Online Appendix B

Creating Task Measures

Task measures are constructed from the raw data in the ONET 4.0. We first standardize the raw level variables to be mean zero and standard deviation one across the 900 ONET-SOC occupation codes. We then collapse to 677 soc2000 codes by taking the simple average across ONET-SOC codes associated with a single soc2000 code.[1] The composites are created as the average of the included variables (see details below) and are standardized.

For analysis that uses data from 1980, 1990, 2000 and 2016 we merge on task data using David Dorn's *occ1990dd* classification system. The *occ1990dd* system consists of 330 codes that provide a balanced panel of occupations covering the 1980, 1990 and 2000 Censuses and the 2005 ACS. For the purpose of our analysis, we extend the coverage to the 2016 ACS by creating a crosswalk from the codes used in the 2016 ACS to the occ1990dd system. We start with the composite task measures at the soc2000 level and merge on soc2000 weights. We create soc2000 weights by pooling data from the 2005, 2006 and 2007 Occupational Employment Statistics (OES) survey.[2] We then collapse task measures to the occ2000 and standardize, yielding composite task measures for 445 occ2000 codes. Lastly, we use the occ2000 to occ1990dd from Dorn (2009) and the sum of soc2000 weights for each occ2000 code to collapse task measures to the occ1990dd level. The final dataset merged onto data for 1980, 1990, 2000 and 2016 consist of task data for 325 occupations standardized to be mean zero and standard deviation one. Thus, there are five

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[1] For example, onetsoccode 11-1011.01 and 11-1011.02 are collapsed into soc2000 code 11-1011.
[2] Specifically, we follow the procedure used by Autor & Acemoglu (2011) to create soc2000 weights from the 2005, 2006 and 2007. Weights are calculated as the mean of employment across the three survey waves for each soc code.

occ1990dd occupations for which we are unable to obtain task data; these map into seven occupations in the 2016 ACS coding system.[3]

We use four composite task measures in our analysis taken previously from the literature. Each measure is constructed as the average of the included variables. For each composite the variable names are given in italics, the variable type in parenthesis and the variable question text in quotations.

1. Social Skills (Deming 2017):
   - *Coordination*: (skill) "Adjusting actions in relation to others' actions."
   - *Negotiation:* (skill) "Bringing others together and trying to reconcile differences."
   - *Persuasion*: (skill) "Persuading others to change their minds or behavior."
   - *Social Perceptiveness*: (skill) "Being aware of others' reactions and understanding why they react as they do."

2. Abstract Analytical (Acemoglu & Autor 2011):
   - *Interpreting the Meaning of Information for Others*: (work activity) "Translating or explaining what information means and how it can be used."
   - *Thinking Creatively*: (work activity) "Developing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions."

[3] The occ1990dd occupations for which we cannot construct task data are occupations 76, 346, 37, 349 and 415.

- *Analyzing Data or Information*: (work activity) "Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts."

3. Manual (Acemoglu & Autor 2011):
   - *Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls*: (context) "How much does this job require using your hands to handle, control, or feel objects, tools or controls?"
   - *Manual Dexterity:* (ability) "The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects."
   - *Operating Vehicles, Mechanized Devices, or Equipment*: (work activity) "Running, maneuvering, navigating, or driving vehicles or mechanized equipment, such as forklifts, passenger vehicles, aircraft, or water craft."
   - *Spatial Orientation*: (ability) "The ability to know your location in relation to the environment or to know where other objects are in relation to you."
4. Routine (Acemoglu & Autor 2011)[4]:
   - *Controlling Machines and Processes*: (work activity) "Using either control mechanisms or direct physical activity to operate machines or processes (not including computers or vehicles)."
   - *Spend Time Making Repetitive Motions*: (context) "How much does this job require making repetitive motions?"

[4] The measure of routine used in Acemoglu & Autor 2011 also included the variable *Structured versus Unstructured Work* ("To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals?") but the variable is unavailable in the ONET 4.0 and responses were not gathered until subsequent installations of the ONET.

