Using Tools and Tasks to Distinguish General and Occupation-Specific Skills

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June 2015

JEL Codes: J31, J24 Keywords: Tool use, Occupation-Specific Skills, Job Skills
Abstract: This work shows that data on tool use from O*Net's Tools and Technologies (T2) Supplement can, in conjunction with task-based measures, provide a new proxy for measuring and distinguishing general and specific skills at the occupational level. Tool use measures allow us to generate reasonable proxies for skill that vary across occupations and appear to capture features of occupations that differ from, and potentially complement, task-based proxies for skill. Wage regressions indicate that "general tools," are associated with higher-paying occupations while "specific tools" are not. It is important to measure tool use in conjunction with tasks. Tool mastery is only one aspect of human capital and regression results confirm that its relative value differs with occupational characteristics. In high-cognitive occupations, "general tools" have a positive and significant coefficient. In occupations emphasizing routine tasks, tool mastery, as measured by the number of tools used, is more likely to be a valuable form of human capital.

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The authors thank Peter Meyer and Jay Stewart for helpful comments. Robert Mohr thanks the University of Canterbury for supporting this work through its Erskine Visiting Scholars program. All views expressed in this paper are those of the authors and do not necessarily reflect the views or policies of the U.S. Bureau of Labor Statistics.

Economists have long thought of human capital acquisition as a mix between general skills that are applicable across many jobs, and specific skills that have a disproportionate value to a particular job, occupation, or industry (Becker, 1964). The concept of specific skills is intuitively appealing and is consistent with the observation that the duration of job tenure correlates to a significant wage premium and a decreased hazard for separation. The major limitation for this type of skill taxonomy is that specific skills are difficult to measure. For example, years of tenure at a particular job may proxy either for job-specific skills or for the quality of a job match (Mortensen, 1988; Nagypál, 2007). Furthermore, the degree of skill-specificity acquired with experience at a given job is hard to determine. Job tenure alone makes it hard to distinguish skills that are valuable to a particular job from those that are valuable for all jobs in a given occupation or industry (Parent, 2000).

As a consequence of this limitation, recent research has turned to identifying measures of occupation-specific and industry-specific skills. These papers tend to take one of two approaches. Some studies show the importance of industry or occupational experience in estimations that predict wages or the likelihood of job separation (e.g. Parent, 2000). This strategy does not measure skills directly, but provide strong indirect evidence that skill acquisition comes in the form of industry or occupation-specific competencies.

The second approach is to develop and measure proxies for skills. Since it is difficult to identify concrete skill measures that are comparable across occupations (Mohr and Zoghi, 2014), only a relatively recent literature attempts to isolate particular characteristics of jobs or occupations that correspond to job skills. These papers often employ what Autor (2013) describes as the "Task Approach" to measuring skills. The goal is to measure the task requirements of a job or occupation and then link those tasks to the skills of the workers. Some examples of this line of research are Gathmann and Schönberg (2010), who show that a task-based measure of skills explains a significant proportion of wage growth, Leping (2009), who uses job advertisements to define the skill-specificity of work, and, most pertinent to this work, Autor and Handel (2013), who find that individual-level data about job tasks significantly improves the explanatory power of a wage regression.[1] The use of occupational-level measures of skills has been especially important to the literature focused on wage inequality. In particular, a number of authors have focused on the link between information technology and the task content of occupations (e.g. Autor, Levy and Murnane, 2003; Autor, Katz and Kearney, 2006; Goos and Manning, 2007; Spitz-Oener, 2006). The hypothesis underlying many of these studies is that the use of computers depresses the relative wages in occupations that have routine tasks that can easily be automated.

The contribution of this essay is to analyze tool use, in conjunction with tasks, to better categorize the skill requirements of various occupations. We argue that, beyond the use of computers, there are a wide range of tools that might correlate to the skill requirements and therefore wages of jobs. Tools relate closely to skills, since the mastery of any particular tool is a skill. The variation of tools across occupations allows a natural way to categorize these skills in terms of their specificity. Some tools (e.g. hammers, computers, or fax machines) are generalist and used in a wide range of occupations. Many other tools are very specific and used only in a very narrow range of occupations. We show

[1] Autor (2013) and Autor and Handel (2013) provide thorough reviews of this literature, including numerous studies not discussed here.

that the range and types of tools used in a particular occupation provides a robust measure of skills.

