Online Appendix to
The Growing Importance of Social Tasks in High-Paying Occupations: Implications for Sorting

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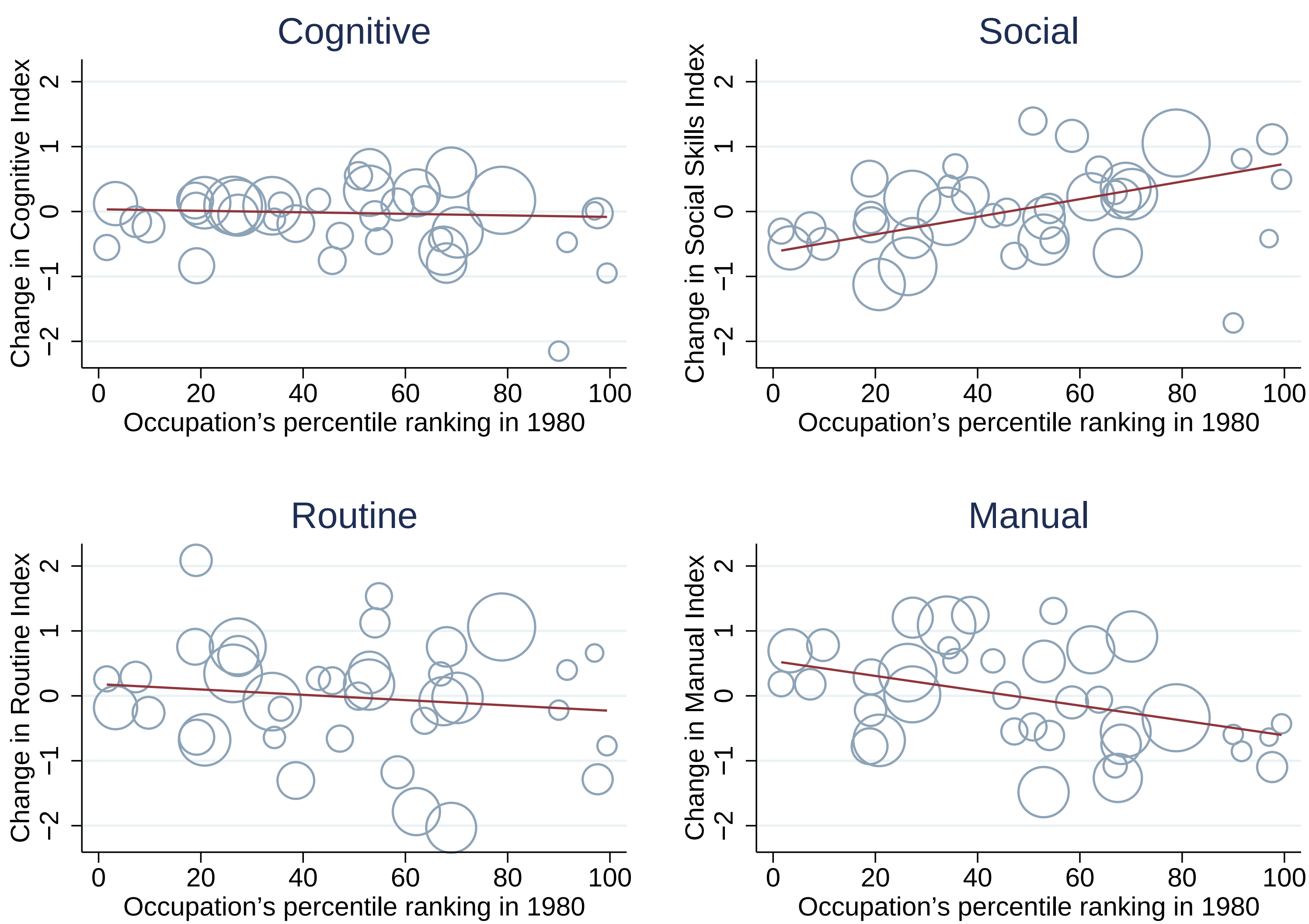
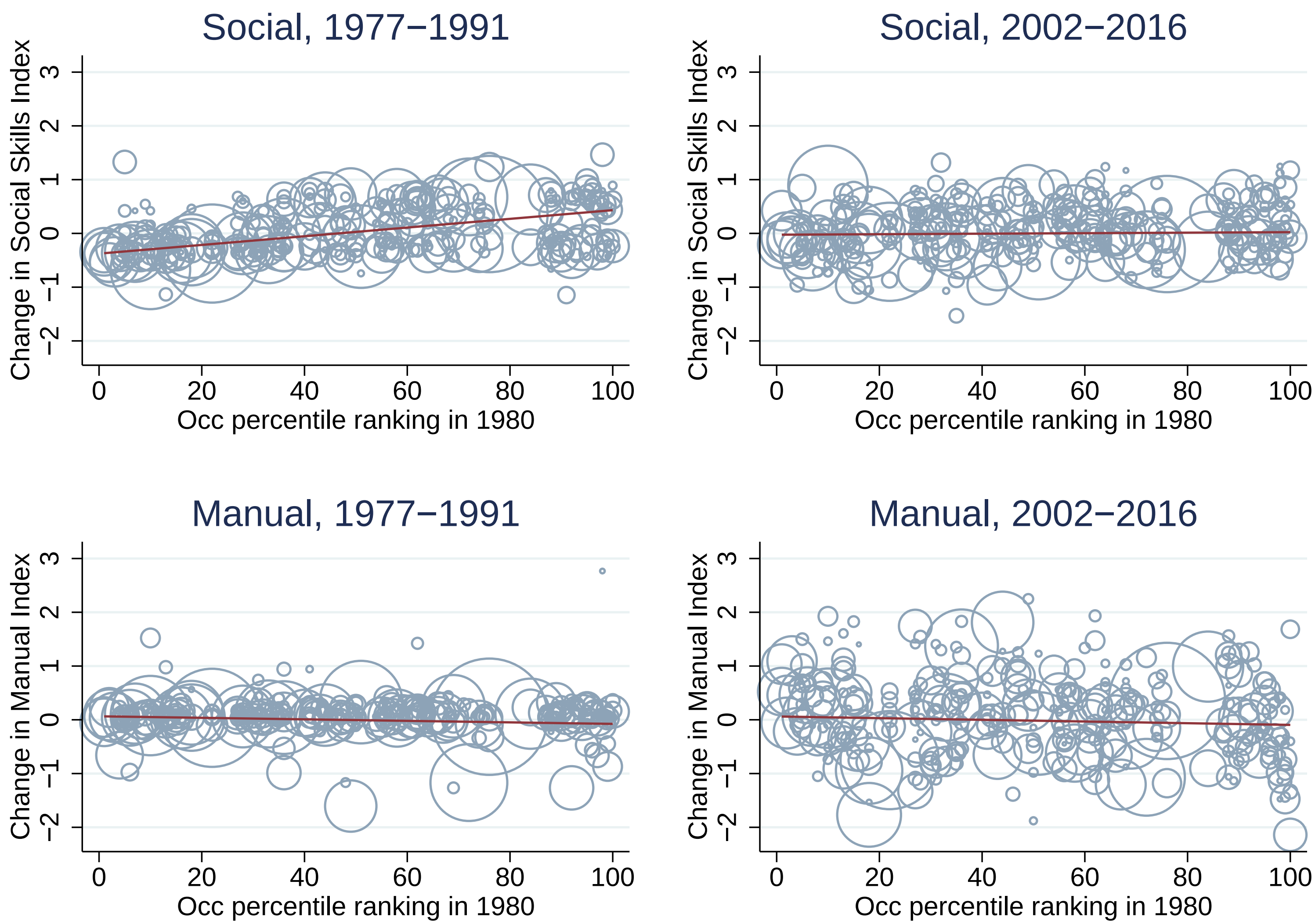
1 Appendix Tables and Figures

