Routine-Biased Technical Change: Panel Evidence of Task Orientation and Wage Effects

Matthew B. Ross*
Ohio State University

August 5th, 2017

Keywords: Labor Dynamics, Occupations, Tasks, Technological Change, Wage Polarization

JEL: J23, J24, J31, J62, J63, J64, O31, O33

Abstract: This analysis explores changes in the premium for abstract relative to routine tasks both across and within occupations over time. Previous theoretical and empirical work has linked growth in the relative task premium to changes in production technology that complement abstract but substitute for routine tasks, i.e. the Routine-Biased Technical Change hypothesis. The supporting empirical literature has relied almost exclusively on repeated cross-sections of workers and single cross-sections of task content. Thus, these studies have been unable to examine the evolution of wages in response to changes in task content within occupations over time and unable to control for unobserved individual and occupational heterogeneity. In this paper, I construct a new panel of occupational task content using incumbent-updated survey data from archived releases of the *O*NET* database. Estimating wage effects in a model with individual and occupation fixed-effects, I find that an increase of ten percentiles in the routine task distribution corresponds with a wage penalty of -0.09 to -0.35 percent in 2004 and declining to between -0.42 and -2.43 percent by 2013. In contrast, an increase of ten percentiles in the abstract task distribution corresponds with a wage penalty of 0.42 to 2.27 percent in 2004 and declining to between 0.42 and 2.43 percent by 2013. In contrasting estimates with and without individual fixed-effects, I also find evidence patterns of self-selection over time that are also consistent with the Routine-Biased Technical Change hypothesis.

* Corresponding Author: M.B. Ross, Department of Economics; Ohio State University; 1945 North High Street; Columbus, OH 43210. Ross.1469@OSU.edu

1. Introduction

This analysis fills a significant gap in the empirical literature on Routine-Biased Technical Change (RBTC) by directly examining wage dynamics using a combined panel of occupational task content and individual workers. In examining wage and employment polarization, the existing literature on RBTC has relied exclusively on cross-sectional measures of occupational task content. In this paper, I exploit variation in task content within occupations over time and develop a natural extension to Autor and Handel (2013) using panel data. Panel data on occupational tasks allows for a more rigorous examination of changes to task premiums predicted by the RBTC hypothesis as well as the consequent sorting of workers based on comparative advantage. Panel data also allows me to fully control for time invariant unobserved heterogeneity by estimating models that include individual, occupation, and employer fixed-effects. Using this novel empirical framework and panel data on occupational tasks, I find new and compelling evidence in support of the RBTC hypothesis. Specifically, I find that the wage premium for routine tasks has declined from 2004 to 2013 while that for abstract tasks has increased markedly. Further, I find evidence suggesting that patterns of self-selection are consistent with prediction that technical change creates stronger selection into routine occupations and weaker selection into abstract occupations.

In describing why RBTC has resulted in some occupations becoming more automated than others, a recent paper by David Autor (2014) outlines a compelling mechanism for observed changes in the labor market. In this paper, Autor refers to tasks that follow explicit rules as routine and suggests that they are more easily codified by technology. Codification of these tasks allows for them to be more easily substituted for capital in the production process. In contrast, tasks that are rich in tacit knowledge are characterized as non-routine or abstract. Abstract tasks serve as complements to technology in production because they are less easily codified and require frequent cognitive judgments as well as high levels of social interaction.

Acemoglu and Autor (2011) provide a detailed theoretical exposition of RBTC that captures the interconnectedness of technology, tasks, skills, and wages. A key feature of their model is the distinction they make between employers' demand for tasks and workers' supply of skills. The model structures production as a function of routine and abstract task where occupations are distinct bundles of these labor inputs. Skills, on the other hand, are either innate or accumulated

through a workers attainment of human capital. The labor market is thus characterized by an imperfect matching of skills to tasks and the sorting of workers across occupations based on comparative advantage. The model uses a fully developed supply and demand framework to derive comparative statics related to task replacing technology, an important characteristic of the RBTC hypothesis. The model has been subsequently expanded to accommodate empirical applications in a stream of literature that has recently been characterized as taking a task-based approach.

This nuanced view of technical change suggests that the primary driving force behind observed changes in the labor market is the falling price of computing power coupled with the increased capability of technology to replicate human tasks. More specifically, these factors have displaced workers in occupations with a high degree of routine task content while simultaneously increasing the demand for workers engaged in abstract tasks. Empirical evidence of this predicted pattern of displacement and wage polarization has been documented by Katz and Murphy (1992); Autor, Katz, and Krueger (1998); Autor, Levy, and Murnane (2003); Autor, Katz, Kearney (2005); Acemoglu and Autor (2011).

More recently, Firpo, Fortin, and Lemieux (2013) develop a cross-sectional Roy model that they use to examine the distribution of wages within occupations. The application of a Roy model accommodates the task-based framework and allows for the cross-occupation transferability of skills described by Gathmann and Schönberg (2010). Autor and Handel (2013) apply a similar Roy model to a cross-sectional survey of self-reported task engagement within occupations. Combining occupation-level task content with self-reported levels of task engagement, the authors find evidence in favor of self-selection on comparative advantage in tasks. Altonji, Kahn, and Speer (2014) use a similar framework to investigate the forces behind changes in the wage distribution across college graduates from different fields of study. Each of these analyses document important aspects of wage and employment polarization using cross-sectional data on occupational task content.[1]

[1] Related work includes Blender (2007), Jensen and Kletzer (2010), and Yamaguchi (2011).

Cortes et al. (2014; 2016) links cross-sectional measures of task content to panel data on individual workers and examines both employment and wage dynamics of those initially employed in routine occupations. Cortes (2016) finds evidence that workers with high ability are more likely to switch into abstract occupations and that workers with low ability have a higher probability of switching to occupations dominated by abstract tasks. In examining task variation across occupations, Cortes et al. (2014) details empirical evidence that an increase in the transition rate from non-employment to employment coupled with a decrease in the transition from employment to non-employment has played a crucial role in the disappearance of routine jobs.

Similarly, Böhm (2015) documents evidence suggesting that the premium for routine tasks has declined through the 1990s and 2000s while that for abstract tasks has grown. Deriving a linear estimation equation from a Roy model of wages, Böhm finds that polarization increased most rapidly for young males from 1999 to 2007 as well as males of all ages. Comparing the estimated to the actual changes in the wage distribution over the last three decades, he finds strong evidence that changes to task premiums and minimum wage laws explain a large portion of the variation in wages. Relative to estimates using traditional measures of skill (i.e. education groups), Böhm concludes that tasks are critical for studying the evolution of the earnings distribution over time.