Along with Snower and Goerlich (2013), this paper is among the first to look closely at tools and their relationship to job tasks.[2] We explore whether tool use, in conjunction with tasks, can allow us to better understand the skill content of occupations and whether such information provides insight into occupational-level differences in wages. We start by creating measures of the number of tools typically used in an occupation, as well as the specificity or generality of those tools. Specific tools are those that used by very few workers. General tools are those that are used by many workers, across numerous occupations. We explore how our measures of tool use correlate to more commonly-used measures of job tasks. We then test whether tool use helps explain wages at the occupation level. In particular, we ask if the explanatory power of a wage regression changes significantly with inclusion of tool variables, if the number and types of tools have differential relationships to occupational-level wages, and if those relationships vary by types of occupations.

The remainder of this paper is organized as follows. Section I discusses several theoretical and conceptual issues relevant our empirical analyses. Section II discusses the O*NET data and develops a measure of tool specificity. Section III studies the relationship between tool specificity and wages. Section IV concludes.

I. Conceptual Discussion

[2] Snower and Goerlich (2013) use data about the use of approximately 30 tools at the individual level as a robustness check to show a positive relationship between multitasking and wages.

A Mincer wage regression is the most common way to measure returns to skill. Such a regression typically takes the form:

$$\ln(w_i) = \alpha + \beta_1 S_i + \beta_2 T_i + \beta_3 T_i^2 + \gamma X_i + \nu_i \qquad (1)$$

where w_i represents the log wage for worker i, S_i measures educational attainment, T_i measures either age or experience, and X_i is a vector of individual-level covariates like gender or race. In it simplest form, this regression uses schooling and experience to proxy for general and specific skills. Other versions of this regression will include tenure in a specific job or industry, on-the-job training, or other measures to get a more precise proxy for skill. Indicator variables for occupation, for example, can be used to control for occupation-specific skills.

The major limitation of estimating equation (1) is that it does not include a measure of the specific skills needed in particular jobs. As Autor and Handel (2013), Levenson and Zoghi (2010), and numerous others point out, these unobserved skills can bias estimates from a wage regression. A natural response is therefore to find better and more direct proxies for skills – such as information about specific job tasks (Autor and Handel, 2013), requirements of occupations (Levenson and Zoghi, 2010), or, in the case of this paper, tools – and use those proxies in the wage regression. Unfortunately, including any of these proxies directly into a wage regression can lead to another source of bias. A reduced-form expression like equation 1 does not control for selection into occupations. Both tasks and tools might be best thought of as a bundle, where the proportions of particular tasks and tools vary by occupation. Estimating the equation with either tasks or tools included individually would quite likely produce negative coefficients for those tasks or tools that are used frequently at low-wage jobs and less frequently at high-wage jobs. Such a cross-sectional result would not, of course, mean that acquiring the skills to perform a given task or use a given tool has negative effect on wages.

In cross-sectional data where the proxy for skill is measured only at the occupational level the potential for biased estimators in a Mincer wage regression can't be eliminated. One option is to develop alternative models for the relationship between wages and skills, as in Autor and Handel (2013), but such models still require variation at the individual level and may have relatively weak testable implications.[3] Barring the use of such an alternative model, one must acknowledge the limitations of including the skill proxies in the wage regression, summarize the bundle of task or tool measures into a small number of indices that are hopefully less susceptible to the form of bias described here, and proceed with the knowledge that such an imperfect measure is likely better than failing to include proxies for specific skills at all.

In order to assess the validity of tool use as a measure of skills, we start by developing some aggregate measures to identify the number and specificity of tools used by occupation. Specific tools are used by very few workers outside of one's own occupation, whereas general tools are used by many workers in other occupations. We explore the relationship between tool specificity and characteristics of occupations and show that the three measures of tool use (number of tools, specific tools, and general tools) correlate to established, task-based, proxies for skill. We then study how the inclusion of

[3] Firpo, Fortin, and Lemiuex (2011) suggest using variation over time to estimate a Roy model where wages are determined by a linear combination of skill components within an occupation.

tools affects a wage regression. Our results give insight into occupational wage differentials.

II. Data and Descriptive Statistics

Occupation-specific information comes from the 2010 Occupational Information Network (O*Net, or ONET) database, which is compiled by the US Department of Labor and contains a broad range of descriptors for various occupations. Although these data have been used in a number of prior studies, work in economics has to our knowledge failed to exploit the Tools and Technologies Supplement, which contains a thorough inventory of the tools used in particular occupations.

The Department of Labor's O*Net database collects data on 774 "high demand" occupations. Dierdorff et. al. (2006) describe the Tools and Technologies (T2) Supplement including the details of data collection and classification. Tools and technologies are identified by occupation, with the criteria for inclusion being that tools are:

> those items necessary to carry out central functions required by an occupational incumbent's work role and responsibilities. In addition to being essential to occupational performance, T2 items must have an expectation of a training requirement that ranges from a minimum of at least some on-the-job training, initial supervision, or 'demonstration of use,' to more formal training or vocational education." (Dierdorff et. al. 2006)

As of 2010, O*Net contained over 20,000 tools[4] that workers need to perform their occupations, identified and organized into a standard taxonomy that is part of the United Nations Standard Products and Services Code. This taxonomy identifies tools both by the specific tool and by broader "classes," "families" or "segments" of similar or related tools. We construct measures using both the individual tools and tool families.

