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The Requirements of Jobs
Evidence from a Nationally Representative Survey

Maury Gittleman, Kristen Monaco, and Nicole Nestoriak

5.1 Introduction

Does the US workforce have the skills needed to be internationally competitive in the twenty-first century? Which jobs are vulnerable to loss as a result of the introduction of new technology, competition from trading partners, or offshoring (Autor 2015; Blinder 2009; Jensen and Kletzer 2010; Oldenski 2014)? Why have the differentials between the earnings of those with a college education and those without widened since 1979 (Bound and Johnson 1992; Katz and Murphy 1992)? What types of skills have a high and/or rising return in the labor market and what skills do not, and which skills are complementary with each other (Murnane, Willett, and Levy 1995; Borghans, ter Weel, and Weinberg 2014; Weinberger 2014; Deming 2015)? More generally, how are worker skills, job tasks, technological change, and international trade interacting to affect the earnings distribution and the employment structure (Acemoglu and Autor 2011; Firpo, Fortin, and Lemieux 2011)? To address these questions, it is useful and, in some cases, essential to have a solid understanding of the skills demanded of the workforce, as well as the tasks that must be performed.[1]

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1. Acemoglu and Autor (2011) distinguish between skills and tasks as follows. They define a task "as a unit of work activity to produce output." On the other hand, skill is considered to be a "worker's endowment of capabilities for performing various tasks."

While there are several data sets that researchers draw upon in studies of these kinds of questions—including the *Dictionary of Occupational Titles* (*DOT*), the Occupational Information Network (O*NET), and the OECD's Survey of Adult Skills (PIAAC)—the Bureau of Labor Statistics (BLS) is currently conducting the Occupational Requirements Survey (ORS), which promises to provide new information at the detailed occupation level. The ORS, developed in collaboration with the Social Security Administration (SSA), collects elements in four categories—educational requirements, mental and cognitive demands, physical demands, and environmental working conditions. While, as will be discussed in greater detail below, the primary reason for the initiation of the ORS is for potential use by SSA as a data source in disability adjudication, the data will be useful for numerous stakeholders due to the type of information collected and the level of detailed estimates that will be available as the first years of collection are completed.

In fiscal year (FY) 2015, BLS completed data collection for the ORS preproduction test. The preproduction test might better be described as a dress rehearsal as the sample design, collection procedures, data capture systems, and review were structured to be as close as possible to those that will be used in full-scale production, when there will be a larger sample size and the estimates will be intended for evaluation for use in the disability adjudication process. The preproduction sample, which is the source of the estimates presented in this chapter, is nationally representative when appropriate sample weights are used.[2]

This chapter is organized as follows: section 5.2 provides context for ORS by briefly describing the disability adjudication process, the data needs of this process, and how ORS is structured to meet those needs. Section 5.3 presents some initial estimates of occupational requirements, including educational, mental and cognitive, and physical demands. Section 5.4 exploits the linkage between ORS and BLS's National Compensation Survey to provide an exploratory analysis of the relationship between ORS elements and wages. Section 5.5 examines the relationship between job requirements and safety outcomes, while section 5.6 concludes and outlines additional potential uses for ORS data.

5.2 The Occupational Requirements Survey

5.2.1 *Dictionary of Occupational Titles* and Disability Determination

A brief history of the *Dictionary of Occupational Titles* (*DOT*) and disability determination by the Social Security Administration (SSA), which is recounted in Handel (2015a), will help to place the ORS data-collection efforts in context. Beginning in 1939, the Department of Labor (DOL) published the first edition of the *DOT*, which was designed as a tool to facilitate

2. The preproduction data will not be used in SSA's disability adjudication process.

matching job seekers to vacancies during the Great Depression. The second, third, and fourth editions of the *DOT* appeared in 1949, 1965, and 1977, respectively, with a partial update, called a "revised fourth edition," published in 1991. While the *DOT* retained its original purpose, beginning with the third edition, the SSA contracted with DOL to publish a supplement known as the *Selected Characteristics of Occupations* (*SCO*), to be used in disability determination. The *SCO* added information on specific vocational preparation (SVP)—the amount of time required for a worker to learn the techniques needed for average performance in a given job—along with elements on physical demands and environmental conditions. The *DOT* is still used in disability determination, though given that it was last updated in 1991, SSA has long wanted to find more current information.

For DOL's purposes, the *DOT* has been replaced by the Occupational Information Network, known as O*NET. As a bridge, early versions of O*NET reviewed raw data collected for the *DOT* in previous decades and recoded them in terms of the new O*NET variables. O*NET began collecting new data from surveys of job incumbents in 2001, replacing the recoded *DOT* data on a rolling basis until June 2008, when the first complete version of O*NET based on new data became available. In contrast to the *DOT*, where jobs were rated by job analysts, O*NET is largely based on responses by incumbents, although job analysts do complete certain sections of it (see Handel [2015b] for further details). O*NET, however, has not been usable from SSA's standpoint because it does not contain the full set of detailed job requirements needed to adjudicate disability claims under current Social Security regulations and policy.

For the purposes of Social Security Administration disability adjudication, the law defines disability as the inability to do any substantial gainful activity by reason of any medically determinable physical or mental impairment that can be expected to result in death or has lasted or can be expected to last for a continuous period of not less than twelve months. The SSA uses a five-step sequential process to determine disability. By the end of the third step,[3] the claimant who has met current earnings and medical hurdles has his/her residual functional capacity to perform work-related activities classified according to the five exertional levels of work: sedentary, light, medium, heavy, and very heavy. The final two steps require occupational information to compare the functional capacities of an individual to those required by available jobs:

- Step 4. *Previous work test*. Can the applicant do the work he or she had done in the past? If the individual's residual functional capacity equals the previous work performed, the claim is denied on the basis that the individual can return to his/her former work. If the claimant's residual

3. Step 1. Is the claimant engaging in substantial gainful activity? Step 2. Does the claimant have a severe impairment? Step 3. Does the impairment(s) meet or equal SSA's medical listings?

functional capacity is less than the demands of his or her previous work, the application moves to Step 5.

- Step 5. *Any work test*. Does the applicant's condition prevent him or her from performing "*any other kind of substantial gainful work which exists in the national economy?*," meaning work that "*exists in significant numbers*" either in the region of residence or in several regions of the country.[4] If yes, the application is accepted and benefits are awarded. If not, the application is denied. In this step, the residual functional capacity is applied against a vocational grid that considers the individual's age, education, and the transferability of previously learned and exercised skills to other jobs. The vocational grid directs an allowance or denial of benefits.

The elements of ORS are designed with the needs of Steps 4 and 5 of disability adjudication in mind. As noted earlier, there are four different categories of information that are collected. Educational requirements include whether literacy is needed, degrees required with respect to formal education, and certifications, licenses, and training. These elements, in turn, are used to calculate specific vocational preparation. Mental and cognitive elements include task complexity, work control, and interaction with regular contacts.[5] A wide range of physical demands is asked about, including hearing, use of keyboarding, visual acuity, sitting, standing, stooping, kneeling, crawling, crouching, pushing, pulling, reaching, strength, climbing, and manipulation. Finally, environmental conditions comprise such elements as the temperature, exposure to fumes, humidity, and wetness. Appendix table 5A.1 contains a full list of data elements.

Despite the fact that ORS is designed for disability adjudication, as noted in the first section, that does not mean it cannot be put to more general research purposes. In section 5.3, we discuss links between a classification of jobs based on ORS elements and the influential job categorization scheme of Autor, Levy, and Murnane (2003).

5.2.2 ORS Procedures and Sampling

The goal of ORS is to collect and publish occupational information that meets the needs of SSA at the level of the eight-digit standard occupational classification (SOC) that is used by the Occupational Information Network (O*NET).[6] The ORS data are collected under the umbrella of

4. Quotations are from the Social Security Act Section 223(d)(2).

5. The wording of the mental and cognitive elements have been changed for production. A sample of the collection form is available at http://www.bls.gov/ncs/ors/occupational_requirements_survey_elements_private.pdf.

6. The occupational classification system most typically used by BLS is the six-digit SOC (https://www.bls.gov/soc/), generally referred to as "detailed occupations." O*NET uses a more detailed occupational taxonomy (https://www.onetcenter.org/taxonomy.html), classifying occupations at eight digits and referring to these as "O*NET-SOC 2010 occupations." There are 840 six-digit SOCs and 1,110 eight-digit SOCs.

the Bureau of Labor Statistics National Compensation Survey (NCS)[7] program. The NCS is an establishment-based survey that provides measures of (a) employer costs for employee compensation (ECEC), (b) compensation trends (Employment Cost Index, or ECI), (c) the incidence of employer-provided benefits among workers, and (d) provisions of selected employer-provided benefit plans. The NCS uses field economists (FEs) to collect data, rather than, for instance, mailing out questionnaires. The FEs are well suited for ORS data collection as their training focuses on identifying the appropriate respondent, probing the respondent to clarify apparent inconsistencies in responses, and following up with respondents to ensure data are complete and accurate. The FEs generally collect data elements through either a personal visit to the establishment or remotely via telephone, email, mail, or a combination of modes.