- *Pace Determined by Speed of Equipment*: (context) "How important is it to this job that the pace is determined by the speed of equipment or machinery? (This does not refer to keeping busy at all times on this job.)"
- *Importance of Being Exact or Accurate*: (context) "How important is being very exact or highly accurate in performing this job?"
- *Importance of Repeating Same Tasks*: (context) "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?"

5. Competitiveness (Cortes and Pan 2018)[5]:
   - *Competitiveness*: (context) "To what extent does this job require the worker to compete or to be aware of competitive pressures?"

[5] This measure is unavailable in the ONET 4.0 and is instead constructed using data from the ONET 14.0.

Online Appendix C

Counterfactual Evolution of the Gender Wage Gap

To construct counterfactual measures of the gender wage gap where the returns to hours did not rise over time, we start by estimating individual level wage regressions separately by year for 1980, 1990, 2000 and 2016. We do so both estimating the relation between wages and hours worked via OLS and also via IV in which we instrument individual hours with occupational average hours. This allows us to consider how the counterfactual wage gap would have evolved had the return to hours not increased. Our primary empirical specification is given by:

$$ln\, w_{it} = \pi^t + \alpha^t female_i + \beta_1^t\, ln\, h_{it} + \gamma^{\mathrm{t}} demos_{it} + \varepsilon_{it}$$

Because changing demographics and the coefficients on those demographics are not the focus of the analysis, while we control for them in our analysis, we ignore them for the purposes of presentation. Taking means of both sides separately for men and women, we can write the gender wage gap (conditional upon demographic covariates) as

$$gap_w^t = \alpha^t + \beta_1^t gap_h^t$$

This expression allows us to consider how the gender wage gap would have increased if the residual wage gap evolved according to the observed time series but the prices on hours remained constant at 1980 levels. To consider how the gender wage gap would have increased if the residual wage gap evolved according to the observed time series but the prices on hours remained constant at 1980 levels, we allow α to vary by period t ($\alpha = \alpha^t$), but fix β_1^t at the 1980 level ($\beta_1 = \beta_1^{1980}$). Put another way, we allow the unexplained part of the gender wage gap to change period by period but fix the returns to hours worked at 1980 levels.

Online Appendix D: Additional Results

Here we present additional results regarding the relationship between hours and wages, both at the individual level and at the occupational level.

Table D.1 presents extensions of the core results presented in Table 1, focusing on individual level regressions of wages on hours. The extensions in Table D.1 are to: estimate this relationship for college educated and non-college educated workers separately, estimate this relationship for full-time workers only (full-time defined as working 35 or more hours a wekk) and to estimate this relationship when controlling for 16 major industry groups (as defined by the 2012 Census Industrial Classification system). In each case, we see that our findings are consistent with those in Table 1 – at the individual level, the relationship between wages and hours worked is weak, and significantly negative when occupational fixed effects are included.

Table D.2 presents extensions of the core results presented in Table 4, focusing on the relationship between average wages and average hours worked at the occupational level. In Table D.2 we present these extensions without controlling for occupational tasks; in Table D.3 we present each of these extensions controlling for occupational tasks. The extensions are to estimate the relationship between occupational hours and wages: for occupations below and above the median occupation's fraction of college-educated workers, for occupations below and above the median occupation's fraction of female workers, for men and women only, for full-time workers only, where we additionally residualize on fixed effects for major industry group, where we include controls for 1 or 2 digit occupation fixed effects, where we control for the fraction of workers who are female in each occupation, and where we omit the largest 5% of occupations.

We see that, in Tables D.2 and D.3, our results in these extensions are generally very similar to our baseline findings in Table 4. A few specific estimated coefficients merit comment.