The average number of tools and tool families used per job, by major occupation (weighted by 2010 CPS Job Tenure Supplement employment totals), are summarized in Table 1. The average worker uses nearly 60 different tools; while many of these may be quite similar to one another, as in bolt cutters, cable cutters and wire cutters, the average worker also uses approximately 13 different families of tools. These include families such as "hand tools," or "heavy construction machinery and equipment." For both levels of aggregation, there are large differences by major occupation. Far fewer tools are used in sales or service occupations relative to the "blue collar" occupations: workers in areas like farming, production or repair are likely to use a wide range of tools. Even within occupational categories there is significant variation. "White collar" workers consist of both professionals, who often use many tools, and managers, who use very few tools. Economists use just six tools: desktop calculators, desktop computers, mainframe computers, notebook computers, personal computers and scanners.

[4] Additionally, O*Net contains information on another 30,000 "technologies" that workers use. These are mainly types of software. We do not use them in this paper because we are unsure whether knowing how to run different types of software represents different types of human capital.

Table 1 Here

Given the training requirements associated with the tools used in the O*Net T2 supplement, we hypothesize that mastery of the tools of an occupation represent a form of human capital. In occupations that have very specific tools and technology, this human capital is occupation-specific. If a given occupation tends to use tools that are more general, in the sense that similar tools are used in many other occupations, then this human capital is not occupation-specific. To define tool specificity, we start by weighting occupations with respect to their employment levels, using data from the Current Population Survey. We then rank tools in terms of the proportion of workers using a given tool. Table 2 identifies tools that are either commonly-used or highly specific.

Table 2 Here

Not surprisingly, the most commonly used tools are computers, printers, scanners, photocopiers and fax machines. Consistent with data from surveys of computer use, O*Net data indicate that around 90 percent of workers use a computer on the job to at least some extent. These particular tools are noteworthy because, to the extent that tool use has been incorporated at all into prior studies, it has been typically limited to items like computers or fax machines (e.g. Autor, Katz and Krueger, 1998; Arabsheibani and Marin, 2006; Moressette, 1998). Our view is that mastery of such tools represents general, rather than specific human capital.

The types of tools that are quite likely associated with highly-specific human capital are listed on the right-hand column of Table 2. This column identifies tools used by the smallest fraction of American workers; mainly these are occupation-specific tools that are used in uncommon occupations, like funeral service workers or atmospheric and space scientists. Over twenty percent of the 20,282 tools in the sample are used in fewer than five occupations.

Given the information about tools, we identify the degree that particular occupations use either specialized or general tools. For a given occupation, we define an "occupation-specific" tool as one that is used by fewer than 10% of workers outside of that occupation. Analogously, for a given occupation, we define a "general" tool as one that is used by at least 20% of all workers outside of that occupation. We label tools that are neither specific nor general (tools used by between 10% and 20% of workers outside an occupation) as "non-specific." Table 3 shows the number of general, non-specific and specific tools by major occupation. Although the table is limited to tools, the pattern is similar for the broader categorizations like tool families or segments. Of the 59 tools used by a typical worker, 47 are occupation-specific, 5 are non-specific and 7 are general.

Table 3 here

The bottom three portions of Table 3 highlight the significant variation in the number of specific and general tools used within each broad occupation group. The most striking correlation is that the production occupations, which use the most tools overall, are also the ones that are most likely to require the use of many specific tools. Farming, forestry and fishing, professional, construction and production occupation workers use many tools, the majority of which are specific to the particular occupation.

In addition to providing information about tool use, the O*Net database also provides direct information about the cognitive and manual requirements of occupations. Acemoglu and Autor (2011) and Autor and Handel (2013) use additive indices for individual O*Net measures to create broad measures of the task requirement of jobs. Based on the description in Acemoglu and Autor (2011), we use four such indices: "Non-routine cognitive," "Routine cognitive," "Routine manual," and "Non routine-manual." Cognitive occupations are ones that emphasize analytical, creative and interpersonal skills. Occupations that score highly on the "routine" measure emphasize repetition, pace, accuracy and the control of machines or processes. Of these four measures, routine-manual is the one that specifically includes the task of "Controlling machines and processes." Occupations that emphasize "non-routine manual" tasks are those that emphasize manual dexterity, spatial orientation, and the use of one's hands for work. Information about how the task-based measures vary by major occupation group is found in the Appendix Table, A1.