The ORS preproduction sample was drawn from the same frame as the NCS—the Quarterly Census of Employment and Wages, which includes all establishments covered by state unemployment insurance laws, and a supplementary file of railroads. The frame contains virtually all establishments in the fifty United States and the District of Columbia in the private sector (excluding agriculture, forestry and fishing, and private households) and in state and local governments.[8] The preproduction ORS sample contains 2,549 establishments. Approximately 15 percent of these units are government owned and 85 percent privately owned. Roughly one-third of the ORS preproduction sample consists of establishments that are also in the NCS sample. This overlap is notable because, as we discuss in greater detail in section 5.3, for this portion of the sample it is possible to obtain wage and other data to match with the ORS elements.

Of the 2,549 establishments contacted by field economists, 1,851 of them provided usable data, indicating a usable establishment response rate of 73 percent. Some 6 percent of the initial sample was either out of business, out of scope, or had no jobs that were within scope, with the remaining 21 percent constituting refusals.

For each establishment in the ORS sample, jobs were selected for inclusion in the survey with probability proportional to incumbent employment; these jobs are referred to as "quotes." The number of jobs selected within a private establishment varies from four to eight, based on establishment size, and, in government, the number of jobs ranges from four to twenty. It is common for multiple individuals within an establishment to have the same job (e.g., elementary school teachers within a school/school district), which can result in fewer individual quotes for that establishment. Because the quote-level information is tied to the job, not the individual, sampling a certain number of jobs within an establishment is not equivalent to sampling a certain number of workers within an establishment.

7. For details on the NCS, see http://www.bls.gov/ncs/.
8. Federal government workers are out of scope for ORS.

The ORS preproduction data collection began in October 2014 and continued until May 2015. At the close of the data-review process, information on 7,109 quotes or jobs had been collected from the 1,851 establishments, slightly fewer than four jobs per establishment. These jobs spanned all twenty-two unique two-digit SOCs in scope for ORS and 704 unique eight-digit SOCs.[9] The 704 eight-digit SOCs represent 63.4 percent of the 1,110 unique eight-digit SOCs. In order to be able to present estimates that cover the economy as a whole and not overload the reader with numbers, most of the occupational estimates we present in the next section are at the more aggregate level of nine major occupations. We also present estimates for eleven major industries.

5.3 Occupational Requirements: Evidence from the ORS Preproduction Sample

5.3.1 Educational Requirements

We now turn to actual estimates of job requirements from the ORS preproduction sample, starting with the category of educational requirements. It is important to note that these are "research" estimates only. Due to alternative categorizations of certain data elements and different approaches to calculating standard errors, estimates presented in this chapter may not match any official estimates from the preproduction data released by BLS.

Spurred in part by the rise in returns to a college education—for instance, between 1979 and 2013, the wage premium earned by college graduates relative to high school graduates widened from 24.95 percent to 50.18 percent for women and from 20.18 percent to 48.44 percent for men[10]—growing attention is being paid in the political arena to boosting attendance at college, in part by making it more affordable. According to the Obama administration, "Earning a postsecondary degree or credential is no longer just a pathway to opportunity for a talented few; rather, it is a prerequisite for the growing jobs of the new economy."[11] With this in mind, the administration asserted that everyone should obtain at least one year of higher education or postsecondary training. In this context, it is interesting to note that, according to ORS estimates shown in table 5.1, an associate's degree is required in 4 percent of jobs, a bachelor's degree in 18 percent, and a graduate or professional degree in 5 percent. Thus, according to ORS, only about one-quarter of

9. There are twenty-three two-digit SOCs in the classification system, but military (SOC 55) is out of scope for ORS.

10. These estimates are from EPI analysis of Current Population Survey Outgoing Rotation Group microdata. The college wage premium is the percent by which wages of college graduates exceed those of otherwise equivalent high school graduates, regression adjusted (http://www.epi.org/chart/swa-wages-figure-4n-college-wage-premium-2/).

11. https://obamawhitehouse.archives.gov/issues/education/higher-education.

Table 5.1 **Educational requirements, ORS and O*NET**

ORS educational category	Percent	O*NET educational category	Percent
No literacy	2.6		
Literacy, no degree	28.1	Less than high school	13.6
High school diploma	43.2	High school diploma	34.9
		Postsecondary certification	8.4
		Some college	7.7
Associate's degree	4.0	Associate's degree	7.6
Baccalaureate degree	17.7	Baccalaureate degree	17.8
		Postbaccalaureate certificate	1.2
Postbaccalaureate degree	4.5	Postbaccalaureate degree	8.7

employment requires any type of college education. A high school degree is, however, required for 43 percent of jobs. No degree is required in 31 percent of employment, with 2.6 percent of all jobs said to not require any literacy whatsoever.

How do these results compare to those from other sources that have tried to measure the same concept? O*NET also assesses the education requirements of occupations, though, because it does not publish economy-wide estimates, we calculated them by averaging estimates at the detailed occupation level using weights obtained from BLS's Occupational Employment Statistics program. The categories used by O*NET, in part because they involve certifications, are somewhat different than those used by ORS, but some comparisons can still be made.

Whereas ORS indicates no degree is required in 31 percent of the jobs, in O*NET the category for less than high school contains only 14 percent of employment.[12] The ORS data indicate that 43 percent of jobs require a high school degree, which is roughly the same as the proportion in the O*NET categories high school or high school plus certification. O*NET, however, has 15 percent of employment in the categories for individuals either with some college or an associate's degree, while only 4 percent of jobs is in the associate's degree category in ORS. The percentages requiring a bachelor's degree are similar across the two sources, but O*NET has a higher proportion in the postbaccalaureate category (10 percent versus 5 percent), which in O*NET includes everything ranging from postbaccalaureate certification to postdoctoral training.

The ORS education requirements estimates can also be compared to a relatively recent source of nationally representative data that has a number of elements in common with ORS, Michael Handel's Survey of Workplace Skills, Technology and Management Practices (STAMP). STAMP's estimates are based on self-reports of job incumbents and its first wave (of two)

12. O*NET estimates used are from version 19.

was conducted between October 2004 and January 2006, with a sample of 2,304 respondents. The data are not publicly available but some comparisons can be made with ORS on the basis of results presented in Handel (2015c). Instead of inquiring directly about literacy, STAMP asked whether any reading was required on the job. According to STAMP, some reading was required of 96 percent of the workforce, compared to the estimate in ORS that 97.4 percent of jobs required literacy. STAMP divided occupations into five groups: upper white collar (management, professional, technical occupations), lower white collar (clerical, sales), upper blue collar (craft and repair workers—e.g., construction trades, mechanics), lower blue collar (factory workers, truck drivers, etc.) and service (e.g., food service workers, home health care aides, childcare, janitors, police and firefighters). The percentage where reading is required ranged from 91 percent for the two blue-collar groups up to 99 percent for the upper white-collar one.

Handel (2015c) also provides information for the educational requirements of jobs. The numbers are fairly close to those from ORS in terms of the shares requiring a bachelor's degree or beyond. According to STAMP, a graduate degree was required in 6.3 percent of the jobs, versus 5 percent in ORS, with a bachelor's degree needed in an additional 20.8 percent (18 percent in ORS) of the jobs. Some college but less than a bachelor's degree was required in 16.5 percent of the jobs, much greater than in ORS. A high school degree by itself was required in 42.6 percent of the jobs and a high school degree plus vocational training in an additional 6.3 percent of the jobs. The remaining 7.6 percent required less than a high school degree.

5.3.2 Specific Vocational Preparation

Aside from formal education requirements,[13] ORS also asked about prior experience, postemployment training, and certificates and licenses. The duration associated with all of these are used to calculate SVP, which, as noted above, is the amount of time needed for an individual to get to an average level of performance. Specific vocational preparation totals time spent both in formal education and certification and training programs that prepared the individual for the job (preemployment training), required prior work experience in related jobs, and the time needed in the job itself to get to average performance (postemployment training). It is important to keep in mind that SVP could be high both because a long period of specialized on-the-job training is needed and because much time must be spent in special-

13. For the purposes of SVP, formal education focuses on the "vocational" component of the education. High school, for example, is not included in formal education, except in the rare case that an individual spent time in a vocational high school program. Generally, a four-year college degree will have two years of general education requirements, which means only two years count toward SVP. Postbaccalaureate degrees tend to be entirely vocational in nature, in which case the entire length of the postbaccalaureate degree is included in the SVP measure as well as two years of college education.

Table 5.2 **Specific vocational preparation by occupation and industry (percent)**

	Short demo/1 month	More than 1 month up to 1 year	More than 1 year up to 4 years	Over 4 years
All workers	33	17	32	18
Occupation				
Management, business, financial	—	—	32	65
Professional and related	4	4	57	35
Service	61	22	15	2
Sales and related	54	13	25	9
Office and admin.	26	25	40	8
Construction and extraction	—	—	25	30
Installation, maintenance, repair	10	2	50	24
Production	41	24	29	6
Transport. and material moving	57	27		
Industry				
Construction	15	25	27	34
Manufacturing	32	21	32	15
Wholesale trade	36	16	30	18
Retail trade	62	15	21	3
Transport and warehousing	45	—	26	—
Financial activities	—	—	48	27
Professional and business services	23	14	35	28
Education and health Services	22	14	44	21
Leisure and hospitality	68	16	11	5
Other services	30	34	25	11
Public admin.	11	22	45	21

Note: Dash indicates no workers in this category or data did not meet publication criteria.

ized formal schooling. Specific vocational preparation is measured in days and then grouped into nine categories ranging from "short demonstration" to over ten years. Owing to the sparseness of responses for some categories,[14] particularly for estimates by industry and occupation, we collapse these nine categories into four: one month or below; more than one month up to and including one year; more than one year up to and including four years; and more than four years.