Figure A.1: Occupational Changes in Relative Task Importance (1977-2016) along the Occupational Wage Distribution (1980), Aggregated to the 2-Digit Level



Notes: Each circle represents a 2-digit occupation (size indicating its share of aggregate employment in 1980). Occupations are ranked using employment and wage data from the 1980 Census. Data on occupational task characteristics from the 1977 DOT and the 2016 O*NET. See text for details.

Figure A.2: Changes in Relative Task Importance within Sub-Periods



Notes: Each circle represents a 3-digit occupation (size indicating its share of aggregate employment in 1980). Occupations are ranked using employment and wage data from the 1980 Census. Data on occupational task characteristics from the 1977 and 1991 DOT and from the 2002 and 2016 O*NET.

Table A.1: Occupations with Largest Increases and Decreases in Task Indices, 1977–2016

Largest Increases				**Largest Decreases**			
occ1990dd Code	Occupation Name	Δ Task Index	1980 Percentile	occ1990dd Code	Occupation Name	Δ Task Index	1980 Percentile
Social							
53	Civil engineers	2.181	98	457	Barbers	-2.175	14
96	Pharmacists	1.895	92	808	Bus drivers	-1.780	31
448	Superv of cleaning & building service	1.767	36	154	Subject instructors, college	-1.716	90
8	HR managers	1.567	88	458	Hairdressers and cosmetologists	-1.650	8
503	Superv of mechanics and repairers	1.439	90	809	Taxi cab drivers and chauffeurs	-1.564	16
Cognitive							
503	Superv of mechanics & repairers	2.551	90	154	Subject instructors, college	-2.151	90
448	Superv of cleaning & building service	1.722	36	174	Social workers	-2.039	47
433	Superv of food prep & service	1.513	13	157	Secondary school teachers	-1.548	74
558	Superv of construction work	1.384	92	27	HR specialists	-1.536	66
386	Statistical clerks	1.266	32	26	Management analysts	-1.490	96
Routine							
318	Transp ticket & reservation agents	3.526	74	507	Bus, truck & engine mechanics	-3.099	62
375	Insurance adjusters & investigators	3.278	41	457	Barbers	-3.030	14
319	Receptionists & info clerks	2.790	10	514	Auto body repairers	-2.923	44
15	Medicine & health occ managers	2.734	75	563	Masons, tilers, and carpet installers	-2.536	62
355	Mail carriers for postal service	2.407	88	599	Misc. construction & related occ	-2.510	47
Manual							
707	Rollers & finishers of metal	2.133	57	277	Door-to-door sales & news vendors	-2.751	13
719	Molders & casting machine operators	1.756	42	417	Fire fighting & fire inspection occs	-2.603	56
885	Garage & service station related occs	1.685	7	808	Bus drivers	-2.493	31
434	Bartenders	1.679	5	55	Electrical engineers	-2.486	99
637	Machinists	1.669	66	218	Surveyors, cartographers, mapping scientists/techs	-2.171	56

Notes: Data on occupational task characteristics from the 1977 Dictionary of Occupational Titles and from the 2016 O*NET. Data on occupational wage rankings from the 1980 decennial census. The table excludes occupations that account for less than 0.1% of aggregate employment in 1980.

Table A.2: Probability of Working in Top Decile Occupations: Oaxaca-Blinder Decomposition

	Prob Top Decile		Percentage Point Difference		
	1980	2016	Total	Explained	Unexplained
Males	11.8	11.0	−0.7	−0.5	−0.2
Females	2.0	5.5	+3.5	−0.3	+3.8
College Males	29.6	24.4	−5.2	+0.1	−5.4
College Females	7.5	12.7	+5.2	−0.1	+5.3
Non-College Males	7.2	5.5	−1.7	−0.5	−1.2
Non-College Females	1.1	2.0	+0.9	−0.2	+1.0

Notes: Labor Force statistics, 20-64 year old, civilian, non-institutionalized population, excluding individuals employed in farming, forestry or fishing occupations. Data from 1980 Census and 2016 ACS. Employment categorized by ranking in occupational wage distribution of 1980. The explanatory variables for the Oaxaca-Blinder decomposition are age (nine 5-year bins), race (dummies for black, Hispanic, and other non-white) and nativity (dummy for whether native-born). See text for details.

