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ON THE DISTRIBUTION OF JOB CHARACTERISTICS

An analysis of the DOT data

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For Peer Review

CHARACTERISING HETEROGENEITY IN LABOUR DEMAND

An analysis of the American DOT data

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Abstract:

We analyze the information in the Dictionary of Occupational Titles to characterize the structure of labor demand. Two dimensions, an intellectual factor and a dexterity factor, capture two-thirds of the variance in job requirements; the remaining (co-)variance cannot be easily structured. Simple linear relationships go a long way in describing the matching between job activities and required worker qualities (Intellect for complex relations to Data and to People, Dexterity for complex relations to Things). There is no dichotomy between mathematical and verbal required skills. Poor working conditions are not restricted to workers in low level jobs. We find strong support for compensating wage differentials. At more intellectual jobs, men receive less wage compensation for working conditions, while in jobs requiring greater dexterity they receive more. Such a relationship is absent for women.

File: DOTDemand.doc

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6 **1. Introduction**
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9 To acknowledge heterogeneity, labour supply is readily differentiated by schooling,
10 experience, age, ability and gender. But how can we acknowledge intrinsic differences in labour
11 demand? Commonly used labels, such as occupations and job titles, are no more than a very
12 mixed bag: they come with some connotation of activities to be performed (“cook”), of
13 circumstances under which the activities have to be accomplished (“forester”), and of the kind of
14 worker that may be able to perform well (“chemist”). The conditions and requirements are
15 seldom spelled out explicitly. At most, jobs and occupations are grouped on the basis of skill
16 level (“low”, “medium”, ”high”) and in some applications they are characterised by required
17 education. There is no standard differentiation on the demand side to mirror or match the
18 standard differentiations on the supply side.
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33 In assignment models, the labour market is portrayed as an institution that has to solve a
34 matching problem, with the wage structure as its instrument. In Sattinger (1975), workers are
35 ranked by ability and jobs are ranked by complexity; abler workers are supposed to have
36 comparative advantage at the more complex jobs, and the wage structure that guides them leads
37 to a positively skewed distribution of wages. The model draws inspiration from Roy (1951) and
38 from Tinbergen (1956). In Tinbergen’s analytical model, a bivariate distribution of the workers’
39 attribute levels has to be matched with a bivariate distribution of worker trait levels required by
40 employers and again, the wage function that will solve this matching problem will in general not
41 be linear in the worker traits. In these models, workers do not simply earn higher wages because
42 they are “better”: the precise rewards for “better” attributes depend on the distribution of
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3 supplied attribute levels relative to the distribution of demanded attribute levels. Empirical
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5 support for these models is given in Hartog (1988), Heckman and Honoré (1990) and Teulings
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7 (1995).
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11 To advance our thinking, it would be useful if we had a clear picture of the structure of
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13 labour demand to which these matching models can be related. Simplification in analytical
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15 models serves its purpose, but how far from reality does that take us? Are simple descriptions of
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17 complexity and difficulty of jobs feasible and sufficient? Few if any data sources describe the
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19 jobs that workers hold in any depth. There is therefore precious little research on the
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21 characteristics of jobs from the demand side of the labor market. A concise description would
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23 also serve other purposes. For a clear understanding and fruitful analysis of the operation of the
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25 labour market, of the distribution of wages, and of the nature of the allocative process, it is quite
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27 helpful if we can evoke a clear picture of the demand side. That might also yield a good tool for
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29 analysing changes in the demand structure over time: to what extent has demand shifted over
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31 time from manual to intellectual activities? To what extent has the information and computer
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33 technology revolution on the one hand shifted demand towards more difficult jobs and on the
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35 other simplified jobs by computerising complicated mental operations? Reflection on how to
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37 characterise and summarise the overwhelming heterogeneity in the tasks that are offered in the
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39 labour market would easily lead to three categories of variables: variables that characterise the
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41 nature of the activities that have to be undertaken, variables that indicate the worker qualities that
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43 are needed to perform, and variables that characterise the environment and the conditions in
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45 which activities have to be accomplished. This is precisely how the American *Dictionary of*
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47 *Occupational Titles* (DOT) is organised. The DOT provides job requirements and working
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49 conditions for some 12,700 jobs. It uses three variables to characterize job activities: it measures
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complexity in the relation to Data, to People and to Things; it lists worker requirements under various headings, such as educational development, training time, aptitudes, and temperaments; and it characterizes the physical demands on workers and the job's environmental conditions. In the next section we will give more details on the information that is contained in the DOT data.

Our goal in this paper is an empirical investigation of the structure of the demand side of the labour market. Which traits are important to characterize jobs in terms of the activities to be performed, can heterogeneity adequately be caught with a modest number of dimensions? Section 2 introduces our data, section 3 analyses worker qualities and their matching with job activity types, and section 4 considers working conditions. Section 5, as a sort of bonus, presents estimates of compensating wage differentials for working conditions. Section 6 concludes. Our most general conclusion is that heterogeneity in required worker qualities and in job tasks can be reduced to a few underlying main dimensions but doing so will miss out on a substantial amount of the variation. Working conditions are even less easy to compress into a few dimensions and are remarkably spread out across the specter of jobs. The conclusions are spelled out in greater detail in section 6.

Earlier studies have also extracted key dimensions of worker requirements. Our contribution differs in the focus on the structure of labor demand as a set of relationships between the three categories. As a corollary, we test the theory of compensating wage differentials. None of the earlier studies uses the most recent version of DOT, the 1992 electronic version data.

2. Utilizing Information from the Dictionary of Occupational Titles

The Dictionary of Occupational Titles (DOT) contains descriptions and ratings of 12,741 jobs (U.S. Dept. of Labor, 1991). The ratings have been performed by professional job analysts, individuals who have been trained to analyse—in situ—activities to be performed in a job and to translate these into requirements on the worker. We have merged DOT information with data from the Census and from the CPS,¹ because to characterise the structure of labour demand we need information on the frequency of jobs, which is lacking in the DOT. The DOT data were published in 1992 but inevitably lag behind developments in the labour market; the Census weights and the CPS-NBER weights refer to 1990. (For the factor analyses below, we use the Census weights.) The merge also gives direct access to the wage data in the Census, which we will subsequently use to estimate compensating differentials for working conditions, for reasons that will become clear below. A full assessment of the wage structure is beyond the scope of this paper. Details on data collection are given in an Appendix.

The DOT characterizes jobs by seven main types of variables. The first group of variables describes the types of activities that workers have to engage in, the object of their efforts: *Worker functions* specify at what level a worker is required to function in relation to *Data*, to *People* and to *Things*. The levels are specified as a ranking from the simple to the complex; there are 7 to 9 levels.

The second group of variables aims at indicating what competencies are required of the worker to be able to perform the activities at the indicated level:

- *Aptitudes* specify the particular capabilities and abilities required of an individual in order to perform a task or job duty adequately. There are 11 aptitudes, relating to dimensions of intellectual ability, spatial ability and physical ability, taken from the General Aptitude Test

¹ To be precise, we make use of the 1-percent public use sample of the Census 1990 and the 1990 Merged Outgoing Rotation Group file that is derived from the monthly rounds of the 1990 U.S. Current Population Survey and is available from the National Bureau of Economic Research (which we shall refer to as the CPS-NBER 1990 data)

Battery. They are ranked on a five level scale, aiming at intervals of the distribution of that ability in the population

- *Physical Demands* specify the overall physical strength requirement of a job as well as specific required body movements (stooping, kneeling) and specific strength applications.
- *Temperaments* describe different types of occupational situations, such as performing a variety of duties or repetitive cycle operations, or situations involving influencing people in their opinions or attitudes.
- *General Educational Development (GED)* embraces formal and informal aspects of education required for satisfactory job performance. It is education of a general nature without specific occupational objective. Ordinarily it is obtained in school but it may also be obtained from experience or self-study. The GED scale has three divisions: *Reasoning Development*, *Mathematical Development* and *Language Development*. There are 6 levels, but for Language Development the two highest levels have been merged into one.
- *Specific Vocational Preparation (SVP)* is defined as the time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in the job. The definition suggests it refers to broadly defined training or specific experience needed before one may qualify for the job. The training may be acquired at school or at work, and it does not include the orientation time that a fully qualified worker needs to get accustomed to the special conditions of a new job. SVP is measured on a time scale of 9 intervals.

