Preliminary and Incomplete

Does Rosie Like Riveting?
Male and Female Occupational Choices

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April 2015

Abstract: Occupational segregation and pay gaps by gender remain large while many of the constraints traditionally believed to be responsible for these gaps have weakened over time. Here, we explore the possibility that women and men have different tastes for the content of the work they do. We run regressions of job satisfaction on the share of males in an occupation. Overall, there is a strong negative relationship between female satisfaction and the share of males. This relationship is fairly stable across different specifications and is not attenuated by personal characteristics or proxies of job flexibility. The effect is muted for women but largely unchanged for men when we include three measures that proxy the content and context of the work in an occupation, which we label 'people,' 'brains,' and 'brawn.' These results suggest that women may care more about job content, and this is a possible factor preventing them from entering some male dominated professions.

JEL classifications: J16, J4
Keywords: Occupational choice, job content, gender, preferences

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Introduction

Women's progress in the labor market has been dramatic since the 1960s. The female employment rate has risen, the pay gap with men has declined, and occupational segregation has decreased. Figure 1 shows the share of males in the occupations in which women work. Despite all the progress, it is a striking feature that female convergence has slowed and possibly stopped since about the turn of the millennium, while sizeable differences remain between the jobs done by women and men. One particular concern is that females are still underrepresented in many high paying professional and managerial occupations (see Figure 2 and Goldin, 2014), while average female earnings still lag behind male earnings (Blau and Kahn, 2006 and Blau and Kahn, 2000). Since occupational earnings differences are large, the underrepresentation of women in many high-paying, male dominated professions remains a major candidate for the residual gender wage gap (Macpherson and Hirsch 1995; Bielby and Baron 1984; Bayard et al, 2003). For example in 2014, the average hourly wage of individuals who work in majority male occupations (proportion of males >=0.70) is about \$23.67, versus \$19.30 for those in minority male occupations (proportion of males <=0.30).[1]

The traditional explanations for these wage gaps are discrimination, labor supply and human capital investments, and barriers, which make it difficult to combine work and family.[2] More recently, the literature has turned towards the role of attitudes, tastes, and gender identity as possible explanations for different labor market choices and outcomes of men and women (e.g. Pinker, 2008, Bertrand, 2010). However, the role of many of the variables suggested as explanations for lower female earnings remain empirically elusive (Manning and Swaffield, 2008).

In this paper we focus on tastes for particular job attributes as an explanation for the remaining occupational segregation. We estimate job satisfaction equations for men and women. We complement these with regressions for more traditional labor market outcomes; namely transitions between occupations and leaving the labor force. One of our key regressors is the share of men in an occupation. Like Usui (2008), who uses the National Longitudinal Survey of Youth 1979 (NLSY79) from 1979-1982, we find that that women are

1. Based on the 2014 Current Population Survey (CPS) monthly outgoing rotation group data.
2. See Altonji and Blank (1999). Women's "Second Shift" when they combine market work with home making is portrayed by Hochschild and Machung (1989).

less satisfied in male dominated jobs, while males either like or are indifferent to the share of males in an occupation**.** In addition, we find that women are more likely to leave occupations with a higher share of males, whereas males are more likely to stay. We document these relationships for the US, Britain, and Russia. The basic patterns are robust to including many other occupation and individual characteristics, as well as individual fixed effects.

The core of our analysis links job satisfaction to attributes of the work done in various occupations. The idea is that women may not like the nature of male dominated jobs. This hypothesis underlies work by Pinker (2008), who argues that females and males have different strengths, which lead them to gravitate towards different occupations. She argues that women tend to prefer jobs that require empathy and interacting with people. Conversely, men like work that requires them to 'make things.' Pinker (2008) sees this as the reason why women are less likely to become aerospace engineers and are more likely to enter teaching. To empirically examine this hypothesis, we parsimoniously summarize occupational content in three latent factors, distilled from descriptions in the ONET database, which we label 'people,' 'brains,' and 'brawn.' The occupational content measures matter for both male and female job satisfaction. We find that female job satisfaction is higher in occupations that have high 'people' and 'brain' content but is lower for 'brawn.' Conversely, males are indifferent to jobs that have high brawn content. Importantly, including these measures reduces the coefficient on the share of men in the occupation by around a third for women, while it does little to the coefficient in the male job satisfaction regressions.

While far from definite, these results suggest that differential tastes by gender may be an important ingredient in explaining the occupational choices of men and women. Preferences could be determined either biologically or through socialization. Using saliva based measures of testosterone, we find no direct evidence for the biology view but this may be due to data imperfections.

While direct preference based explanations have been gaining prominence in some quarters they have not featured prominently in the economics literature so far. Economists have focused on differentials in risk aversion or attitudes towards competition (see Bertrand, 2010) rather than on the nature of the work per se. We hope our results will spark the interest of economists to engage in more research on this topic.

Data

US:

We use the NLSY79, a panel of 12,686 individuals who were between 14 and 22 years old when first surveyed in 1979. These individuals were interviewed annually through 1994 and then on a biennial basis. The NLSY79 sample spans 1979 to 2012.

The question on job satisfaction was asked in every wave. Specifically, respondents were asked, "How do you feel about the job you have now?" and were given the following response option: I like it very much; I like it fairly well; I dislike it somewhat; I dislike it very much. We coded responses so that higher values represent higher satisfaction. Our analysis is restricted to an unbalanced panel of employees who responded to this job satisfaction question. The NLSY79 uses the US Census Bureau occupation definitions. Specifically, the 1982-2000 and 2002-2012 waves use the 1980 and 2000 codes respectively. Our analysis sample spans the years 1982 to 2012.

We create two additional dependent variables that capture movements in the labor market.[3] The first is defined equal to 1 in period t+1 if a person changed employer and had a different occupation in t+1 compared to the occupation that they held in t, and 0 otherwise.[4] We call these individuals movers. The second measure for leavers is 1 in period t+1 if a person was employed in period t but left the labor force in period t+1 and 0 otherwise.

We use the pooled monthly CPS samples from 1983-1991 and 2003-2010 to calculate the proportion of males in each occupation for the 1980 and 2000 three-digit occupation codes respectively.[5] In particular, the share of males (SOM) is calculated as the count of men within occupation j divided by the total number of workers in the same occupation. Additionally, we calculate averages of the hourly wage,[6] hours, the proportion college graduates, and age for each occupation. We match the CPS averages derived from the 1980 occupation codes to the 1982-2000 NLSY data and the averages derived from the 2000 occupation codes to the 2002-2012 NLSY data. There is a single average for all the years within the sub-periods when occupation codes are unchanged. Hence, we exploit cross-sectional variation and variation

3. Give that both of these outcomes rely on comparing occupation codes across periods, this analysis omits the year 2000 from the analysis.
4. Practically, this is equal to 1 if a person's occupation code in t+1 is different to that documented in t, and they started a job with a new employer between the two survey periods.
5. From 1992- 2002 the CPS uses 1990 occupation codes.
6. Hourly wages are calculated from the Merged Outgoing Rotation Groups.

due to occupation switchers but not variation over time in these averages in the estimation. In order to allow for the break in the occupation coding, we control for individual times sub-period specific fixed effects in some of our regressions. We also utilize sampling weights that reflect that the NLSY79 oversampled blacks, Hispanics, and the economically disadvantaged (see online appendix D for the unweighted results).

