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Sorting in the Labor Market: Do Gregarious Workers Flock to Interactive Jobs?

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Abstract

This paper tests a central implication of the theory of equalizing differences, that workers sort into jobs with different attributes based on their preferences for those attributes. We present evidence from three new time-use data sets for the United States and France on whether workers who are more gregarious, as revealed by their behavior when they are not working, tend to be employed in jobs that involve more social interactions. In each data set we find a significant and sizable relationship between the tendency to interact with others off the job and while working. Additionally, people's descriptions of their jobs and their personalities accord reasonably well with their time use on and off the job.

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"Musicians cannot be tone-deaf; football players tend to be large; while lawyers, and many economists, have a propensity to talk.

What matters for economic allocations in all of these cases are the direct manifestations of tastes."

-- Sherwin Rosen (2002, p. 9)

I. Introduction

A central implication of an equalizing differences equilibrium in the labor market is that workers should sort into jobs with different attributes based on their preferences for those attributes. Workers who enjoy interacting socially, for example, should seek jobs that entail frequent interactions with co-workers or customers, while workers who are introverted by nature should eschew such jobs, all else being equal. At the same time, it is in employers' interests to search for gregarious workers when they seek to fill vacancies for jobs that involve social interactions, and to search for more reclusive personalities when they seek to fill jobs that entail social isolation. This simple yet fundamental feature of a competitive labor market has not been adequately tested, however, owing primarily to the difficulty of assessing workers' preferences toward work attributes.[1]

In this paper, we present evidence on whether workers who are more gregarious, as revealed by their behavior when they are not working, tend to be employed in jobs that involve more social interactions. Because psychologists find that the tendency to be introverted or extroverted is a persistent personality trait (see Roberts and DelVecchio, 2000 for a review), and because many employers administer personality tests specifically

[1] One paper that studies sorting by tastes is Viscusi and Hersch (2000), who find that smokers are more likely than nonsmokers to be employed in industries with high injury and illness rates. It is unclear, however, whether smokers have a preference for risk generally, or whether they have addictive personalities.

to identify extroverted job applicants for some positions (Hough and Oswald, 2000), we consider this a worthwhile attribute to study. We conduct our analysis using three new data sets on the time use of working women in the United States and France. We also assess the reliability of our measures using a fourth data set that consists of workers who were interviewed twice, two weeks apart.

In each data set, we find a significant and sizable relationship between the tendency to interact with others off the job and while working. In addition, people's self-descriptions of their jobs and their personalities seem to accord reasonably well with their time use on and off the job. The results suggest that sorting of workers and jobs based on personality types and work attributes does take place, although it is unclear if the extent of sorting reaches the efficient level. Our results complement those in recent work by Borghans, ter Weel and Weinberg (2006a, 2006b), who find that workers who report being more sociable as youths tend to be employed in occupations that involve more people skills as adults. Extensive sorting by tastes could explain why compensating wage differentials for many work attributes are often found to be small or zero (e.g., Brown, 1980), although sorting cannot account for the weak evidence for compensating wage differentials for working conditions that are uniformly disliked or liked.

In the next section, we briefly summarize the main implications of equalizing differences for sorting. In Section III we describe our data. Section IV presents our main findings and considers issues of the reliability of the data, and Section V offers concluding remarks.

II. Sorting and the Labor Market

We borrow liberally from Rosen's (1986) model of equalizing differences to illustrate the role of sorting of workers over jobs with varying social requirements. Define S as the percentage of the day that a job requires a worker to be engaged in conversations with customers, clients or co-workers. For now, we assume workers are productively homogenous, and ignore all other work attributes.[2] To simplify, suppose S takes on two values, 0 or 1. We will focus on the employee side of the matching market, so we take it for granted that by the nature of technology and costs some employers choose to offer jobs with S=1 and others with S=0.[3] For example, the job of telemarketer naturally involves a great deal of interaction with customers, while the job of night security watchman involves little contact with others.