As detailed above, the existing empirical literature on RBTC has been limited by the use of cross-sectional data of occupational tasks. Autor and Handel (2013) use self-reported cross-section of task engagement to test an integral component of the RBTC hypothesis, specifically that comparative advantage drives self-selection across occupations. Thus, panel data on occupational task content allows for further testing of the model outlined by Autor and Handel as well as how wages change over time in response to changes in task content. Further, combining panel data on occupational tasks with a panel of workers allows for the estimation of wage effects related to RBTC and the ability to control for unobserved individual and occupation heterogeneity. In this analysis, I develop such a dataset and use these data to isolate the effect of changes to task content related to RBTC on the variation of wages over time.

There exist two notable exceptions to the use of cross-sectional data in the prior literature where authors use German panel data that includes reported levels of task engagement within occupations over time, Spitz-Oener (2006) and Gathmann and Schönberg (2010). Although distinct

in both purpose and scope from the focus of this paper, these analyses provide additional evidence in support of an empirical strategy that relies on within occupation variation in task content. In particular, Spitz-Oener (2006) examines changes in reported task engagement both within and across occupations over a twenty-year period and relates these changes to technology. The author finds evidence that the most significant changes in task content have occurred in occupations that have experienced a rapid adoption of computer technology since 1979. Using the same data, Gathmann and Schönberg (2010) explore the differences between task-specific (semi-portable) occupational skills and more general forms of human capital. The authors find evidence that individuals are more likely to transition to an occupation with similar task engagement to their source occupation and that patterns of wage growth persist through these transitions.

This analysis constructs a similar dataset as the previously mentioned German panel but focuses on U.S. and explicitly examines the RBTC hypothesis via a direct examination of wage and employment dynamics. Specifically, I use the combined panel to examine changes in the premium paid for abstract relative to routine task content as well as wage effects in response to changes in task content over time. Further, I explore how unobserved worker heterogeneity effects wage estimates and find evidence of the consequent sorting of workers in response to RBTC. Since identification comes from within occupation variation in task content over time, I am able to control for time invariant unobserved occupation and worker heterogeneity through fixed-effects estimation. My findings provide compelling new evidence supporting the RBTC hypothesis and the related mechanisms driving observed wage and employment polarization.

This paper proceeds as follows: The next section contains an extension of the existing theory underlying the RBTC hypothesis and derives several empirically testable implications. The third section details the construction of a synthetic panel of occupational task content and provides descriptive statistics from that data as well as the panel of individual workers. The fourth section provides an empirical analysis of changes to the relative task premium. The fifth section contains a robustness check using a two-step estimation procedure. The final section summarizes the findings and provides some concluding remarks.

2. Theory

To frame the empirical analysis, I follow the existing literature by detailing a task-based model of the labor market and derive important implications related to the effect of RBTC on wages.

2.A Theoretical Model: Production and Occupational Choice

I begin following Autor and Handel (2013), where workers are endowed with skills $\Phi_i = \{\phi_{i,a}, \phi_{i,r}\}$ measured in task efficiency units that are normalized to one unit of time. I assume that $\phi_{i,a}$ and $\phi_{i,r}$ have a strictly positive value and a continuous support. A worker spends $\ell_{t,i}$ units of time performing abstract tasks and $(1 - \ell_{t,i})$ performing routine tasks. A worker's total supply of abstract and routine tasks, is simply $a_{t,i} = (\ell_{t,i})^{\delta}\phi_{i,a}$ and $r_{t,i} = (1 - \ell_{t,i})^{\delta}\phi_{i,r}$. The parameter $\delta \in (0,1)$ captures decreasing returns from task engagement and prevents specialization.

As in Autor, Levy, and Murnane (2003), I model production as a function of abstract and routine task inputs as well as technological capital. Specifically, the output of worker *i* in occupation *j* at time *t* takes the form

$$y_{t,i} = a_{t,i}{}^{\rho_j}(k_t + r_{t,i})^{1-\rho_j} \tag{1}$$

where $\rho \in (0,1)$ captures the output elasticity of each task. The variable k_t represents capital which substitutes for routine tasks content supplied by the worker. Assuming a competitive labor market and perfect competition, workers receive log wages equal to their marginal product such that

$$w_{t,j,i} = \alpha_j + \lambda_{t,j,a}\left((\ell_{t,j,i})^{\delta}\phi_{i,a}\right) + \lambda_{t,j,r}\left((1 - \ell_{t,j,i})^{\delta}\phi_{i,r}\right) \tag{2}$$

where the relative task premium is just

$$\frac{\lambda_{t,j,a}}{\lambda_{t,j,r}} = \frac{\rho_j\left(k_t + r_{t,i}\right)}{\left(1-\rho_j\right)a_{t,i}} \tag{3}$$

The production structure for a single occupation can be summarized by $\Lambda_{t,j} = \left\{\alpha_j, \lambda_{t,j,a}, \lambda_{t,j,r}\right\}$. Taking the production structure across occupations as given, each period the worker selects into an occupation by solving the following maximization problem

$$w_{t,i} = \max_j \ \left\{\Lambda_{t,1}, \Lambda_{t,2}, \dots, \Lambda_{t,j}\right\} \tag{4}$$

Thus, the economy is characterized by self-selection based on comparative advantage.[3]
The intuition being that workers first consider the optimal allocation of their labor within each occupation before selecting into an occupation where they receive the highest market wage given that allocation and their skill.[4]

2.B Theoretical Model: Routine-Biased Technical Change

In the present model, technical change will be biased towards routine occupations and will have an impact on both wages and self-selection. For parsimony, I model technical change as an exogenous increase in the capital where $k_{t+1} > k_t$ rather than a reduction in requisite prices. Taking the partial derivative of (3) with respect to capital, it is clear that a technology shock increases the relative premium between abstract and routine tasks. As noted by Autor, Levy, and Murnane (2003), the factor productivity of routine tasks will have a differential impact depending the output elasticity of the occupation.

To see how a change in the relative task premium impacts self-selection, consider a similar to that outlined by Autor and Handel (2013) where there are only two occupations *j* and *k*. In this

[3] Assuming a continuum of occupations would imply that the marginal worker in occupation *j* in period *t* is indifferent to the next best alternative but there is no need for such a restrictive assumption.