Finally, the third group of variables describes what is normally referred to as working conditions: *Environmental Conditions* characterize the work environment in terms of whether it is

hot or cold, whether it is located inside or outside, whether it brings dangers of explosives or toxic conditions, and so forth. In an extensive appendix on our website² we copy the description of the variables from the DOT and characterize the dataset through means and dispersions of these variables.

We will proceed to analyse these data in three steps. First, we will search for structure in the variables that seek to describe the type of worker envisaged for a given job. Next, we will investigate whether worker types match up with sorts of activities in any systematic way. Finally, in section 4, we will check how the quality level of the work environment is distributed among the structure of activities and worker qualities.

3. The structure of worker requirements and job activities

3.1 Worker requirements

We start with considering the variables that describe the worker qualities that are perceived to be necessary in a job. In the DOT, these variables are grouped under Aptitudes and Temperaments. Aptitudes describe an individual's capabilities and abilities in several dimensions. Temperaments are somewhat mixed. Some of them describe what an individual has to do, ("Directing"), some refer to what an individual should be able to ("Performing under Stress"). These two groups appear to interact and, therefore, together define the structure that we seek to define. But the two groups together consist of 18 variables, which is too many to provide an insightful perspective on labour market structure. We apply factor analysis as a method to reduce the dimensionality of this set of variables.

² At www.utdallas.edu/~vijver/DOT.Appendix.pdf

Factor analysis is a statistical technique that extracts a few underlying dimensions (factors) from a large group of variables (the facets) (e.g., Johnson and Wichern 1998). Factors are mean-0, variance-1 constructs; factor loadings are parameters linking factors to variables in their standardized form. These factor loadings help to interpret the factors: they allow us to give a name to the factors that, by assumption, generate the nature of each job. Factors capture the main differences (variance) among jobs, but they will not capture all variance. With more factors, more variance is captured, but that brings us back to square one: too many factors is as problematic as too many variables. The choice of the number of factors hinges on the amount of variance they capture individually and collectively, which is indicated by the calculated eigenvalues. A rule of thumb is to retain as many factors as there are eigenvalues greater than 1,³ but practical considerations sometimes suggest deviating from this rule.⁴

As columns 2 and 3 of Table 1 show, the first factor explains 37% of the variance; the first two explain 64%.⁵ The first factor loads exclusively high on General intellect, on Verbal ability and on Numerical ability. We will dub this factor the Intellect factor. The second factor loads highest on Motor Coordination, Finger Dexterity and on Manual Dexterity, and also relatively high on Spatial Orientation and Form Perception. We dub this factor the Dexterity

³ Technically, the sum of all eigenvalues equals the number of variables entered in the analysis. The average value of the eigenvalues is therefore equal to 1.

⁴ Reduction of the DOT information by factor analytic methods has been done before. Gittleman and Howell (1995) apply cluster analysis to jobs covered in the 1980 Census and various editions of the CPS. They are interested in applying the segmentation view of the labor market and base their clusters not only on DOT variables, but also on hourly earnings, annual earnings and institutional features like union coverage. Shu, Fan, Li and Marini (1996) link the fourth edition DOT (1977) scores to the jobs in the 1960, 1970 and 1980 Censuses and stress that the underlying factor structure is highly stable over time. Gittleman and Howell discuss a few other applications of factor analysis; none of these uses the DOT 1992 edition. Hartog (1980) used DOT factors to explain the wage structure. Recently, Ingram and Neumann (2006) applied factor analysis to the DOT data, with results that are comparable (and complementary) to ours; they stress different implications.

⁵ We use the iterated principal factor method of Stata 8. The standard principal factor method yielded a series of negative eigenvalues that confuse the interpretation of the percentage of the variance explained by the selected factors.

factor. With a third factor, explained variance would go up to 75%, thus further highlighting the strong intercorrelation of the variables, but we decided not to use it: this factor is less easily labeled than the other two, because its highest factor loading is only 0.47; and while the eigenvalues of the first two factors are 4.41 and 3.30, that of the third factor equals only 1.21.

Columns 4 and 5 of Table 1 add the GED variables. These variables specify dimensions of cognitive ability that may or may not be acquired in school. The DOT indicates at what schooling level each of the GED levels can normally be attained, but also acknowledges that they can be attained outside school. Not unexpectedly, they are smoothly subsumed in the Intellect Factor.

With or without the GED variables inserted, the Temperaments give modest factor loadings: the structure is mostly determined by Aptitudes⁶. Thus, we may conclude that a simple dichotomy on required worker abilities carries us a long way, since Intellect and Dexterity together already explain 2/3 of the total variance, but relying on this dichotomy we also miss out on a substantial amount (1/3) of variation in job structure.

Table 1: Factor analysis of General Educational Development, GATB Aptitudes, and Temperaments

The abstract mathematical insight into the job structure that Table 1 offers comes to life when we depict the job structure as a distribution of the two main required worker qualities. However, the DOT describes jobs that were selected in a non-random manner, implying the distribution of worker qualities across DOT jobs is biased and lacks meaning. We therefore connect jobs to occupations and thereby connect the DOT information with both the Census 1990 and the CPS-NBER 1990 samples. This visualises the two key dimensions of the labour

⁶ We have refrained from including SVP in the factor analysis as it is not so much a worker trait, but time needed to attain proficiency. In practice this is inconsequential, as SVP would be a strong contributor to Intellect.

market (but note again that they do not tell the full story). Figure 1 shows the distribution of jobs, measured by Intellect and Dexterity (discretized into six categories), among male and female workers in graphical form with “balloon plots,” where the size of each balloon is proportional to the frequency mass for the variable values at its center.⁷ Thus, the balloon plots depict job structure as a landscape with high and low densities of job requirement combinations. For men, the figures remind of the classical distinction between white-collar intellectual and blue-collar menial jobs, with the biggest clusters separated at the mean value of Intellect. Yet the male labour market is far removed from a simple dichotomy. For women, there is even less of a dichotomy and the separating discontinuity is absent. The results are robust in the sense that they are identical for the Census data and the CPS-NBER data.

Figure 1: Distribution of jobs for male and female workers, 1990

3.2 Matching worker requirements and worker functions

The Worker Functions specify the focus of workers’ effort, whether they are directed towards Data, People or Things (DPT). The structure is certainly not tri-polar. As the correlations in Table 2 show, complexities in Data and People tend to go together to some extent, with a correlation at 0.6. Complexity in relation to Things does stand apart; it is independent of complexity in Data and even opposite to complexity in People. Table 2 also shows that the GED variables of Reasoning, Math and Language skill correlate highly. Of course, these correlations describe job requirements. If among individuals mathematical skills and verbal (language)

⁷ Technically, a joint distribution between any pair of variables could be depicted as a scatterplot, but with a great many data points, a scatterplot becomes an impenetrably dense mass of black dots. More importantly, a scatterplot is suitable only when observations are all weighted equally. With varying weights, some points should count more heavily than other points. A balloon plot solves both problems simultaneously. It parcels the two-dimensional area into cells and shows the frequency mass in each cell by the size of a balloon that sits on the cell’s centroid.

abilities would be polar opposites (and correlate hardly or even negatively), one would expect a wage premium for the scarce individuals who can supply both abilities at a high level, as predicted by Mandelbrot (1960).