As shown at the top of table 5.2, across all workers, according to ORS respondents, about one-third of jobs can be learned within one month's time. At the other end of the spectrum, a bit more than one-sixth of jobs require over four years to get to average performance. Looked at differently, roughly half of employment requires less than one year of SVP, and the other half needs more.

14. Estimates are not shown on the tables if their relative standard errors (RSEs) exceed 0.3. In addition, when the sum of a group of estimates is equal to one, a suppression for RSE reasons generally necessitates a secondary suppression, given that it would be possible to deduce the suppressed estimate's value from the values of the other estimates.

We now examine SVP by major occupation (nine categories) and major industry (eleven categories) to get a better understanding of what is behind the distribution for the economy as a whole. As occupation is what one does, while industry is where one does it, in general, one would expect there to be larger differences by occupation than industry in education requirements, skills demanded, and tasks performed. Support for this supposition can be found in the fact that occupations have more explanatory power than industries with respect to other measures related to the labor market, such as wages (e.g., see Pierce 1999). Though a given occupation may differ across industries, much of the differences we will note across industries are a result of their differing occupational compositions.

As table 5.2 shows, there is substantial variation by major occupation in SVP. Both management, business, and financial occupations and professional and related occupations have more than 90 percent of employment in categories where the SVP exceeds one year. In contrast, service, sales and related, and transportation and material-moving occupations all have a majority of employment where SVP is one month or lower.

Examining SVP by major industry, one sees less variation than by occupation, with a few of the industry SVP distributions being fairly close to that of the economy as a whole. There are notable exceptions, though. On the low SVP side are those industries where SVP is less than a year for substantially more than half of employment, which include retail trade, transport and warehousing, leisure and hospitality, and other services. On the high SVP side, where SVP is substantially greater than one year for much more than 50 percent of employment, are the following industries: financial activities, professional and business services, education and health services, and public administration.

As previously mentioned, the value of SVP can be driven by requirements of formal education, preemployment training, prior work experience, or postemployment training (see figure 5.1). Across all workers, the largest shares of SVP are postemployment training (37 percent) and prior work experience (39 percent). This varies markedly by SVP categories. For those in jobs requiring little preparation, nearly all of the SVP component is captured in postemployment training. At the other extreme, jobs with the highest levels of SVP have nearly all vocational preparation captured by required formal education (29 percent) and prior work experience (62 percent).

5.3.3 Mental and Cognitive Demands

We now turn to the second category of data collected by ORS, mental and cognitive demands, and begin with the element of task complexity. In response to the question "how complex are tasks in this occupation?" respondents were able to choose from five different categories: very complex, complex, moderate, simple, and very simple. Once again, we collapse categories (complex and very complex, moderate, simple and very simple) to obtain

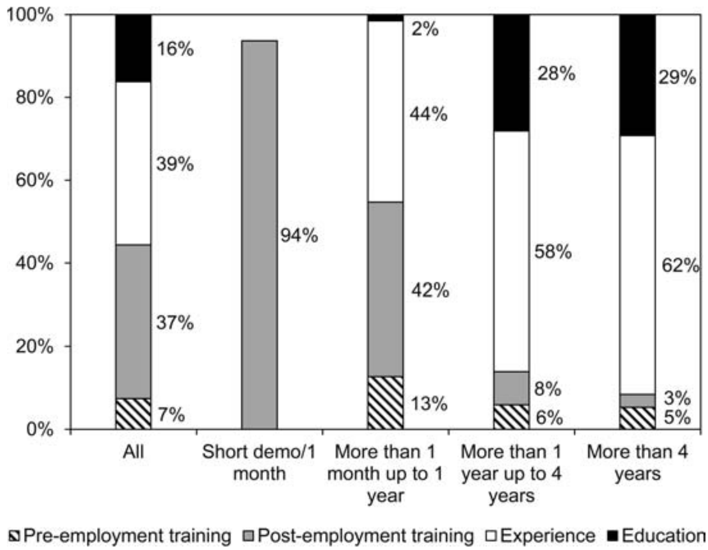

Fig. 5.1 Components of specific vocational preparation

Note: The bar for short demo/one-month duration shows only postemployment training, due to the percentages in the remaining categories not meeting publication criteria.

more reliable estimates. About one-half (51 percent) of jobs were rated in the simplest category, around one-third (34 percent) as moderate, with the remaining 15 percent in jobs rated in the most complex category. These shares show large differences across major occupations. Management, business, and financial occupations (56 percent), and professional and related occupations (36 percent) are the only occupation groups where the share of the most complex category exceeds that for the economy as a whole, with the next highest occupation having a share of only 14 percent. Examined from the other end of the complexity spectrum, transportation and material-moving occupations (85 percent) and service occupations (81 percent) have the highest shares of the simplest jobs, with sales and related, office and administration and production also having more than a majority share in this category (see table 5.3).

Are there major differences by industry in terms of the distribution of task complexity? Such differences are, once again, less notable than those for occupation, though still present. For instance, leisure and hospitality (83 percent), transport and warehousing (77 percent), and retail trade (74 percent) have higher than average shares of the simplest jobs, while public administration (26 percent), professional and business services (23 percent), financial activities (21 percent), and education services (20 percent) have above average shares of the most complex jobs.

A second dimension of cognitive demands is how closely controlled an

Table 5.3 **Cognitive elements by occupation and industry (percent)**

	Task complexity			Work control			Regular contacts		
	Complex/ very complex	Moderate	Simple/ very simple	Closely/ very closely	Moderate	Loose/ very loose	Structured/ very structured	Semi-structured	Unstructured/ very unstructured
All workers	15	34	51	58	29	13	72	22	6
Occupation									
Management, business, financial	56	—	—	14	38	48	28	48	24
Professional and related	36	53	10	20	53	28	41	48	11
Service	2	17	81	84	13	3	90	8	2
Sales and related	5	29	66	69	22	9	71	21	8
Office and admin.	2	36	62	70	27	3	85	—	—
Construction and extraction	12	41	47	59	—	—	78	—	—
Installation, maintenance, repair	—	62	—	—	52	—	85	—	—
Production	2	27	71	79	—	—	95	—	—
Transport. and material moving	—	—	85	85	—	—	96	—	—
Industry									
Construction	15	45	40	52	37	11	78	—	—
Manufacturing	11	35	54	62	27	11	81	16	3
Wholesale trade	15	38	47	53	29	18	65	—	—
Retail trade	3	23	74	79	18	3	86	—	
Transport and warehousing	—	—	77	77	—	—	87	—	—
Financial activities	21	51	29	48	34	18	56	32	13
Professional and business services	23	33	44	48	33	19	62	29	9
Education and health services	20	41	39	47	38	16	63	31	6
Leisure and hospitality	3	14	83	85	11	4	91	—	—
Other services	—	—	57	62	26	12	78	—	—
Public admin.	26	45	29	36	44	20	57	27	16

occupation's work is. We collapse five categories for work control (very loosely, loosely, moderately, closely, and very closely) to three (closely and very closely, moderately, and loosely and very loosely) for reasons of reliability. Nearly three-fifths of employment was rated as being closely or very closely controlled, with a further 29 percent moderately controlled, and 13 percent loosely or very loosely controlled. There is similar variability across major occupations, as with task complexity. Management, business, and financial occupations (48 percent) and professional and related occupations (28 percent) are the only occupation groups where the share of loosely or very loosely controlled jobs surpasses the economy-wide average. Service and transportation and material-moving occupations have about 85 percent of employment in closely or very closely controlled jobs, with production occupations not far behind at 79 percent.

Major industries with a much higher than average proportion of closely or very closely controlled jobs include leisure and hospitality (85 percent), retail trade (79 percent), and transport and warehousing (77 percent). Public administration (20 percent), professional and business services (19 percent), and financial activities (18 percent) rank highest in terms of the share in the loosely or very loosely controlled category.

The final cognitive element we will consider involves responses to the question, "What type of work-related interactions does the occupation have with regular contacts?" As with the other two cognitive elements, five categories have been collapsed into three (structured and very structured, semistructured, unstructured and very unstructured).[15] For the economy as a whole, structured or very structured contacts predominate, being the case in nearly three-quarters of employment (72 percent). Semistructured contacts account for about one-fifth of employment (22 percent), with the remaining 6 percent in unstructured or very unstructured contacts. Those in management, business, and financial occupations are much less likely to have unstructured or very unstructured contacts (24 percent), while the contacts of those in transportation and material moving (96 percent), production (95 percent), service (91 percent), office and administration (85 percent), and installation, maintenance, and repair (85 percent) are more likely to be structured or very structured.

By industry, once again, there is less variability than by occupation, though leisure and hospitality (91 percent), transport and warehousing (87 percent), and retail trade (86 percent) stand out as sectors where contacts are particularly structured.