Tables 4 and 5 explore how the use of tools and tasks vary with the task-based measures. Table 4 shows the types of tools used when occupations are sorted according to their task requirements. We partition the data into the high-cognitive and low-cognitive occupations using the highest and lowest tertiles of the combined cognitive tasks, and make an analogous partition into non-routine and routine occupations. High-cognitive and non-routine occupations use more tools and different types of tools. In particular, these occupations have relatively more emphasis on general tools, with over 98% of workers using three or more general tools.

Table 4 here

Table 5 presents correlation coefficients. The correlations indicate that tool use is likely to pick up aspects of occupation-specific human capital that are distinct from the task-based indices developed by Acemoglu and Autor (2011). The correlations between the four task indices range from .18 to .69. The correlations between the four measures of tool use are all positive and range from .45 to over .99. The correlations across the two types of measures are lower, indicating that tool use may present a measure of human capital that is distinct from the human capital associated with tasks.

Table 5 here

It is worth mentioning that the fact that the extremely high correlation between the total number of tools and the number of specific tools is to some extent an artifact of how the measures are created. The most general tools, like computers, are used in nearly all occupations. Therefore, variation in tool use is driven largely by the variation in specific tools. Finally, most of the largest correlations (both positive and negative) between tasks and tool use come from the use of general tools. This suggests that the human capital associated with the four task indices tends more towards general rather than occupationally-specific human capital.

III. Tools and Wages

In order to link tool use to wages, we draw individual-level data on wages, demographic information, job tenure and occupation from the 2010 Current Population Survey Job Tenure Supplement. We estimate a wage regression, as described in equation (1) with task indices, and various measures of tool use and tool specificity as explanatory variables. Additionally, we control for the standard worker demographic variables—age, education, race, gender, marital status, and job tenure. Since the task indices and the use of tools vary only by occupation, standard errors are clustered. Coefficients on tool use therefore indicate occupation-level differences. A positive coefficient would indicate that workers in occupations that use more, or more specific, tools tend to garner higher wages.

Table 6 shows the results of 5 different OLS estimations for a wage regression, where the log of weekly wages is the dependent variable. Clustered standard errors are used for all estimations. The first column represents a baseline: it estimates equation (1) using just the four task index measures used in prior research. Column 2 adds the total number of tools used in an occupation. Column 3 instead breaks this number into component parts: the number of the occupation's tools that are "specific," the number of tools that are "non-specific" (neither "specific" nor "general") and the number of the occupation's tools that are "general." Column 4 includes all the measures in Column 3 plus controls for ten separate broad occupation groups. Column 5 drops both the indicator variables for occupation and the counts of the types of tools. Instead, it includes indicator variables for each of the 164 major tool families, assigning a value of one if any tool in a given family is used in an occupation.

Table 6 here

The differences between column 1 and columns 2 and 3 in Table 6 indicate that previously-published results based on task-based measures are likely to be robust. Here, we find a positive association between non-routine tasks and occupational level wages. Neither the sign nor the significance of the coefficients on any of the four task measures change substantially when controlling for tool use. The count measures of tool-use add only slightly to the explanatory power of the regression. Coefficient estimates on either the number of tools, the number of non-specific tools, and the number of general tools are all insignificant. In a model using the full population of all occupations and imposing a linear relationship, there is no consistent statistically significant pattern between the number of tools and wages. The only association is a weak negative relationship between the number of specific tools and wages in column 3.

Column 4 of Table 6 shows that adding indicator variables to control for occupation increases the explanatory power of the regression, but does not significantly affect coefficients of interest. Column 5 is noteworthy for the significant increase in R-squared. Comparing columns 3, 4, and 5, shows that tools, when one allows for differential effects by tool family, add significant explanatory power to a wage regression and even more explanatory power than an indicator variable controlling for occupation groups. Tools do explain occupational differences in wages, but the effect is difficult to capture in a linear measure of the number of tools.

While Table 6 reveals that there are few consistent patterns between tool use and wages in a sample that incudes all occupations, the correlations in Tables 4 and 5 suggest that relationship between tools and wages at the occupation level may vary by occupation type or characteristic. Furthermore, the last column of Table 6 indicates that coarse linear measures of the number of tools used in an occupation may be insufficient to clearly discern the pattern between tool use and wages. Table 7 explores regressions where we allow for differential effects of tool use on wages by occupation group and allow for non-linear relationships between tool use and wages.