Britain:

We use all 18 waves of the original sample of the British Household Panel Survey (BHPS), a longitudinal study of around 5,500 households and over 10,000 individuals that began in 1991. This main sample was supplemented in later years with a Welsh extension from 1999 (about 1500 households), a Scottish extension from 1999 and a Northern Ireland extension from 2001 (about 1900 households). We present unweighted results from the unbalanced panel of all individuals included in the data between 1991 and 2008.[7]

The BHPS contains a number of different job satisfaction questions, which are available for the full 18 waves. In particular, we use the questions asking respondents how satisfied or dissatisfied they are with i) their current job overall and ii) the actual work itself. Answers are on a 7-point scale. The BHPS uses occupation codes based on the Standard Occupational Classification 1990 (SOC90) up to 2001; in 2002 this was replaced with SOC 2000 (SOC00).

We again create two additional dependent variables that capture whether a person moved occupations between two periods and whether they left the labor force between the two periods.[8] These are binary outcomes and are consistent with the definitions described for the NLSY79 analysis.

We measure the SOM in an occupation using the 1993-2012 Quarterly Labor Force Survey (QLFS). The QLFS is the main survey of individual economic activity in the Britain, and

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[7.] We have investigated the sensitivity of our results to i) unweighted regressions of the original BHPS sample only ii) weighted regressions of the main BHPS sample, where the weights are the longitudinal weights described in Taylor et al (2010) (these are the weights recommended for use in longitudinal analysis, however we lose a significant amount of our sample owing to these weights only being provided when an individual was present in all waves. The conclusions in this work are robust to these changes. Additionally, the Understanding Society Study is a successor to the BHPS (see https://www.understandingsociety.ac.uk/documentation). The BHPS sample forms part of Understanding Society from Wave 2 (equivalent to wave 19 in the BHPS) onwards. Thus, we have also considered analysis, which includes the BHPS respondent's responses from waves 19 through 21. This is not our main sample, given that Understanding Society does not routinely ask the job satisfaction question that pertains to work itself. Again, the conclusions are robust to this additional analysis. See online appendix D for these results.

[8.] Give that both of these outcomes rely on comparing occupation codes across periods, this analysis omits the year 2002 from the analysis.

provides the official measure of the national unemployment rate. It uses SOC90 codes from 1993 through 2000 and UK SOC00 from 2001. Thus, we calculate the same occupation averages as for the NLSY for each sub-period when the SOC90 and SOC00 were used. These are then matched into the BHPS data. We allow for individual sub-period specific fixed effects in some of our regressions.

Russia:

Our measure of job satisfaction for Russia comes from the Russian Longitudinal Monitoring Survey (RMLS). This is a series of nationally representative annual surveys, with data available from 1994-2012. However, job satisfaction data is only available from 2002-2012. We restrict our sample to employees who answer the question: "How satisfied or unsatisfied are you with your job in general?" Response options are absolutely satisfied, mostly satisfied, neutral, not very satisfied and absolutely unsatisfied. We code responses so that higher values represent being more satisfied. We create two binary dependent variables that capture labor market movements whose definition is consistent with the definitions described for the NLSY analysis.[9]

We do not have a large labor force survey that allows us to calculate occupation averages for Russia, like the US CPS or British QLFS. Instead, we rely on merging the RMLS from 1994-2012 with two other data sources, the International Social Survey Program (ISSP) 1995-2011[10] and the European Social Survey (ESS) from 2002-2012.[11] Pooling the ISSP 1995-2011, the ESS 2002-2012 and the RMLS 1994-2012, we calculate the SOM in each occupation, along with the other occupation averages, age, hours and proportion of college graduates. Only the RMLS reports individual earnings and, as a result, we calculate the average wage from this data source only. Our RMLS regressions use weights that allow for the complex design of the RMLS where many observations are derived from following the housing unit rather than the person, as well as having oversamples from the first wave to allow for forecasted attrition. However, the overall conclusions are not sensitive to weighting, and unweighted regressions can be seen in appendix D.

[9] With the exception that for movers we do not observe if the person is with a new employer so the definition simply relies on a person switching their occupation

[10] http://www.issp.org/page.php?pageId=4

[11] http://www.europeansocialsurvey.org/

Methods and Results

Our starting point is a linear regression for job satisfaction or mobility of the form

$$Y_{ijt} = \delta SOM_j + X_j\beta + X_{ijt}\gamma + \mu_t + \varpi_a + \varepsilon_{ijt} \qquad (1)$$

where Y_{ijt} is either job satisfaction or a binary labor market outcome of individual i in occupation j and year t, SOM_j is the proportion of males in a particular occupation, X_j is a vector of other occupational averages, X_{ijt} is a vector of individual-level control variables, μ_t are wave effects, and ϖ_a are region effects.[12] In the baseline specification, X_j contains average wages, hours, age, and the proportion college graduates, while X_{ijt} contains age and age squared. We calculate standard errors using two-way clustering by individual and occupation.[13]

The coefficient of interest in equation (1) is δ. For example, in mover regressions, a positive coefficient implies that a higher SOM in an occupation is associated with a higher tendency to move occupation. For the job satisfaction regressions a negative coefficient implies that a higher SOM in an occupation is associated with lower levels of job satisfaction. To make the interpretation of δ more intuitive in the job satisfaction regressions (given that the job satisfaction scales differ across country) we follow van Praag and Ferrer-i-Carbonell (2008) and normalize the job satisfaction variables by using the fitted values from an ordered probit on the raw sample fractions. We estimate equation (1) separately for males and females.

Table 1 displays our baseline results for job satisfaction. The SOM in an occupation is consistently associated with lower levels of job satisfaction for women, and the magnitudes seem sizeable. For the US, the coefficient on the SOM is -0.263. This implies that a 10-percentage point increase in the SOM (approximately the effect of moving from more female accounting to more male pharmacy (see Figure 2)) is associated with 2.6% of a standard deviation lower job satisfaction. For the BHPS, a 10-percentage point increase in the SOM

12. For the BHPS this amounts to the inclusion of 19 fixed effects representing the following regions: inner London, outer London, rest of the South East, South West, East Anglia, East Midlands, West Midlands Conurbation, Rest of the West Midlands, Greater Manchester, Merseyside, Rest of the North West, South Yorkshire, West Yorkshire, Rest of Yorks and Humberside, Tyne and Wear, Rest of the North, Wales, Scotland and Northern Ireland. For the United States, regions are at a higher level, so we control only for whether the respondent resides in the North East, North Central, South or West. For Russia we include eight individual site indicators

13. See Cameron, Gelbach, and Miller (2011). Practically this is implemented using ivreg2 and xtivreg2 as appropriate in Stata.

has a lower association at 1.4%. For Russia a 10-percentage point increase in the SOM is associated with 1.8% of a standard deviation lower job satisfaction. For the BHPS, in addition to overall job satisfaction, we also have a measure of satisfaction with work itself. A 10-percentage point increase in the SOM in an occupation is associated with a larger 3.2% of a standard deviation decline in satisfaction, compared to the 1.4% lower effect for overall job satisfaction.