Write a worker's utility function as U(W,S), where W is the wage rate. There is no saving, so consumption equals the wage. The wage has a positive effect on utility for all workers, while utility rises with S for some workers and falls with S for others. In our data, the average worker appears happier when interacting at work than when not (as long as the interaction is not with their boss), so $U(W,1) > U(W,0)$ for most workers, but clearly some people find interactions more stressful than others, and for some it may be that $U(W,1) < U(W,0)$.[4]

Define z as the compensating variation necessary for a worker to be indifferent between accepting a job with S=0 or S=1. That is, implicitly define z by the equation

[2] Notice that we are treating a worker's tendency to be extroverted or introverted as a taste. We do so because extroversion is identified in the psychology literature as a personality trait, and because people engaged in social interaction to varying degrees while not working. From an employer's perspective, a tendency to extroversion could also be thought of as a productive skill in some jobs.

[3] A more complete model would allow for a distribution of employers' costs for providing or eliminating S. This would add very little to our story about sorting of workers as long as enough employers find it unprofitable to switch from S=0 to S=1 jobs given the nature of their technology and business.

[4] See Saffer (2005) for further evidence that individuals receive consumption value from social interaction.

$U(W_1+z,0) = u(W_1,1)$. The z that makes a worker indifferent between the two types of jobs is her reservation compensating wage differential. If the offered wage differential between S=0 and S=1 jobs, denoted $\Delta W = W_0 - W_1$, is less than z for a particular worker, that worker would prefer to be in a job with S=1. And if $\Delta W > z$, that worker would prefer to be in an S=0 job. Notice that z is a personal taste variable that differs over members of the labor force. Extroverted workers have higher values of z than introverted workers. Denote the probability density function of z across members of the labor force as g(z) and the cumulative distribution of z as G(z), and normalize the total labor force to 1. Then the supply of workers to S=0 jobs is $\int_0^{\Delta W} g(z)dz = G(\Delta W)$ and the supply to S=1 jobs is $1-G(\Delta W)$.

In equilibrium, the number of workers in S=1 jobs depends on the distribution of the cost to firms of modifying jobs. But the sorting of workers should be clear: workers who have a taste for social interaction (high z) will seek jobs that entail frequent contact with customers, clients or co-workers and firms that offer jobs with high S will seek such workers, while workers with little taste for social interaction (low z) will seek jobs that entail a more solitary work environment. If $g(\bullet)$ is normal, then we have the familiar selection bias term as the discrepancy between the conditional and unconditional expectation of z given D:

$$(1)\ \ E(z \mid D=0) = \mu_z - \sigma\phi\left(\frac{\Delta W - \mu_z}{\sigma}\right) / \Phi\left(\frac{\Delta W - \mu_z}{\sigma}\right)$$

where μ_z and σ are the unconditional mean and standard deviation of z, and $\phi(\bullet)$ and $\Phi(\bullet)$ are the normal probability density function and cumulative distribution function.[5]

The extent of social interactions that a worker engages in while not working is a plausible proxy for z. To test for sorting by preferences, we examine whether workers who have frequent contact with others while on the job also tend to interact relatively frequently with others while they are not working.

III. Data

Our analysis makes use of three time-use data sets that we collected as part of a project on subjective well-being. All of the data sets have a similar structure. The data were collected using the *Day Reconstruction Method* (DRM), which asks respondents to segment their preceding day into episodes as if they were going through a movie, and then to briefly summarize each episode in a diary.[6] Next respondents describe each episode by indicating: (1) when the episode began and ended; (2) what they were doing, by checking as many activities that applied from a list of 16 possible activities (plus other) that included working, watching television, socializing, etc.; (3) where they were; (4) whether they were interacting with anyone (including on the phone, in teleconference, etc.); and (5) if so, whom they were interacting with (boss, co-workers, clients/customers/students/patients, friends, spouse, children, etc.). Respondents next reported how they felt during each episode on selected affective dimensions (such as happy, frustrated, angry, enjoyment), using a scale from 0 to 6, where 0 signifies that the feeling was not present and 6 signifies that it was very much part of the experience.

[5] A pioneering application of the normal selection-bias model is Gronau (1974).
[6] Kahneman, et al. 2004 provide a discussion of the development of the DRM. The complete questionnaire is available from http://sitemaker.umich.edu/norbert.schwarz/files/drm_documentation_july_2004.pdf.

This DRM approach was first applied to a sample of 909 working women in Dallas and Austin, Texas who reported on their experiences during a workday in November 2001. (See Kahneman, et al., 2004 for more details about the sample and method.) The data set, which we henceforth call the Texas DRM, consists of 535 respondents who were recruited through random digit telephone dialing plus a screen for employment, and another 374 workers in three occupations: nurses, telemarketers and teachers. A flag identifies the over sampled occupations. Although the results are similar, we mostly work with the randomly selected subsample. Subjects were paid $75 for filling out the questionnaire, which usually took 45 minutes to 75 minutes to complete.