[4] The optimal labor allocation $\ell^*_{t,j,i}$ in each occupation is the value that maximizes wages and solves the following equality $\ell_{t,j,i}/\left(1-\ell_{t,j,i}\right) = \left(\lambda_{t,j,a}\phi_{i,a}/\lambda_{t,j,r}\phi_{i,r}\right)^{1-\delta}$.

economy, we allow for full specialization where occupation *j* compensates only abstract tasks and occupation *k* only routine tasks implying that $\delta = 1$, $\lambda_{t,j,a}, \lambda_{t,k,r} > 0$, and $\lambda_{t,j,r} = \lambda_{t,k,a} = 0$. Further, assume that the population's endowment for abstract and routine skills takes a bivariate unit normal distribution where

$$\begin{bmatrix} \varepsilon_a \\ \varepsilon_r \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \sigma_{r,a} \\ \sigma_{a,r} & 1 \end{bmatrix} \right) \tag{5}$$

and where the difference in a worker's skill endowment is simply $v = (\varepsilon_a - \varepsilon_r)$.

The expected skill endowment of workers, again measured in task efficiency units, can be written as

$$\begin{aligned} E[\varepsilon_a | i = j] &= \frac{\lambda_{t,j,a}\lambda_{t,k,r}}{\sigma_v}\left(\frac{\lambda_{t,j,a}}{\lambda_{t,k,r}} - \rho\right)\left(\frac{\gamma(-z)}{\Gamma(z)}\right) \\ E[\varepsilon_r | i = k] &= \frac{\lambda_{t,j,a}\lambda_{t,k,r}}{\sigma_v}\left(\rho - \frac{\lambda_{t,k,r}}{\lambda_{t,j,a}}\right)\left(\frac{\gamma(-z)}{\Gamma(z)}\right) \end{aligned} \tag{6}$$

where $\sigma_v = (\alpha_k - \alpha_j)/\sigma_v$, $\rho = (\lambda_{t,j,a}\lambda_{t,k,,r}\sigma_{a,r})/(\lambda_{t,j,a}\lambda_{t,k,,r}\sigma_r\sigma_a)$, and $\gamma(z)/\Gamma(-z)$ is the inverse mills ratio. These two equations characterize the self selection in this simple two occupation economy. A necessary condition for positive self-selection is that $\rho < min(\lambda_{t,j,a}/\lambda_{t,k,,r}, \lambda_{t,k,,r}/\lambda_{t,j,a})$ and a sufficient condition is that $\rho \leq 0$, implying that the correlation between worker abilities is weakly negative. In their empirical analysis using a single cross-section of self-reported measures of task engagement, Autor and Handel (2013) find sufficiently strong evidence supporting this condition and suggesting that self-selection does in fact occur through comparative advantage.

Assuming for simplicity that technology simply increases the relative task premium between abstract and routine tasks. Since $\lambda_{t,j,r} = 0$, the relative premium grows only through a decrease in the price for routine tasks (i.e. $\partial\lambda_{t,k,r}/\partial k_t < 0$). Taking the partial derivative of the equations in (6) with respect to routine task productivity yields

$$\frac{\partial E[\varepsilon_a|i=j]}{\partial k_t} = -\frac{\partial \lambda_{t,j,r}}{\partial K_t}\frac{\lambda_{t,j,a}}{\sigma_v}\left(\frac{\gamma(-z)}{\Gamma(z)}\right)(\rho)$$

$$\frac{\partial E[\varepsilon_r|i=k]}{\partial k_t} = \frac{\partial \lambda_{t,j,r}}{\partial K_t}\frac{\lambda_{t,j,a}}{\sigma_v}\left(\frac{\gamma(-z)}{\Gamma(z)}\right)\left(\rho - 2\frac{\lambda_{t,k,r}}{\lambda_{t,j,a}}\right).$$

As seen above, an increase in the price routine task content causes the expected skill endowment for abstract tasks to decrease in occupation *j* while the routine skill endowment for occupation *k* increases. Thus, an increase in the relative task premium between abstract and routine tasks driven by technical change, will result in weaker self-selection into more abstract occupations and stronger self-selection into routine occupations. The intuition from this simple two occupation model carries over directly to the more general case of an economy with multiple occupations that utilize both abstract and routine tasks.[5]

2.C Theoretical Model: Empirical Implications

The model has several important implications related to RBTC and the wages of workers. In particular, theory suggests that the routine task premium should decrease across all occupations while the premium for abstract tasks should increase. Further, the model predicts that the relative task premium will change more in occupations with a higher output elasticity for routine tasks. The changes in task premiums will also create stronger self-selection into routine intensive occupations and weaker self-selection into abstract intensive occupations.

Assuming that technology is continuously increasing over time and compliments abstract tasks while substituting for routine tasks, I should expect to find empirical evidence that

1. the relative task premium between abstract and routine tasks is growing across all occupations over time,

[5] Note that in the more general setting, a change in routine task productivity will create stronger (weaker) self-selection in occupations with an initial higher share of routine (abstract) task content.

2. the growth in the relative task premium is larger in occupations that are initially more routine intensive,
3. and that there is stronger (weaker) self-selection into routine (abstract) intensive occupations.

The empirical analysis contained in Section 5 examines the first two predictions and controls for the third prediction, related to self-selection, by applying models with individual fixed-effects. In the analysis, I utilize a panel of occupational task content linked to panel data on workers and their employment arrangements. The advantage of this combined dataset is that I can exploit variation in task content across and, more importantly, within occupations over time. The within occupation variation in task content is particularly useful because it allows for identification from changes in task premiums while allowing me to control for self-selection and unobserved skill using individual fixed-effects.

3. Data

The data used in this analysis combines a panel of individuals and their work activities with a panel of occupational task content. The individual data comes from the 2004 and 2008 panels of the *Survey of Income Program Participation* (*SIPP*). The 2004 panel contains 12 waves of three months in length that stretch from October 2003 to December 2007 and the 2008 panel contains 16 waves that stretch from May 2008 to November 2013. A panel of occupational task content was constructed exclusively from the survey data contained in 14 archived versions of the Occupational Information Network (*O*NET*) production database (i.e. analyst-updated data was dropped) released between April 2003 (*O*NET* 5) and July 2014 (*O*NET* 19). The panel of *O*NET* task content was then linked to the *SIPP* panel by the occupation code of employed individuals.