The results for males, on the other hand, are much smaller in magnitude, not significant and centered more closely around zero. These regressions control for a number of other occupation averages: the log of wages, hours, age, and the fraction of college graduates. Particularly age, wages, and the fraction of educated workers are important correlates with job satisfaction but for women the SOM certainly plays a sizeable role in explaining job satisfaction**.**

The results from the mover and leaver regressions are documented in Table 2. For brevity, coefficients for occupation averages other than the SOM are not shown in the table. For all three countries, higher shares of males in period *t* increase the likelihood that women change occupation in *t*+1. For males, our findings for all three countries suggest the opposite. For example, the associations for the US imply that a 10-percentage point increase in the SOM in an occupation increases the probability of a female changing her occupation by 2.4 percentage points. Conversely, for males the same increase implies that they are about 1-percentage points less likely to change their occupation. Females in the US and Britain are also significantly more likely to leave the labor force in *t*+1 if they are working with higher SOM in period *t* but the size of the effect is lower than for occupational switches. However, males in the US are also more likely to leave jobs with higher SOM in the same period.[14] The associations are not significant for Russia, as well as for British males.

One important issue in interpreting the results from a regression like (1) is how people sort into heterogeneous occupations. The standard compensating differentials framework suggests that workers pick among packages of wages and job attributes while employers offer such packages in order to attract workers. To the degree that workers differ, they will sort into the type of jobs they prefer in equilibrium. Wages adjust to eliminate any excess

[14] This seems to be driven by blue-collar roles and is in line with the idea that blue collar male jobs were shed over this period (Autor and Wasserman, 2013).

supplies and demands, so that occupation wage differentials reflect the compensating differentials required by marginal workers who are indifferent between two different jobs. This framework predicts that men and women may end up working in different jobs in equilibrium if they have different preferences for job attributes or if they face different constraints (say in terms of hours choices or flexible schedules an occupation offers). In this scenario, it is unlikely that job satisfaction will reflect preferences. One reason is that much of the variation in (1) is cross-sectional, and it is unclear whether the answers to job satisfaction questions are comparable across individuals. The fixed effects specifications we explore below address this issue. Another reason is that everybody works in their most preferred occupation, given equilibrium wages, in the competitive compensating differentials model, and hence should report their maximum job satisfaction attainable.

The frictionless, full information framework underlying the standard model is unlikely to be a good representation of actual labor markets, where individuals often make choices subject to constraints and frictions. Modeling occupational choices and wage differentials in a framework with frictions can lead to very different equilibrium outcomes (see Manning, 2003). One implication is that wages no longer reflect compensating differentials. Rather, employers with wage setting powers will use wage-amenity packages to attract workers, and wages and amenities may be positively correlated in equilibrium. Furthermore, workers may end up in jobs other than their preferred one, and they will switch jobs in search of better matches. This "frictional disequilibrium" constitutes a natural source for interpreting the results from job satisfaction equations like (1). As there are good jobs and bad jobs, as well as high and low quality matches in this framework, the coefficients on occupation characteristics have a more natural interpretation as individual preferences for these characteristics in this framework. It also offers a natural point of departure for interpreting the mobility regressions, as there is no reason for systematic job changes in the frictionless model. However, the caveat that within person comparisons should be more accurate still applies in the model with frictions as well.

In Table 3 we add individual fixed effects to equation (1). Including these effects amounts to identifying the effect of the share of men from occupation switchers, while controlling for time invariant individual differences. Recall that the occupation coding changed in the US and British data sets over time. In order to exploit only variation within periods with consistent occupation codes, we interact the individual fixed effects with indicators for the sub-periods without coding changes. Denoting these sub-periods by *s*, we estimate:

$$Y_{ijt} = \alpha_{is} + \delta SOM_{js} + X_{js}\beta + X_{ijt}\gamma + \mu_t + \varpi_a + \varepsilon_{ijt} \quad (2)$$

From Table 3, including the fixed effects attenuates the female coefficients on the SOM somewhat in the US and Russia but has little impact in Britain. In fact, the coefficient for overall job satisfaction is significantly larger in absolute value. The SOM coefficients for males also change little for Britain while in Russia and the US, the coefficients for males are now negative and significant. However, the male coefficients always remain substantially smaller than the female coefficients. Overall, accounting for fixed effects fails to explain the negative correlation between job satisfaction and the SOM.

Occupational mobility also remains strongly related to the SOM in all three countries. In particular, as the SOM increases in an occupation a female is more likely to change occupation, whereas a male is more likely to stay. Table 3 also suggests that females are more likely to leave the labor force in Britain if they work in occupations with more men.

We have also considered adding a number of individual factors to the specification outlined in equation (2). In particular we include covariates that are traditional in the job satisfaction literature in the spirit of Clark (1996) and Clark and Oswald (1996), the log of own income, own working hours, household size, number of children, a dummy for college graduates, and marital status. In addition, we created measures for the flexibility of hours in an occupation. The importance of flexibility for females in the workplace has been emphasized in the literature (Goldin, 2014; Goldin and Katz, 2008; Goldin and Katz, 2011; Goldin and Katz, 2012), with some suggesting that career women are 'opting elsewhere' in choosing occupations that allow them to accommodate family responsibilities (Polachek, 1981; Belkin, 2003; Stone, 2007). Adding these variables leaves the coefficients on the SOM unchanged or increases them slightly in absolute value when compared to Table 3 (see Appendix A).

People, brains, and brawn

Why do women report lower job satisfaction when they work in occupations with a high share of males? One hypothesis is that men and women have different preferences for characteristics and attributes of jobs, as well as the environment in which they work. Individuals sort to some degree into jobs according to these preferences, and the observed SOM therefore reflects male and female preferences. Difference in tastes by gender for particular occupation traits may also explain why our coefficient on the SOM is not significant in the male regressions documented in Table 3, but for females it is mostly negative and significant. That is, over time females have entered into roles that were previously male dominated so they now have some presence in these relatively male jobs. If these are bad matches this will show up in reports of low job satisfaction. However, the gender revolution has been an asymmetric one (see, for example, Figure 2). That is, it is a revolution in which females have increasingly assumed male jobs, but males have not to the same extent moved into traditional female jobs (like nursing and teaching). So, males remain less likely to find themselves working in occupations that require the empathy they lack, while females may more often find themselves in environments that are focused on tasks they care little about.

In order to probe the possibility that the SOM proxies for the content of the work, which is what women may care more about, we would like to control for the occupation characteristics which are related to such preferences directly. Therefore we turn to the ONET database version 5.[15] ONET provides a diverse set of information on occupational attributes, requirements, and characteristics of the workers in an occupation; all in all it offers about 249 distinct items. Out of these we start with the 79 items describing the work activities and context of a person's occupation at the US 2000 SOC level. For each individual item, a level from 1 to 7 is reported. For example, in activities, an item might describe to which degree an occupation involves 'assisting and caring of others,' 'analyzing data or information,' or 'repairing and maintaining of mechanical equipment.' Examples for context are the level of 'contact with others,' 'the importance of being exact or accurate,' and 'being exposed to hazardous conditions' (see Appendix C Table C.3 for all attributes). We standardize each of these variables to have a mean of 0 and a standard deviation of 1.

