discrete choice between two alternatives. The omission of these trends likely causes our estimates to biased in favor of growing occupations in the service sector and against shrinking occupations, e.g. those with high routine-manual task content. Additional work would explicitly model occupational demand and weigh observed occupational switches accordingly. A potential avenue would be to acquire detailed occupational vacancy data to proxy changing demand for different occupations over time.

Similarly, this paper does not account for possible heterogeneity in preferences or skills over occupations. This is partly due to design: our implied model is one of frictional search for new opportunities rather than the conventionally used Roy model of occupational choice (see Roy (1951) and French and Taber (2011) for a review). Understanding the bias of the presence of these selection forces and modelling their effect correctly would be an important next step[11].

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[11] See for example Taber and Vejlin (2020) and Lamadon et al. (2022) for recent advances in this direction in the context of firms.

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A Further tables and figures

Table A.4: Earnings regression

	Real log earnings	
Age	0.036***	0.029***
	(0.002)	(0.002)
Age^2	-0.000***	-0.000***
	(0.000)	(0.000)
Hours	0.040***	0.035***
	(0.000)	(0.000)
Female	-0.258***	-0.211***
	(0.002)	(0.002)
HS, some college		0.163***
		(0.003)
College		0.291***
		(0.004)
Year fixed effects	Yes	Yes
Occupation fixed effects	No	Yes
Industry fixed effects	No	Yes
Observations	270,901	270,901
R^2	0.444	0.539
Adjusted R^2	0.444	0.539
Residual Std. Error	0.511(df = 270876)	0.465(df = 270517)
F Statistic	9007.980*** (df = 24.0; 270876.0)	826.759*** (df = 383.0; 270517.0)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.6: Occupation-ranking with different methods. The output is restricted to occupations with more than 30 observations in the GSS.

Occupation code (name)	Revealed-pref. rank	Value	Survey rank	Value
2850 (Writers and Authors)	1	0.977	26	-0.053
310 (Food Service and Lodging Managers)	2	0.704	70	-0.141

Continued on next page

Table A.6: Occupation-ranking with different methods. The output is restricted to occupations with more than 30 observations in the GSS.

Occupation code (name)	Revealed-pref. rank	Value	Survey rank	Value
2040 (Clergy)	3	0.582	1	0.182
9140 (Taxi Drivers and Chauffeurs)	4	0.535	81	-0.159
3160 (Physical Therapists)	5	0.411	6	0.077
350 (Medical and Health Services Managers)	6	0.398	25	-0.050
130 (Human Resources Managers)	7	0.394	16	-0.001
620 (Human Resources, Training, and Labor Rela...	8	0.330	40	-0.082
3060 (Physicians and Surgeons)	9	0.322	38	-0.074
710 (Management Analysts)	10	0.318	75	-0.149
410 (Property, Real Estate, and Community Asso...	11	0.306	54	-0.109
230 (Education Administrators)	12	0.302	22	-0.028
5410 (Reservation and Transportation Ticket Ag...	13	0.296	137	-0.243
540 (Claims Adjusters, Appraisers, Examiners, ...	14	0.272	83	-0.162
120 (Financial Managers)	15	0.252	48	-0.100
2000 (Counselors)	16	0.251	35	-0.069
6240 (Carpet, Floor, and Tile Installers and F...	17	0.247	4	0.088
4820 (Securities, Commodities, and Financial S...	18	0.244	47	-0.096
3410 (Health Diagnosing and Treating Practitio...	19	0.239	43	-0.092
2340 (Other Teachers and Instructors)	20	0.238	5	0.084
4200 (First-Line Supervisors of Housekeeping a...	21	0.232	79	-0.154
1820 (Psychologists)	22	0.232	11	0.015
4620 (Recreation and Fitness Workers)	23	0.215	2	0.116
2540 (Teacher Assistants)	24	0.214	32	-0.063
3010 (Dentists)	25	0.207	84	-0.164
5110 (Billing and Posting Clerks)	26	0.204	136	-0.243
4210 (First-Line Supervisors of Landscaping, L...	27	0.183	8	0.040
530 (Purchasing Agents, Except Wholesale, Reta...	28	0.179	99	-0.181
4700 (First-Line Supervisors of Sales Workers)	29	0.165	62	-0.125
5330 (Loan Interviewers and Clerks)	30	0.156	159	-0.299
2330 (Special Education Teachers)	31	0.150	31	-0.059
3800 (Sheriffs, Bailiffs, Correctional Officer...	32	0.148	133	-0.240
4810 (Insurance Sales Agents)	33	0.147	74	-0.146
5000 (First-Line Supervisors of Office and Adm...	34	0.145	104	-0.185
8650 (Crushing, Grinding, Polishing, Mixing, a...	35	0.145	106	-0.187
5520 (Dispatchers)	36	0.143	107	-0.188
2200 (Postsecondary Teachers)	37	0.143	15	-0.001
4850 (Sales Representatives, Wholesale and Man...	38	0.141	93	-0.175
4920 (Real Estate Brokers and Sales Agents)	39	0.140	50	-0.106
430 (Managers, nec (including Postmasters))	40	0.139	59	-0.119
5120 (Bookkeeping, Accounting, and Auditing Cl...	41	0.135	64	-0.127
4030 (Food Preparation Workers)	42	0.128	114	-0.203
800 (Accountants and Auditors)	43	0.124	78	-0.153
7720 (Electrical, Electronics, and Electromech...	44	0.123	149	-0.271