The advantage of combining the *SIPP* with a synthetic panel of task content is that I can exploit variation in task content within occupations over time while also controlling for unobserved differences in individual productivity when assessing wage effects using the repeated measures on individuals. Specifically, this combined framework allows me to track how the distribution of wages between and within occupations responds to short-run changes in task content. Focusing on short-run changes in task content ensures that identification is abject of occupation-specific institutional changes like the decline of unionization. Relative to using repeated cross-sections of

the *Dictionary of Occupation Titles* (*DOT*), the *O*NET* panel developed here has the advantage of being constructed solely from incumbent survey data and is thus less subject to mismeasurement.

3.A Data Overview: Panel of Occupational Tasks

The *O*NET* database was constructed as a replacement for the *DOT* (NRC 2010). Unlike the analyst-updated *DOT*, the *O*NET* was created with the goal of populating the database with survey data collected from incumbent workers. The completed database was released in June 2002 (*O*NET* 4) with the initial measures having values that were only assigned by job analysts who referenced *DOT* releases from the 1980s. As a result, the initial release of the *O*NET* database was composed of an entirely new rating system but was populated with old analyst data using judgment-based methods.

Each year beginning in 2002, these initial analyst-updated fields were repopulated with data from surveys administered to random samples of workers within specific occupations. An average of 110 different target occupations have been revised in each of the 14 subsequent releases (*O*NET* 5 to 19) using newly collected incumbent survey data. For updated occupations, each of the data fields is replaced with the mean survey response from newly collected data. The determination to update an occupation is made by analysts based on relative employment size, labor demand, and changes in the nature of work.[6]

Although the *O*NET* is reported at a 7-digit SOC taxonomy, there are no other available data sources (including employment) that describe occupations at this level of granularity. Thus, I construct the panel by first combining incumbent-updated measures from the work context and activity sections of each *O*NET* release and aggregating the data to a 6-digt SOC taxonomy by simply taking the raw average of all nested 7-digit occupations. As of the *O*NET 19* (the latest release used to construct the panel), there have been 471 of 809 6-digit *SOC* occupations updated at least twice using surveys data. Of the reaming occupations 338 occupations there were 264 that had only received a single survey update, 14 that received no update, and 60 that were updated

[6] Analysis update occupations in *O*NET* by considering a number of important factors that include but are not limited to the occupation's last update and a Department of Labor classification of a "demand-phase" occupation as well as recent changes to the content of occupations (Tippins & Hilton 2010, p. 5).

with non-survey data. For those occupations that received more than two survey updates, the value of each occupational task measure was linearly trended between the earliest and latest incumbent update and extrapolated to the bounds of the panel. For those occupations with only a single observation, the data value was carried through the panel as a constant. To account for potential mismeasurement related to occupations with only a single update as well as those that received no update with survey data, I aggregate the data from a 6-digit to a 3-digit SOC level using a rolling 5-year national employment weight constructed using the Occupational Employment Statistics.

In the resulting panel, changes in task content is driven solely by survey responses from workers within each requisite occupation. These changes in task content within occupations over time are the primary source of variation that I exploit in the empirical analysis. Although the *O*NET* has cautioned about using their data for time series analysis, the main concern pertained to comingling analyst and survey-updated data. As detailed above, I am able to overcome this challenge by constructing the panel using trended survey updated data and aggregating to a 3-digit SOC taxonomy with employment weights.[7] Operating at the 3-digit *SOC* taxonomy also ensures a sufficiently large and robust occupational sample size in both the *O*NET* and *SIPP*. Figure A.3 of the Technical Appendix provides a histogram of the raw incumbent-updated sample sizes for all 7-Digit and 3-digit *SOC* occupations in *O*NET 19*. A histogram of the occupational sample size in the *SIPP* is also shown graphically in Figure A.4 of the Technical Appendix

The abstract and routine task index in time period *t* for each occupation *j* is constructed as a weighted sum of the underlying task measures such that

$$\bar{a}_{t,j} = \pi_t \left[\sum_{j \in J} W_j \sum_{k \in a} \left(LV_{t,j,k}{}^{\frac{1}{3}} IM_{t,j,k}{}^{\frac{2}{3}} + CX_{t,j,k} \right) \right] \tag{7}$$

[7] Our use of employment weights also addresses problems related to changes in the *SOC* taxonomy during the analysis period. Specifically, I accomplish this by matching occupation codes in the *SIPP* to those in the *O*NET* panel at the 5,3, and 2-digit level respectively. Changes in the *SOC* taxonomy occur most frequently at the 6-digit level and, as a result, matching on higher level task measures provides an accurate imputation.

and

$$\bar{r}_{t,j} = \pi_t \left[\sum_{j \in J} W_j \sum_{k \in r} \left(LV_{t,j,k}{}^{\frac{1}{3}} IM_{t,j,k}{}^{\frac{2}{3}} + CX_{t,j,k} \right) \right]$$

For each underlying task measure *k*, I utilize the level ($LV_{t,j,k}$) and importance ($IM_{t,j,k}$) scales if the measure is from the work activity category of the *O*NET* database but only the context ($CX_{t,j,k}$) scale when the measure is from the context category. Following Blinder (2007) and Firpo et al. (2013), I assign a Cobb-Douglas weight of one third to level and two thirds to importance. After summing across all task measures $k \in (\cdot)$, each index is weighted by W_j which is equal to employment in occupation $j \in J$ (i.e. 6-digit *SOC* employment) relative to overall employment in occupation category *J* (i.e. 3-digit *SOC* employment).[8] The function π_t maps the raw employment-weighted task index to a percentile rank in each period. Thus, the resulting index represent an occupation's engagement in abstract or routine task content relative to other occupations in period *t*. The underlying task variables within each of the requisite indices follow Autor and Handel (2013) and are detailed in Table 1. In relation to the theory, the distributions of the two task indices are assumed to be equivalent and suitable proxies for the true distribution of task content where $\bar{a}_{t,j} = \frac{\sum_{i \in j} a_{t,i}}{\sum_{i \in j} \ell^*_{t,j,i}}$ and $\bar{r}_{t,j} = \frac{\sum_{i \in j} r_{t,i}}{\sum_{i \in j} \ell^*_{t,j,i}}$. The indices should only be considered proxies for task content because the *O*NET* does not provide sufficient differentiation between the significance and time spent on tasks. Further, the data does not provide information that allows for scaling time usage across or within occupations.

[Insert Table 1]

[8] As noted, the task indices were constructed with variable employment weights aggregated to a 3-digit *SOC* taxonomy. However, the estimates in the empirical analysis are robust to constructing the task indices using constant employment weights or to aggregating to a 5 or 2-digit *SOC* taxonomy.