- When limiting the sample to full-time workers only, without task controls, the coefficient on hours worked is substantially larger than our baseline, but with task controls, substantially smaller than our baseline (with tasks). However, both of these coefficients have large standard errors. This reflects the fact that once part-time workers are removed from the sample, variation in average hours worked across occupations shrinks substantially.[6] As a result, we cannot reject that these point estimates are different from our baseline estimates.
- Absent task controls, inclusion of 1 digit and 2 digit occupation fixed effects do reduce the estimated relationship between occupational hours and wages when, though the coefficient magnitudes remain sizable. However, when task controls are added, the magnitudes of these coefficients are not unusually different from other estimates. This simply reflects the fact that these fixed effects are (unsurprisingly) highly correlated with task variation across occupations.
- We note that when we residualize hours and wages across industries, we do observe somewhat smaller coefficient magnitudes, particularly when controlling for occupational tasks. This suggests that some of the relationship between hours and wages at the occupational level can be explained by industry features, such as productivity, production technologies or social norms. Whether or not this estimate of the hours-wage relationship is appropriate for assessing the return to

[6] The fraction of workers working full-time in an occupation can explain 80% of the variation in hours worked across occupations.

expected hours depends on how a worker views industry in their job choice. If conditional on occupation and hours worked, industry is irrelevant to the worker, then controlling for industry will understate the return to hours. However, if a worker's willingness to work longer hours depends on the products produced by the firm she works in, as measured by industry, then this coefficient may be more suitable.

- Although the relationship between hours and wages does not vary much when considering men and women separately, or when controlling for the fraction of workers in each occupation who are female, these specifications may be difficult to interpret if the aim is to estimate the expected returns to hours. The challenge with is that these specifications implicitly control for selection of workers into occupations. For example, if men and women sort into occupations differentially on the basis of hours worked, then we would expect the fraction of workers who are female to be correlated with hours worked. In this case, including this control, though it does not affect our results, would partially control for an outcome of a worker's job choice, which could inaccurately represent the returns to hours when making job decisions. However, a key input to job choices may be the likelihood of working with certain types of colleagues, in which case controlling for fraction female in an occupation could be important for estimating the returns to expected hours. As a result, such specifications may be difficult to interpret.

Table D.1 - Regressions of Log(Wage) on Log(hours), ACS Individual-Level Data, Additional Specifications

	(1) Baseline	(2) College Educated	(3) Less than College	(4) FT Only	(5) Ind Controls	(6) Ind Controls
Log Hours	-0.117***	-0.086***	-0.146***	-0.215***	-0.011	-0.131***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.022)	(0.040)
Demo. Controls	Yes	Yes	Yes	Yes	Yes	No
Occ FE	Yes	Yes	Yes	Yes	No	Yes
Ind FE	No	No	No	No	Yes	Yes
N	633,927	279,330	354,597	554,917	633,927	633,927

All columns use standard errors clustered at the occupation level. Columns (1)-(4) and (6) include occupation fixed effects. Column (2) is for a sample of workers who have at least a college degree; Column (3) is for a sample of workers with less than a college degree. Column (4) is for a sample of workers who report working full-time, defined as at least 35 hours a week. Columns (5) and (6) include fixed effects for 16 major industry groups, as defined by the 2012 Census Industrial Classification System. Observations are weighted using perwt. Sample includes prime-age workers aged 25-55. Demographic controls include a quartic in age, indicators for race/ethnicity (black, Hispanic, Asian, other), sex, and indicators for educational attainment (HS degree, some college, college degree or more). Hours are derived from usual hours worked per week. Hourly wage is calculated as total reported wage and salary income for the prior year divided by the product of usual hours worked and weeks worked in the previous year. We trim wages that are below half of the federal minimum wage and inflate wages to 2012 dollars using the Bureau of Economic Analysis (BEA) National Income and Product Accounts Personal Consumption Expenditures.

Table D.2 - OLS Regressions of Ln(Wage) on Ln(Hours), 2016 ACS at the Occupational Level, Additional Specifications

	(1) Baseline	(2) High Skill Occ	(3) Low Skill Occ	(4) Male Dom. Occ	(5) Female Dom. Occ	(6) Male Only	(7) Female Only	(8) FT Only	(9) Indus. Resid.	(10) 1 Dig. Occ FE	(11) 2 Dig. Occ FE	(12) Control Frac. Female	(13) No Largest Occs
Avg. Log Hours	1.952***	1.764***	1.380***	2.192***	1.921***	2.252***	1.628***	2.578***	1.795***	1.599***	1.349***	2.017***	1.862***
	(0.188)	(0.296)	(0.151)	(0.324)	(0.226)	(0.215)	(0.150)	(0.639)	(0.205)	(0.189)	(0.193)	(0.192)	(0.200)
Demo. Resid.	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Resid.	No	No	No	No	No	No	No	No	Yes	No	No	No	No
1 Digit Occ FE	No	No	No	No	No	No	No	No	No	Yes	No	No	No
2 Digit Occ FE	No	No	No	No	No	No	No	No	No	No	Yes	No	No
Frac. Female	No	No	No	No	No	No	No	No	No	No	No	Yes	No
Task Controls	No	No	No	No	No	No	No	No	No	No	No	No	No
N	474	237	237	237	237	474	471	474	474	474	474	474	450