Continued on next page

Table A.6: Occupation-ranking with different methods. The output is restricted to occupations with more than 30 observations in the GSS.

Occupation code (name)	Revealed-pref. rank	Value	Survey rank	Value
30 (Managers in Marketing, Advertising, and Pu...	45	0.118	57	-0.112
3300 (Clinical Laboratory Technologists and Te...	46	0.117	27	-0.057
3650 (Medical Assistants and Other Healthcare ...	47	0.108	95	-0.177
560 (Compliance Officers, Except Agriculture)	48	0.098	110	-0.193
4740 (Counter and Rental Clerks)	49	0.091	141	-0.252
4250 (Grounds Maintenance Workers)	50	0.081	61	-0.122
5600 (Production, Planning, and Expediting Cle...	51	0.075	90	-0.171
7420 (Telecommunications Line Installers and R...	52	0.073	87	-0.169
4840 (Sales Representatives, Services, All Other)	53	0.072	85	-0.168
5610 (Shipping, Receiving, and Traffic Clerks)	54	0.071	158	-0.293
1300 (Architects, Except Naval)	55	0.070	42	-0.088
3050 (Pharmacists)	56	0.068	123	-0.214
2630 (Designers)	57	0.065	36	-0.069
4220 (Janitors and Building Cleaners)	58	0.062	126	-0.222
2810 (Editors, News Analysts, Reporters, and C...	59	0.062	45	-0.094
1000 (Computer Scientists and Systems Analysts...	60	0.058	34	-0.066
5400 (Receptionists and Information Clerks)	61	0.052	91	-0.175
2430 (Librarians)	62	0.052	21	-0.025
5510 (Couriers and Messengers)	63	0.051	162	-0.310
2310 (Elementary and Middle School Teachers)	64	0.051	24	-0.038
4010 (First-Line Supervisors of Food Preparati...	65	0.046	128	-0.225
3240 (Therapists, nec)	66	0.043	28	-0.059
2300 (Preschool and Kindergarten Teachers)	67	0.042	12	0.014
2750 (Musicians, Singers, and Related Workers)	68	0.042	13	0.010
5860 (Office Clerks, General)	69	0.040	88	-0.171
4000 (Chefs and Cooks)	70	0.040	94	-0.176
5810 (Data Entry Keyers)	71	0.039	164	-0.312
2010 (Social Workers)	72	0.039	117	-0.206
730 (Other Business Operations and Management ...	73	0.038	67	-0.134
5850 (Mail Clerks and Mail Machine Operators, ...	74	0.037	150	-0.272
5310 (Interviewers, Except Eligibility and Loan)	75	0.036	112	-0.197
3130 (Registered Nurses)	76	0.033	58	-0.115
9130 (Driver/Sales Workers and Truck Drivers)	77	0.031	130	-0.232
4950 (Door-to-Door Sales Workers, News and Str...	78	0.029	41	-0.088
2600 (Artists and Related Workers)	79	0.024	9	0.035
2320 (Secondary School Teachers)	80	0.021	65	-0.128
4800 (Advertising Sales Agents)	81	0.019	132	-0.239
4760 (Retail Salespersons)	82	0.019	129	-0.231
520 (Wholesale and Retail Buyers, Except Farm ...	83	0.016	109	-0.192
7950 (Cutting, Punching, and Press Machine Set...	84	0.013	108	-0.191
5140 (Payroll and Timekeeping Clerks)	85	0.010	68	-0.135
7010 (Computer, Automated Teller, and Office M...	86	0.004	122	-0.211

Continued on next page

Table A.6: Occupation-ranking with different methods. The output is restricted to occupations with more than 30 observations in the GSS.