[15.] We choose to work with this level as we have a crosswalk between the US and British occupation codes mapping ONET 5 to the SOC00.

We utilize a crosswalk provided by the Bureau of Labor Statistics to assign a Census 2000 occupation code to each occupation in the ONET file.[16] We then rely on the crosswalks from Autor and Dorn (2013) and Dorn (2009) to convert occupations to Census 1970, 1980 and 2000 codes. Using these two crosswalks we match the ONET data to the CPS from 1979-2012. This gives us a data set that represents the distribution of occupation characteristics for the US from 1979-2012.

We could add the 79 context and activities variables to our regressions directly. However, we are worried about the dangers of overfitting by using a large number of covariates, so we follow the psychometric literature (Gorsuch, 1983, 2003; Thompson, 2004) and use exploratory factor analysis to reduce the dimensionality of the ONET variables first.[17] This exercise leads us to three latent factors that can loosely be labeled 'people,' 'brain,' and 'brawn'. We choose these names based on the items that load onto each factor (see Appendix C Table C.3 for full details of loading). We next match the occupation specific factors into the NLSY data.

We note that our approach is different to that taken by Beaudry and Lewis (2014), who utilize the DOT (the predecessor to ONET) to manually pick the attributes that they view as being associated with physical, cognitive and people skills in an occupation. We rely on a more mechanical method to reduce the dimensionality of the data to avoid handpicking occupational attributes, which fit our prejudices. Nonetheless, we arrive at a roughly similar classification. Table 4 lists the top and bottom ten occupations for each of the three factors. In addition, Table 5 documents the scores for a number of white-collar occupations, which we find useful to think about occupational segregation. The factors have a mean 0 and standard deviation 1, so mechanical engineers, for example, score half a standard deviation below the mean on people, and a bit more than 2 standard deviations above the mean on brains. We note that many occupations that females seem to avoid tend score negative on the people factor (like engineering, mathematics, economics, and software development) while occupations that females are dominant in are high on people (teaching, nursing and social work). From Table 4, the highest levels of brawn are associated with blue-collar workers,

16. https://www.census.gov/people/eeotabulation/documentation/jobgroups.pdf

17. To extract the underlying latent factors, we first determine the number of factors to retain based on a scree plot from an orthogonal exploratory analysis and the eigenvalue of each individual factor (see Appendix C; results are robust to considering correlated factors). Confirmatory factor analysis (CFA) is then performed to extract the final latent variables. (Gorsuch, 2003; Thompson, 2004).

however engineering is also high on brawn. We note that physicians and nurses are also associated with positive brawn, but differ from engineering in that they are high on people as well. As expected, all white-collar jobs are associated with positive brains. Unsurprisingly, the most cerebral of occupations are the hard sciences and mathematics, as well as high-level management.

For the British analysis, we match the US SOC00 codes in the ONET data directly to the British SOC00 in the QLFS data using a crosswalk provided by Anna Salomons.[18] We then proceed and extract underlying latent factors. These differ only from the US analysis in the fact that the distribution of workers across occupations is slightly different in Britain. Unsurprisingly, we again obtain three latent factors corresponding to ‘people,’ ‘brains,’ and ‘brawn’ from the QLFS analysis, which we match to the BHPS. For the Russian data (complementing the RMLS with ISSP and ESS data in order to get more observations in the occupation cells) we match the ISCO code to the US SOC00 using a crosswalk provided by the Bureau of Labor Statistics. The factor analysis again yields the three familiar factors labeled ‘people,’ ‘brains,’ and ‘brawn.’

Finally, adding the three latent factors denoted PBB_j to equation (2), we estimate:

$$Y_{ijt} = \alpha_{is} + \delta SOM_{js} + PBB_j \chi + X_{js}\beta + X_{ijt}\gamma + \mu_t + \varpi_a + \varepsilon_{ijt} \qquad (3)$$

Including PBB_j allows us to investigate whether the negative correlation between the SOM and overall satisfaction in the female regressions might be driven by the fact that some females are employed in jobs that don’t match their preferences for job attributes. Hence we are both interested in the coefficients associated with ‘people,’ ‘brains,’ and ‘brawn’ as well as with the impact the PBB_j factors have on the coefficient on the SOM.

Table 6 shows the results from an analysis that adds the three latent factors to the job satisfaction regressions. The addition of the people, brains and brawn variables does not change the coefficients for the SOM in the male job satisfaction regressions significantly for the US or Britain, they remain small and centered around zero. The coefficient for Russia is

18. For the years in the LFS where the UK SOC90 code is used, we use a translation to SOC00 that is implicitly provided by the BHPS. That is, SOC00 appears for the respondent’s primary occupation post 2000 and SOC90 appears for all waves of the survey. So we, have a translation between the two coding systems.

no longer statistically significant. On the other hand, the inclusion of these variables has reduced the magnitudes of the SOM coefficients in the female regressions. Specifically, for all countries the coefficient on the share of males is about two-thirds or less of its original value. For example, the US coefficient has decreased from -0.182 to -0.111. These reductions are not only sizeable but also statistically significant, as indicated by a generalized Hausman test in the last row comparing the SOM coefficients in Table 6 to the corresponding ones in Table 3. These findings suggest that job attributes play an important role in explaining female job satisfaction. However, job satisfaction still remains negatively correlated with whether the occupation is male dominated as well.

The coefficients on the PBB variables suggest that women tend to be happier in ‘people’ and in ‘brain’ jobs. British males are also happier in people jobs, however these effects are not significant in the other two countries. The sexes bifurcate most with respect to ‘brawn:’ women tend to dislike these jobs and the effects are always strong and significant for women. In contrast, the same coefficients are small and not significant for men.

While the job satisfaction regressions paint a picture, which supports the idea that men and women have different preferences, this is not born out in terms of their job mobility. The mover and leaver results in Table 7 hardly change when the PBB variables are added. Moreover, the coefficients on the PBB variables show less of a clear pattern and are typically not significant**.**

Notice that the mover regressions only tell us about job changes, not the overall allocation of individuals to jobs, which is also driven by initial job choices. In order to see how these results compare to the overall allocation, Table 8 presents a linear regression where the SOM is dependent variable and the three latent factors are regressors, along with some occupational averages, time dummies and area dummies (though we run this at the individual level, note that this is essentially an occupation level regression and the individuals here only serve to give different weights to different occupations). These regressions use the CPS, QLFS, and RMLS. This table highlights that there is substantial sorting in all three countries along the PBB dimension. Women are overrepresented in people jobs, men in brawn jobs, and they share brain jobs (with the exception of Britain which has a higher proportion of women in brain jobs). Occupational segregation along these lines is strongest in Russia and weakest in the US.