All columns use robust standard errors. Regressions of occupation average of residualized log wage on occupation average of residualized log hours. Residuals are constructed by regressing log wage (hours) on demographic controls and a full set of occupation fixed effects. We use the coefficients on the occupation fixed effects as measures of average residualized log wage and log hours. Demographic controls used in the residualization include black, hispanic, asian, other race, hs only, some college, ba plus and a quartic in age. Person fixed effects are included using Outgoing Rotation Group samples from the CPS which include multiple observations per worker. Hours are usual hours worked per week. Hourly wage is calculated as total reported wage and salary income for the prior year divided by the product of usual hours worked and weeks worked in the previous year. We trim wages that are below half of the federal minimum wage and inflate wages to 2012 dollars using the Bureau of Economic Analysis (BEA) National Income and Product Accounts Personal Consumption Expenditures. Occupations are weighted by the occupation total of individual weights. Column (1): baseline (as in Table 4, column 2). Columns (2) and (3): only occupations above (2) or below (3) the median occupation's fraction of workers with a college degree. Columns (4) and (5): only occupations above (4) or below (5) the median occupation's fraction of workers who are male. Columns (6) and (7): construct residualized average hours and wages separately for men (6) or women (7). Column (8): construct residualized hours and wages only for full-time workers. Column (9): include 16 major industry groups (as defined by 2012 Census codes) in the residualization. Column (10) and (11): Include as controls fixed effects for either 7 major occupation groups (10), which we term "1 digit occupations," or 25 detailed occupation groups (11), which we term "2 digit occupations." Column (12): Include as a control the fraction of workers who are female in each occupation. Column (13): Drop occupations whose size is above the 95th percentile for all occupations.

Table D.3 - OLS Regressions of Ln(Wage) on Ln(Hours), 2016 ACS at the Occupational Level, Additional Specifications with Task Controls

	(1) Baseline	(2) High Skill Occ	(3) Low Skill Occ	(4) Male Dom. Occ	(5) Female Dom. Occ	(6) Male Only	(7) Female Only	(8) FT Only	(9) Ind. Resid.	(10) 1 Dig. Occ FE	(11) 2 Dig. Occ FE	(12) Control Frac. Female	(13) No Largest Occs
Avg. Log Hours	0.925***	1.011***	1.270***	0.887***	0.988***	1.123***	0.804***	0.530	0.602***	0.932***	0.828***	0.882***	0.999***
	(0.198)	(0.209)	(0.206)	(0.246)	(0.231)	(0.226)	(0.150)	(0.417)	(0.197)	(0.192)	(0.169)	(0.210)	(0.158)
Demo. Resid.	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Resid.	No	No	No	No	No	No	No	No	Yes	No	No	No	No
1 Digit Occ FE	No	No	No	No	No	No	No	No	No	Yes	No	No	No
2 Digit Occ FE	No	No	No	No	No	No	No	No	No	No	Yes	No	No
Frac. Female	No	No	No	No	No	No	No	No	No	No	No	Yes	No
Task Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	467	231	236	235	232	467	464	467	467	467	467	467	443

See notes to Table D.2. Task data is constructed from the ONET 4.0 aggregated to the occ1990dd level. There are five occ1990dd occupations missing task data in the ONET 4.0 which yield missing task data for seven occs. Task controls include social skills, as defined in Deming (2017), and abstract analytical, manual and routine, as in Acemoglu & Autor (2011), and competitiveness as in Cortes and Pan (2018). See appendix A for an explanation how of these composites were created. Task measures are standardized to be mean zero and standard deviation one across the occ1990dd distribution.