Occupation code (name)	Revealed-pref. rank	Value	Survey rank	Value
7700 (First-Line Supervisors of Production and...	87	0.001	76	-0.150
5620 (Stock Clerks and Order Fillers)	88	-0.004	151	-0.278
6260 (Construction Laborers)	89	-0.007	46	-0.094
4510 (Hairdressers, Hairstylists, and Cosmetol...	90	-0.011	7	0.047
6200 (First-Line Supervisors of Construction T...	91	-0.012	23	-0.033
8300 (Laundry and Dry-Cleaning Workers)	92	-0.024	97	-0.179
5540 (Postal Service Clerks)	93	-0.024	146	-0.266
5260 (File Clerks)	94	-0.033	115	-0.204
7340 (Maintenance and Repair Workers, General)	95	-0.036	101	-0.184
6440 (Pipelayers, Plumbers, Pipefitters, and S...	96	-0.037	52	-0.107
4230 (Maids and Housekeeping Cleaners)	97	-0.047	124	-0.218
3820 (Police Officers and Detectives)	98	-0.051	37	-0.073
2100 (Lawyers, and judges, magistrates, and ot...	99	-0.051	72	-0.144
4050 (Combined Food Preparation and Serving Wo...	100	-0.051	163	-0.311
8000 (Grinding, Lapping, Polishing, and Buffin...	101	-0.052	148	-0.267
1410 (Electrical and Electronics Engineers)	102	-0.052	139	-0.250
4750 (Parts Salespersons)	103	-0.071	100	-0.182
6320 (Construction equipment operators except ...	104	-0.075	30	-0.059
4040 (Bartenders)	105	-0.075	131	-0.235
8740 (Inspectors, Testers, Sorters, Samplers, ...	106	-0.076	134	-0.241
7000 (First-Line Supervisors of Mechanics, Ins...	107	-0.086	89	-0.171
1430 (Industrial Engineers, including Health a...	108	-0.094	121	-0.211
150 (Purchasing Managers)	109	-0.094	14	-0.000
4600 (Childcare Workers)	110	-0.097	63	-0.127
3740 (Firefighters)	111	-0.099	3	0.088
9640 (Packers and Packagers, Hand)	112	-0.104	157	-0.289
2140 (Paralegals and Legal Assistants)	113	-0.104	71	-0.144
7020 (Radio and Telecommunications Equipment I...	114	-0.106	60	-0.119
4130 (Food preparation and serving related wor...	115	-0.108	168	-0.361
9600 (Industrial Truck and Tractor Operators)	116	-0.114	153	-0.281
9000 (Supervisors of Transportation and Materi...	117	-0.117	69	-0.140
8610 (Stationary Engineers and Boiler Operators)	118	-0.121	20	-0.020
2700 (Actors, Producers, and Directors)	119	-0.123	17	-0.010
1550 (Engineering Technicians, Except Drafters)	120	-0.124	105	-0.186
5820 (Word Processors and Typists)	121	-0.129	160	-0.300
3500 (Licensed Practical and Licensed Vocation...	122	-0.130	29	-0.059
8140 (Welding, Soldering, and Brazing Workers)	123	-0.131	98	-0.180
7140 (Aircraft Mechanics and Service Technicians)	124	-0.131	18	-0.013
9610 (Cleaners of Vehicles and Equipment)	125	-0.137	156	-0.285
9620 (Laborers and Freight, Stock, and Materia...	126	-0.138	144	-0.263
1010 (Computer Programmers)	127	-0.139	66	-0.131
5550 (Postal Service Mail Carriers)	128	-0.151	102	-0.185

Continued on next page

Table A.6: Occupation-ranking with different methods. The output is restricted to occupations with more than 30 observations in the GSS.