We are now in a position to consider the matching between the required worker qualities and the nature of job activities. Figure 2 visualises the relation between DPT and Intellect and Dexterity in graphical form. In these two-variable joint distributions, with other variables integrated out, Data and Intellect clearly correlate positively, and the same holds for Things and Dexterity. The correlation between People and Intellect is weakly positive, between People and Dexterity weakly negative. The other distributions exhibit no clear correlation. These observations are confirmed by the correlation coefficients in Table 2, but the evidence in Figure 2 is clearly richer than a simple correlation coefficient could manifest. The results confirm anticipations on the structure of labour demand: complex relations with data require intellect, complex relations with people also require intellect, but the connection is less tight, and complex relations with things require dexterity.

Table 2: Correlation among selected job requirements

Figure 2: Frequency Distribution of DTP against Intellect and Dexterity

Regression analysis further explores the matching in a multivariate context (Table 3). The linear specifications confirm the patterns found in the balloon plots. Complex relations to Data and to People make high intellectual demands, complex relations to Things impose no intellectual requirement but require dexterity. Relation to people also correlates negatively with dexterity. The regressions also reveal that training time (SVP) is most important for functioning in relation to Data; jobs with complex relations to things do not require long vocational

preparation. For a proper understanding, note that SVP does not refer to a specific and explicit training program associated with the job. The “specific vocational preparation” may also be covered in a series of jobs preceding the present job, as in a required career profile.

A quadratic specification brings out that training time has a different relationship with each of the worker functions. Jobs that require complex functioning in relation to Data have long introductory trajectories (training or experience in other jobs). This is far less so for complex functioning in relation to Things, where the effect strongly declines at the higher levels of SVP. By contrast, the relation of People to SVP has a markedly increasing slope, indicating especially high training times for jobs that involve a very complex relation to people. Compared to the other worker functions, the relationship with SVP is least precisely estimated in case of complex relations to people, suggesting more heterogeneity than in the relationship with the other worker functions.

The quadratic specifications show significant nonlinearity, but yield only a modest gain in the explained variance. The largest advance occurs for the relation to Data. Considering also other specifications that we have estimated but do not report here, it appears that Data relates better to the available worker quality variables than the other worker functions. A specification that is fully quadratic in SVP and the two factors from Aptitudes and GED explains 82% of the variation (R^2). A linear specification with just the three GEDs and SVP already yields an R^2 of 0.73. In contrast, for People, a model that is fully quadratic in SVP and Factors explains no more than 52% of the variance, whereas just the three GED dimensions and SVP would explain 43%. For Things, the regression model captures 57% of the variance with the full quadratic, whereas just the three GEDs and SVP would explain a mere 6%.

Condensing aptitudes and temperaments into factors generally comes at a cost, as information is lost. It turns out, from regressions not reported here, that the cost is only marked for complexity in dealing with people. In the Things equation, adding the separate Aptitude variables to GEDs and SVP gives a big boost in explained variance (from 6% to 52%); adding Temperaments helps to get up to 60%; replacing these Aptitudes and Temperaments with the Intellect and Dexterity factors gives modest loss. Thus, for complexity in relation to Things, the Aptitudes are essential variables, but the reduction into factor analytic constructs does not ignore much information. For Data, adding separate Temperaments or Aptitudes only modestly improves explained variation. For People, the marginal contribution of Temperaments is substantial: it raises the explained variance from 49 to 64% if the separate Aptitudes are already included, and subsuming Temperaments under factor analysis gives a large loss in explained variance. This indicates that for the complexity in dealing with People, some specific temperaments stand out in a way that is lost in the factor analytic reduction. The important temperaments are directing, giving instructions, and dealing with people (positive) and precise tolerances (negative).

The evidence on matching between type of complexity of the job duties and worker qualities as perceived by job analysts may be summarised as follows. Judging the tightness of the matching process by the explained variation, the link between worker qualities and Data complexities is tightest; tightness is lowest for People complexity; and tightness is slightly higher for Things complexity. For Things, nonlinearity in the matching relation is important and Aptitudes are essential. Specific temperaments are essential only for People; in the other dimensions of job complexity, Aptitudes and Temperaments can be factor-analytically reduced.

Table 3: Worker functions explained by vocational preparation and aptitudes

In Figure 1, we reported a difference in the Intellect/Dexterity distributions between men and women. This will no doubt have consequences for the association between worker requirements and worker functions in relation to Data, People and Things. For reasons of space we cannot explore this further.

4. Working conditions

4.1 The distribution of working conditions

The DOT reports extensively on physical burdens and environmental conditions. Again, it is useful to consider the amount of independent variation here, and the structure of relations between variables. In the listing of Physical Demands, there are seven variables related to pure physical activities (Strength, Climbing, Balancing, Stooping, Kneeling, Crouching, Crawling). With factor analysis, a single factor captures 74% of the variance, and the eigenvalues of the other factors are all less than 1. It has high loadings on all variables (above 0.44) and dominant loadings on Climbing, Stooping, Kneeling, and Crouching. We will call this variable the Movement factor.

There are 13 more variables under Physical Demands that can be grouped in 4 factors that jointly capture 91% of the variance. The first loads high on Reaching and Handling, and that is how we will label it; it has very low loadings on all other variables, with one exception all virtually zero. The second factor loads high on Far Acuity and Field Vision, fairly high on Depth Perception and Color Vision, and very low on all others, so we will label it Vision. The third factor loads fairly high on Near Acuity and Fingering; we will refer to it as Precision. The fourth factor loads exclusively high on Talking and Hearing, and we will label it Communication.⁸ The factor analysis produces a

⁸ The fourth eigenvalue is actually less than 1. However, the fourth factor explains 10 percent of the variance, which amounts to half of the variance unexplained by the first three factors. Furthermore, the fourth factor has a clear

clear-cut result because of the strong demarcations in factor loadings. Each of the four factors loads high on a small number of related variables and very low if not zero on all other variables.⁹

There are 13 variables to characterize the environment in which the job has to be performed. Five variables describe, in a broad sense, the atmospheric conditions: exposure to the outside weather conditions, to hot and cold temperatures, to wetness and to atmospheric conditions. A single factor picks up 67% of the variance, even though its eigenvalue is less than 1, and loads modestly on each of the variables (loadings between 0.19 and 0.55). We will call this factor Atmosphere.

There are eight other variables, but factor analysis produced no meaningful reduction here. We choose to retain six of these as separate variables: Noise, Electric Shock, High and Exposed Places, Radiation, Explosives, and Toxics. We drop Vibrations, Move/Mechanical Parts, and Other Environmental Conditions as not sufficiently interesting to retain separately.

Table 4 presents the correlations among this set of working conditions.¹⁰ Interestingly and perhaps remarkably, most correlations are very low: these groups of working conditions are quite independent of each other. Clustering of working conditions is strongest for Movement, which correlates with Atmosphere and at lower levels with Noise, Shocks and Exposure. Many of the other correlations between working conditions are about zero. Atmosphere, perhaps an archetypical working condition, as exposure to hot and cold temperatures and unpleasant outside weather conditions, only correlates at more than a modest level with one variable (Movement).

interpretation.