In order to impose fewer restrictions on the relationship between tools and wages, we partition the sample by groups of occupations and allow for a non-linear relationship between the number of tools and wages. In Table 7, column 1 uses the full sample, and columns 2-4 split the sample into "white collar" (management and professional), "pink collar" (sales, service and administrative) and "blue collar" (agriculture, construction and production) jobs. While this split by major occupation groups conforms to the commonly used taxonomy of white and blue-collar work, it is problematic in that it combines jobs with very different requirements for job tasks or tool use. For example, the white-collar grouping includes both the tool-intensive professional occupations and the relatively tool-sparse management occupations. For this reason, columns 5-6 instead use the task indices to partition the data into the high-cognitive and low-cognitive occupations (using the highest and lowest tertile of the combined cognitive tasks), and columns 7-8 use an analogous partition into non-routine and routine occupations.

The rows of Table 7 are split into sections, with each section reporting results from a different regression. Each regression uses a full set of control variables, including the task measures, from Table 6, but we report only the coefficients on tool use. The top row reports results from a regression that uses the number of tools as the independent variable. Thus, the very top left cell of Table 7 repeats of the estimate from the analogous cell in Column 2 of Table 6. The next set of rows show coefficient estimates where we replace the linear measure of the number of tools used with four indicator variables showing ranges for the number of tools used (0-9 tools is the reference group). The cutoff values for the indicator variables were selected to roughly represent quartiles in the full sample. The third section similarly extends column 3 of Table 6 by replacing each count measure for the three types of tool use (specific, non-specific, or general) with four indicator variables. The reference category is normally zero tools, but for a few cases no occupations used zero tools of a particular type, so a different reference category is identified in the table.

Table 7 here

The results in Table 7 confirm that the relationship between wages at the occupational level and tool use does vary by occupation characteristics. In white collar, high-cognitive and non-routine jobs, increased tool use is associated with lower wages. In these occupations, abstract or cognitive forms of human capital may be particularly valuable, while the ability to use tools is less valued. An occupation like financial analyst meets the definitions of white collar, high-cognitive, and non-routine, uses relatively few tools, and has wages that are relatively high to other similarly classified occupations. Amongst blue-collar and routine occupations, where tool use presumably more closely correlates to the core skills of an occupation, there is a strong positive correlation between tool use and wages, with some evidence of diminishing returns.

The bottom section of the table verifies that different types of tools have very different associations with wages. Specific tools are associated with lower-wage occupations. Across all columns, general tools are associated with higher wages. If specific tools are indicative of occupations that can be more easily automated or mechanized, and general tools are indicative of occupations that require broader and wide-ranging skills that cannot be easily automated, then this finding is relevant both to the literature on wage inequality and to the literature that distinguishes the value of various occupationally-specific skills.

Finally, it is worth noting that, in addition to the results in Table 7, we performed several robustness checks using alternate specifications. First, we redefined our tool use variables to measure the proportion, not number, of tools within an occupation that are either general or specific. Second, we redefine tool specificity or generality by blue, white and pink collar. In other words a tool is defined as general for a blue-collar occupation only if it used in numerous other blue-collar occupations. Third, because tool use varies significantly even within the three broad occupational groups, we partition the data into separate occupational groups and regress wages on the tool use measures at the occupation level. Finally, we experiment with other non-linear specifications for the count of tools, measuring either a logged measure or including a squared term. All of these alternate specifications produce results consistent with our main findings: the number of tools has a positive association with wages only for blue-collar workers, specific tools tend to have negative correlation to wages, and general tools are more likely to be positively correlated to wages. Results are available upon request.

Discussion

Economists have long understood the importance of distinguishing general from specific skills. One particularly promising approach to measuring specific skills at the occupation level is to study the tasks associated with each occupation. Our contribution is to show that task-based measures can be extended and potentially improved by supplementing these measures with information about tool use. O*Net's Tools and Technologies (T2) Supplement provides a new and previously unexplored way to proxy for skills. In particular, since many tools are used across multiple occupations, tool mastery allows for a natural way of distinguishing general from occupationally-specific skills. We show that tool use measures allow us to generate reasonable proxies for skill that vary across occupations. Correlation coefficients indicate that tool-use measures are likely to capture features of occupations that differ from task-based proxies for skill. Wage regressions indicate that tools explain some of the occupational-level variation in wages and that "general tools," those used by 20% or more of all workers, are associated with higher paying occupations.

While our work indicates the potential for using detailed information about tools and technologies as a way to identify occupation-specific and general skills, it also suggests some caveats. For example, it is important to measure tool use in conjunction with tasks. Tool mastery is only one aspect of a worker's human capital and its relative value will differ with occupational characteristics. In our regression results, the relationship between tool use and wages differs by occupation type. In high-cognitive occupations, the most valuable human capital is in the mastery of cognitive and abstract tasks, some of which may be supported by general tools. In occupations emphasizing routine tasks, tool mastery, as measured by the number of tools used, is more likely to be a valuable form of human capital.