At a given point in time, each index represents the relative level of task content or, put differently, the occupational requirements necessary to produce a single unit of output. The advantage of using panel data on task content, as opposed to a single cross-section, is that the task indices vary both across occupations and within occupations over time. In examining the distribution across the panel (i.e. comparing the 6-digit distribution in 2004 with 2014), there is a pronounced rightward shift for both tasks that is statistically significant at the 98 percent level according to a Kolmogorov–Smirnov test. Asymptotic kernel density estimates of the 6-digit occupational distribution for the abstract and routine task index are contained in Figures A.1 and A.2 of the Technical Appendix.

As noted, the empirical analysis operates at the 3-digit level to control for potential measurement error in the survey data as well as potential bias created by movements of workers to similar occupations within the panel. The variation in task content by 3-digit occupation from 2004 to 2013, measured in terms of changes in percentile rank, are shown below in Figure 1. The mean within variation in routine task content was approximately equal to zero but the standard deviation was a sizeable movement of 19.80 percentiles. The mean within variation in abstract task content was also approximately equal to zero with a standard deviation of 22.62 percentiles.

[Insert Figure 1]

The highest growth in abstract tasks from 2004 to 2013 occurred within *Fire Fighting and Prevention Workers* with growth of 92.31 percentiles followed by *Nursing, Psychiatric, and Home Health Aides* (72.53 percentiles) and *Supervisors of Farming, Fishing, and Forestry Workers* (56.04 percentiles). The most significant decline in abstract task content was seen in *Animal Care and Service Workers* (57.14 percentiles) followed by *Other Protective Service Workers* (50.55 percentiles) and *Media and Communication Equipment Workers* (31.97 percentiles). The highest growth of routine task content occurred in *Entertainment Attendants and Related Workers* (70.33 percentiles) followed by *Supervisors of Building and Grounds Cleaning and Maintenance Workers* (64.84 percentiles) and *Nursing, Psychiatric, and Home Health Aides* (60.44 percentiles). The most significant decline in routine task content was seen in *Top Executives* (46.15 percentiles) followed

by *Mathematical Science Occupations* (38.46 percentiles) and *Supervisors of Protective Service Workers* (35.17 percentiles).

3.B Data Overview: Panel of Individual Workers

The 2004 and 2008 *SIPP* panels were combined to create an unbalanced panel of approximately two million observations. The *SIPP* is a household-based survey designed as a continuous representative series of national panels where the same individuals are interviewed over a multi-year period lasting approximately four years. The *SIPP* is the only available individual panel that contains the necessary components to conduct an occupational analysis of prime-age workers. The *SIPP* has more detailed occupational codes, frequent interviews, and a larger sample than other comparable data sources.[9]

Descriptive statistics from the combined *SIPP* panels are presented in Table 2 where the sample has been restricted to individuals of prime working age (25 to 55 years), who were not in the military, and who were employed with an occupation recorded. There were a total of 67,216 individuals in the sample who were observed an average of 29.47 months, totaling 2,003,557 observations.[10] On average, individuals reported working for 1.69 different employers and in 1.44 different occupations. As previously noted, the analysis considers occupations at a 3-digit *SOC* taxonomy. In a given time period, the average sample size in one of 91 distinct 3-digit SOC occupations reported in the *SIPP* was 912.3 people in a given occupation in a given month with a standard deviation of 1006.40 individuals. A histogram of the occupational sample size in the *SIPP*

[9] Compared to the Current Population Survey, its main advantage is the longitudinal nature that allows individuals and their job changes to be observed over time. Relative to the Panel Study of Income Dynamics, it provides a larger sample size, more frequent interviews and more detailed occupational codes. Although the level of detail of occupation codes is similar to that reported in the National Longitudinal Survey of Youth, the *SIPP* has much more frequent interviews and a larger sample with a more representative range of working age adults. In addition, the 2004 and 2008 *SIPP* panels were better aligned with the timing of the *O*NET* releases than National Longitudinal Survey of Youth.

[10] Our focus on wages limits the effective sample size to only those months where an individual reports employment and an occupation code.

is shown graphically in Figure A.3 of the Technical Appendix where it is important to note that the majority of occupations have reasonably large sample size.[11]

[Insert Table 2]

Employment information is reported in the *SIPP* under four distinct classifications: primary employment, secondary employment, primary self-employment, and secondary self-employment. Only the information recorded under an individual's primary employment arrangement is used in this analysis. Primary employment wages averaged 19.62 dollars per hour having been earned by workers who were on average 41.02 years of age with more working experience than formalized education. The sample was largely made up of workers with a high school degree or less and who reported their race as white and ethnicity as non-Hispanic. Although the *SIPP* does over sample low skill workers, the demographics of the estimation sample do resemble the overall U.S. population.

4. Empirical Analysis

This section details the results of an empirical analysis examining the implications derived from the model of RBTC outlined in Section 3. Namely, I investigate whether (1) the premium for abstract (routine) task content is growing (declining) over time, (2) changes in the relative premium between these tasks are larger in occupations that are initially more routine, and (3) changes in the relative task premium is causing self-selection to become stronger (weaker) in routine (abstract) occupations. The empirical analysis directly examines the first two points and addresses the third point, related to self-selection, by contrasting estimates with and without individual fixed-effects.

[11] The three 3-digit occupations with a sample size of less than 30 individuals on average per period were distributed evenly across major 2-digit occupations. The results are reasonably robust to estimation at the 2 and 5-digit *SOC* levels .

In the first subsection (4.A), I estimates a model using cross-sectional variation in the 2004 distribution of task content attached to individuals based on their first occupation in the *SIPP*. This first set of estimates allows me to examine what happens to wages for people who are initially in more routine and abstract occupations. To control for potential unobserved variable bias in these estimates, I restrict the sample to observation months surrounding occupation changes and re-estimate a model from this source of cross-sectional variation. In the second subsection (4.B), I investigate what happens to wages when task content within occupations changes over time, i.e. occupations become more or less abstract or routine. I examine this dimension of wage variation by attaching the full *O*NET* panel to the *SIPP* and estimating a model where wages are a function of task content as well as occupation and time fixed-effects. To address self-selection based on time invariant unobserved worker and firm heterogeneity, I re-estimate the model and include individual and employer fixed-effects. In contrasting the estimates with and without individual fixed-effects, I find that the coefficient on the task indices change in a manner consistent with patterns of selection described by the model of RBTC in Section 3.