A slightly modified version of the original DRM was used for the other samples. In this version, respondents were asked: (1) when the episode began and ended; (2) where were you? (3) "Were you alone?" (4) "Were you talking with anyone?" (5) With whom were you talking or interacting (list includes customers, co-workers, boss, friends, etc.)? (6) What were you doing (check all that apply)? For the last item, the list of activities available to choose from was expanded and included "talking, conversation" in addition to "working" and 20 other activities. Again, respondents could check more than one activity. This version of the DRM was first administered to a sample of 229 women in Austin, Texas who were interviewed on two Wednesdays a fortnight apart in March and April 2005 to examine the reliability of the data. Henceforth, we will call this the "Re-Interview Sample". In addition, in May and June of 2005 we administered this questionnaire to a sample of 810 working and nonworking women in Columbus, Ohio, who were recruited by random digit dialing, and another sample of 820 working and nonworking women in Rennes, France, who were also recruited by random digit dialing.[7] (For the latter survey, the questionnaire was translated into French.) The Rennes and Columbus questionnaires also pertained to a single day, which was a weekend for one third of respondents and a weekday for the remainder. We limit the sample below to workdays.

In addition to time-use information, respondents provided demographic information and answered personality-type questions, such as whether they enjoy being with other people. The Texas DRM survey also contained additional questions about work, including occupation and subjective information about the nature of the respondents' main job, such as whether "frequent interactions with co-workers is an important part of my job" and whether the respondent "can chat with others while on job."

Using the Texas DRM sample, we computed the proportion of time that each individual was *not interacting* with someone else during non-work episodes. We also computed the proportion of time during non-work episodes that was spent interacting with a friend. To measure the extent of interaction on the job, we computed the proportion of time each respondent spent interacting with co-workers, customers, clients, students, patients or their boss during episodes that involved work.[8]

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[7] Respondents were paid $75 for completing the questionnaire in the Columbus survey and 50 Euros (approximately $60 at the time) in the Rennes survey. In the Reinterview Sample, respondents were paid $50 upon completing the first questionnaire and $100 upon completing the second one; only 3 individuals who completed the first questionnaire failed to return and complete the second one.

[8] Note that an episode that involved worked is potentially different from an episode that took place at work. Some episodes at work (e.g., lunch, coffee break) do not involve work, and are not included in our universe of episodes that involve work. In the Texas DRM data, 10.6 percent of the time spent at work did not involve working; most of this time was spent eating or socializing. Hamermesh (1990) reports that 8 percent of work plus break time consisted of break time in 1975-76.

These variables were computed in a somewhat different fashion in the other data sets, because the activity list enabled respondents to indicate if they were talking or engaged in conversation during each episode, and because of the different phrasing of the interaction question. For the Columbus, Rennes and Re-Interview samples, we computed the proportion of time that each individual was *alone* while not working, and the proportion of time spent talking or engaged in conversation during work episodes.

Table 1 presents summary statistics for the three main analysis samples. The median episode duration was 45 minutes. According to the definition used in the Texas DRM, almost 90 percent of work time is spent *interacting* with others. Because this figure is so high, we have computed this variable differently in the other data sets, explicitly requiring that the respondent checked that she was talking or in a conversation during a work episode to classify the episode as involving a social interaction. (If we use a definition that comes as close as possible to that used for the Texas DRM, we find that 72 percent of work time in Columbus and 62 percent of work time in Rennes involved interacting with customers, co-workers or the boss.) Forty-four percent of working time in Columbus and 34 percent of working time in Rennes was spent talking or in conversation.

Interactions are less common off the job than on the job, but still make up a majority of the time. According to the Texas data, for example, 57 percent of the time that people are not working they are interacting with someone. Sixteen percent of nonworking time is spent interacting with friends. A slightly different concept was used in the Columbus and Rennes data. In both cities, we find that workers are alone about a third of the time when they are not working, and are interacting with friends about 11 percent of the time when they are not working.