⁹ The other variables, not yet mentioned, are: Feeling, Tasting/Smelling, and Accommodation. Feeling and Accommodation load on the Precision factor with factor loadings that are half the size of the Near Acuity and Fingering variables. Tasting/Smelling appears to be a unique data component that we will not pursue further.

¹⁰ We do not present the factor analyses *in extenso*, to save both space and the reader.

Table 4: Correlations among working condition variables

It is often alleged that there exist correlations between worker qualities (as reflected in level of education) and amenities on the job. High wage workers are supposed to be able to buy better working conditions by accepting a lower wage. Conversely, poor working conditions (fumes, noise, toxics) should predominantly affect low wage manual workers who cannot afford to buy improvements in their working environment. Table 5 presents correlations between working conditions and worker functions (Data, People, Things) and aptitudes (SVP, Intellect, Dexterity). Note that there are good reasons to distinguish between the factors based on Physical Burdens (the first five variables in Table 4) and the Environmental Conditions (the last seven variables). Environmental conditions may be seen as the classical job disamenities that workers want to avoid, whereas high levels of Physical Burdens and Demands to many may not be unpleasant at all. Many people enjoy communication, precision work, moving around rather than sedentary work, etc.

High requirements on the Intellect factor come with high scores on Communication, and the same holds for high levels of involvement with Data and People. There is also a substantial positive correlation between the Intellect and Precision factors. The correlations between the Intellect factor and Movement, Reaching/Handling, Atmosphere and Noise are negative but smaller. All the other correlations are very low. Exposure to radiation and exposure to explosives are independent of the job level as measured by intellectual or dexterity requirements. It is true that the intellectual factor correlates negatively with unpleasant working conditions, and the dexterity factor correlates positively, evoking the familiar image of “good” white-collar jobs and “bad” blue-collar jobs, but the correlations are quite low. Poor working conditions are therefore not associated merely with jobs with low intellectual requirements or high dexterity (or manual) requirements. If we take the Intellect factor to be an indicator of job level, then Atmosphere and Noise correlate negatively with

job level. The other environmental conditions are independent. Among the Physical Burdens/Demands, both positive and negative correlations occur.

Table 5: Correlation of worker functions and aptitudes with working conditions

4.2 Compensating differentials?

There is a long tradition of searching for wage compensation for unpleasant working conditions (for an overview, see Rosen, 1986). Straightforward regressions do not always support the theory, and authors reporting positive effects often take pride in the special features of their dataset or their methodological edge (cf. Duncan and Holmlund, 1983; Brown, 1994). Merged with wage data from the Census and the CPS-NBER samples, the DOT information allows measurement of the effect of working conditions on wages. It turns out that this exercise sheds an interesting light on the contradictions found in this literature.

Table 6 reports estimation results for male employees. The dependent variable in each model is the logarithm of the hourly wage. Model 1 includes factors (Intellect, Dexterity), worker functions (Data, People, Things), Special Vocational Preparation (SVP), region of residence, and working conditions as explanatory variables. Models 2 adds second order terms (including interactions) among factors, worker functions and SVP. Since the focus of this paper is on the impact of working conditions on wages, Table 6 only reports the parameter estimates of these variables. The results illustrate the sensitivity to data and specification. As mentioned before, six original DOT variables and one factor reflect a job's environmental conditions. Table 5 shows that five of these seven variables have virtually no correlation with the other explanatory variables in the wage equation. Such independence is an ideal setting for estimating the wage effects. Indeed, any coefficient that is significant is positive and none of the estimated

coefficients is significantly negative; i.e., none of the estimated wage effects rejects the theory of compensating differentials. These conclusions are not sensitive to whether the specification of the job requirements is linear or quadratic. Between the two variables that do correlate with the other job characteristics (Atmosphere and Noise), Atmosphere indeed gets a coefficient that violates the hypothesis of a compensating differential, while the coefficient for Noise is still solidly positive.

The situation is different however for the factor analytic composite working conditions, i.e., the Physical Burdens/Demands. Here, as was illustrated in the first five rows of Table 5, correlations with worker functions, SVP and job requirements range from -0.33 to 0.60 , and 22 of the 25 correlation coefficients are statistically significant. Thus, Physical Burdens/Demands are quite multicollinear with the other explanatory variables. Indeed, estimated wage effects are sometimes positive, sometimes negative. This should actually not be too surprising since, as noted, these conditions indeed will not uniformly be experienced as unpleasant. But for these variables also, the coefficients are more sensitive to the specification: it makes a difference whether control for other job characteristics is crude or fine, i.e., whether we distinguish between jobs with a coarse linear scale or with a more refined quadratic scale. We even find sign reversals for significant coefficients (Reach-handle and Precision, for the quadratic on CPS-NBER). The sensitivity to the controls is also manifest in estimates of the same model for women (not reported in the table): as for men, estimates are robust and have proper signs for working conditions that are uncorrelated with job requirements, but the patterns are somewhat weaker. When the observations on men and women are pooled (also not reported here), results become rather unstable. For example, one coefficient that is negative for both men and women separately turns positive in the pooled sample. This underscores the basic interpretation of the empirical

literature, that finding compensating wage differentials requires very precise control for other job traits and (required) worker qualities.

Table 6: Wages and working conditions: male wage employees

For each individual, the total value of the environmental conditions may be calculated as the sum of the products of each variable with its wage regression coefficient from the quadratic specification. Figure 3 plots the joint distribution of the compensating wage differential and Intellect and Dexterity, for both men and women and both Census and CPS-NBER data. As before, the balloons plots require a discretization of the variables to be graphed: each range is divided into six equally sized intervals, but as Figure 3 illustrates, the upper tail of the compensation distribution is very thin.¹¹ The reason is that a few employees enjoy a sizable compensation for working with explosives, danger of radiation exposure and risk of electric shock (Table 6). The plot indicates that for men the compensation for working conditions declines in relation to the Intellect factor. In contrast, the plot with Dexterity shows an upward sloping relationship with compensation. For women the figure offers no visible relationship between compensating wage differentials and intellectual and dexterity level of the job. Simple correlation coefficients equal 0.025 for Intellect and 0.145 for Dexterity, but these coefficients are driven mostly by the factors' association with explosives, radiation and electricity among the women's sample. Note that the wage effects are calculated at the estimated regression coefficients ("prices") for men and women separately, and that the differences by gender in Figure 3 reflect differences in both the parameter estimates of the log wage equation and the distributions of working conditions.

Figure 3: Contribution of working conditions to log hourly wages by level of Intellect and Dexterity

¹¹ For example, for the highest compensation group at a value of 1.21, there is one microscopically small balloon that has only 3/1000th of the size of the largest balloon in the Dexterity plot.

5. Conclusion

Distinction by occupation is often all the information a researcher has about the demand side of the labor market. This paper taps into a wealth of information about jobs that is available in the Dictionary of Occupational Titles (DOT), to paint a picture of the landscape of labour demand. We can meaningfully reduce the observed heterogeneity to differences in a few dominant dimensions, but these dimensions are not sufficient to capture all the information: substantial irreducible heterogeneity remains. We can sum up our specific conclusions as follows

- Work as activity in relation to Data, People and Things

The DOT specifies worker functions as the degree of complexity in dealing with Data, People and Things. The relation to Things is an independent dimension. Relations to Data and People correlate, but less than perfectly, at 0.60.

- Required worker qualities

Two factor analytical constructs, Intellect and Dexterity, jointly explain 2/3 of the variation in required worker qualities. The GED skills of Reasoning, Math, and Language easily fit within the Intellect factor, and in their high inter-correlations disprove a dichotomy between demand for verbal and mathematical skills. Reduction of required worker qualities to two underlying dimensions is a sensible simplification for many purposes, but misses out on 1/3 of the variance. The latter cannot be represented with one or more recognisable dimensions. A plot of the frequency distribution of jobs on these two dimensions does not show a simple dichotomy with intellectual jobs and dexterity jobs. Moreover, the job structures in terms of these frequency plots are markedly different between men and women.