Testosterone

The finding that preferences matter for job choice squares with Pinker's (2008) idea that women inherently prefer careers in which they spend time with other people. She suggests that careers with a need for empathy provide better job matches for females. Women tend to have higher levels of oxytocin, a hormone that acts as a neuromodulator in the brain, and which has been labeled the "bonding hormone." Conversely, males with higher levels of testosterone tend to seek out jobs where they 'make things' (see also Browne, 2006).

Average hormone levels differ between the sexes but there are large differences across individuals as well. Hence, in order to investigate the idea that differences in job choices by women and men may have a biological basis, we would ideally add the biological determinants of these differences to our regressions. There are various practical limitations to this exercise. Oxytocin and testosterone may play an important role for differences of male and female behaviors but they are unlikely the only biological determinants. Moreover, we don't even have data on oxytocin. Testosterone, on the other hand, is fairly easy to measure from saliva samples, and such data were gathered for Britain in the successor to BHPS data, which can be matched to a subsample of the individuals used in our previous analyses. In particular, a single saliva sample was gathered for each respondent between the years 2010-2012. While testosterone levels measured in saliva reflect blood levels of this hormone (e.g., Kahn et al., 1988; Shirtcliff et al., 2002; Granger et al., 2004), testosterone concentrations fluctuate over the course of the day and in response to external factors. This will introduce noise and is likely to attenuate any estimated hormonal effects.

As a result, the testosterone measure we have is at best a very crude proxy for any permanent biological differences across the sexes which may matter for occupational choices, should these exist. Despite these shortcomings, other studies have related similar measures to occupational outcomes. Sapienza, Zingales, and Maestripieri (2009) use saliva based testosterone measures to study risk aversion and career choices in a small sample of male and female MBA students. Dabbs (1992) and Manning et al. (2010) relate testosterone levels (or correlates of it) to occupational choices in much larger single sex samples. Here we turn to the question whether differences in individual testosterone levels may help explain attitudes of men and women in different jobs in our job satisfaction regressions.

Table 9 returns to the simple fixed effects specifications from Table 3 excluding the PBB variables for the subsample of BHPS respondents for whom we have a testosterone measure. Moreover, we pool men and women and restrict the coefficients on the occupation averages other than the SOM (i.e. wages, hours, education levels, and age) to be the same across sexes. The initial columns for each dependent variable show regressions on the SOM and the SOM interacted with a female dummy. Commensurate with our earlier findings, the main effect is close to zero, and the female interaction is negative at around -0.2 for the job satisfaction variables, and 0.2 for occupational mobility.

The second column for each dependent variable adds an interaction between the SOM and testosterone levels to the regressions. This regression is basically a horse race to test whether sex or hormone levels work as stronger predictors for job satisfaction and labor market transitions. Throughout, the coefficients on the female SOM interaction change relatively little while the testosterone interactions are small. The difference between average male and female testosterone levels is about 15 nanomol/l and the overall standard deviation around 8 nmol/l. The standard deviation among men is around 6 nmol/l while there is basically no variation in testosterone levels among females (and little overlap with the male distribution as a result).

Crucially, standard errors have increased a lot when we add the testosterone interactions. Standard errors on the female SOM interaction at least double when we include the testosterone SOM variable. The standard errors on the latter are 0.012 in the job satisfaction regression. Multiplying this by 15, the average male-female difference, yields a value of 0.18, the order of magnitude of the female SOM coefficient. While the point estimates favor sex per se in these regressions, we don’t have enough statistical power to distinguish cleanly between the hormone measures and sex. This problem is compounded by the fact that we expect the testosterone estimate to be attenuated due to measurement problems. But our results do not suggest that biology is crying out as the culprit for male-female differences in attitudes in the labor market.

This result is roughly in line with Sapienza, Zingales, and Maestripieri (2009), who also find that sex is a more potent explanatory variable for job choices than testosterone levels (unless they focus on subsamples). However, it contrasts with the strong correlations between digit ratios and height (variables correlated with prenatal testosterone exposure and adult levels, respectively) in Manning et al. (2010). Clearly, more research with large samples and a broader set of high quality biomarkers will be necessary to make headway on these issues.

Discussion

Stigler and Becker (1977) have famously cautioned economists against relying on variation in preferences to explain economic outcomes, suggesting that the most worthwhile focus is instead on the comparative statics induced by variation in constraints. The literature on differences in labor market outcomes and behaviors between men and women has indeed for a long time adopted this approach, and studied the impact of discrimination, human capital investments, and labor supply. Less than two decades ago, Altonji and Blank (1999) devoted two paragraphs of their handbook chapter on race and gender to differences in preferences before moving on to the traditional constraint based explanations.

But stubborn differences in male and female pay and occupational segregation remain as disparities in many of the constraints faced by men and women seem to have diminished. At the same time, economists have grown more relaxed about thinking about differences in tastes. The handbook chapter by Bertrand (2010), a mere ten years after Altonji and Blank, focuses almost entirely on explanations based on differences in psychological traits between men and women, as well as gender identity. A powerful form in which such psychological differences manifest themselves is in different tastes of men and women for the type of work they do. We argue that economists should be open-minded towards this explanation, and subject it to scrutiny.

Here we have offered an attempt at this by analyzing the differences in job satisfaction of women in male and female dominated jobs. Overall we find that women are happier in the jobs which women frequently choose--those that are relatively low in brawn and relatively high in people and brains. Adding various average characteristics of the workers in an occupation (education, age, hours, and wages) to these job satisfaction equations does not change this relationship substantially. Hence, it is noteworthy that the content of the work, which we have captured in the PBB variables, changes the results markedly. Mind you, PBB come nowhere near wiping out the effect of the SOM regressor as this stays large and significant. This is not surprising since actual choices likely remain a good proxy for many hard to observe characteristics of an occupation, which matter to individuals. That the SOM coefficient moves at all is a crude indicator that women may indeed care more about the content of the jobs they do.

Regression models for actual job choices paint a somewhat different picture. When we run regressions to test whether women leave male dominated occupations, as we do in Tables 2, 3, and 7, we find that adding the PBB regressors makes no substantive or systematic difference to the coefficients on the SOM. Women are more likely than men to move out of male dominated occupations no matter whether we control for occupation content or not.

Economists tend to favor evidence based on revealed behaviors over stated preferences. Nevertheless, there are reasons to look to the job satisfaction regressions as a useful alternative to the mobility regressions. The SOM variable itself captures the sorting of men and women into occupations. The lower the SOM, the fewer opportunities there are to change occupations and end up in an occupation with an even lower SOM. Suppose that the SOM captures occupational characteristics, which men and women care about. If the SOM is lower in an occupation then it is more difficult for women to find another occupation, which is very different because they basically only have higher SOM occupations to choose from. This is not true for women who work in occupations where the SOM takes on intermediate values, as these women can go in both directions when changing jobs. Of course, this problem due to the boundedness of the SOM distribution is symmetric, and equally applies to high SOM occupations. Of course, women are mechanically overrepresented in low SOM occupations. This may be a strong force leading to a positive coefficient in the mobility regressions. This problem doesn't arise for the job satisfaction regressions, where the left and right hand side variables are distinct. A caveat is that the regressions where we look at leavers from the labor force also shouldn't face this problem but they generally mirror the occupational mover results.