Based on the Bureau of Labor Statistics' American Time Use Survey (ATUS), 46 percent of women's non-work time (on days in which they worked at least one hour for pay) is spent alone, and 6 percent of non-work time is spent in the company of friends.[9] These figures are not terribly far out of line from what we find with the DRM data. Unfortunately, the ATUS does not ask whether individuals are alone or with someone while they are at work so the analysis presented below cannot be conducted with the ATUS.

Tables 2a and 2b provide some evidence that individuals' descriptions of themselves and their jobs correspond to their actual time allocation. Specifically, in the Texas DRM we asked respondents whether people who knew them would say the respondent enjoys being in the company of other people less than others, about average, or more than others. Respondents who answered much less or less did indeed spend less time with others when they were not working (See Table 2a). We found a similar pattern in the Columbus and Rennes surveys. In addition, in those surveys we asked, "How much pleasure and joy do you get from each of these domains of life?" Friends was one of the domains inquired about. Those who marked that they received "a lot" of pleasure and joy from friends did spend a higher proportion of non-working time in the company of friends than did those who marked "some" or "little or none".

In the Texas DRM we also asked respondents the extent to which the following statement described their situation at work: "Frequent interactions with co-workers is an important part of my job?" Table 2b reports the average proportion of working time

[9] We are grateful to Marie Connolly for these tabulations from the ATUS.

involving no interactions, or interactions with co-workers by responses to this job descriptor. Those who answered "definitely yes" spent 80 percent of their working time on the reference day interacting with co-workers, while those who answered "definitely not" spent 58 percent of their time interacting with co-workers.

Together, these results give us some reason to believe that our time-use measures do reflect social engagement during individuals' work and non-work activities.

IV. Empirical Results on Sorting

A. Texas DRM

Table 3 reports estimates of Tobit models where the dependent variable is the proportion of time spent interacting at work using the Texas DRM sample. The statistical model allows for censoring at 0 or 1. The key explanatory variable is the proportion of time that the individual was not interacting with someone else during non-work episodes (columns 1 and 2), or the proportion time the individual was interacting with a friend while not at working (columns 3 and 4). Either measure of a person's "sociability off work" has the expected relationship with the amount of time spent interacting at work.[10] The effects are also sizable: a 10 percentage point increase in the share of time spent interacting while not working is associated with a 5 percentage point increase in the share of time interacting at work in column 1.

Variables such as education, marital status, age and tenure are included as explanatory variables in columns 2 and 4. The rationale for including these variables is that they may be related to worker productivity, and sorting by tastes is predicted to take

[10] If we restrict the sample to those who said the reference day was a typical day, the coefficient on non-interacting time in columns 1 and 2 tends to rise while the coefficient on interaction time with friends in columns 3 and 4 tends to fall. In neither case is the qualitative conclusion different, however.

place among workers who are equally productive. For purposes of estimating the extent of sorting, however, it is unclear whether all of these variables should be held constant. For example, suppose marriage is unrelated to productivity for women, but more gregarious women are more likely to become married (and also more likely to interact with someone off the job) and more likely to work on a job that requires social interaction.[11] In this case, we would be over controlling for tastes. Nonetheless, we find that our proxies for sociability off work remain significantly related to the extent of social interactions on the job after controlling for the effects of these other variables.

Some of the additional variables are of interest for their own sake. Hispanic workers spend about 25 percent less of their working time interacting with others than do non-Hispanic workers. Controlling for 19 occupation dummies has no effect on this differential. This finding may, in part, be a manifestation of language differences that reduce communication opportunities for Hispanics at work. Unfortunately, we did not collect information on facility with English. More than language may be at work, however, because we also find that Hispanics are less likely than non-Hispanics to spend time interacting with friends or others off work, where they presumably could interact with Spanish speakers.

Union members also spend less time interacting with others at work than do non-union members. Unlike Hispanic workers, however, union members are not less likely to interact with friends or others when they are off work. The lower proportion of work time spent interacting by union members may partially explain why union members

[11] In case you were wondering, married women spend 9 percent (p=.025) more time interacting with someone when they are not at work than do single women. Married women spend considerably less time interacting with friends when not working than do single women, however, which is part of the reason why adding the covariates has a different effect on off-work sociability in column 2 than column 4.

typically report lower job satisfaction than nonunion members, a phenomenon first documented by Freeman (1978). Work interactions tend to decline with company tenure, while time interacting with others away from work is unrelated to tenure. Lastly, older workers are less likely to interact with others while working and while not working.