Table 1. Number of different tools and types of tools used, by major occupation				
	All workers	Managers & professionals	Sales, service & administrative	Production
Number of tools	59.3	79.0	29.7	75.4
Number of tool families	12.9	15.2	9.1	15.4

2010 O*NET tools, weighted by 2010 CPS Job Tenure Supplement employment by occupation

Table 2. Percent of workers using most and least commonly-used tools

Tool	% using	Tool	% using
Personal computers	88.5568	Wing bender	0.00109
Desktop computers	81.1428	Embalming cavity injectors	0.00117
Notebook computers	68.2289	Hair care supplies	0.00117
Laser printers	46.9278	Makeup kits	0.00117
Scanners	41.1926	Manicure implements	0.00117
Personal digital assistant PDAs	40.3604	Medical body bag	0.00117
Laser fax machine	38.7767	Morgue cabinet refrigerators	0.00117
Photocopiers	38.5773	Postmortem incision clips	0.00117
Special purpose telephones	36.4111	Hydraulic quick connectors	0.00174
Screwdrivers	29.9656	Pile driver tools or its parts or access.	0.00174
Tablet computers	28.9991	Wire rope	0.00174
Digital cameras	27.0668	Brachytherapy units	0.00232
Hammers	26.9946	Medical linear accelerator inten. mod.	0.00232
Two way radios	24.6948	Radiotherapy teletherapy cobalt 60 equip	0.00232
Adjustable wrenches	22.3624	Animal calls	0.00271
Ladders	22.0954	Archery arm guards	0.00271
Pocket calculator	22.0624	Archery bow strings	0.00271
Forklifts	21.0248	Archery gloves	0.00271
Portable data input terminals	20.9759	First aid blankets	0.00271
Power saws	20.4972	Funnels	0.00271
Desktop calculator	20.2491	Gun barrel	0.00271
Power drills	20.1214	Gun cases	0.00271
Digital camcorders or video cam.	20.0188	Leather straps	0.00271
Adjustable widemouth pliers	19.6947	Lighting pole or post and hardware	0.00271
Safety glasses	19.6502	Metallic mirrors	0.00271
Bar code reader equipment	19.5624	Mining headlamp	0.00271
Air compressors	19.5280	Paddles	0.00271
Protective gloves	18.0829	Parts of guns or pistols	0.00271
Tape measures	17.5556	Radios	0.00271
Calipers	17.4718	Screw hooks	0.00271
Cash registers	17.3367	Sifters	0.00271
Goggles	17.1030	Sporting decoys	0.00271
Liquid crystal display projector	16.6120	Sporting rifles	0.00271
Electr. funds transfer point of sale	16.4323	Sporting shotguns	0.00271
Levels	15.5918	Storm lights	0.00271
GPS receiver	15.2528	Tents	0.00271

2010 O*NET tool usage, weighted by 2010 CPS Job Tenure supplement employment totals

Table 3. Tool specificity by occupation				
	Full sample	**Managers & professionals**	**Sales, service & administrative**	**Production**
# tools used by <10% of other workers	46.7	65.8	20.5	58.1
# tools used by 10-19% of other workers	5.3	4.8	3.4	9.8
# tools used by 20+ % of other workers	7.3	8.4	5.9	7.7
no tools used by <10%	6.4%	15.2%	2.2%	0.0%
1-2 tools used by <10%	7.7%	9.6%	11.9%	0%
3-10 tools used by <10%	23.9%	17.2%	47.6%	4.7%
11+ tools used by <10%	61.9%	58.1%	38.3%	95.3%
no tools used by 10-19%	10.9%	17.7%	11.9%	0.7%
1-2 tools used by 10-19%	24.6%	28.7%	36.0%	6.8%
3-10 tools used by 10-19%	41.8%	39.2%	51.2%	50.4%
11+ tools used by 10-19%	22.8%	14.3%	1.0%	42.1%
no tools used by 20+%	0.7%	0.0%	1.9%	0.1%
1-2 tools used by 20+%	4.8%	2.6%	8.3%	5.2%
3-10 tools used by 20+%	68.7%	69.9%	83.3%	73.5%
11+ tools used by 20+%	25.8%	27.5%	6.6%	21.2%

Rows 1-3: the average number of tools used per worker, weighted by 2010 CPS Job Tenure supplement employment totals. Remaining rows: the proportion of workers using the given number of tools within a particular specificity.