- Required qualities in relation to Data, People, Things

Data complexity has a tight relationship with required Intellect. Complexity in People and in Things have no tight matching relationships with required worker qualities. Complexity in Things requires dexterity. Complexity in relation to dealing with People requires intellect and long vocational preparation (SVP). Linear relations go a long way in describing the matching between job activities and required worker qualities. Required training time (SVP) has a convex relationship with Data and Things complexities, but a concave relationship with People complexity.

- The distribution of working conditions

Working environments and physical demands cannot be described with a few underlying dimensions: there is too much uncorrelated variety. One cannot simply speak of good jobs and bad jobs. Good and bad working conditions are also spread out all over the specter: there is no simple association with high levels of Intellect or Dexterity.

- Compensating wage differentials for working conditions

In our data, undesirable environmental conditions occur virtually independently of other job characteristics. Under these favorable econometric conditions, we find significant wage compensation, thus supporting the theory of compensating wage differentials. The only exception to these results is Atmospheric conditions, a variable that is indeed not independent of other job traits. For men, the wage received as compensation for working conditions decreases with Intellect, while it increases with Dexterity. For women there is no such relationship.

Data Appendix

The Dictionary of Occupational Titles (DOT) contains descriptions and ratings of 12,741 jobs (U.S. Dept. of Labor, 1991). We use the fourth revised edition, including the minor modifications published in 1992.¹² Even though the objective of DOT is to provide up-to-date information about the nature of jobs in the economy, one may expect it to lag behind, especially in its description of jobs in newly emerging sectors. For research purposes, the DOT information is therefore subject to a measurement error by understating the role of new technology and its required cognitive skills. Nonetheless, the information is unique and potentially very valuable.¹³

The DOT job classification and the common coding scheme used by the Census Bureau are not identical. We want to relate the DOT information to the Census job classification for two reasons. First, this information may be of great value in explaining the structure of wages. Second, and most relevant, it allows construction of weights for each DOT job that are necessary to analyze the structure of labor demand. It is known that the DOT database does not represent a random sample of jobs in the U.S. labor force (Miller et al., 1980). For example, manufacturing jobs are substantially over-sampled. This nonrandom sampling procedure may be less problematic within each occupational code: there is less variation in the work that defines a specific occupation.¹⁴

¹² Data collected by the O*NET consortium may soon be a good alternative data source. Starting in 1998 with a pretest and in 2001 with the actual project, the O*NET consortium operates a continuous data collection as a follow-up on the data collected in the DOT. The family of occupations has been reorganized to improve homogeneity within families, new variables have been defined, and there is a rolling schedule of updating occupational information. The dataset has information on some 1000 occupations. However, the recent nature of the data and the change in methodology prevents historical trend analysis, which is our long-term research objective. At present, this paper aims for a picture of the labor demand structure at the beginning of the 1990s.

¹³ A more detailed assessment of the DOT data is given in Vijverberg and Hartog (2005), which also surveys related earlier studies that use DOT data. An extensive data Appendix is available on the internet at www.utdallas.edu/~vijver/DOT.Appendix.pdf

¹⁴ Even so, when an occupational job content variable is extracted from DOT, the information content of this variable is subject to the within-occupation sampling probabilities of the jobs that make up the occupation. To give an example, let an occupation (“baker”) consist of two types of jobs (“bread baker” and “pastry baker”). Let there be four times as many bread bakers as pastry bakers in the labor force. DOT may well include only one description of each baker job. The description of the average “baker” job should assign four times more weight to the bread baker description. However,

However, as we also extract information from the DOT database through factor analysis, the lack of random sampling between occupations could severely bias the extracted factors unless some kind of weighting is employed. We solve the problem by tabulating a frequency distribution of wage/salary workers across occupations from the 1990 Census (employing the Census weights in this tabulation), merging this frequency by occupation into the DOT database, and computing a weight as the ratio of the Census frequency divided by the number of DOT jobs assigned to that occupation. The weight measures the relative importance of a given DOT job in the U.S. wage/salary labor force. A comparison of results shows that measured correlations differ substantially according to whether one employs weights. Factor scores are computed from correlations and are similarly influenced.

The National Occupational Information Coordinating Committee (NOICC) in cooperation with, among others, the Occupational Analysis Field Centers of the U.S. Department of Labor (which are responsible for the DOT) developed a database that contains the DOT-Census link. The database is called the NOICC Master Crosswalk and is available on the internet. In this study, we use this database with some relatively minor modifications.¹⁵

To be precise, the DOT data are supplemented with information from the 1-percent public use sample of the Census 1990 and the 1990 Merged Outgoing Rotation Group file that is derived from the monthly rounds of the 1990 U.S. Current Population Survey and is available from the National Bureau of Economic Research (which we shall refer to as the NBER-CPS 1990 data). As

such weights are not available, and we are forced to assign equal weights to each job within an occupation.

¹⁵ When we started with this research, one of us worked on building a linkage. We became aware of the NOICC Master Crosswalk database when about seventy five percent had been linked. In terms of the detailed 1990 Census occupational codes, 54.1 percent of these matched exactly. If one were to distinguish only 19 broad occupational groups, there is an 86.25 percent match. In reviewing some of the differences, it became apparent that the NOICC Master Crosswalk linkage could be questioned in some cases. On the basis of the DOT job description, 227 of the 12741 code links have been changed.

mentioned, this permits an estimate of the frequency distribution of jobs, which is needed in order to describe the labor market by means of the various DOT characteristics. We use the two data sets to consider the robustness of results. As to wages, the CPS-NBER data appear to be more reliable, because (i) the information is based on a telephone interview sample rather than self-reported responses on the long form of the Census and (ii) the interviewer asks for earnings on the current job in the time unit (e.g., hourly, weekly, monthly) with which the respondent feels most familiar, thus eliminating a source of response error and reducing the well-known division bias that arises when annual earnings are divided by usual hours. In contrast, the Census asks for annual earnings in the previous year, which for many respondents is less familiar than current wages. The analyses focus on full-time employees. Thus, the samples consist of individuals working between 30 and 70 hours a week, working at least 4 weeks during the year, and aged between 16 and 65 years of age.

After dealing with these issues, the end result of the DOT/Census linkage is the merging of occupational content information with person-specific Census information. For each Census occupational code, the job content represents the arithmetic average across the DOT jobs that have been allocated to it.

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For Peer Review

Table 1: Factor analysis of General Educational Development, GATB Aptitudes, and Temperaments^a

Variable	Rotated Factor Loadings		Rotated Factor Loadings	
	Intellect	Dexterity	Intellect	Dexterity
Reasoning development			0.954	0.055
Mathematical development			0.892	0.073
Language development			0.944	-0.045
Apt: General learning ability	0.907	0.071	0.906	0.032
Apt: Verbal aptitude	0.932	-0.041	0.919	-0.083
Apt: Numerical aptitude	0.820	0.110	0.835	0.078
Apt: Spatial aptitude	0.241	0.646	0.275	0.634
Apt: Form perception	0.293	0.724	0.307	0.708
Apt: Clerical perception	0.687	-0.038	0.672	-0.070
Apt: Motor coordination	-0.118	0.738	-0.093	0.738
Apt: Finger dexterity	0.050	0.731	0.070	0.725
Apt: Manual dexterity	-0.363	0.690	-0.322	0.706
Apt: Eye-hand-foot coordination	-0.310	0.247	-0.279	0.263
Apt: Color discrimination	0.081	0.436	0.088	0.433
Temp: Directing	0.598	-0.241	0.589	-0.267
Temp: Influencing	0.375	-0.303	0.364	-0.322
Temp: Expressing feelings	0.105	0.097	0.102	0.091
Temp: Performing under stress	-0.037	0.115	-0.019	0.117
Temp: Precise tolerances	-0.094	0.516	-0.063	0.526
Temp: Dealing with people	0.531	-0.334	0.502	-0.359
Temp: Making judgments	0.562	0.200	0.580	0.178
Variance proportion ^b	0.368	0.644	0.462	0.688

Notes: ^a Rotated factor loadings computed by means of varimax rotation.