We have also looked at the extent of interaction during work episodes by occupation, assigning 19 two-digit Census occupation codes to the data. An F-test of the null hypothesis that occupation dummies jointly have no predictive power for the proportion of time spent interacting at work has a p-value of .026. Because the sample sizes are small, however, the occupational estimates are very imprecise and the results should be taken with a large grain of salt. With that caveat in mind, we find that the legal profession (which includes legal support jobs) and healthcare practitioners have the highest rates of interaction at work for an occupation with more than 20 observations, which seems plausible.

B. French-American Data

Next we consider the data from Columbus, Ohio and Rennes, France. Two-limit Tobit models for the proportion of time spent talking or engaged in conversation during work episodes are presented in Table 4a for Columbus and Table 4b for Rennes. A test of the hypothesis that the two samples can be pooled is rejected for each model at the 0.01 level.

The model in column 1 shows that workers who spend more time alone while not working are less likely to engage in conversations while on the job. The effect is attenuated when demographic variables are included in the model in column 2, especially marital status, but, as mentioned, marital status may be related to workers' gregariousness. The fraction of time spent interacting with friends has a positive effect on interactions at work that is almost statistically significant for the Columbus sample, but it is small and insignificant in the Rennes sample. In Columbus, we find an even larger gap in interactions at work for Hispanic workers than we found for the Texas sample, although this result should be treated extremely cautiously given that there were only 6 Hispanic workers in the Columbus sample. We also find that married workers are more likely to engage in conversations while working.[12]

Despite the greater extent of government intervention in the French than American labor market, and the higher rate of unionization in France, there is no sign in these results that sorting in the labor market along lines of the propensity for social interactions is less efficient in Rennes than in Columbus.

C. Limits of One Working Day

A potential concern is that the data we use to estimate the extent of social interactions by workers while they are working and not working are noisy because the data pertain to just one day in the life of the individuals in the sample. How representative is one working day? To assess this question, we collected data on an additional sample of 229 women in Austin, Texas who were interviewed on two Wednesdays, two weeks apart, on March 30 and April 13, 2005. In both waves, respondents reported on the preceding day. We restrict the sample to 207 women who worked on both days. The version of the DRM used in these surveys is virtually identical ot that used in the Columbus and Rennes surveys.

[12] While not working, married women in both Columbus and Rennes spend 17 percent less of their time alone than do single women. At the same time, married women spend 6 percent less of their non-work time with friends than do single women in Columbus, and 7 percent less in Rennes.

Table 5 reports the correlations and means of key variables used in the study: the proportion of the day alone, the proportion of the day talking, and the proportion of the day spent in the company of friends. The variables are computed over working episodes and over non-working episodes, and the first two variables are also computed over the entire day. The good news is that the key explanatory variable in Tables 4a and 4b, the proportion of time spent alone while not working, has the highest autocorrelation: 0.64. This suggests there is a reasonable amount of signal in one day's measure of reclusiveness, but the coefficients are nonetheless attenuated because of noise inherent in using one day's experience to infer a person's personality. The correlation between the proportion of non-work time spent with a friend is just 0.32. The effect of this variable is probably severely attenuated in the regressions.

The dependent variable, the proportion of working time spent talking has a 0.44 autocorrelation two weeks apart. If one day's fluctuations in interactions at work is just white noise, then the precision of the estimates will be reduced but they should still be unbiased. To reduce the noise, we averaged over each day in the Reliability Data Set and regressed the average proportion of time talking during work episodes on the average proportion of time spent with friends during non-work episodes. The slope coefficient from this bivariate regression is 0.342 with a standard error of .156.[13] If the same regression is estimated just using Session 1 data, the coefficient (standard error) is 0.273 (0.149) and if it is estimated for Session 2 the coefficient (standard error) is 0.224 (0.149). If the first period proportion of time spent with friends is used as an instrument for the second period proportion of time with friends in an Instrumental Variables

[13] If we use the average amount of time spent alone while not working as the explanatory variable, the coefficient (standard error) is -.115 (0.101).

regression that uses the second period proportion of time talking at work as the dependent variable, the coefficient is considerably larger: 1.003 (0.493). All of these results suggest that noise has attenuated our earlier estimates.