Table A.3: Correlation Between Female-vs-Male Employment Probability Changes by Occupation (1980-2016) and Occupational Wage Ranking (1980), Aggregated to the 2-Digit Level

	Propensities			*Cond on Working*		
	(1)	(2)	(3)	(4)	(5)	(6)
Occup Rank	0.037***	0.030*	0.024**	0.059***	0.025	0.042***
	(0.008)	(0.017)	(0.009)	(0.012)	(0.023)	(0.013)
Observations	37	37	37	37	37	37
R^2	0.377	0.084	0.174	0.414	0.032	0.222

Notes: Observations are at the 2-digit occupation level, weighted by their aggregate employment share in 1980. The dependent variable is the differential change in the probability of working in a particular occupation for women relative to men between 1980 and 2016. Occupations are ranked by their median wage in 1980 and assigned to percentiles according to their position in the hours-weighted distribution of employment in that year. Statistical significance at $^{*}=10\%$, $^{**}=5\%$, $^{***}=1\%$ levels.

2 Construction of Task Measures

Following Autor, Levy, and Murnane (2003), we measure cognitive tasks in the DOT as the average of "adaptability to accepting responsibility for the direction, control or planning of an activity" and "GED-mathematical development." Routine tasks are measured as the average of "adaptability to situations requiring the precise attainment of set limits, tolerances or standards" and "finger dexterity," and manual task intensity is based on the importance of "eye-hand-foot coordination." In the O*NET, Deming (2017) defines analytical task intensity as the average of: (i) the extent to which an occupation requires mathematical reasoning (question 12 in the Abilities questionnaire; item 1.A.1.c.1), (ii) whether the occupation requires using mathematics to solve problems (question 5 in the Skills questionnaire; item 2.A.1.e), and (iii) whether the occupation requires knowledge of mathematics (question 14 in the Knowledge questionnaire; item 2.C.4.a). In keeping with the definition of cognitive tasks from ALM, our measure of O*NET cognitive tasks averages the three mathematical measures of Deming (2017) with three measures that capture direction, control and planning responsibilities, namely the "level" ratings for three measures from the Skills questionnaire: (i) "Management of Financial Resources" (question 33; item 2.B.5.b), (ii) "Management of Material Resources" (question 34; item 2.B.5.c), and (iii) "Management of Personnel Resources" (question 35; item 2.B.5.d).

O*NET Routine tasks, as in Deming (2017), are measured as the average of two measures from the Work Context questionnaire: (i) "how automated is the job?" (question 49; item 4.C.3.b.2) and (ii) "how important is repeating the same physical activities (e.g. key entry) or mental activities (e.g. checking entries in a ledger) over and over, without stopping, to performing this job?" (question 51; item 4.C.3.b.7). Finally, we develop a measure of manual task intensity in O*NET based on the average of the "level" ratings for two measures from the Abilities questionnaire (i) "Multilimb Coordination" (question 26; item 1.A.2.b.2), and (ii) "Gross Body Coordination" (question 39; item 1.A.3.c.3).

To construct a measure of the importance of social tasks from the DOT, we focus on the data regarding occupational "temperaments," defined as "adaptability requirements made on the worker by specific types of job-worker situations" (see ICPSR 1981). These are assessed by analysts from the US Department of Labor based on their importance with respect to successful job performance (see, for example, U.S. Department of Labor (1991)). The DOT indicates the presence or absence of a given temperament (rather than the level or degree required) for a large set of detailed occupation codes. Out of a total of ten temperaments, we identify four as relating to the importance of social tasks:

1. Adaptability to situations involving the interpretation of feelings, ideas or facts in terms of personal viewpoint;
2. Adaptability to influencing people in their opinions, attitudes, or judgments about ideas or things;
3. Adaptability to making generalizations, evaluations, or decisions based on sensory or judgmental criteria;
4. Adaptability to dealing with people beyond giving and receiving instructions.

These are motivated by and, hence, very similar to the measures used by Borghans, Ter Weel, and Weinberg (2014) and Deming (2017) in the DOT and O*NET, respectively, to identify social skill intensity.[1]

In the O*NET dataset, we use the same four measures used by Deming (2017), namely the "level" measures for the following four items from the Skills questionnaire:

A. Social Perceptiveness: being aware of others' reactions and understanding why they react as they do (Question 11; item 2.B.1.a);

B. Coordination: adjusting actions in relation to others' actions (Question 12; item 2.B.1.b);

[1]In particular, Borghans, Ter Weel, and Weinberg (2014) use items 1, 2 and 4, plus two measures from the "interests" module of the DOT: preference for activities involving business contact with people, and preference for working for the presumed good of people. Our choice differs because the latter two questions better measure worker aspirations of occupational outcomes, as compared to skills required to perform in a job. In addition, our choice allows for greater consistency with the O*NET measures used by Deming (2017).