We feel that the idea that men and women may have different tastes for occupational attributes potentially has some traction and we offer evidence pointing in that direction. Economists should explore this possibility because the policy implications of taste based sorting into occupations differ substantially from explanations based on constraints. The latter suggest that policies should remove constraints, for example through anti-discrimination legislation or mandates to employers to allow workers more flexibility when combining family responsibilities with work. One goal of these policies is to close gender gaps in occupational allocations, which in turn should help close the gender pay gap. On the other hand, if women do not want to do the same jobs as men there seems less sense in trying to tackle occupational segregation. Instead, governments may want to look towards increasing the demand in the types of jobs often done by women in order to close the gender pay gap directly. Many of these jobs are concentrated in health, social care, and education sectors, which are largely under government control. So, more funding for these areas seems a potential solution with the costs being covered by higher taxes on male dominated jobs.

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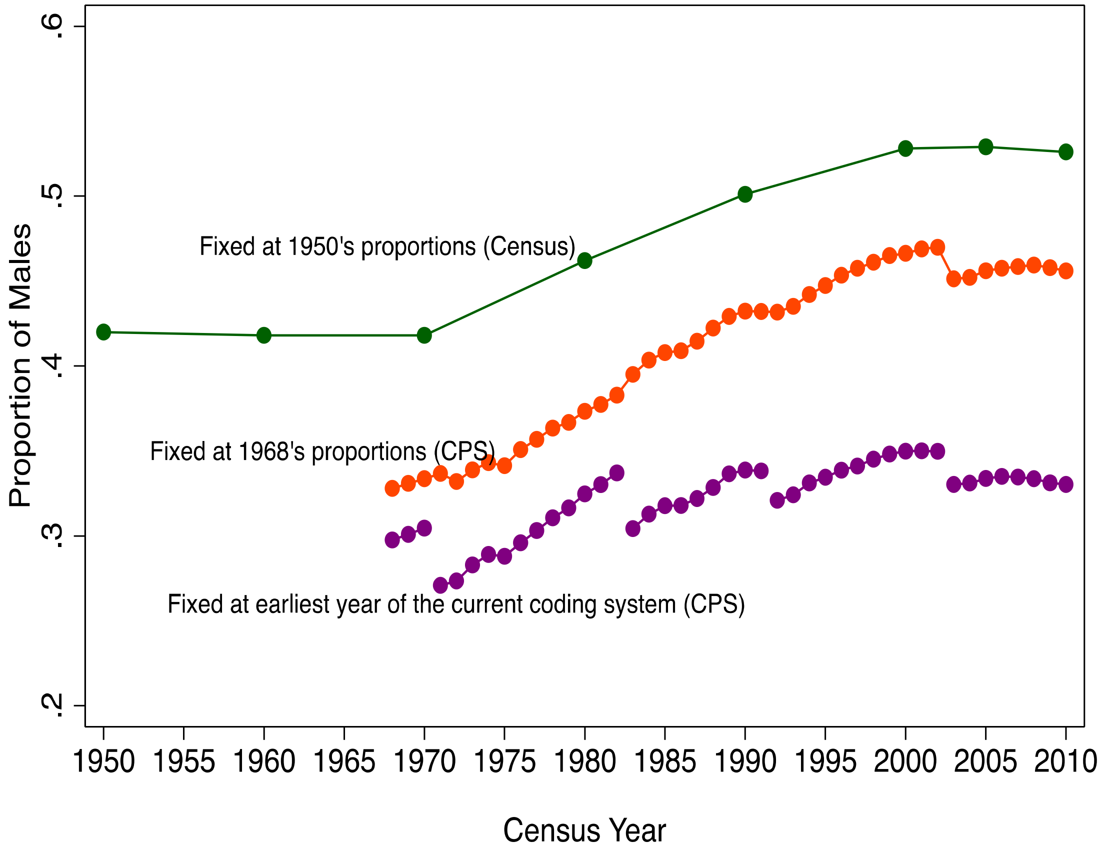
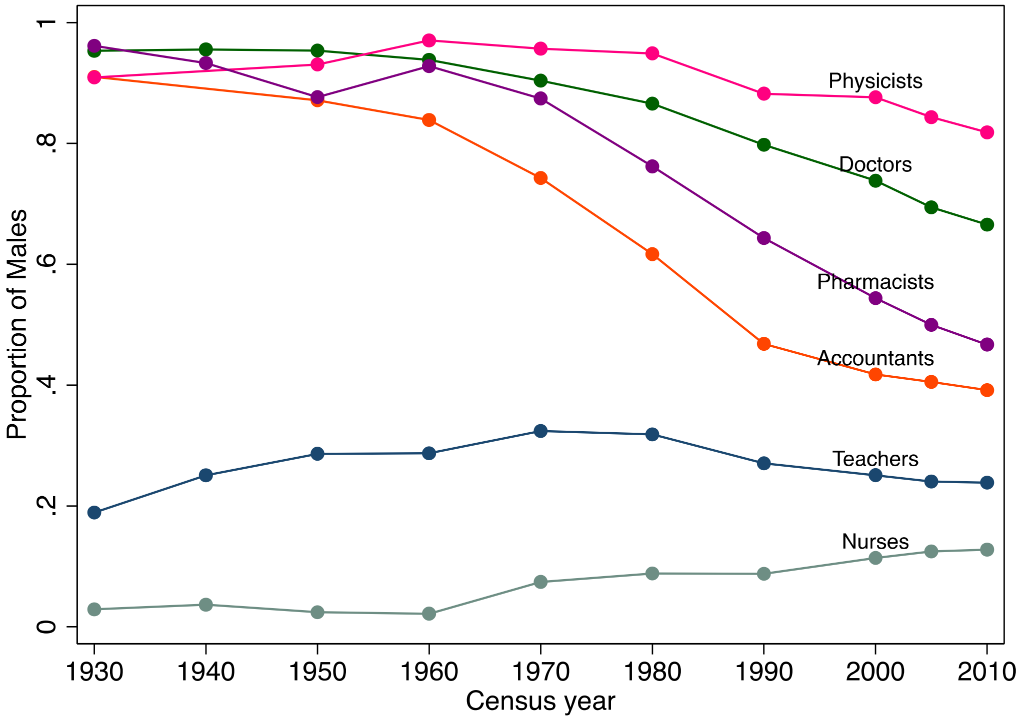
Figure 1: The Share of Males in Female Jobs



Notes: The lines in this graph show the share of males (SOM) in the occupations in which females work in a particular year in the US. The top line uses Census data and is based on the SOM in each occupation in 1950 using the IPUMS 1950 consistent occupation code. The second line uses annual CPS data; the proportion of males in an occupation is calculated based on the 1968 data (this also requires a cross-walk between the different occupation coding systems). The bottom line uses the current occupation codes and fixes the SOM in the year the current code was first introduced. The line is broken whenever a new set of occupation codes comes into use.

Figure 2: Trends in the Share of Males in Selected White Collar Jobs



Notes: This graph shows the share of males in selected white collar occupations in the US Census.