4.A Empirical Analysis: Changes in Tasks and Wages Across Occupations

I begin by examining changes in wages for people who are initially in more routine and abstract occupations by estimating

$$w_{t,j,i} = \gamma_t + \lambda_r \bar{r}_{04,j} + \lambda_a \bar{a}_{04,j} + \mu_{t,j,i} \tag{8}$$

where $w_{t,j,i}$ is the log monthly wages of an individual employed in occupation *j* at time *t*. The coefficients λ_r and λ_a are estimated using variation across the 2004 distribution of routine $\bar{r}_{04,j}$ and abstract $\bar{a}_{04,j}$ task content where the units correspond with percentile ranks. Task content is attached to the analytical sample based on each individual's first occupation in the *SIPP* panel. Exploiting the cross-sectional variation in task content, allows me to examine how wages change for individuals who are initially in more (or less) routine and abstract occupations. Across all of the specifications in Table 3, the log of an individual's monthly wage is regressed on abstract and

routine task content as well as time fixed-effects.[12] Additional specifications include human capital and demographic controls as well as an interaction between tasks and a linear time trend.[13]

According to the first specification of Table 3, initial employment in more routine and abstract occupations corresponded with higher average wages overall. However, interacting task content with a time trend illustrates that the premium for more abstract occupations has increased while that for more routine occupations has decreased from 2004 to 2013. Adding demographic and human capital controls improves the precision but reduces the size of the point estimates by an order of magnitude. Overall, I find that an increase of ten percentiles across the initial routine task distribution was associated with wages between 0.77 and 1.64 percent higher in 2004. That premium declined by between 0.02 and 0.03 percent every 1.5 years reaching a level of about 0.67 to 1.52 percent by 2013. An increase of ten percentiles across the abstract task distribution was also associated with wages that were between 5.02 and 9.66 percent higher in 2004. Unlike the previous case, the wage premium for abstract tasks grew by between 0.11 and 0.18 percent every 1.5 years reaching about 5.68 to 10.26 percent by 2013. These results are consistent with the idea that individuals employed in more routine and abstract occupations initially earned higher wages but that the routine task premium has declined while the abstract task premium has increased over time.

[Insert Table 3]

To control for the possibility that additional unobserved heterogeneity is creating bias in the previous estimates, I limit the sample to only observation months directly surrounding when an

[12] Here and in all subsequent estimation equations, time fixed-effects include 121 binary indicators for each month reported in the combined 2004 and 2008 *SIPP* panels.

[13] Demographic controls here and throughout include binary indicators for Hispanic ethnicity, gender, marital status, and four racial categories. Human capital controls include five binary indicators of education attainment, job tenure, and job tenure squared. Each increment in the linear time trend corresponds with four survey waves from the combined *SIPP* panels that roughly correspond with 1.5 years. The base year for the linear time trend is 2004 where it is zero and extends to 2014 where it has a value of six.

individual changes their occupation and re-estimate equation (8). Estimating wage effects from cross-sectional variation in task content when individuals change occupations allows me to implicitly control for combinations of unobserved worker and firm heterogeneity. The first two specifications exploit variation in task content occurring as a result of an occupation change regardless of whether there is an intervening period of non-employment. Additional specifications further restrict the sample to direct employment-to-employment occupational transitions and disaggregate results by corresponding employer changes. The last two specifications include only observations surrounding occupation transitions within the same employer and thus control for both individual and firm heterogeneity.

As detailed in Table 4, I find that an increase of ten percentiles across the routine task distribution was associated with wages between 0.95 and 3.26 percent higher in 2004. That premium declined by between 0.01 and 0.10 percent every 1.5 years reaching a level of about 0.56 to 2.66 percent by 2013. Similarly, an increase of ten percentiles across the abstract task distribution was also associated with wages that were between 8.94 and 12.21 percent higher in 2004. The wage premium for abstract tasks grew by between 0.46 and 1.13 percent every 1.5 years reaching about 13.59 to 15.72 percent by 2013. Although the coefficient estimates of both task premiums were reasonably comparable in magnitude to those in Table 3, the change in the routine task premium was much larger and the abstract task premium was smaller in magnitude.

[Insert Table 4]

To add additional context to the results from Tables 3 and 4, I graphically present the coefficient estimates of the change over time in the routine and abstract task premium in Figure 2. I limit the coefficient estimates to a subset of the most restrictive specifications from Table 3 (specification 4) and Table 4 (specification 2 and 4). The groupings in Figure 2 represent changes in the task premium associated with downward and upward movements of 25 and 75 percentiles across the 2004 distribution of occupational tasks. As seen in the figure, the premium across occupations for routine task content has declined over time while the premium for abstract task content has increased. As noted previously, the figure illustrates that controlling for unobservable

heterogeneity increases the magnitude of the change in the routine task premium but decreases the abstract task premium. These estimates provide new insight into an important facet of the RBTC hypothesis detailed by the model in Section 3, namely that the wages of workers initially in more routine occupations have declined over time while wages more abstract occupations have grown.

[Insert Figure 2]

4.B Empirical Analysis: Changes in Tasks and Wages Within Occupations

I now explore what happens to wages when task content within occupations changes over time by fully utilizing the *O*NET* panel and estimating a model where

$$w_{t,j,i} = \gamma_t + \delta_j + \lambda_r \bar{r}_{t,j} + \lambda_a \bar{a}_{t,j} + \mu_{t,j,i} \tag{9}$$

In estimating the above equation, coefficients are identified using variation in task content occurring within occupations over time. The variable γ_t represents time and δ_j is an occupation fixed-effects. Thus, the model estimates how wages respond to changes to task content within occupations over time.

Table 5 indicates that as an occupation increases over time in routine task content, wages grew by between 0.66 and 1.26 percent.[14] The wage premium for routine tasks declined by between 0.08 and 0.11 percent every 1.5 years reaching a level of about 0.30 to 0.60 percent by 2013. In response to an increase of ten percentiles over time in abstract task content, wages for workers declined by between 0.12 and 0.40 percent.[15] This premium increased by between 0.02

[14] Recall, that the mean within variation in abstract task content was also approximately equal to zero with a standard deviation of 22.62 percentiles and the maximum (minimum) increase (decrease) was 92.31 (-57.14) percentiles.