^b Proportion on the basis of unrotated factors.

Table 2: Correlation among selected job requirements

	Reasoning	Math	Language	SVP	Intellect	Dexterity	Data	People	Things
Reasoning	1.000								
Math	0.853	1.000							
Language	0.914	0.836	1.000						
SVP	0.730	0.698	0.679	1.000					
Intellect	0.960	0.898	0.950	0.738	1.000				
Dexterity	0.057	0.076	-0.047	0.048	0.001	1.000			
Data	0.834	0.785	0.806	0.687	0.871	-0.005	1.000		
People	0.615	0.510	0.643	0.491	0.650	-0.302	0.600	1.000	
Things	0.046	0.040	-0.054	0.016	-0.023	0.728	0.017	-0.247	1.000

Table 3: Worker functions explained by vocational preparation and aptitudes

	Data		People		Things	
	Coef.	t	Coef.	t	Coef.	t
A: <u>Linear</u>						
SVP	0.0798	15.44	0.0475	9.19	-0.0029	0.30
Intellect	1.5262	124.59	1.2168	66.43	-0.0547	2.41
Dexterity	-0.0206	2.42	-0.6285	49.33	1.8907	119.84
Intercept	2.6358	201.25	1.8971	96.90	2.2110	91.17
R ²	0.7629		0.5151		0.5312	
B: <u>Quadratic</u>						
SVP	0.4738	35.36	0.0098	0.43	0.4770	17.56
Intellect	1.4249	64.06	1.2750	33.90	-0.4495	-9.97
Dexterity	-0.2140	-17.31	-0.6401	-30.62	1.8483	73.73
SVP ²	-0.0212	-11.14	0.0089	2.76	-0.0462	-11.97
SVP × Intellect	-0.1199	-12.08	-0.0643	-3.83	0.0439	2.18
SVP × Dexterity	0.0060	1.42	-0.0011	-0.16	0.0063	0.74
Intellect ²	-0.2573	-17.49	0.0769	3.09	-0.4312	-14.46
Intellect × Dexterity	0.1579	12.98	-0.1564	-7.60	-0.0681	-2.76
Dexterity ²	0.0012	0.17	0.1439	12.03	-0.0937	-6.53
Intercept	2.5165	146.71	1.7893	61.67	2.1351	61.38
R ²	0.8182		0.5242		0.5690	

Table 4: Correlations among working condition variables

	Movement ^a	Reach/ Handling ^b	Vision ^b	Precision ^b	Communic ⁿ ^b	Atmosphere ^c	Noise
Movement ^a	1.00						
Reach/Handling ^b	0.10 **	1.00					
Vision ^b	0.20 ***	0.01	1.00				
Precision ^b	-0.07	0.04	-0.01	1.00			
Communication ^b	-0.29 ***	-0.01	0.00	0.02	1.00		
Atmosphere ^c	0.40 ***	0.09 *	0.15 ***	-0.12 **	-0.23 ***	1.00 ***	
Noise	0.32 ***	0.13 ***	0.28 ***	-0.02	-0.26 ***	0.27 ***	1.00
Electric	0.20 ***	0.02	0.04	0.09 *	-0.05	0.10 **	0.07
High/Exposed	0.26 ***	0.02	0.04	-0.01	-0.07	0.22 ***	0.08
Radiation	-0.01	0.01	-0.01	0.04	0.00	-0.02	-0.03
Explosives	0.04	0.01	0.07	0.02	-0.01	0.14 ***	0.05
Toxic/Caustic	0.08	0.01	0.03	0.03	-0.06	0.16 ***	0.06

	Electric	High/Exposed	Radiation	Explosives	Toxic/Caustic
Electric	1.00				
High/Exposed	0.30 ***	1.00			
Radiation	0.06	0.00	1.00		
Explosives	0.07	0.11 **	0.00	1.00	
Toxic/Caustic	0.05	0.13 ***	0.00	0.14 ***	1.00

Notes: ^a Factor score resulting from a factor analysis on physical activities variables
^b Factor score resulting from a factor analysis on physical demands variables
^c Factor score resulting from a factor analysis on job environment variables
*** significant at 1 percent level
** significant at 5 percent level
* significant at 1 percent level

Table 5: Correlation of worker functions and aptitudes with working conditions.

	Data	People	Things	SVP	Intellect	Dexterity
Movement	-0.27 ***	-0.25 ***	0.18 ***	-0.13 ***	-0.33 ***	0.22 ***
Reach/Handling	-0.33 ***	-0.34 ***	0.19 ***	-0.34 ***	-0.38 ***	0.25 ***
Vision	-0.14 ***	0.01	0.11 **	-0.07	-0.11 **	0.11 **
Precision	0.27 ***	0.02	0.45 ***	0.17 ***	0.29 ***	0.46 ***
Communication	0.51 ***	0.61 ***	-0.27 ***	0.28 ***	0.55 ***	-0.32 ***
Atmosphere	-0.21 ***	-0.17 ***	0.06	-0.11 **	-0.27 ***	0.12 **
Noise	-0.24 ***	-0.20 ***	0.18 ***	-0.11 **	-0.30 ***	0.15 ***
Electric	0.04	-0.03	0.13 ***	0.05	0.00	0.15 ***
High/Exposed	-0.02	-0.06	0.07	0.01	-0.06	0.10 **
Radiation	0.02	0.00	0.06	0.03	0.04	0.07
Explosives	-0.03	-0.01	0.00	-0.01	-0.03	0.03
Toxic/Caustic	0.00	-0.04	0.08	0.00	-0.01	0.10 **

Notes *** significant at 1 percent level

** significant at 5 percent level

* significant at 1 percent level

Table 6: Wages and working conditions: male wage employees^a

Data source: Job characteristics: Variable ^b	Census 1990				CPS-NBER 1990			
	Model 1		Model 2		Model 1		Model 2	
	b	t	b	t	b	t	b	t
Movement ^c	-0.0167	-2.85	-0.0040	-0.61	-0.0010	-0.27	-0.0145	-3.61
Reach-Handle ^c	-0.0108	-1.15	-0.0373	-3.73	0.0184	3.27	-0.0123	-1.94
Vision ^c	0.0035	0.81	-0.0109	-1.71	0.0440	15.66	0.0171	4.38
Precision ^c	0.0438	4.59	0.0045	0.41	0.0217	3.66	-0.0137	-1.98
Communication ^c	0.0531	5.03	-0.0324	-2.66	-0.0149	-2.12	-0.0832	-10.18
Atmosphere ^d	0.0039	0.40	-0.0256	-2.40	-0.0235	-3.91	-0.0441	-6.75
Noise	0.1074	11.42	0.1045	10.33	0.1335	22.59	0.0956	14.95
Electric shock	0.2857	3.81	0.3185	4.11	0.2350	4.70	0.2568	5.00
High and exposed places	0.1054	0.61	-0.0052	-0.03	0.6803	6.15	0.4739	4.41
Radiation	-0.0492	-0.19	0.4995	1.76	0.0626	0.39	0.2629	1.47
Explosives	0.6774	2.85	0.9131	3.29	1.1543	7.32	0.9294	5.25
Toxic/caustic materials	-0.0324	-0.20	0.0673	0.38	0.1712	1.60	0.2825	2.44
R-squared	0.2186		0.2337		0.2927		0.3104	
Standard error of regression	0.5406		0.5355		0.4587		0.4530	
Number of observations	40229		40229		73209		73209	

Notes: a. Model 1 includes factors (Intellect, Dexterity), worker functions (Data, People, Things), Special Vocational Preparation (SVP), region of residence, and working conditions as explanatory variables. Models 2 adds second order terms (including interactions) among factors, worker functions and SVP. The dependent variable is the logarithm of the hourly wage.