Table 1: Basic Job Satisfaction Regressions

	Sample and Dependent Variable							
	US – NLSY Overall Job Satisfaction		Britain – BHPS Overall Job Satisfaction		Britain – BHPS Satisfaction with Work Itself		Russia – RMLS Overall Job Satisfaction	
Occupation averages	Females	Males	Females	Males	Females	Males	Females	Males
Share of Males	-0.263	-0.055	-0.141	-0.081	-0.320	-0.042	-0.182	-0.073
	(0.058)	(0.058)	(0.071)	(0.065)	(0.100)	(0.080)	(0.083)	(0.063)
Log of Wage	0.319	0.193	-0.064	0.118	-0.040	0.146	0.203	0.204
	(0.075)	(0.074)	(0.059)	(0.052)	(0.083)	(0.055)	(0.057)	(0.042)
Hours/100	-0.524	0.514	-0.368	0.713	0.424	0.820	1.067	0.184
	(0.515)	(0.466)	(0.328)	(0.257)	(0.413)	(0.289)	(0.790)	(0.392)
Degree holders	0.216	0.315	-0.117	0.005	0.020	0.040	0.559	0.392
	(0.092)	(0.107)	(0.068)	(0.075)	(0.091)	(0.078)	(0.123)	(0.058)
Age/100	0.650	0.751	1.209	0.932	0.782	0.941	-0.595	0.698
	(0.351)	(0.427)	(0.354)	(0.333)	(0.441)	(0.377)	(0.562)	(0.439)
Number of Obs.	64,053	68,812	49,764	47,187	49,764	47,187	23,211	17,106

Notes: All regressions also include age and age squared of the individual, as well as time and area effects. Standard errors are two-way clustered (by individual and their occupation) and shown in parentheses. Models are estimated using ivreg2.

Table 2: Job Satisfaction and Mobility Regressions

	Samples					
	US – NLSY		Britain – BHPS		Russia – RMLS	
	Females	Males	Females	Males	Females	Males
	Dependent Variable: Overall Job Satisfaction					
Share of Males	-0.263	-0.055	-0.141	-0.081	-0.182	-0.073
	(0.058)	(0.058)	(0.071)	(0.065)	(0.083)	(0.065)
Number of Observations	64,053	68,812	49,764	47,187	23,211	17,106
	Dependent Variable: Satisfaction with Work Itself					
Share of Males			-0.320	-0.042		
			(0.100)	(0.080)		
Number of Observations			49,764	47,187		
	Dependent Variable: Movers					
Share of Males	0.236	-0.090	0.114	-0.082	0.240	-0.132
	(0.055)	(0.038)	(0.026)	(0.021)	(0.046)	(0.042)
Number of Observations	62,648	67,246	40,303	38,727	25,684	18,758
	Dependent Variable: Leavers					
Share of Males	0.034	0.028	0.055	0.006	0.010	-0.005
	(0.007)	(0.006)	(0.011)	(0.008)	(0.009)	(0.011)
Number of Observations	65,956	70,665	40,303	38,727	25,681	18,756

Notes: All regressions also include age and age squared of the individual, the averages of the log hourly wage, hours, fraction college graduates, and age in the occupation, as well as time and area effects. Standard errors are two-way clustered (by individual and their occupation) and shown in parentheses. Models are estimated using ivreg2.

Table 3: Individual Fixed Effects Regressions

	Samples					
	US – NLSY		Britain – BHPS		Russia – RMLS	
	Females	Males	Females	Males	Females	Males
	Dependent Variable: Overall Job Satisfaction					
Share of Males	-0.182	-0.098	-0.228	-0.078	-0.166	-0.117
	(0.039)	(0.038)	(0.043)	(0.048)	(0.065)	(0.065)
Number of Observations	64,053	68,812	49,764	47,187	23211	17106
	Dependent Variable: Satisfaction with Work Itself					
Share of Males			-0.317	-0.029		
			(0.057)	(0.053)		
Number of Observations			49,764	47,187		
	Dependent Variable: Movers					
Share of Males	0.210	-0.083	0.120	-0.082	0.233	-0.045
	(0.014)	(0.014)	(0.027)	(0.030)	(0.040)	(0.033)
Number of Observations	62,648	67,246	40,303	38,727	25,684	18,756
	Dependent Variable: Leavers					
Share of Males	0.008	0.015	0.062	0.024	-0.008	-0.003
	(0.006)	(0.007)	(0.015)	(0.013)	(0.050)	(0.014)
Number of Observations	65,956	70,665	44255	40773	25,681	18,756

Notes: All regressions also include age and age squared of the individual, the averages of the log hourly wage, hours, fraction college graduates, and age in the occupation, time and area as well as individual fixed effects. Standard errors are two-way clustered (by individual and their occupation) and shown in parentheses. Models are estimated using xtivreg2.

Table 4: High and Low Ranked Occupations According to the Content of the Work (US)

Rank	People	Brains	Brawn
		10 Highest Ranked Occupations	
1	Occupational Therapist (99)	Engineers and Other Professionals, n.e.c. (59)	Explosive Workers (615)
2	Sales Supervisors and Proprietors (243)	Chemical engineers (48)	Fire Fighting, Prevention, & Inspection Occs (417)
3	Licensed Practical Nurses (207)	Aerospace engineers (44)	Miners (616)
4	Managers of Medicine and Health Occupations (15)	Electrical Engineers (55)	W ater and sewage treatment plant operators (694)
5	Social Workers (174)	Engineering Technicians (214)	Other Mining Occupations (617)
6	Registered Nurses (95)	Biological Scientists (78)	Millwrights (544)
7	Urban and Regional Planners (173)	Petroleum, mining, and geological engineers (47)	Bolier-makers (643)
8	Physical Therapists (103)	Physicists and astronomists (69)	Industrial machinery repairers (518)
9	Child Care Workers (468)	Chemists (73)	Heating, air conditioning, and refrigeration mechanics (534)
10	Business and Promotion Agents (34)	Medical Scientists (83)	Roofers and Slaters (595)
		10 Lowest Ranked Occupations	
1	Statistical Clerks (386)	Messengers (357)	Accountants and Auditors (23)
2	Actuaries (66)	Baggage porters, bellhops and concierges (464)	Economists, market and survey researchers (166)
3	Administrative support jobs, n.e.c. (389)	Sheriffs, bailiffs, correctional institution officers (423)	Interviewers, enumerators, and surveyors (316)
4	Brains Entry Keyers (385)	Athletes, sports instructors, and officials (199)	Lawyers and Judges (178)
5	Mathematicians and statisticians (68)	Misc. food preparation and service workers (444)	Actuaries (66)
6	Photographic process workers (774)	Ushers (462)	Art/entertainment performers and related occs (194)
7	Motion picture projection (467)	Public transportation attendants and inspectors (471)	Payroll and timekeeping clerks (338)
8	Tool and die makers and die setters (634)	Waiters and Waitresses (435)	Statistical Clerks (386)
9	Other plant and system operators (699)	Personal service occupations, n.e.c (469)	Other financial specialists (22)
10	Economists, market and survey researchers (166)	Housekeepers, maids, butlers, and cleaners (405)	Writers and Authors (183)