[15] Recall, that the mean within variation in routine task content was approximately equal to zero with a standard deviation of 19.80 percentiles and the maximum (minimum) increase (decrease) was 70.33 (-46.15) percentiles.

and 0.04 percent every 1.5 years reaching a level of about 0.06 to 0.12 percent by 2013. Although the change in task premiums correspond with the predictions from the RBTC hypothesis, the primary effect of an increase in routine or abstract content do not. In particular, we would have expected to find that an increase in routine task content corresponds with lower wages while an increase in abstract task content relates to higher wages. However, we should also expect that workers who have relatively lower ability will respond to the increase in the relative task premium by sorting away from routine-intensive occupations and into abstract intensive occupations. Thus, since I have not yet controlled for unobserved heterogeneous ability in these estimates, i.e. the worker's skill endowment from the model, a possible interpretation is that the unexpected signs are driven by the secondary effect of stronger and weaker selection into routine and abstract occupations.

[Insert Table 5]

In Table 6, I control for self-selection on time invariant unobserved heterogeneity by re-estimating (9) and including individuals and individual-employer fixed-effects. As an occupation increases over time by ten percentiles in the routine task distribution, the wage of workers declined by between -0.09 and -0.35 percent. The wage penalty declined by between 0.03 and 0.04 percent smaller every 1.5 years reaching -0.33 to -0.48 percent by 2013. In response to an increase of ten percentiles in abstract task content over time, wages for workers increase by between 0.42 and 2.27 percent. This wage premium changed by about 0.03 percent every 1.5 years reaching a level of about 0.42 and 2.43 percent by 2013. In opposition to the previous set of estimates in Table 3, I find that controlling for unobserved heterogeneity produces the expected sign where an increase in relative routine or abstract task content corresponds with a decrease and increase in wages respectively. The sign of the primary effect of changes to task content aligns with the model of RBTC outlined in Section 3. Contrasting these estimates with those estimated without individual or individual-employer fixed-effects provides additional support for the idea that technical change has altered patterns of self-selection along the distribution of occupational tasks.

[Insert Table 6]

Figure 3 presents coefficients estimates of the interaction of abstract and routine task content with a linear time trend from Tables 5 and 6. In particular, I graphically present estimates from Table 5 (specification 4) where demographic and human capital controls have been added as well as estimates from Table 6 with individual fixed-effects (specification 2) and individual-employer fixed-effects (specification 4). The groupings represent within occupation changes to task content in the order of two standard deviations (39.164 percentiles) and one standard deviation (19.582 percentiles) respectively. As seen below, the penalty for routine task content is uniformly declining while the premium abstract task content is increasing across occupations over time. Relative to the estimates in Section 5.A, wage effects estimated using within variation in task content are approximately half as large as those identified using variation in task content across occupations.

[Insert Figure 3]

5. Robustness Checks

This section contains a robustness check using a two-step estimation procedure where wages are first regressed on demographic and human capital controls independently for each year before running a second regression of residual wages on task content. This procedure follows the estimation procedure outlined by Peri and Sparber (2009) who use wage residuals to construct relative task premiums for the purpose of examining immigrant task specialization. Although here I reproduce two-step estimates for only Tables 4 and 6 of Section 5, i.e. those where I control for unobservables, two-step variants of Tables 3 and 5 are contained in Tables A.1 and A.2 of the Technical Appendix. In addition, the Technical Appendix contains additional robustness checks in Tables A.3 through A.6 where the upper and lower bound of a 95 percent confidence interval of occupational task content is used rather than the point estimates from *O*NET*. The Technical Appendix also contains estimates in Tables A.7 through A.10 where task content is constructed at

the 5-digit rather than the 3-digit SOC level. Across the estimates presented in this section as well as those in the Technical Appendix, I consistently find evidence that the premium for abstract relative to routine task content is increasing over time both across and within occupations.

In the first step of the estimation procedure, the *SIPP* panel is treated as separate monthly cross-sections and wages are regressed on demographic and human capital controls. In the second step, the residual wages from the first step are used as the dependent variable to re-estimate Table 4 where unobserved individual and employer heterogeneity are accounted for by restricting the sample to observations surrounding an occupation change. As seen in Table 7, the primary effect of an increase in routine and abstract content across occupations is strongly related to higher wages. As before, the interaction between abstract task content and a linear time trend illustrates that the premium for abstract task content is growing over time. This alternative estimation procedure provides additional evidence that, even after supply-side demographic and human capital factors are removed from the variation in wages, the relative premium of abstract relative to routine task is growing over time.

[Insert Table 7]

Re-estimating Table 6 using the same two-step procedure, I find strong evidence supporting the initial conclusion that the relative premium between abstract and routine task content is growing over time. In particular, the fourth specification which includes individual and occupation fixed-effects provides evidence suggesting that the premium for routine task content is declining over time. Restricting the variation to that occurring within the same employer over time, the final specification provides evidence suggesting that the abstract task premium is growing over time. Although these estimates are less robust than those from Table 6 with respect to which particular task premium is driving the change in wages within occupations, these estimates do provide additional evidence that the relative premium of abstract relative to routine tasks is growing over time.

[Insert Table 8]

6. Conclusion

In this study, I construct a new panel of occupational task content from incumbent updated survey data in *O*NET*. Attaching these data to a panel data on individual workers from the combined 2004 and 2008 *SIPP*, I am able to ask how the wage of workers who are initially in more routine and abstract occupations change over time. In constructing panel data on occupational task content, I am also able to provide new empirical evidence about how wages respond to changes in task content within occupations over time. By exploiting the nature of the *SIPP* panel, I am able to control for unobservables and self-selection by including occupation, individual, and individual-employer fixed-effects in my estimates. In estimating wage effects using both cross-sectional and within occupation variation in task content, I find strong evidence in support of the RBTC hypothesis as an explanation for increase wage and employment polarization.

Estimating a model of wages using cross sectional variation in tasks from individual's first occupation in the SIPP (Tables 3 and 4), I find evidence that workers are initially paid more if they are employed in more routine and abstract occupations. However, I also find evidence that the premium for routine tasks is declining while that for abstract tasks is growing over time. Using within occupation variation in task content over time and controlling for unobservables, I found that an increase in routine task content corresponds with a decrease in wages while an increase in abstract content lead to an increase. Here, I find evidence that the primary effect of an increase in routine task content has declined over time while the effect of an increase in abstract task content has grown larger. In contrasting estimates with and without individual fixed-effects, I find evidence suggesting the presence of self-selection corresponding with the predictions made by Autor and Handel (2013) as well as the model detailed in the theoretical section.