Thus far, we have been examining education requirements and cognitive

15. Very structured is defined as exchanging straightforward, factual information; structured involves coordinating and routine problem solving; semistructured includes problem solving, discussing, soft selling; unstructured includes influencing, persuading, hard selling; and very unstructured includes defending, negotiating, and resolving controversial or long-term issues.

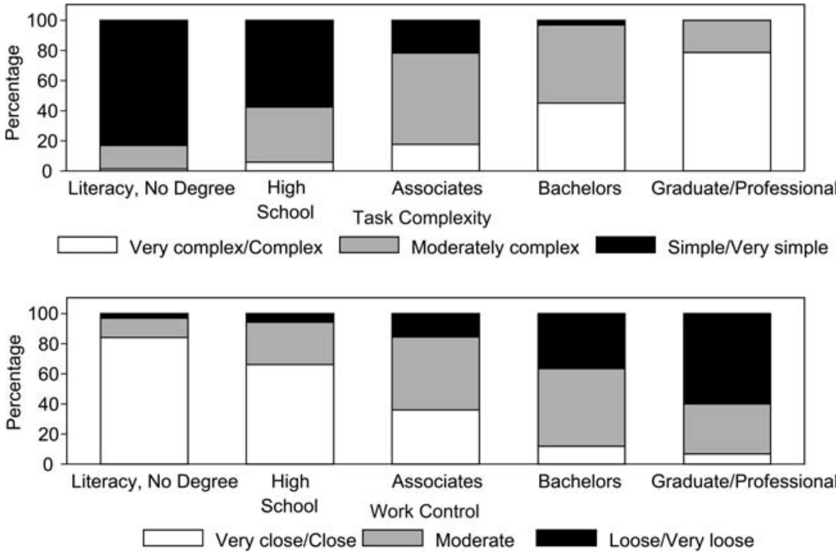

Fig. 5.2 Mental and cognitive elements by educational requirements

demands independently, but it is also of interest to see how they are interrelated. For instance, how do cognitive demands vary by education requirement? Figure 5.2 makes it apparent that both task complexity and work control are strongly ordered by the amount of education required.

As one would expect, as education requirements increase, the share of simple and very simple jobs decreases and the proportion of complex and very complex jobs increases. Work control is related in a similar fashion, as higher educational requirements are associated with jobs that are controlled more loosely. Figure 5.3 is similar to figure 5.2, except cognitive demands are arrayed against four (collapsed) levels of specific vocational preparation instead of against degrees required. As with education, as the level of SVP rises, task complexity rises, while jobs become more loosely controlled.

Indirectly apparent in figures 5.2 and 5.3 is the relationship between task complexity and work control. Looking at the lowest level of educational attainment depicted (literacy, no high school degree) or at the lowest level of SVP (short demo/one month) shows that these jobs are characterized by simple/very simple tasks and are closely/very closely controlled. A direct comparison between complexity and control is presented in figure 5.4.

The graph depicts the joint probabilities of the categories of task complexity and work controls. Roughly 48 percent of jobs in the economy can be classified as simple/very simple and closely/very closely controlled. As the complexity level rises, the level of control decreases—the diagonal joint probabilities (from lower left to upper right) have the highest density. The lower-right corner, jobs that are simple/very simple and very closely/closely

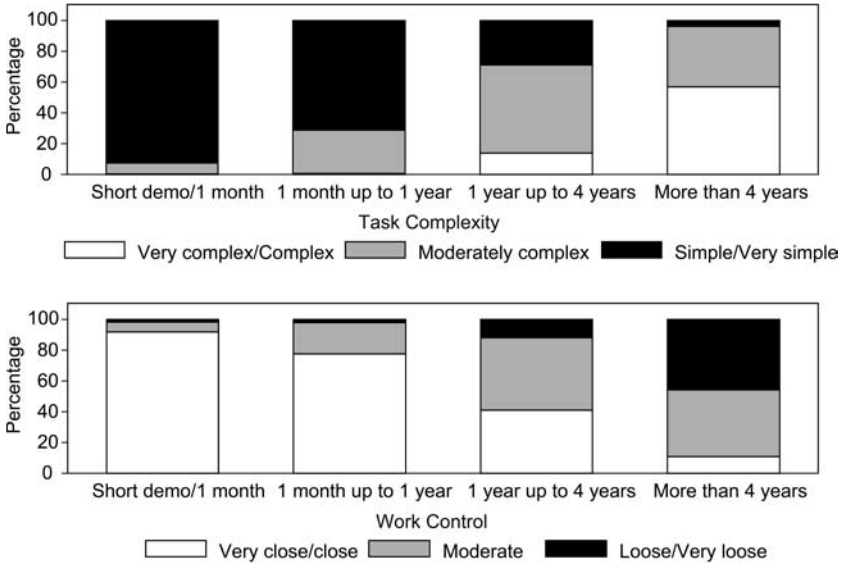

Fig. 5.3 Mental and cognitive elements by specific vocational preparation

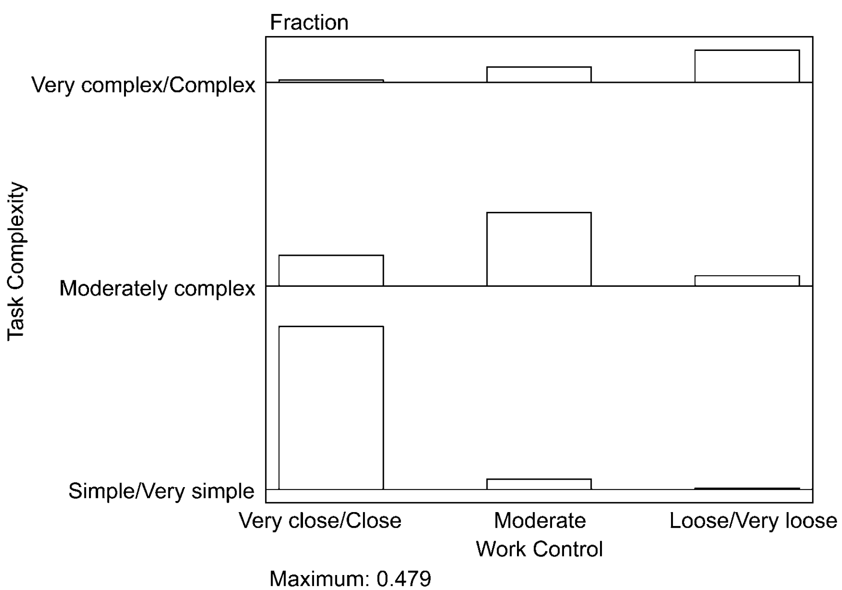

Fig. 5.4 The relationship between task complexity and work control

controlled, include occupations such as cashiers and laborers and freight, stock, and material movers. Moving up diagonally, jobs that are both moderately complex and moderately controlled include teaching occupations and very complex/complex and loose/very loosely controlled jobs include specialized nurses and software designers. Simple jobs that are moderately controlled include jobs with low barriers to entry that are typically performed off-site from one's direct employer, such as landscapers and personal care aides. Complex jobs that are moderately controlled include accountants.

Not surprising, but notable, is the very small percentage of jobs that are both simple and loosely controlled. This intersection represents a key set of job alternatives for individuals with certain types of cognitive impairments.

Autor, Levy, and Murnane (2003) developed a task model to predict the impact of computerization on different kinds of jobs. They divided occupations into a 2 × 2 grid, with one dimension defined by whether the tasks in the occupations are routine or nonroutine, and the other defined on the basis of whether the tasks are manual or analytical. They hypothesize substantial computer substitution for routine tasks, whether manual or analytical. For nonroutine tasks, they hypothesize strong possibilities for complementarities for the analytical occupations, but limited possibilities for substitution or complementarities for the manual occupations.

While ORS does not contain the same variables as Autor, Levy, and Murnane, one can compare the jobs in our 3 × 3 grid in figure 5.4 to those in Autor, Levy, and Murnane's 2 × 2 grid. The closely controlled/simple cell in figure 5.4 appears to contain jobs similar to those in Autor, Levy, and Murnane's routine/manual category (picking and sorting, repetitive assembly). Their nonroutine/analytical box (e.g., medical diagnosis and legal writing) also has much in common with the four categories in figure 5.4 having moderate or greater complexity and moderate or less control.

5.3.4 Strength Requirements

We now turn to physical demands and examine a variable called strength, which is a key element in SSA's disability process. The variable captures a number of different dimensions of physical demands and is used to categorize work as either sedentary, light, medium, heavy, or very heavy. For instance, sedentary work is where the job requirements are as follows: standing for no more than 3/8 of the day; lifting of up to ten pounds occasionally; lifting a negligible weight frequently; lifting no weight constantly; no pushing with arms/hands; no pushing with legs/feet; and no pulling with feet only. At the other end of the spectrum, a heavy job requires the incumbent to lift more than 100 pounds occasionally, lift more than fifty pounds frequently, and lift more than ten pounds constantly. As before, we show estimates with the categories collapsed into three (sedentary and light, medium, heavy and very heavy).