Table 4. Tool specificity by tasks	Less cognitive occupations	Medium cognitive occupations	Highly cognitive occupations	Less non-routine occupations	Medium non-routine occupations	Highly non-routine occupations
# tools	42.32	45.65	68.27	27.40	71.27	71.26
# tools used by <10% of other workers	31.36	33.03	55.15	18.25	58.09	57.13
# tools used by 10-19% of other workers	5.95	5.02	4.81	3.46	5.80	5.98
# tools used by 20+ % of other workers	5.01	7.60	8.31	5.70	7.38	8.15
no tools used by <10%	0.0%	2.6%	18.3%	4.0%	10.6%	5.3%
1-2 tools used by <10%	0.5%	8.1%	15.3%	5.0%	8.3%	9.1%
3-10 tools used by <10%	20.2%	43.8%	13.7%	42.5%	24.1%	11.7%
11+ tools used by <10%	79.3%	45.1%	53.8%	47.8%	60.4%	72.0%
no tools used by 10-19%	5.5%	11.2%	14.5%	8.0%	13.8%	10.9%
1-2 tools used by 10-19%	20.6%	28.4%	27.0%	36.6%	22.8%	17.9%
3-10 tools used by 10-19%	52.6%	39.7%	35.6%	40.5%	45.4%	40.2%
11+ tools used by 10-19%	26.4%	22.1%	17.7%	14.4%	26.8%	25.6%
no tools used by 20+%	2.6%	0.0%	0.0%	1.7%	0.8%	0.0%
1-2 tools used by 20+%	10.2%	4.4%	1.4%	9.9%	5.0%	1.4%
3-10 tools used by 20+%	68.0%	70.9%	68.3%	66.6%	68.0%	70.5%
11+ tools used by 20+%	19.2%	24.7%	30.3%	21.9%	26.2%	28.1%
Number of obs	14,284	15,341	16,678	15,125	15,373	23,901

Rows 1-3: the average number of tools used per worker, weighted by 2010 CPS Job Tenure supplement employment totals. Remaining rows: the proportion of workers using the given number of tools within a particular definition of specificity.

Table 5. Correlations between tasks and tools							
	Non-routine cognitive	Routine cognitive	Routine manual	Non-routine manual	# tools	# tools <10% workers use	# tools 10-19% workers use
Routine cognitive	.258						
Routine manual	-.577	-.179					
Non-routine manual	-.291	-.315	.685				
# tools	.119	-.307	.103	.119			
# tools <10% workers use	.110	-.024	.093	.105	.997		
# tools 10-19% workers use	-.033	-.235	.364	.377	.655	.603	
# tools 20+% workers use	.401	.159	-.167	-.088	.500	.447	.582

Table 6. Wage regressions

	(1)	(2)	(3)	(4)	(5)
Tenure (years)	0.006***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Non white	-0.007	-0.009	-0.006	0.001	0.010
	(0.018)	(0.019)	(0.019)	(0.020)	(0.020)
Female	-0.093***	-0.099***	-0.094***	-0.080***	-0.057***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Married	0.079***	0.088***	0.087***	0.084***	0.077***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Age	0.016***	0.015***	0.015***	0.014***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High school	0.136***	0.140***	0.139***	0.143***	0.136***
	(0.030)	(0.032)	(0.032)	(0.031)	(0.031)
Some college	0.089***	0.091***	0.092***	0.095***	0.083***
	(0.032)	(0.033)	(0.033)	(0.033)	(0.031)
College	0.186***	0.187***	0.189***	0.191***	0.175***
	(0.037)	(0.038)	(0.039)	(0.037)	(0.035)
Non-Rout, Cogn.	0.010***	0.011***	0.010***	0.002	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Routine, Cogn.	0.002	0.002	0.003	-0.002	-0.005
	(0.004)	(0.005)	(0.005)	(0.005)	(0.008)
Routine, Manual	-0.009	-0.009	-0.011*	-0.011*	-0.022***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
Non-Routine, Man.	0.011**	0.008**	0.008*	0.015***	0.015**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
Number of tools		**-0.000**			
		(0.000)			
Number of tools used by <10% workers			**-0.000****	**-0.000**	
			(0.000)	**(0.000)**	
#of tools used by 10-19% of workers			**0.004**	**-0.001**	
			(0.004)	**(0.004)**	
Number of tools used by 20+% of workers			**0.002**	**0.004**	
			(0.005)	**(0.004)**	
Occupation Indicator	no	no	no	yes	No
Tool families	no	no	no	no	Yes
Observations	46286	41934	41934	41934	41934
R-squared	0.015	0.015	0.015	0.017	0.023