Table 5: Factor Scores for Selected Occupations (US)

Occupation	SOM	People	Brains	Brawn
Mechanical Engineers (57)	0.942	-0.501	2.131	0.823
Engineers and Other Professionals (59)	0.892	-0.941	3.562	1.142
Chemical Engineers (48)	0.867	-0.089	3.339	1.583
Architects (43)	0.784	0.616	1.841	0.208
Chief executives, public administrators, and legislators (4)	0.750	1.262	2.046	-0.678
Physicians (84)	0.722	0.752	1.951	0.750
Computer Software Developers (229)	0.723	-0.558	2.251	-0.274
Mathematicians and Statisticians (66)	0.640	-2.048	1.647	-1.455
Financial managers (7)	0.572	0.323	2.135	-0.779
Pharmacists (96)	0.540	0.083	1.579	-0.129
Economists, market and survey researchers (166)	0.510	-1.749	0.741	-1.923
Editors and Reporters (195)	0.500	-0.478	0.309	-0.997
Accountants and auditors (23)	0.423	-0.236	1.646	-1.126
Psychologists (167)	0.372	0.247	0.830	-1.244
Social Workers (174)	0.251	1.659	0.113	-1.066
Primary School Teachers (156)	0.165	1.091	0.452	-0.303
Registered Nurses (95)	0.068	1.652	0.916	1.172

Table 6: Job Satisfaction Regressions Including People, Brains, and Brawn

	Sample and Dependent Variable							
	US – NLSY Overall Job Satisfaction		Britain – BHPS Overall Job Satisfaction		Britain – BHPS Satisfaction with Work Itself		Russia – RMLS Overall Job Satisfaction	
	Females	Males	Females	Males	Females	Males	Female	Males
Share of Males	-0.111	-0.091	-0.161	-0.027	-0.234	0.023	-0.128	-0.106
	(0.043)	(0.044)	(0.049)	(0.053)	(0.066)	(0.065)	(0.066)	(0.066)
People	0.037	0.017	0.019	0.023	0.038	0.033	0.014	0.022
	(0.008)	(0.010)	(0.011)	(0.010)	(0.013)	(0.012)	(0.016)	(0.027)
Brains	0.026	0.015	0.023	0.019	0.050	0.007	0.028	-0.023
	(0.016)	(0.012)	(0.012)	(0.010)	(0.013)	(0.010)	(0.016)	(0.020)
Brawn	-0.031	0.005	-0.027	-0.015	-0.028	-0.007	-0.041	(0.012)
	(0.014)	(0.011)	(0.013)	(0.010)	(0.016)	(0.013)	(0.018)	(0.017)
Number of Observations	64,053	68,812	49,764	47,187	49,764	47,187	23,211	17,106
Hausman Test (p-value)	0.004	0.544	0.041	0.044	0.041	0.073	0.073	0.640

Notes: All regressions also include age and age squared of the individual, the averages of the log hourly wage, hours, fraction college graduates, and age in the occupation, time and area as well as individual fixed effects. Standard errors are two-way clustered (by individual and their occupation) and shown in parentheses. Models are estimated using xtivreg2.

Table 7: Mobility Regressions Including People, Brains, and Brawn

	Samples					
	US – NLSY		Britain – BHPS		Russia – RMLS	
	Females	Males	Females	Males	Females	Males
	Dependent Variable: Movers					
Share of Males	0.233	-1.111	0.127	-0.090	0.239	-0.018
	(0.016)	(0.015)	(0.030)	(0.031)	(0.043)	(0.051)
People	-0.022	-0.019	-0.003	-0.008	-0.007	-0.008
	(0.003)	(0.003)	(0.007)	(0.005)	(0.010)	(0.013)
Brains	0.002	-0.010	0.010	-0.000	0.010	0.006
	(0.005)	(0.004)	(0.007)	(0.007)	(0.015)	(0.011)
Brawn	-0.027	0.006	-0.001	-0.003	-0.020	-0.027
	(0.005)	(0.004)	(0.008)	(0.006)	(0.015)	(0.012)
Number of Observations	62,648	67,246	40,303	38,727	25,684	18,758
Hausman Test (p-value)	0.790	0.053	0.685	0.524	0.541	0.368
	Dependent Variable: Leavers					
Share of Males	0.011	0.015	0.063	0.019	-0.012	-0.004
	(0.008)	(0.007)	(0.017)	(0.015)	(0.016)	(0.015)
People	-0.000	0.001	-0.004	-0.002	-0.003	-0.001
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
Brains	-0.000	-0.005	0.005	-0.002	-0.003	0.004
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)
Brawn	-0.002	-0.000	0.010	0.001	0.003	-0.001
	(0.003)	(0.002)	(0.007)	(0.004)	(0.004)	(0.004)
Number of Observations	65,956	70,665	44,255	40,773	25,681	18,756
Hausman Test (p-value)	0.699	0.848	0.916	0.342	0.271	0.625

Notes: All regressions also include age and age squared of the individual, the averages of the log hourly wage, hours, fraction college graduates, and age in the occupation, time and area as well as individual fixed effects. Standard errors are two-way clustered (by individual and their occupation) and shown in parentheses. Models are estimated using xtivreg2.

Table 8: The Relationship Between the Share of Males and People, Brains, and Brawn

	Samples		
	US – CPS	Britain – LFS	Russia – RMLS
People	-0.035	-0.070	-0.155
	(0.008)	(0.016)	(0.024)
Brains	-0.013	-0.059	0.019
	(0.007)	(0.020)	(0.027)
Brawn	0.050	0.103	0.150
	(0.023)	(0.017)	(0.028)
Number of Observations	21,274,249	4,263,055	81,706

Notes: All regressions also include the averages of the log hourly wage, hours, fraction college graduates, and age in the occupation, as well as time and area effects. Standard errors are clustered by occupation.

Table 9: BHPS Regressions Including Testosterone

	Sample and Dependent Variable							
	Overall Job Satisfaction		Satisfaction with Work Itself		Mover		Leaver	
	Females	Males	Females	Males	Females	Males	Female	Males
Share of Males	-0.012	-0.112	-0.037	-0.028	-0.092	-0.182	0.020	0.056
	(0.076)	(0.203)	(0.079)	(0.205)	(0.043)	(0.101)	(0.020)	(0.041)
Female * SOM	-0.224	-0.127	-0.219	-0.228	0.187	0.275	-0.015	-0.051
	(0.085)	(0.197)	(0.094)	(0.206)	(0.044)	(0.098)	(0.026)	(0.042)
Testosterone * SOM		0.006		-0.001		0.006		-0.002
		(0.012)		(0.012)		(0.006)		(0.002)
Number of Observations	21,233	21,233	21,233	21,233	19,177	19,177	20,560	20,560

Notes: All regressions also include age and age squared of the individual, the averages of the log hourly wage, hours, fraction college graduates, and age in the occupation, time and area as well as individual fixed effects. Standard errors are two-way clustered (by individual and their occupation) and shown in parentheses. Models are estimated using xtivreg2.