As shown in table 5.4, some 70 percent of employment is estimated to be in the sedentary and light, 22 percent in the medium, and the remaining

Table 5.4 **Strength by occupation and industry (percent)**

	Light/sedentary	Medium	Heavy/very heavy
All workers	70	22	8
Occupation			
Management, business, financial	90	—	—
Professional and related	84	12	4
Service	65	28	6
Sales and related	69	—	—
Office and admin.	88	9	3
Construction and extraction	28	42	30
Installation, maintenance, repair	32	45	23
Production	45	35	20
Transport. and material moving	52	28	20
Industry			
Construction	32	42	26
Manufacturing	51	33	16
Wholesale trade	61	—	—
Retail trade	58	35	7
Transport and warehousing	59	—	—
Financial activities	90	—	—
Professional and business services	84	—	—
Education and health services	79	16	5
Leisure and hospitality	70	—	—
Other services	81	—	—
Public admin.	63	26	11

Note: Dash indicates no workers in this category or data did not meet publication criteria.

8 percent in the heavy categories. Around 85 to 90 percent of employment in management, business, and financial occupations, professional and related occupations, and office and administration occupations is in the sedentary and light category. Major occupations with smaller proportions of sedentary and light work include construction and extraction (28 percent), installation, maintenance and repair (32 percent), production (45 percent), and transportation and material moving (52 percent). By industry, financial activities (90 percent) and other services (81 percent) have the highest proportions of sedentary and light work.

5.4 Occupational Requirements and Wages

In this section, we explore the relationship between various ORS elements and wages, measuring the returns associated with various skills and illustrating the use of ORS data for labor market analysis. Because ORS itself does not measure wages, we take the 2,106 ORS quotes that overlap with the NCS sample and are able to obtain average hourly wage measures for 1,523 of these from the fourth quarter of 2014. It is rare that one has measures of skill and pay for the same job, as most of the research on pay and skills, at least in the United States, relies on merging in occupation-level measures from the *DOT* or O*NET onto data sets with measures of pay.[16]

Before turning to regressions containing ORS elements, it may be useful to say more about the dependent variable, average hourly wages, which comes from the Employer Costs for Employee Compensation (ECEC) portion of the National Compensation Survey. In the ECEC, earnings are defined to include incentive pay but exclude premium pay for overtime, holiday, and weekend work; shift differentials; bonuses not directly tied to production; payments by third parties such as tips; and payment in kind such as room and board. The ECEC data are converted to a cost per hour worked using work schedule information common to all workers and averaged over the incumbents within a job. Wage data from the ECEC or related components of the NCS have been used in a number of different studies, including ones on public-private compensation differentials (Gittleman and Pierce 2012, Munnell et al. 2011), inequality (Pierce 2010), and interindustry wage differentials (Gittleman and Pierce 2011).

These average hourly wage data can be linked to the ORS data by job. While the fact that these data are averages over incumbents is, in certain circumstances, a disadvantage relative to having data on each individual worker, the ORS data elements apply to each incumbent so there is a match between the level of aggregation of the wage data and that of the ORS elements. The key advantage to this approach is that the data on earnings and requirements are directly linked. Most studies that examine the returns to job attributes rely on linking microdata on individuals (typically the Current Population Survey or census public-use microdata) with jobs (from *DOT* or O*NET) by aligning occupation codes and merging in occupational averages (e.g., Autor, Levy, and Murnane 2003; Abraham and Spletzer 2009; Ingram and Neumann 2006). As Abraham and Spletzer acknowledge, inaccurate detailed occupation coding in the CPS and census raise data-quality concerns when data sets are matched based on occupation. As the NCS and ORS data are collected based on the same "quote" or job at the establishment, the linkage between pay and ORS elements should be accurate.[17]

We first present the average hourly wage (and associated 95 percent confidence interval) for categories defined by the key variables of interest—SVP, education, task complexity, regular contacts, and strength. With the possible exception of strength, the mean wage associated with the different categories for each of these variables follows a predictable pattern, as is evident in figures 5.5, 5.6, and 5.7.[18]

16. See Autor and Handel (2013) for an exception and further discussion.

17. The fact that ORS has data by the job rather than averages for the occupation as a whole means that it should be possible to use ORS elements to explain within-occupation wage variation. Such an undertaking will have to wait, however, until ORS is a full-scale survey (with a larger sample) and is dependent on funding to collect wages along with ORS elements.

18. Average wages for jobs with no literacy requirement are not provided, though this category is included in the regression models.

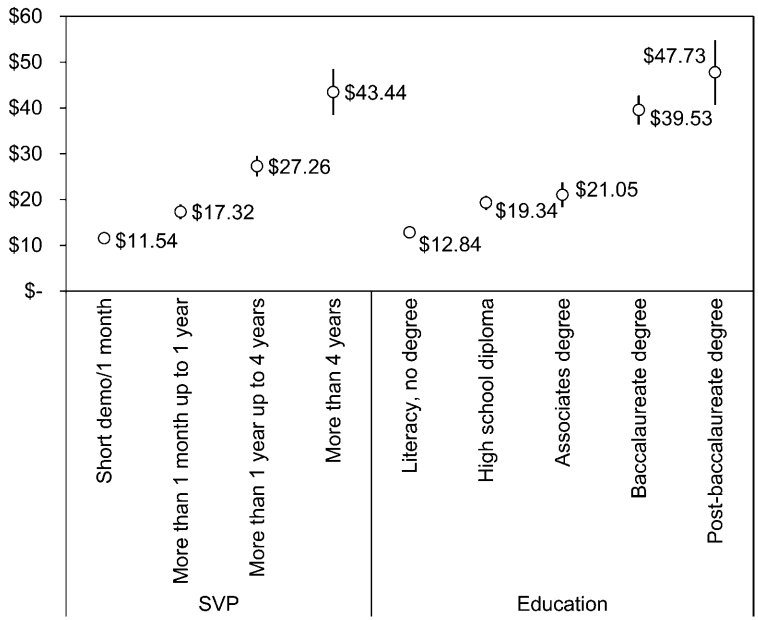

Fig. 5.5 Average hourly wages by SVP and education categories

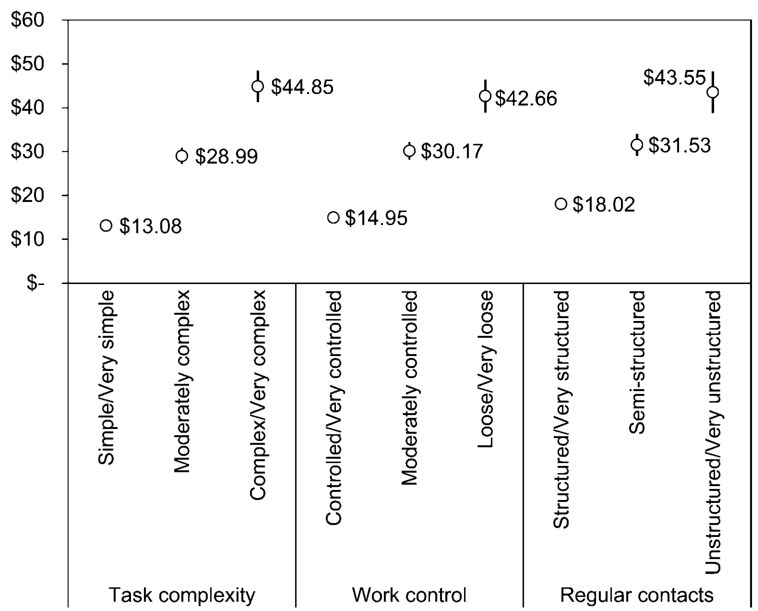

Fig. 5.6 Average hourly wages by cognitive categories

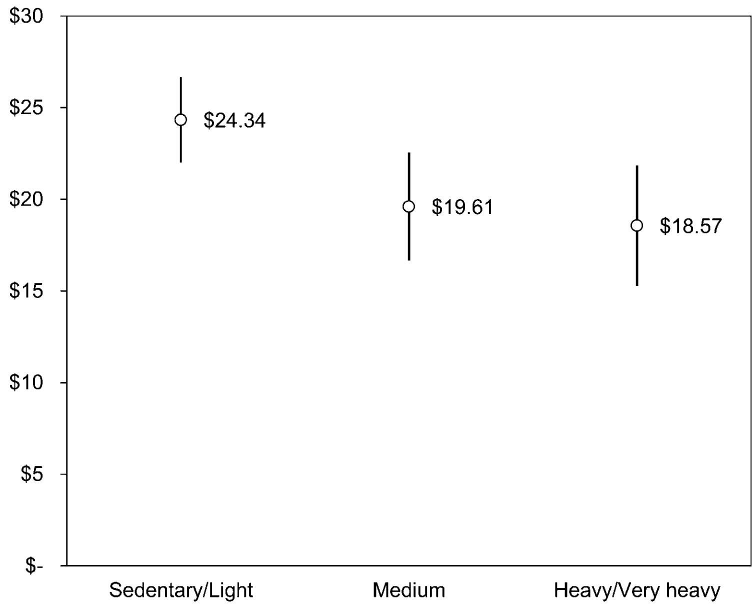

Fig. 5.7 Average hourly wages by strength category

Turning to the multivariate analysis, all models regress the natural log of the wage on a set of NCS establishment (size, industry, and private/public sector) and job characteristics (full-time/part-time and union/nonunion). Establishment size is captured by four categories: 0–49 (the reference group), 50–99, 100–499, and 500 or more workers. Controls for industry are made at the broad NAICS grouping: mining and utilities (reference group), construction, manufacturing, wholesale trade, retail trade, transportation and warehousing, information, financial services, professional and business services, education and health services, leisure and hospitality, other services, and public administration. Ownership is controlled for with a dummy variable for private sector (state and local government is the reference group).