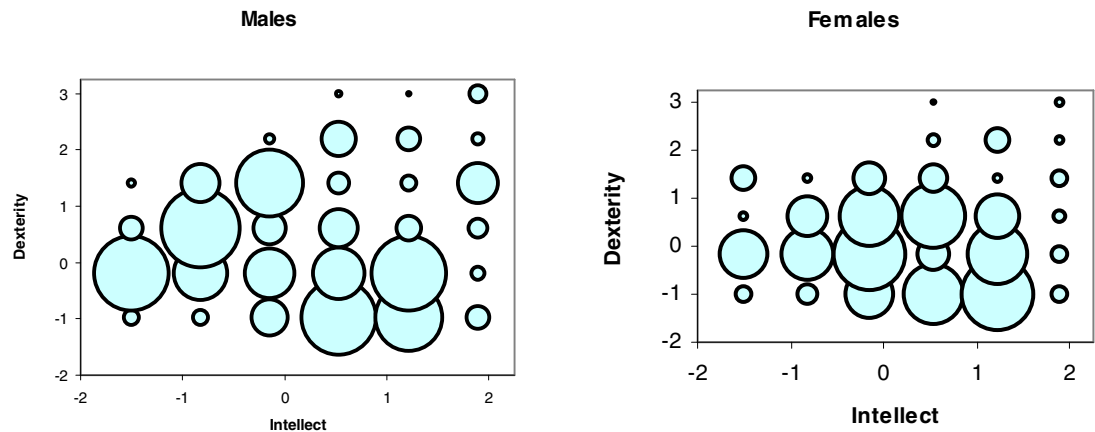
b. The regression also includes the two factors Intellect and Dexterity computed from GED, GATB and Temperament variables, the worker function variables, and SVP

c. Factors computed from physical demands variables.

d. Factor computed from environmental conditions variables.