An alternative way to avoid relying on one day's measures is to use individual's own descriptions of their jobs and personalities. As was shown in Tables 2a and 2b, these measures are correlated with objective circumstances on and off the job. If we use the Texas DRM data to regress individuals' assessments of whether "Frequent interactions with co-workers is an important part of my job?" on their assessments of whether people they know would say that they enjoy being in the company of others, we find a significant and positive relationship (r=.11; p=.01). Reliance on self-reported personality and job traits is common in the personnel selection literature. We consider a focus on actual time allocation to be a contribution of our study, but it is nonetheless reassuring that we find sorting based on a tendency for extroversion when we use self-reported data as well.

D. Affect at Work

We measure individuals' *net affect* or mood as the average of the positive emotions less the average of the negative emotions recorded for each episode in the DRM. Emotions are reported on a scale of 0 (not at all) to 6 (very much part of the experience). Positive emotions are "happy" and "enjoying myself" and negative emotions are "impatient for it to end", "frustrated/ annoyed", "depressed/blue", "worried/anxious" and "angry/hostile". These emotions were selected because they do not necessarily require social interaction to be present.

Table 6 reports average net affect during episodes that involved selected work and non-work activities for the full sample and random subsample of the Texas DRM survey. Notice that work is ranked as a relatively unpleasant activity and leisure activities such as socializing and exercising have relatively high net affect ratings. This pattern is not surprising – and, indeed, presumably it is the reason why wages are positive -- but it contrasts with earlier research based on more general questions about enjoyment with various activities (Juster, 1985 and Robinson and Godbey, 1997). Juster (1985), for example, finds that work ranks near the middle of activities in terms of enjoyment. The difference appears to stem from our using a recall diary method as opposed to a domain satisfaction approach.

Average net affect during work episodes that involve interactions with the boss is particularly low, while net affect is higher during interactions with customers, clients, students or patients are associated. Workers in the full sample report especially low affect when they are working alone. All of the averages in Table 6 are potentially affected by sorting, as not every worker engaged in each activity.

Another limitation of self-reported feelings like those in Table 6 is that respondents may utilize the scales in idiosyncratic ways. We therefore examined the pattern of net affect during various types of work interactions after removing individual fixed effects. Specifically, we regressed net affect during each episode on three dummy variables indicating whether that episode involved an interaction with the boss, co-workers, or clients, customers, students and patients, and a set of unrestricted individual fixed effects. This fixed effects model is identified by workers who had at least one work episode involving social interactions and at least one work episode without interactions on the survey reference day. Within a person's work day, we find that interactions have a large effect on net affect. For the random sample, compared with not interacting with anyone, net affect was 0.53 (0.14) points lower when an episode involved interacting with the boss, 0.24 (0.12) points higher when co-workers were interaction partners and 0.40 (0.18) points higher when customers, clients, students, or patients were involved.

We also find considerable heterogeneity. For the random subsample, for example, 47 percent of workers had lower net affect when they interacted with clients, customers, students and patients than when they were alone at work, despite the fact that average net affect was significantly higher for this group when they interacted with clients, customers, students or patients than when they were alone at work. This figure is undoubtedly dominated by noise from idiosyncratic events of a given day and the features of the interaction partner (e.g., a friendly versus angry customer), but it is also consistent with there being a good deal of heterogeneity in workers' tastes for workplace interactions.

Conclusion

We have documented a positive and statistically significant relationship between a worker's tendency to interact with others (particularly with friends) while not working and the relative frequency of work-related interactions on the worker's job. We interpret this pattern as evidence of sorting: more extroverted workers tend to work in jobs that require greater social interaction.

Other interpretations are possible, however. For example, it is possible that jobs that require more social interactions cause workers to become more extroverted in their non-working time. Although extroversion is apparently among the more stable personality traits (Roberts and DelVecchio, 2000), we acknowledge that work experiences could affect an individual's tendency to extroversion.

Biasing our results in the opposite direction, however, one could imagine that workers who spend their entire work day talking would seek some solitude when they are off work. This effect, if it exists, is not strong enough to overturn the positive relationship between the prevalence of work-related and non-work-related interactions.

Competitive markets are presumed to raise welfare by enabling buyers and sellers, workers and employers, to make efficient matches according to their tastes, talents and technology. The extent to which workers are actually sorted across jobs according to their tastes has not previously been examined. An important feature of our work is that we identify workers' tastes toward social interactions by their revealed behavior while not working. Similar results are found, however, if we use self-reported indicators of individuals' personality traits.