Four models are estimated. Model 1 includes only additional controls for education and Model 2 expands this to include cognitive elements and strength. Models 3 and 4 are similarly structured, but include SVP rather than education. Consistent with past research, the establishment variables indicate the presence of establishment-size effects (Brown and Medoff 1989) and interindustry differentials (Gittleman and Pierce 2011), and little difference by whether employment is in the private sector or in state and local government (Gittleman and Pierce 2012). In terms of job characteristics, there are premiums for union status (Gittleman and Pierce 2007) and full-time status (Lettau 1997). These and all our estimation results are presented in appendix table 5A.2.

We first consider education requirements, where the omitted group is jobs

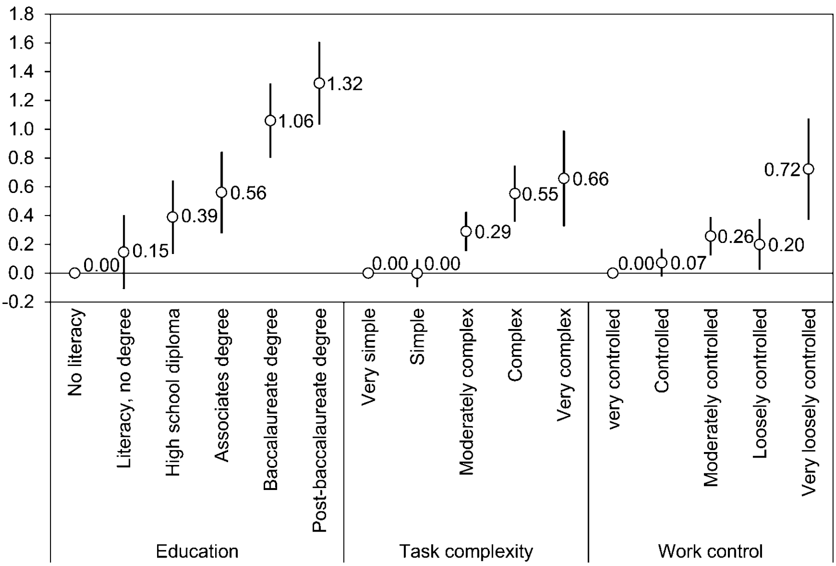

Fig. 5.8 Returns to education, task complexity, and work control

where no literacy is required. The point estimates are ordered in terms of increasing education, but the standard errors are large, in part because of item nonresponse. Nonetheless, there is support for the hypothesis that those jobs requiring bachelor's degrees or higher have greater earnings than other jobs. The *R*-squared, including establishment and job characteristics, is 0.67, high compared to what one would get in a comparable regression using household data. With just establishment and job controls, the *R*-squared is 0.43. The magnitude of the return from an associate's degree relative to a high school diploma is similar to that in Card (1999) and Carneiro, Heckman, and Vytlacil (2011), who find returns to additional years of education post–high school on the order of 6–11 percent per year (depending on model specification). The return to a college degree from our model is generally larger in magnitude than in the literature, though the overall ordering of the returns to education follow a sensible pattern when taken as a whole.

Figure 5.8 presents coefficients on education, task complexity, and work control from Model 2. Adding cognitive variables to the model decreases the returns to education considerably—roughly halving them for most categories. This is similar to analysis of the PIAAC, which finds that the returns to education decrease by approximately one-third when skills variables are included in the model (OECD 2013). The *R*-squared for the model with a full set of controls for work requirements is 0.77.

It may be worth highlighting again the distinction between tasks (a unit of work activity to produce output) and skills (a worker's endowment of capabilities for performing various tasks). As Autor and Handel (2013) note, in the Mincer earnings model, skills, as proxied by education and experience, have an economy-wide price. But because of the ongoing self-selection of workers into tasks and the bundling of task demands within jobs, these authors view the Roy model as a more appropriate one for analyzing returns to tasks. One implication of this model is that a Mincer-type regression will not generally recover the average returns to the tasks. While the cognitive demands that we use in the regression analysis may not fit neatly into the skill-task distinction, we nonetheless view this as a useful exploratory exercise.

The first cognitive demand we consider in the regression analysis is task complexity. Wages are ordered by the levels of this element. Those in very complex jobs earn 0.66 log points more than those in simple ones and those in the moderately complex jobs earn 0.29 log points more than those in the very simplest (see figure 5.8). The positive relationship between cognitive tasks and wages corroborates Autor and Handel (2013), though the magnitude of the relationship cannot be easily compared with theirs. Additionally, if we consider task complexity as roughly synonymous with analytical content, then these results also roughly align with those of Abraham and Spletzer (2009) and Ingram and Neumann (2006).

The results from work control are similar to those from task complexity in that wages are increasing in how loosely the job is controlled. In the final cognitive demand that we consider, type of regular contacts is not significant in the model, which is consistent with the finding by Pierce (1999) that coefficients on contacts variables tend to be small and imprecisely estimated in log-wage regressions using NCS wage data. The controls for strength are also jointly insignificant. There is no consensus in the literature on the empirical relationship between physical demand and wages. Abraham and Spletzer (2009) and Autor and Handel (2013) find negative returns to jobs requiring physical skills, while Ingram and Neumann (2006) estimate positive returns to jobs requiring physical effort (though they also include education controls in their models).

The results for specific vocational preparation (SVP) are similar to those for education requirements. All the coefficients are significantly positive relative to the omitted group of short demonstration. The R-squared for Model 3, which controls for SVP, establishment and job characteristics, is similar to that for education requirements at 0.66. Much like the Model 2 results, including controls for the cognitive and strength requirements roughly halves the coefficients on SVP (Model 4 in appendix table 5A.2). Owing to relatively large standard errors, the adjacent categories are not significantly different at the 10 percent level.

As seen in figure 5.9, there are substantial returns to task complexity and work control requirements after controlling for SVP. The pattern of returns to these cognitive skills is similar to those in the education model (figure 5.8). Also similar to that model, the returns to regular contacts and strength are not statistically significant.

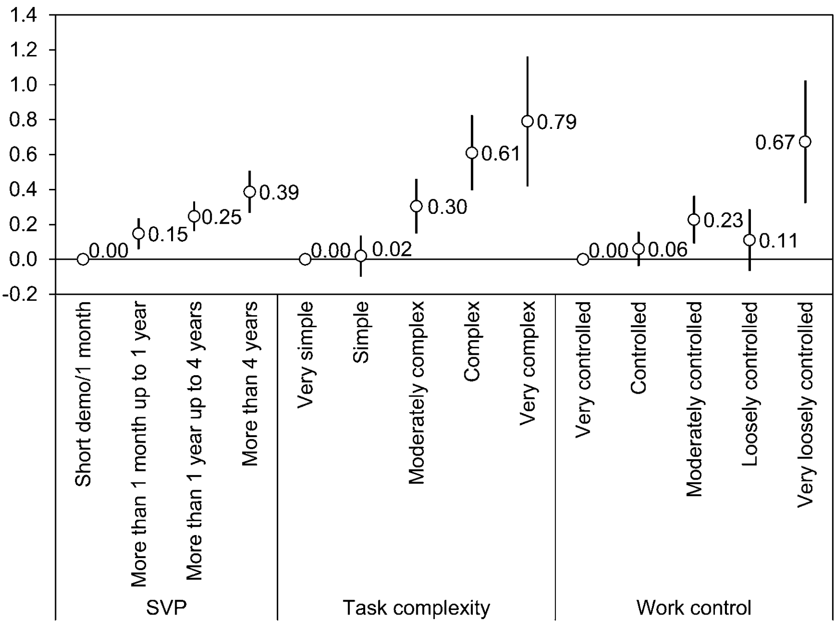

Fig. 5.9 Returns to SVP, task complexity, and work control

5.5 Occupational Requirements and Safety Outcomes

How do the physical demands and environmental conditions measured by ORS affect injury and illness rates? In this section, we present a second type of illustrative multivariate analysis, examining the relationship between the risk of an occupation, as measured by various ORS elements, and the outcomes of that risk, as captured by the injury and illness rate. Ideally, we would take the approach we did with the wage data, and match a job's ORS elements to its own injury and illness rate from the Survey of Occupational Injuries and Illnesses (SOII).[19] If we were to do this, however, the resulting sample would be both very small and unrepresentative, given that there is likely to be little overlap between the ORS sample and the SOII sample. Instead, the approach we use here is to aggregate both the risk and the injury and illness data by three-digit SOC, as this seems to be the lowest level of aggregation we can use where there is enough sample per occupation to adequately measure risk in the ORS data.

Similar research in this area has used the O*NET to calculate occupational risk and used panel data on a worker's occupational history to calculate the impact of accumulated risk on chronic diseases later in life (Dembe et al. 2014). In contrast, our work here focuses on the impact of occupational risks on occupational injuries and illnesses. Without the occupational his-

19. For more information on the SOII, see http://www.bls.gov/iif/.

tories used in earlier work, we are unable to calculate the cumulative effect of exposure to risk over long time periods, and therefore focus primarily on traumatic injuries. One advantage of the ORS data is that, in addition to knowing the mean level of risk for the occupation, we also have information on the distribution of risk within the occupation. This additional information allows us to focus on elements of risk that are more closely associated with specific occupations.