Figure 1: Distribution of jobs for male and female workers, 1990

A: Census 1990



B: CPS-NBER 1990

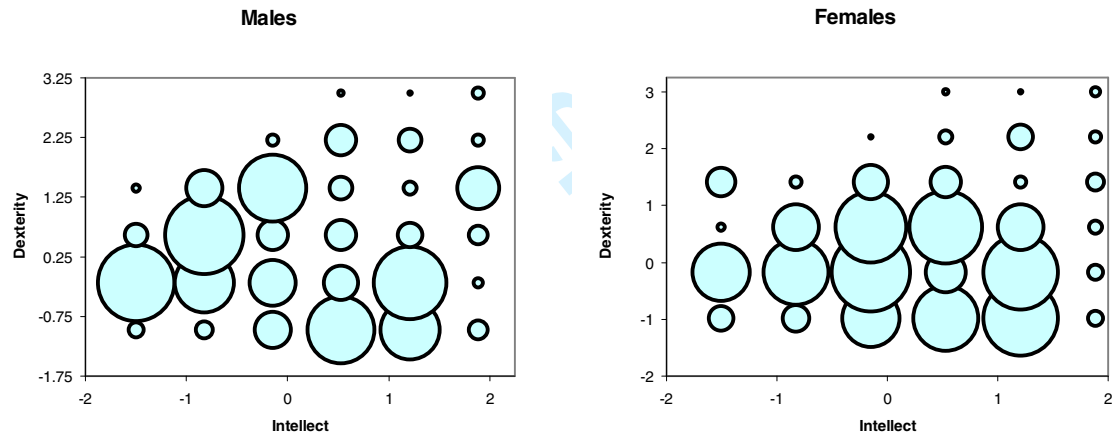


Figure 2: Frequency Distribution of DPT against Intellect and Dexterity

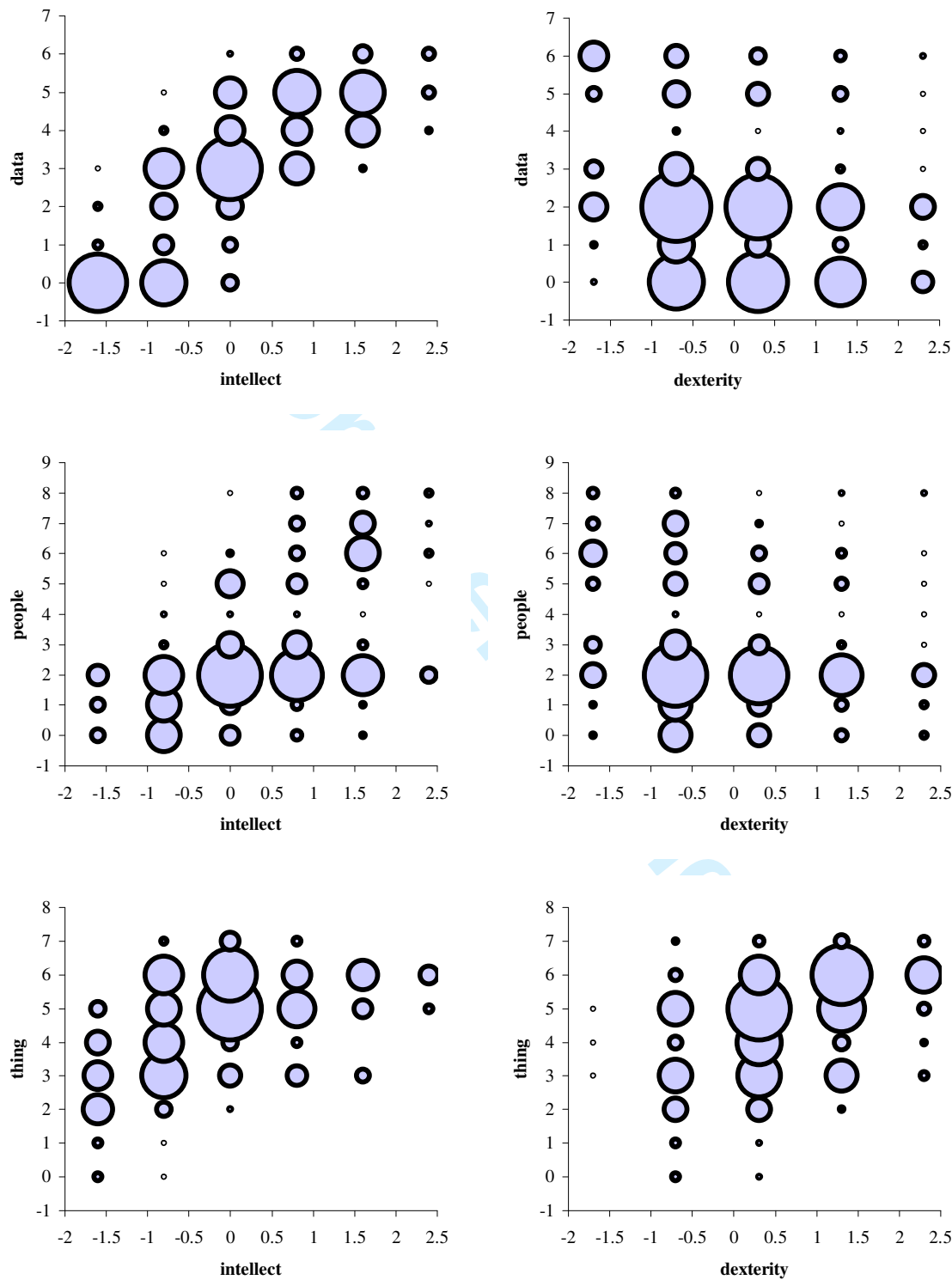
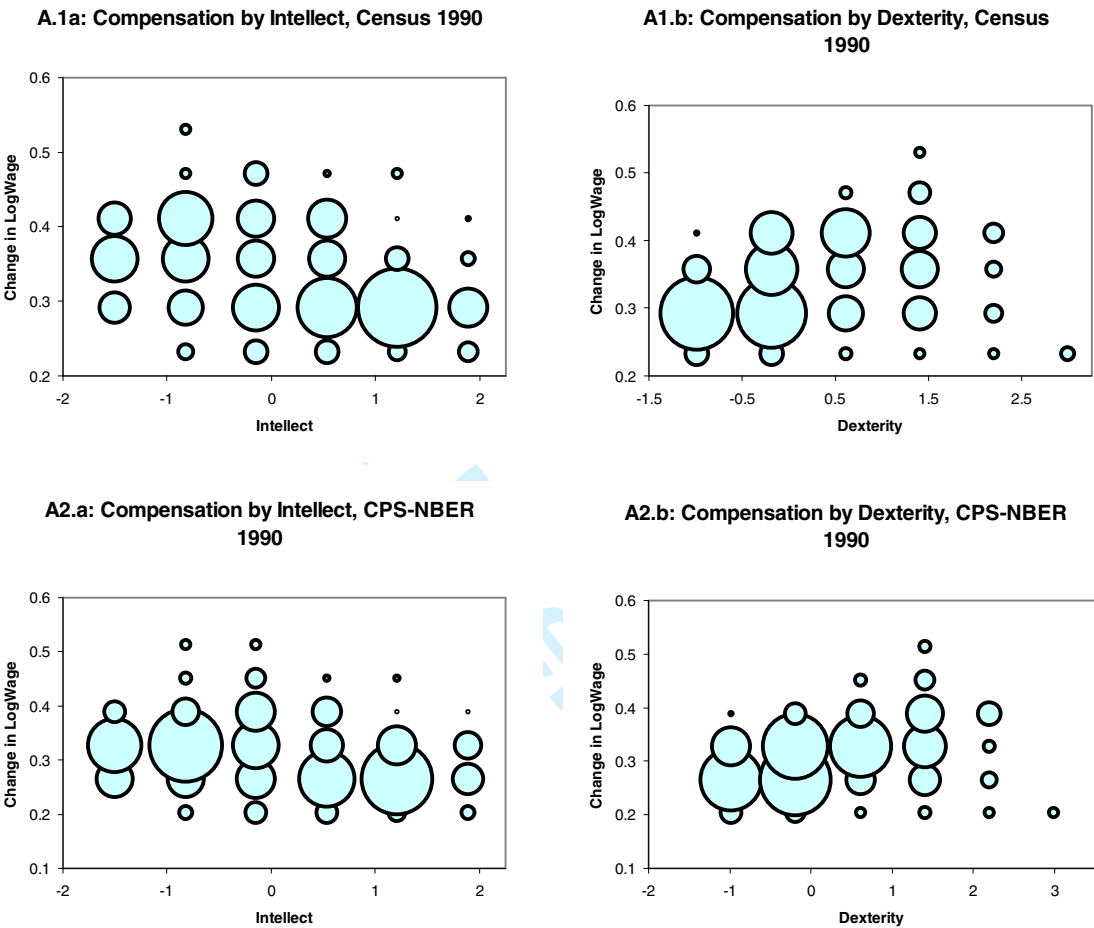
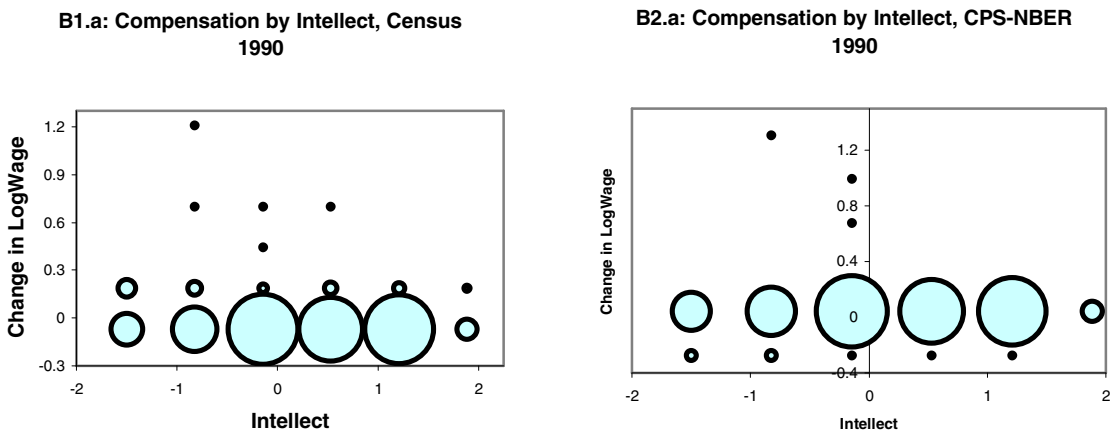


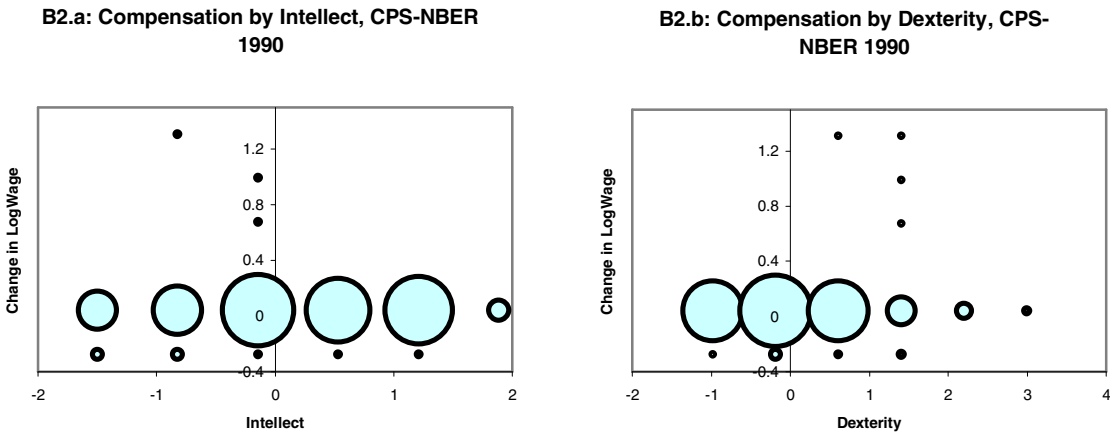
Figure 3: Contribution of working conditions to log hourly wages by level of Intellect and Dexterity

A : Males



B : Females^a





Note: ^a Due to the sparse nature of the diagrams for females, some nonempty cells that would not show with the automatic scaling of the balloon sizes are indicated by a minimally sized dot of a size that remains visible in these diagrams.