C. Persuasion: persuading others to change their minds or behavior (Question 13; item 2.B.1.c);

D. Negotiation: bringing others together and trying to reconcile differences (Question 14; item 2.B.1.d).

We create a single *social tasks index* for each occupation at a point in time by combining the occupation's scores for the four items: 1–4 in the DOT, and A-D in the O*NET.

We use information from the 4th Edition of the DOT, published in 1977, and made available through the Interuniversity Consortium for Political and Social Research (ICPSR 1981; ICPSR 1991). Regarding O*NET, we rely on information from the August 2016 release (O*NET version 21.0), which is available at `https://www.onetcenter.org/db_releases.html`.

DOT-77 has its own occupational coding scheme, which is much more disaggregated than the Census Occupation Code (COC) classification. In order to aggregate the information to the COC level, we follow an approach similar to Autor, Levy, and Murnane (2003). Specifically, we use the April 1971 CPS Monthly File, in which experts assigned both 1970-COC and DOT-77 codes to respondents. We augment the dataset by attaching the harmonized codes from Autor and Dorn (2013) (hereafter "Dorn codes") corresponding to each 1970 COC. We use the sampling weights from the augmented April 1971 CPS Monthly File to calculate means of each DOT temperament in 1977 at the Dorn code level.[2]

There are some Dorn codes that do not have a corresponding 1970-COC code. For these occupations, we have employment and earnings information from the Census and ACS, but no direct measures of tasks from DOT, so we impute the task information using a closely related occupation for which we do have task data. The details are in Table B.1.

Following Deming (2017), we rescale all of the task variables from DOT so that they

[2]Measures from the 1991 DOT, which are used in Appendix Figure 1, are computed in a similar manner, by first using DOT crosswalks (ICPSR 1991) in order to attach the corresponding 1991 DOT code to each 1977 DOT code in the April 1971 CPS file, and then calculating means of each relevant DOT 1991 measure at the Dorn code level.

range from 0 to 10. We then construct our composite task measures. The social task measure is generated by adding the (rescaled) scores for the four temperaments listed above. Other task measures are generated as in ALM. These composite measures are then rescaled to range from 0 to 10, and then normalized to have mean zero and standard deviation one across the employment-weighted occupational distribution in the 1980 Census.

O*NET data is available at the O*NET-SOC Code level, a more disaggregated version of the Standard Occupational Classification (SOC) coding system. We also need to aggregate these measures to the Dorn code level. To do so, we proceed as follows:

1. We generate task measures at the SOC code level by computing simple averages across all of the O*NET-SOC occupations that fall within the same SOC code.
2. We merge in information from the Bureau of Labor Statistics' Occupational Employment Statistics (OES) dataset, which provides data on employment by occupation at the SOC code level.[3]
3. We use crosswalks from the Census Bureau and from O*NET to map SOC-2010 codes to 2010 Census Occupation Codes.
4. We compute weighted averages of all of the task measures at the corresponding Census Occupation Code level using OES employment levels by SOC code as weights.
5. We map the Census Occupation Codes to Dorn codes, and we compute weighted averages of the task measures at the Dorn Code level using employment levels by Census Occupation Code as weights.

We match our employment data from the Census and the ACS to the O*NET task data at the Dorn code level. There are a small number of Dorn codes for which the corresponding SOC codes do not appear in O*NET. As with the DOT data, we impute the task information for these occupations using a closely related occupation for which we do have O*NET data. The details are in Table B.2.

[3]We use national-level data from the 2016 OES. In some cases, SOC codes need to be slightly aggregated to the "broad" level (i.e. ignoring the last digit) in order to match to OES.

Finally, there are a few Dorn codes for which we do not have ACS data in 2016. The reason is that the occupation codes used by the ACS are a slightly aggregated version of the 2010 Census Occupation Codes. Certain 2010 Census Occupation Codes that would map to particular Dorn codes do not exist in the 2016 ACS Occupation Coding system. In order to work with a consistent set of occupation codes, we re-assign workers in the Dorn code categories that do not appear in the 2016 ACS. The details are in Table B.3. Workers who in 1980 would have been categorized into the Dorn codes in the left-hand column are re-assigned to the Dorn codes in the right-hand column instead. The Dorn code system has a total of 330 codes, of which 7 correspond to occupations in farming, which we exclude from our analysis. Given the reassignment of the 11 codes detailed in Table B.3, we end up with a consistent set of 312 codes for all of our analyses at the 3-digit Dorn code level.