While the ORS sample contains ninety-two unique three-digit SOCs, to get reliable measures we require twenty observations for each of these, which reduces the number to sixty. An additional eleven three-digit SOCs were dropped because of item-level nonresponse (if there were fewer than twenty responses per item), and for one three-digit SOC no injury and illness rate was available from the SOII. Thus, forty-eight three-digit SOCs remained for analysis.[20]

Risk of injury and illness in the ORS is captured by many variables, with most of these in the categories environmental conditions and physical demands. We have both dichotomous measures of the presence of risk, as well as measures of the percentage of time at job with risk. While the latter is potentially a better measure, it is often not available for a large fraction of the sample. Thus, we are more likely to use the dichotomous variables, which can make use of cases where the respondent answered that the risk was present, but the duration was unknown.

Having forty-eight three-digit SOCs for analysis leaves us with a relatively small number of degrees of freedom compared to the number of ORS elements that can potentially explain injury rates. Because we are running regressions at the three-digit SOC level, we are, moreover, interested in restricting ourselves to those ORS elements where occupation has considerable explanatory power. To address both considerations, we regress each ORS element individually on three-digit SOC dummy variables. We choose as regressors those ten elements where occupation has the most explanatory power, in all cases with an R-squared exceeding 0.35.

Eight of the ten elements are environmental conditions or physical demands that may affect risk directly. They are traditional keyboarding, encountering wetness, sitting (percentage of hours), working near moving mechanical parts, working in high exposed places, driving required, amount ever lifting/carrying and gross manipulation (percentage of hours).[21] The other two elements are cognitive demands considered above—task complexity and work control—which may capture other dimensions of occupations that affect risk.

In table 5.5, we examine injury and illness rates at the occupation level

20. We estimate that the dropped three-digit SOCs account for less than 15 percent of total employment.

21. Unless otherwise indicated, element indicates presence or absence.

Table 5.5 Occupational requirements and injury/illness rates

Variables	Total incidence rate	Event: Transportation incidents	Event: Falls to lower level	Event: Struck by object or equipment	Nature: Sprains, strains, tears	Nature: Soreness, pain	Nature: Carpal Tunnel Syndrome	Source: Parts and materials	Source: Ladder	Source: Vehicles
Keyboarding:	−28.54	−13.25**	−1.14	−0.04	5.60	−11.59	−0.32	4.78	4.17**	−15.10
traditional	(50.23)	(6.50)	(3.60)	(8.45)	(21.73)	(10.65)	(0.78)	(7.21)	(1.66)	(10.84)
Sitting (%)	98.98**	24.76***	4.61	2.16	41.73**	24.36**	1.47**	4.87	−6.59***	43.29***
	(46.74)	(6.05)	(3.35)	(7.86)	(20.22)	(9.91)	(0.72)	(6.70)	(1.60)	(10.09)
Wetness	−15.51	−6.63	−4.34	−8.72	−3.30	0.35	0.24	−14.49***	−1.53	−13.49*
	(35.97)	(4.65)	(2.58)	(6.05)	(15.56)	(7.63)	(0.61)	(5.14)	(1.21)	(7.76)
Exposed places	−5.18	−21.29***	25.41***	8.56	−10.42	5.28	−2.79***	19.02**	25.00***	−40.72***
	(58.20)	(7.53)	(4.17)	(9.79)	(25.18)	(12.34)	(0.87)	(8.30)	(1.91)	(12.56)
Moving parts	−34.56	−20.20***	−10.95***	24.48***	−37.50*	−21.65**	4.79***	30.51***	−4.32***	−23.61**
	(46.86)	(6.06)	(3.36)	(7.88)	(20.27)	(9.94)	(0.72)	(6.69)	(1.54)	(10.11)
Driving	9.81	15.07***	3.79	−6.51	14.34	6.38	−1.04	−2.13	2.59*	24.17***
	(38.60)	(4.99)	(2.76)	(6.49)	(16.70)	(8.18)	(0.62)	(5.51)	(1.41)	(8.33)
Gross	217.63*	21.63	26.15***	65.75***	94.85*	26.19	−2.02	53.50***	8.38**	71.99***
manipulation (%)	(109.20)	(14.12)	(7.82)	(18.36)	(47.25)	(23.15)	(2.01)	(15.67)	(3.60)	(23.57)
Lift/carry, ever	3.62***	0.45***	0.02	0.00	1.64***	0.72***	0.01	−0.05	−0.11***	0.57***
amount	(0.73)	(0.09)	(0.05)	(0.12)	(0.32)	(0.16)	(0.01)	(0.10)	(0.02)	(0.16)
Work control	18.23	4.93	1.91	4.18	−3.40	3.57	−0.88	4.44	−1.76	6.56
	(46.78)	(6.05)	(3.35)	(7.87)	(20.24)	(9.92)	(0.83)	(6.68)	(1.54)	(10.10)
Task complexity	−45.38	−7.37	−2.27	−0.80	−12.39	−12.55	−0.27	−0.80	1.13	−11.37
	(50.97)	(6.59)	(3.65)	(8.57)	(22.05)	(10.81)	(0.86)	(7.27)	(1.72)	(11.00)
Observations	48	48	48	48	48	48	40	47	40	48
R-squared	0.86	0.83	0.85	0.86	0.84	0.82	0.70	0.87	0.92	0.84

Note: Numbers are coefficients from regressions of injury/illness rates on occupational requirements variables. Standard errors in parentheses.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

from the SOII, overall, and then by the event causing the injury, nature of the injury, and source of the injury. The rates are measured as cases per 10,000 full-time equivalent workers. Looking at the overall incidence rate, we see that those occupations where there are higher levels of lifting and carrying have a higher injury and illness rate, which is also true of those occupations with more sitting and more gross manipulation. While sitting may not seem to be a risky activity, we will see when we turn to events, nature, and sources why it is associated with higher incidence rates.

First to be examined is event causing an injury. It is no surprise that those occupations with a high rate of injuries caused by transportation incidents are strongly positively associated with driving and lifting/carrying, as these are activities associated with the jobs of transportation workers. Standard keyboarding, working in high exposed places and near mechanical moving parts have a negative relationship with transportation injury rates, presumably because these elements are less common among transportation workers.

Falls to lower levels are, quite sensibly, positively associated with working in high exposed places. They also have a positive relationship with gross manipulation, while being negatively related to working with mechanical moving parts. The final event we consider, struck by object or equipment, is, appropriately, positively associated with working with mechanical moving parts, as well as with gross manipulation.

Some interesting relationships are also evident in our examination of the nature of the injuries. Both strains, sprains, and tears and soreness and pain are positively related to gross manipulation and lifting/carrying. Carpal tunnel syndrome, in contrast, is more likely to be found in jobs where there are mechanical moving parts and where there is a relatively high amount of sitting.

Finally, we consider the source of the injury. Parts and materials injuries are more likely to come in jobs with gross manipulation and mechanical moving parts, but less likely when there is exposure to wetness. Injuries where the ladder is the source are more common in jobs where workers are in high exposed places. They also have positive relationships with gross manipulation and standard keyboarding, and negative relationships with large amounts of sitting, working near mechanical moving parts, and the amount of ever lifting and carrying. Injuries where vehicles are the source are somewhat similar to transportation incidents in that both are more apt to be present in jobs where there is driving, lifting/carrying, much sitting, and where there isn't work in high exposed places or with mechanical moving parts.

5.6 Conclusion: The Potential of ORS for Research

Employing information from the preproduction version of ORS, we have presented a set of estimates of some key occupational requirements for all workers, as well as by broad occupation and industry categories. We have also illustrated how ORS data can be used in analysis, focusing on wage determination and the role of job requirements in injury and illness rates.

As BLS moves into production collection, ORS data will be collected annually on a substantially larger sample (roughly 6,000 establishments planned in year 1). The ORS is currently approved for an initial three years of collection with the goal of having reliable estimates for the vast majority of the data elements at the eight-digit O*NET SOC level at the end of the period. While the data elements and collection procedures are intended to support SSA in disability adjudication, these data elements will likely also be useful for a variety of other stakeholders, including researchers.

In addition to the research questions discussed in the introduction, we propose some other areas of research in which ORS data may prove useful. First, our initial analysis linking ORS estimates of job requirements, particularly the physical requirements, to safety outcomes suggests that ORS may be a valuable data set for occupational safety and health researchers. As ORS will ultimately have full sets of estimates on the types of physical and environmental conditions required at a detailed occupation level, it can be used in research focused on a particular occupation (truck driving, for example) or focused on a specific injury that may occur across occupations, linked to underlying physical requirements (such as the relationship between reaching and musculoskeletal injuries).