Occupation code (name)	Revealed-pref. rank	Value	Survey rank	Value
7800 (Bakers)	129	-0.152	119	-0.208
1540 (Drafters)	130	-0.153	53	-0.108
8030 (Machinists)	131	-0.154	120	-0.210
5700 (Secretaries and Administrative Assistants)	132	-0.155	73	-0.145
4430 (Entertainment Attendants and Related Wor...	133	-0.161	116	-0.205
8800 (Packaging and Filling Machine Operators ...	134	-0.165	143	-0.262
7750 (Assemblers and Fabricators, nec)	135	-0.168	154	-0.281
8810 (Painting Workers and Dyers)	136	-0.168	56	-0.110
4720 (Cashiers)	137	-0.174	165	-0.314
5800 (Computer Operators)	138	-0.176	125	-0.221
1960 (Life, Physical, and Social Science Techn...	139	-0.182	135	-0.242
7810 (Butchers and Other Meat, Poultry, and Fi...	140	-0.192	147	-0.266
7330 (Industrial and Refractory Machinery Mech...	141	-0.196	138	-0.244
5160 (Bank Tellers)	142	-0.204	96	-0.178
8320 (Sewing Machine Operators)	143	-0.209	166	-0.324
7210 (Bus and Truck Mechanics and Diesel Engin...	144	-0.213	39	-0.076
6520 (Sheet Metal Workers, metal-working)	145	-0.218	118	-0.206
1530 (Engineers, nec)	146	-0.219	111	-0.197
1460 (Mechanical Engineers)	147	-0.224	127	-0.223
1920 (Chemical Technicians)	148	-0.225	145	-0.264
6420 (Painters, Construction and Maintenance)	149	-0.231	103	-0.185
7360 (Millwrights)	150	-0.240	169	-0.396
1360 (Civil Engineers)	151	-0.249	49	-0.102
6050 (Agricultural workers, nec)	152	-0.254	77	-0.153
4110 (Waiters and Waitresses)	153	-0.265	140	-0.252
6230 (Carpenters)	154	-0.269	44	-0.092
7220 (Heavy Vehicle and Mobile Equipment Servi...	155	-0.294	92	-0.175
8220 (Metal workers and plastic workers, nec)	156	-0.295	113	-0.202
8230 (Bookbinders, Printing Machine Operators,...	157	-0.304	86	-0.169
4060 (Counter Attendant, Cafeteria, Food Conce...	158	-0.325	161	-0.308
2910 (Photographers)	159	-0.327	33	-0.066
2720 (Athletes, Coaches, Umpires, and Related ...	160	-0.341	10	0.018
5100 (Bill and Account Collectors)	161	-0.359	155	-0.284
8100 (Molders and Molding Machine Setters, Ope...	162	-0.360	152	-0.278
7200 (Automotive Service Technicians and Mecha...	163	-0.404	80	-0.156
8350 (Tailors, Dressmakers, and Sewers)	164	-0.425	55	-0.109
1720 (Chemists and Materials Scientists)	165	-0.458	142	-0.253
7150 (Automotive Body and Related Repairers)	166	-0.485	82	-0.161
3640 (Dental Assistants)	167	-0.496	19	-0.014
5560 (Postal Service Mail Sorters, Processors,...	168	-0.498	167	-0.345
6220 (Brickmasons, Blockmasons, and Stonemasons)	169	-0.608	51	-0.107

Table A.5: Regression of job satisfaction on demographics and earnings. The dependent variable corresponds to an indicator of the variable "satjob" of the General Social Survey (conducted between 1974 and 2021). The dependent variable is 1 whenever the respondent selected "Very satisfied" as a response.

	Job satisfaction	
Age	0.005***	0.005***
	(0.000)	(0.000)
Female	0.042***	0.036***
	(0.006)	(0.007)
Hours	0.002***	0.002***
	(0.000)	(0.000)
Race: Black	0.016	0.088
	(0.113)	(0.115)
Race: Other	0.071	0.136
	(0.114)	(0.115)
$<$ 1000$	0.096	0.208*
	(0.117)	(0.123)
1000-2999$	0.101	0.213*
	(0.116)	(0.123)
3000-3999$	0.117	0.235*
	(0.117)	(0.123)
4000-4999$	0.068	0.180
	(0.117)	(0.124)
5000-5999$	0.123	0.231*
	(0.117)	(0.123)
6000-6999$	0.105	0.208*
	(0.117)	(0.124)
7000-7999$	0.070	0.186
	(0.117)	(0.124)
8000-9999$	0.075	0.184
	(0.116)	(0.123)
10000-14999$	0.107	0.212*
	(0.116)	(0.123)
15000-19999$	0.114	0.207*
	(0.116)	(0.123)
20000-24999$	0.120	0.214*
	(0.116)	(0.123)
$>$25000$	0.178	0.250**
	(0.116)	(0.123)
Occupation fixed effects	No	Yes
Year fixed effects	Yes	Yes
Observations	30,723	30,545
R^2	0.039	0.078
Adjusted R^2	0.038	0.063
Residual Std. Error	0.490(df = 30675)	0.484(df = 30051)
F Statistic	26.762*** (df = 47.0; 30675.0)	5.136*** (df = 493.0; 30051.0)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.7: Regressions of Earnings, Stated-preferences and Revealed-preferences on the share of women and college-educated workers per occupation. The Earnings ranking is based on the occupational fixed effects of earnings from table A.4. The Stated-preference ranking is based on the occupational fixed effects of job-satisfaction based on table A.5. The Revealed-preference ranking is based on the estimates from model (3) in table 2.

	Earnings	Stated-pref.	Revealed-pref.
Share: women	-0.218***	-0.031	0.111**
	(0.031)	(0.023)	(0.050)
Share: college-educated	0.634***	0.175***	0.295***
	(0.035)	(0.026)	(0.057)
Observations	171	171	171
R^2	0.681	0.219	0.174
Adjusted R^2	0.677	0.210	0.164
Residual Std. Error	0.124(df = 168)	0.092(df = 168)	0.203(df = 168)
F Statistic	178.976*** (df = 2.0; 168.0)	23.596*** (df = 2.0; 168.0)	17.663*** (df = 2.0; 168.0)
Note:			*p<0.1; **p<0.05; ***p<0.01