The approach we have taken can be used to compare the efficiency of different labor markets. Although our evidence is admittedly sketchy and preliminary -- and dependent on the assumption that opportunities for socializing while not working are similar in the two countries -- we do not find much evidence of differential sorting by workers' preferences for social interactions in France and the United States. If correct, this finding suggests that the rigidities in the French labor market do not obstruct the efficient sorting of workers across jobs in a noticeable way. A useful direction for future work would be to examine the extent to which the matching of workers and jobs according to workers' tastes are affected by labor market institutions.

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Table 1: Descriptive Statistics for the Three Analysis Samples

	Texas All	Texas Random Smpl	Columbus	Rennes
Age	38.0	38.0	43.0	37.9
Annual Household Income	$53,659	$47,915	$69,510	€ 30,826
Married	0.44	0.42	0.61	0.40
College + (a)	0.54	0.38	0.55	0.43
Union	0.20	0.12	NA	NA
Tenure	6.30	5.59	NA	NA
Black	0.24	0.27	0.17	NA
Hispanic	0.22	0.24	0.01	NA
Number of Work Episodes	4.48	3.70	3.86	3.90
Number of NonWork Episodes	9.63	9.88	9.78	11.04
Proportion of Time Alone while Working (b)	0.08	0.08	0.14	0.23
Proportion of Time Alone while Not Working (b)	0.44	0.43	0.32	0.33
Proportion of Time w/Friends while Not Working	0.15	0.16	0.11	0.11
Proportion of Time Interacting (or conversing) while Working (c)	0.89	0.89	0.44	0.34
Maximum Sample Size	908	535	409	372

Notes:
(a) In France, college + is baccalauréat plus 3 or more years.

(b) In Texas, time alone is time spent not interacting with anyone; in Columbus and Rennes, it is time spent alone.

(c) Proportion of Time Interacting while Working is measured differently in Texas than in the other data sets; see text. In Columbus and Rennes, proportion of time interacting while working is the proportion of time that an individual indicated she was talking or engaged in conversation during work episodes. In the Texas data set, it is the proportion of time interacting with customers, clients, co-workers, patients, students or boss, as indicated in the follow-up to the interaction question.

Table 2a: Non-Work Time Allocation by Self-Described Gregariousness

What would the people who know you say about you? *Enjoys being in company:*	Proportion of non-work time spent noninteracting	Proportion of non-work time spent with friends
Much less than others (n=50)	0.51	0.09
About average (n=75)	0.42	0.14
Much more than others (n=390)	0.43	0.17
p-value	0.106	0.017

Note: p-value is from a regression of percent of time on reported in each category on self-reported enjoyment from being in company, which runs from -3 to +3. Sample is TX DRM, random sample.

Table 2b: Work Time Allocation by Self-Reported Job Description

Does this statement describe your situation at work? *Frequent interactions with co-workers is an important part of my job:*	Proportion of work time spent noninteracting	Proportion of work time interacting with co-workers
Definitely Not (n=18)	0.16	0.58
Mostly Not (n=49)	0.10	0.71
Mostly Yes (n=129)	0.13	0.73
Definitely Yes (n=337)	0.06	0.80
p-value	0.001	0.000

Note: p-value is from a regression of percent of time reported in each category on self-reported job description, which runs from 1 to 4. Sample is TX DRM, random sample.

Table 3: Tobit Models for Proportion of Time Spent Interacting at Work
Texas DRM Sample, Random Component

Explanatory Variable	(1)	(2)	(3)	(4)
Prop. of time not interacting	-0.472	-0.395	---	---
while not working	(0.146)	(0.154)		
Prop. of time interacting w/friend(s)	---	---	0.533	0.522
while not working			(0.214)	(0.225)
Age	---	-0.007	---	-0.008
		(0.004)		(0.004)
College +	---	-0.047	---	-0.102
		(0.084)		(0.086)
Married	---	0.084	---	0.140
		(0.082)		(0.083)
Black	---	-0.113	---	-0.104
		(0.098)		(0.099)
Hispanic	---	-0.281	---	-0.257
		(0.099)		(0.100)
Union	---	-0.151	---	-0.167
		(0.114)		(0.116)
Tenure	---	-0.011	---	-0.011
		(0.006)		(0.006)
Log Likelihood	-337.229	-303.426	-339.234	-304.024
Sample Size	534	502	534	502

Note: Dependent variable is proportion of time interacting with co-workers, clients, students, patients, or boss while working. Tobit allows for censoring at 0 and at 1. Mean (SD) of dependent variable is 0.89 (.24) in columns 1 and 3, and .90 (.24) in columns 2 and 4. In column 1 and 3, 19 observations are censored at 0, 129 are uncensored, and 386 are censored at 1. In columns 2 and 4, 17 observations are censored at 0, 120 are uncensored and 365 are censored at 1.