In addition to considering the direct links between more obviously "risky" job requirements and injuries, ORS data may inform studies of the role of job requirements and illness. Occupational illnesses are typically less well understood than injuries since they tend to result from longer-term exposure to risk factors. Recent research focuses on the relationship between sedentary behavior (including prolonged periods of sitting while at work) and a variety of long-term adverse health outcomes including obesity, type II diabetes, and cardiovascular disease (Dunstan et al. 2012; van der Ploeg et al. 2012; Proper et al. 2011). The ORS data can be used to identify the sets of occupations where workers sit most and the duration/percent of time of sitting, as well as the ability of workers to alternate between sitting and standing at will.

Finally, the current financial strain on the SSI and SSDI programs has led to a great deal of research regarding the barriers involved in getting persons with disabilities to return to the workforce. Extensive research exists that documents the negative relationship between SSDI receipt and labor force participation (Autor and Duggan 2006; Maestas, Mullen, and Strand 2013; von Wachter, Song, and Manchester 2011). The ORS does not ask respondents about accommodations for workers with disabilities; however, disability researchers and advocates may be able to use the ORS data on physical requirements to identify jobs in which specific accommodations may result in more employment opportunities for individuals with disabilities. For example, understanding the characteristics of establishments where some production workers are able to sit or stand at will may lead to recommendations for translating this flexibility into other sectors.

Similarly, identifying jobs that are moderately or loosely controlled but require relatively low levels of SVP provides opportunities to identify the training programs necessary to place individuals with cognitive impairments and relatively low levels of education in such jobs. Recent research has found that participation in state workforce programs increases the likelihood of return to work among SSDI beneficiaries. Information on the amount of training needed to perform certain jobs may help workforce boards target their programs to such workers.

Appendix

Table 5A.1 **List of ORS elements**

Specific vocational preparation—Four elements	
Minimum formal education or literacy required	Prior work experience
Preemployment training (license, certification, other)	Postemployment training
Mental and cognitive demands—Nine elements	
Closeness of job-control level	Frequency of verbal work-related interaction with other contacts
Complexity of task level	Frequency of verbal work-related interaction with regular contacts
Frequency of deviations from normal work location	Type of work-related interactions with other contacts
Frequency of deviations from normal work schedule	Type of work-related interactions with regular contacts
Frequency of deviations from normal work tasks	
Auditory/Vision—Ten elements	
Driving, type of vehicle	Hearing: Other sounds
Communicating verbally	Passage of hearing test
Hearing: One on one	Far visual acuity
Hearing: Group	Near visual acuity
Hearing: Telephone	Peripheral vision
Environmental conditions—Eleven elements	
Extreme cold	Noise-intensity level
Extreme heat	Outdoors
Fumes, noxious odors, dusts, gases	Proximity to moving mechanical parts
Heavy vibration	Toxic, caustic chemicals
High, exposed places	Wetness
Humidity	

Table 5A.1 (continued)

Physical demands, exertion—Fourteen elements	
Most weight lifted/carried ever	Standing and walking
Push/pull with feet only: One or both	Weight lifted/carried 2/3 of the time or more (range)
Push/pull with foot/leg: One or both	Weight lifted/carried 1/3 up to 2/3 of the time (range)
Push/pull with hand/arm: One or both	Weight lifted/carried from 2 percent up to 1/3 of the time (range)
Pushing/pulling with feet only	Weight lifted/carried up to 2 percent of the time (range)
Pushing/pulling with foot/leg	
Pushing/pulling with hand/arm	
Sitting	
Sitting versus standing at will	
Physical demands, reaching/manipulation—Fourteen elements	
Overhead reaching	Gross manipulation: One hand or both
Overhead reaching: One or both	Foot/leg controls
At/below shoulder reaching	Foot/leg controls: One or both
At/below shoulder reaching: One or both	Keyboarding: Ten key
Fine manipulation	Keyboarding: Other
Fine manipulation: One hand or both	Keyboarding: Touch screen
Gross manipulation	Keyboarding: Traditional
Physical demands, postural—Seven elements	
Climbing ladders/ropes/scaffolds	Crouching
Climbing ramps/stairs: Structural only	Kneeling
Climbing ramps/stairs: Work related	Stooping
Crawling	

Table 5A.2 **Full-estimation results**

Variable grouping	Variable	Education only (1)	Ed., cognitive, strength (2)	SVP only (3)	SVP, cognitive, strength (4)
Education	Literacy, no degree	0.147	0.133		
		(0.131)	(0.104)		
	High school diploma	0.390***	0.211*		
		(0.131)	(0.108)		
	Associate's degree	0.561***	0.275**		
		(0.145)	(0.123)		
	Baccalaureate degree	1.060***	0.511***		
		(0.132)	(0.116)		
	Postbacc. degree	1.317***	0.632***		
		(0.147)	(0.127)		
SVP	More than 1 month, up to 1 year			0.229***	0.147***
				(0.0495)	(0.0461)
	More than 1 year, up to 4 years			0.551***	0.246***
				(0.0454)	(0.0431)
	More than 4 years			1.015***	0.386***
				(0.0612)	(0.0623)

(*continued*)

Table 5A.2 (continued)

Variable grouping	Variable	Education only (1)	Ed., cognitive, strength (2)	SVP only (3)	SVP, cognitive, strength (4)
Task complexity	Very complex		0.658***		0.790***
			(0.171)		(0.191)
	Complex		0.553***		0.607***
			(0.104)		(0.110)
	Moderately complex		0.290***		0.304***
			(0.0702)		(0.0779)
	Simple		−0.000783		0.0190
			(0.0514)		(0.0581)
Work control	Controlled		0.0735		0.0599
			(0.0525)		(0.0485)
	Moderately controlled		0.258***		0.227***
			(0.0684)		(0.0650)
	Loosely controlled		0.200**		0.109
			(0.0902)		(0.0907)
	Very loosely controlled		0.723***		0.674***
			(0.179)		(0.178)
Regular contacts	Structured contacts		0.00759		0.00709
			(0.0387)		(0.0389)
	Semi-structured contacts		0.00543		0.0576
			(0.0485)		(0.0525)
	Unstructured contacts		0.0441		0.105
			(0.100)		(0.0986)
	Very unstructured contacts		−0.0794		−0.0413
			(0.0584)		(0.0761)
Strength	Light		0.0401		0.0386
			(0.0439)		(0.0467)
	Medium		0.00860		−0.0301
			(0.0489)		(0.0506)
	Heavy		0.00523		0.0122
			(0.0818)		(0.0903)
	Very heavy		0.0496		0.0394
			(0.0667)		(0.0700)
Establishment size	50–99 employees	0.0319	−0.0265	0.0375	−0.0409
		(0.0594)	(0.0527)	(0.0586)	(0.0523)
	100–499 employees	0.0918*	0.104**	0.0918*	0.110**
		(0.0484)	(0.0507)	(0.0522)	(0.0533)
	500 or more employees	0.229***	0.166***	0.169***	0.144**
		(0.0601)	(0.0585)	(0.0635)	(0.0588)
Sector	Private sector	0.0318	−0.104**	−0.0578	−0.157***
		(0.0540)	(0.0511)	(0.0626)	(0.0533)
Union coverage	Union	0.268***	0.289***	0.367***	0.316***
		(0.0380)	(0.0418)	(0.0499)	(0.0474)
Time base	Full time	0.264***	0.167***	0.182***	0.140***
		(0.0360)	(0.0373)	(0.0453)	(0.0393)
Industry	Construction	−0.195	0.250**	−0.162	0.297***
		(0.129)	(0.107)	(0.154)	(0.104)

Table 5A.2 (continued)

Variable grouping	Variable	Education only (1)	Ed., cognitive, strength (2)	SVP only (3)	SVP, cognitive, strength (4)
	Manufacturing	−0.455***	0.0510	−0.208	0.153
		(0.103)	(0.111)	(0.150)	(0.0944)
	Wholesale trade	−0.523***	0.0312	−0.333**	0.157*
		(0.133)	(0.115)	(0.142)	(0.0943)
	Retail trade	−0.548***	−0.0889	−0.282**	0.000860
		(0.103)	(0.0995)	(0.137)	(0.0930)
	Transportation and warehousing	−0.375***	0.117	−0.230	0.139
		(0.114)	(0.0819)	(0.164)	(0.0985)
	Information	−0.357***	−0.112	−0.0399	−0.00751
		(0.111)	(0.195)	(0.164)	(0.212)
	Financial activities	−0.434***	−0.00682	−0.0931	0.134
		(0.119)	(0.0986)	(0.148)	(0.0907)
	Professional and business services	−0.426***	0.0599	−0.0706	0.177
		(0.125)	(0.114)	(0.155)	(0.111)
	Education and health services	−0.658***	−0.170**	−0.263**	−0.0366
		(0.0926)	(0.0719)	(0.134)	(0.0632)
	Leisure and hospitality	−0.835***	−0.338***	−0.571***	−0.265***
		(0.102)	(0.0960)	(0.139)	(0.0911)
	Other services	−0.494***	−0.0132	−0.339**	0.0398
		(0.130)	(0.123)	(0.152)	(0.116)
	Public administration	−0.528***	−0.264***	−0.306**	−0.225***
		(0.103)	(0.0705)	(0.141)	(0.0585)
	Constant	2.572***	2.180***	2.518***	2.239***
		(0.173)	(0.145)	(0.151)	(0.0983)
	R-squared	0.673	0.769	0.662	0.766

Note: Standard errors in parentheses.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

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