As with the DOT, and following Deming (2017), we rescale all of the O*NET task variables so that they range from 0 to 10. We then construct our composite task measures, and rescale these to range from 0 to 10. Finally, we normalize the task indices to have mean zero and standard deviation one across the employment-weighted occupational distribution in the 1980 Census. Hence, a one unit increase in any of our normalized task measures for a given occupation can be interpreted as a one standard deviation increase in the *relative* position of that occupation within the employment-weighted distribution of that task.

Table B.1: Imputation of DOT task data for occ1990dd codes without a corresponding 1970 Census code

occ1990dd codes with no 1970 code	occ1990dd codes used for imputation	occ1990dd codes with no 1970 code	occ1990dd codes used for imputation
4, 8, 37	22	461	462
24, 25, 26	23	470	469
27	13	503, 507, 509	505
34	256	518	516
83	78	536	535
98, 99, 103, 104	105	539, 543	549
106	84	558	35
158	156	614	598
184	183	617	616
234	313	684	637
243	258	688	687
317, 326, 379	319	694	695
336, 356	335	699	696
377	375	729, 733	727
415	423	743, 747	749
427	426	753, 755, 757, 763, 765	779
433	436	803, 834	804
439	444	853	594
448	453	865	869
450, 455	451	873, 878	889

Table B.2: Imputation of O*NET task data for occ1990dd codes without a corresponding SOC code that appears in O*NET

occ1990dd codes with no SOC code in O*NET	occ1990dd codes used for imputation
349	348
415	423

Table B.3: Dorn code reassignment

original occ1990dd code	re-assigned occ1990dd code
583	579
644, 645	634
703, 708, 709	707
723, 724	719
745	744
764	763
825	824

3 Investigating the Role of New Occupations

In this section we investigate the role of the introduction of new detailed occupational categories in driving the changes in task content that we document at the 3-digit occupational level, relative to changes in task content within detailed job categories.

To do so, we explore changes between the 1977 and the 1991 waves of the DOT. Information in the DOT is available for very detailed job categories, and the 1991 DOT introduced a number of new occupations: roughly 5% of detailed 1991 DOT codes did not exist in the 1977 DOT. We can therefore analyze the extent to which we observe changes in task content within 3-digit occupations, either including or excluding the new occupations that appear in the 1991 DOT and do not have a counterpart in the 1977 DOT.