Dependent variable: natural log of weekly earnings. Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Wage regressions using indicator variables for intensity of tool use								
	Full Sample	**White Collar**	**Pink Collar**	**Blue Collar**	**Hi Cognitive**	**Low Cognitive**	**Non-routine**	**Routine**
Number of tools	**-0.000*** (0.000)	**-0.000*** (0.000)	-0.000 (0.001)	0.000 (0.000)	**-0.000*** (0.000)	0.000 (0.001)	**-0.000*** (0.000)	0.001 (0.001)
R-Squared	.015	.011	.011	.013	.013	.013	.011	015
10-24 tools	**-0.064** (0.031)**	-0.052 (0.051)	0.013 (0.045)	**0.641*** (0.046)**	-0.037 (0.046)	-0.099 (0.067)	**-0.173*** (0.049)**	-0.020 (0.040)
25-74 tools	-0.056 (0.038)	-0.034 (0.058)	-0.033 (0.060)	**0.761*** (0.042)**	-0.024 (0.062)	-0.060 (0.054)	**-0.133** (0.062)**	-0.006 (0.045)
75+ tools	**-0.070* (0.036)**	**-0.087* (0.051)**	0.065 (0.069)	**0.729*** (0.046)**	**-0.079* (0.047)**	-0.030 (0.062)	**-0.193*** (0.048)**	0.013 (0.062)
R-Squared	.015	.011	.012	.016	.012	.014	.015	014
1-2 specific tools	0.020 (0.049)	**0.123* (0.065)**	0.003 (0.066)	N/A	0.079 (0.076)	**-0.576*** (0.152)**	0.014 (0.076)	0.020 (0.088)
3-10 spec. tools	**-0.073** (0.034)**	0.013 (0.060)	-0.013 (0.074)	Reference	-0.013 (0.061)	**-1.014*** (0.130)**	**-0.136*** (0.045)**	-0.067 (0.049)
11+ spec. tools	**-0.069** (0.033)**	-0.008 (0.049)	-0.016 (0.081)	**-0.190* (0.105)**	0.011 (0.050)	**-0.917*** (0.109)**	**-0.097** (0.043)**	0.003 (0.063)
1-2 non-spec tools	0.052 (0.037)	0.057 (0.039)	0.047 (0.070)	**0.883*** (0.104)**	0.015 (0.034)	**0.288*** (0.063)**	-0.021 (0.044)	0.076 (0.055)
3-10 non-spec tools	0.058 (0.037)	-0.001 (0.037)	0.079 (0.073)	**0.983*** (0.117)**	0.010 (0.033)	**0.223*** (0.050)**	0.004 (0.038)	0.011 (0.068)
11+ non-spec tools	0.044 (0.052)	**-0.135** (0.056)**	0.051 (0.109)	**1.036*** (0.120)**	**-0.115** (0.055)**	**0.263*** (0.063)**	-0.081 (0.055)	-0.085 (0.132)
1-2 general tools	**0.129* (0.068)**	Reference	0.064 (0.067)	0.141 (0.092)	Reference	**0.166** (0.073)**	Reference	0.156 (0.123)
3-10 gen. tools	**0.175*** (0.064)**	-0.022 (0.046)	**0.149** (0.057)**	**0.159** (0.075)**	-0.026 (0.079)	**0.190*** (0.067)**	0.023 (0.133)	0.159 (0.122)
11+ gen. tools	**0.187*** (0.070)**	0.080 (0.061)	0.121 (0.081)	**0.202** (0.082)**	-0.004 (0.092)	**0.255*** (0.074)**	0.057 (0.139)	0.215 (0.150)
R-Squared	0.015	0.013	0.012	0.017	0.014	0.015	0.012	0.016
Number of obs	43022	18219	15971	8832	16255	12433	15583	13297

Dependent variable: natural log of weekly earnings. Each column reports results from three separate regressions, where each regression includes a full set of control variables, as in Table 6. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table A1. Task variables by occupation				
	All workers	Managers & professionals	Sales, service & administration	Production
Non-routine cognitive	-1.12	3.43	-3.37	-3.60
Routine cognitive	-0,22	0.27	-0.95	-1.21
Routine manual	0.54	-1.25	0.07	4.78
Non-routine manual	0.66	-1.55	0.44	3.83
Less cognitive	33.0%	2.9%	38.6%	58.9%
Medium cognitive	33.0%	17.8%	48.2%	32.1%
Highly cognitive	34.0%	79.3%	13.3%	9.0%
Less non-routine	28.3%	9.6%	52.8%	14.9%
Medium non-routine	28.7%	27.2%	26.6%	30.7%
Highly non-routine	43.0%	63.3%	20.7%	54.4%

Rows 1-3: the average number of index score per worker, weighted by 2010 CPS Job Tenure supplement employment totals. Method for determining index scores from Acemoglu and Autor, 2011. Remaining rows: the proportion of occupations falling into the top, middle, or bottom terciles of the cognitive and non-routine indices by major occupation group.

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