Table 4a: Tobit Models for Proportion of Time Spent Interacting at Work
Columbus DRM Sample

Explanatory Variable	(1)	(2)	(3)	(4)
Prop. of time alone while not working	-0.286	-0.136	---	---
	(0.175)	(0.188)		
Prop. of time interacting w/friend(s) while not working	---	---	0.447	0.449
			(0.294)	(0.300)
Age	---	-0.003	---	-0.003
		(0.005)		(0.005)
College +	---	0.072	---	0.078
		(0.099)		(0.098)
Married	---	0.204	---	0.247
		(0.115)		(0.108)
Black	---	0.256	---	0.250
		(0.141)		(0.140)
Hispanic	---	-0.796	---	-0.807
		(0.453)		(0.453)
Log Likelihood	-435.005	-425.489	-435.187	-424.625
Sample Size	408	403	408	403

Table 4b: Tobit Models for Proportion of Time Spent Interacting at Work
Rennes DRM Sample

Explanatory Variable	(1)	(2)	(3)	(4)
Prop. of time alone while not working	-0.467	-0.311	---	---
	(0.202)	(0.216)		
Prop. of time interacting w/friend(s) while not working	---	---	0.054	0.166
			(0.272)	(0.288)
Age	---	-0.003	---	-0.003
		(0.005)		(0.005)
College +	---	-0.065	---	-0.075
		(0.100)		(0.100)
Married	---	0.204	---	0.266
		(0.112)		(0.106)
Log Likelihood	-367.066	-363.868	-369.752	-364.743
Sample Size	371	369	371	369

Note: Dependent variable is proportion of time talking or engaged in conversation while working. Tobit allows for censoring at 0 and at 1. For Panel A, mean (SD) of dependent variable is 0.44 (0.42) in columns 1-4; in column 1 & 3, 147 observations are are censored at 0, 168 are uncensored and 93 are censored at 1; in column 2 & 4 145 observations are censored at 0, 166 are uncensored and 92 are censored at 1. For Panel B, mean (SD) of dependent variable is 0.34 (0.39) in colums 1-4; in column 1 & 3, 172 observations are censored at 0, 148 are uncensored and 51 are censored at 1; in column 2 & 4 171 are censored at 0, 147 are uncensored and 51 are censored at 1.

Table 5: Reliability of Data

Two-Week-Apart Correlations of:

	r	Average Session 1	Average Session 2
1. Proportion of Day Alone	0.56	0.26	0.27
2. Proportion of Day Alone While Not Working	0.64	0.35	0.35
3. Proportion of Day Alone While Working	0.30	0.15	0.16
4. Proportion of Day Talking	0.46	0.44	0.44
5. Proportion of Day Talking While Working	0.44	0.47	0.48
6. Proportion of Day Talking While Not Working	0.43	0.42	0.42
7. Proportion of Day with Friends While Not Working	0.32	0.13	0.15

Notes: Sample consists of 207 women in Texas who were sampled on March 30 and April 13, 2005 and worked on the preceding day. Both surveys were conducted on a Wednesday, and the responses refer to the preceding day. The average respondent reported 9.7 nonworking episodes and 4.6 working episodes per day. The definition of the variables conforms to those used in the Columbus and Rennes DRM samples.

Table 6: Net Affect During Various Activities; Texas DRM Sample

	Random	Full Smpl.
Exercising	4.00	3.97
Socializing	3.86	3.99
Watching TV	3.45	3.59
Doing Housework	2.63	2.79
Commuting	2.15	2.22
Working	2.06	2.13
While Working:		
Not Interacting	2.05	1.65
Boss	1.96	1.89
Co-worker	2.05	2.11
Clients/customers/ students/patients	2.15	2.28