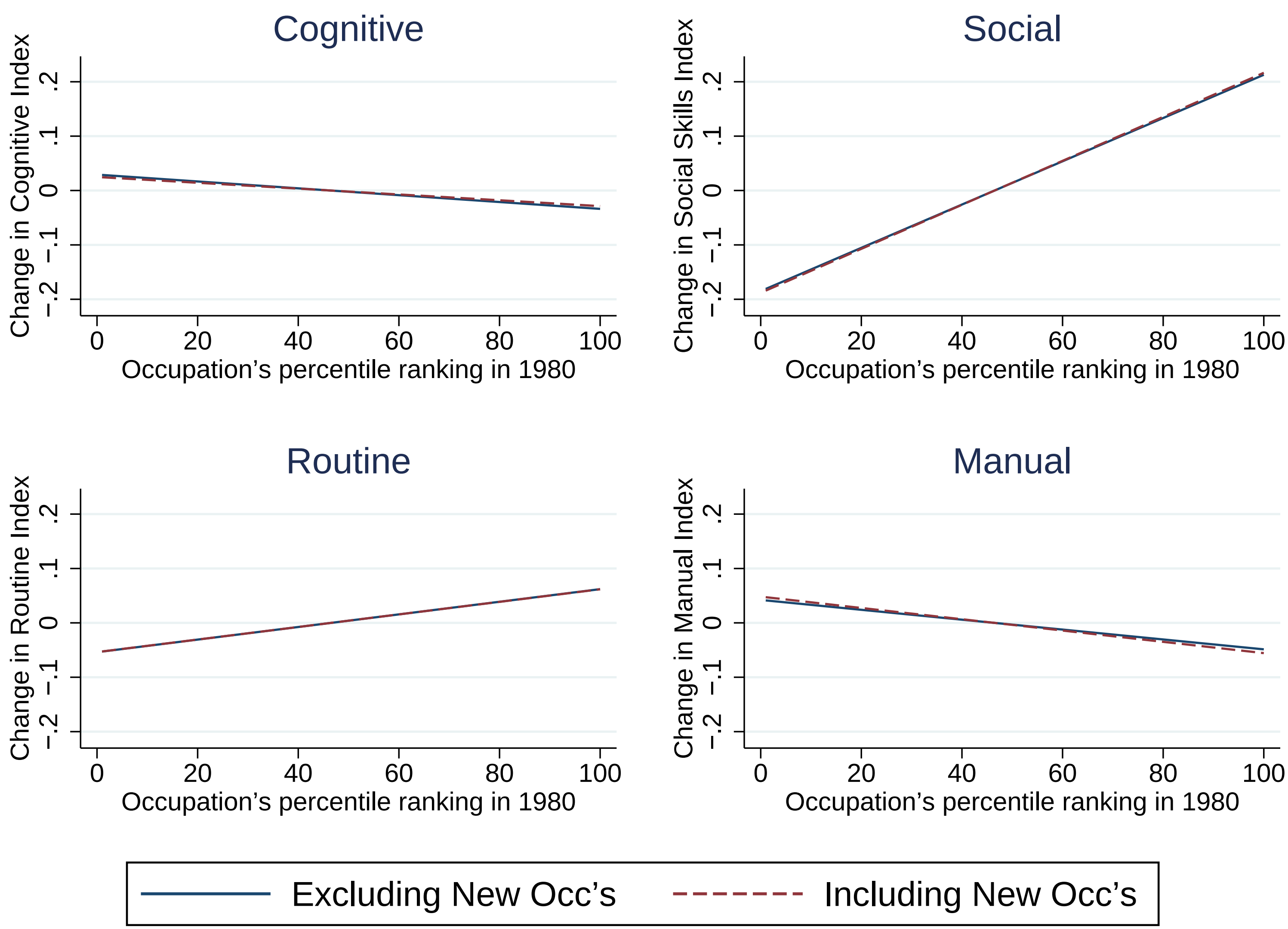
As explained above, to aggregate DOT task data to 3-digit occupation codes, we use the April 1971 CPS Monthly File, in which experts assigned both 1970 Census Codes and 1977 DOT codes to respondents.

In order to consider the importance of new occupations that first appear in the 1991 DOT, we consider two approaches for computing task measures from the 1991 DOT. Specifically, we focus on the first 3 digits of the detailed DOT codes, which correspond to "occupation group" categorizations, and compute an unweighted average of the relevant task measures in the 1991 DOT for each of these "occupation group" categories, either including or excluding the detailed 1991 DOT occupations that did not exist in the 1977 DOT. We then match these two measures of DOT 1991 tasks to the April 1971 CPS Monthly File based on the first 3 digits of the DOT 1977 codes that appear in that file. Finally, we compute 1977 task scores for each Dorn occupation code, and the corresponding 1991 task scores based on the two approaches (either including or excluding new occupations).

The solid and the dashed line in Figure C.1 represent the lines of best fit for the 1977-1991 changes in the relative importance of each of the four task dimensions that we consider in the paper, either including or excluding the new occupations. The results show that including or excluding the new 1991 occupations has no noticeable impact: the lines of best fit for these two approaches are nearly exactly on top of each other for all four task dimensions.

These results suggest that the emergence of new occupations is unlikely to be the primary driver of the results that we have identified; changes occurred almost entirely within detailed job categories, at least during this early period.

Figure C.1: Occupational Changes in Relative Task Importance (1977-1991) along the Occupational Wage Distribution (1980) using Different Matching Procedures



Notes: Occupations are ranked using employment and wage data from the 1980 Census. Data on occupational task characteristics from the 1977 and 1991 DOT. The figure plots the line of best fit for the relative change in task importance, using different matching procedures that either include or exclude detailed occupational codes that first appear in the 1991 DOT. See text for details.

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