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Tables and Figures

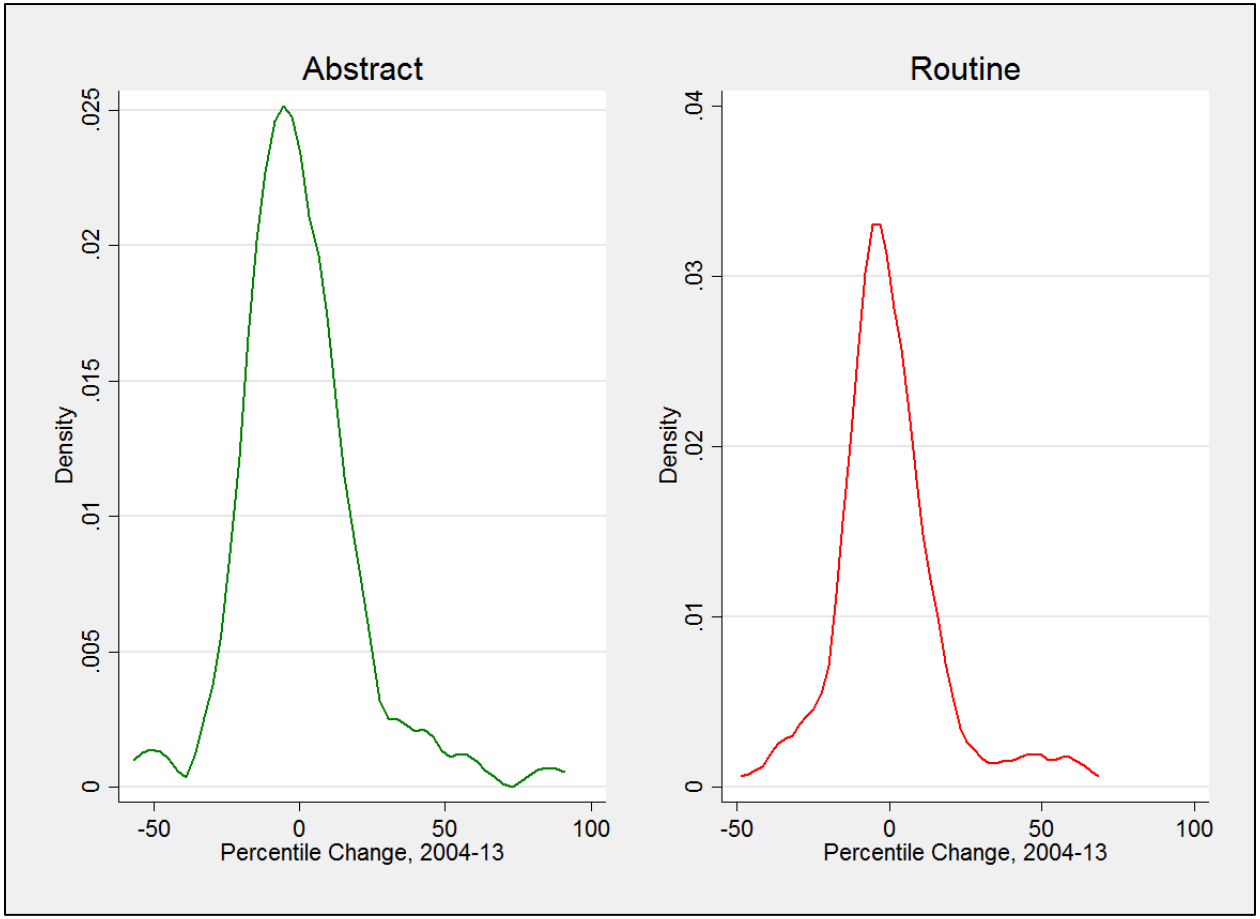
Table 1: Composition of the Abstract and Routine Task Indices

Task Index	Variable Code	Task Measure	Model	Scale
Abstract	4.A.2.a.4	Analyzing Data or Information	Activities	LV/IM
	4.A.2.b.2	Thinking Creatively	Activities	LV/IM
	4.A.4.a.1	Interpreting the Meaning of Information for Others	Activities	LV/IM
	4.A.4.a.4	Establishing and Maintaining Interpersonal Relationships	Activities	LV/IM
	4.A.4.b.4	Guiding, Directing, and Motivating Subordinates	Activities	LV/IM
	4.A.4.b.5	Coaching and Developing Others	Activities	LV/IM
Routine	4.C.3.b.4	Importance of Being Exact or Accurate	Context	CX
	4.C.3.b.7	Importance of Repeating Same Tasks	Context	CX
	4.C.3.b.8	Structured versus Unstructured Work (Reverse)	Context	CX
	4.A.3.a.3	Controlling Machines and Processes	Activities	LV/IM
	4.C.2.d.1.i	Spend Time Making Repetitive Motions	Context	CX
	4.C.3.d.3	Pace Determined by Speed of Equipment	Context	CX

Table 2: Descriptive Statistics from the Analytical Sample

Total Obs	Total Ind.	P2004 Obs	P2004 Ind.	P2008 Obs	P2008 Ind.
2,003,557	67,216	950,175	35,399	1,189,008	32,921
Avg. No. Response		Avg. No. Jobs		Avg. No. SOC3	
29.47		1.81		1.51	
Monthly Wage	Hourly Wage	Hours (Mon)	Age (Yrs)	Job Tenure (Mon)	Occ Change
3,415.51	19.62	174.23	41.02	84.97	34.37%
(3,294.67)	(21.70)	(74.28)	(8.66)	(86.57)	(47.50%)
< HS	HS	Some College	College	Post-College	Years Ed
7.71%	39.22%	20.06%	20.84%	12.17%	13.69
White	Black	Asian	Other	All Hisp.	White Non-Hisp.
79.32%	12.41%	4.44%	3.84%	12.09%	68.16%
Female		Married		Children	
50.45%		60.54%		1.13	

Figure 1: Kernel Density Estimates of Percentile Change in Abstract and Routine Task Index, 2004-13



Note: The density estimates are estimated using the change in task content across 91 3-digit SOC occupations from 2004 to 2013 with an Epanechnikov kernel and optimal bandwidth selection.

Table 3: Regression of Wages on Variation in Task Content across Initial Occupation

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)
Routine, 2004	0.00158***	0.00164***	0.00077***	0.00085***
	(0.00002)	(0.00004)	(0.00002)	(0.00004)
Abstract, 2004	0.00966***	0.00918***	0.00531***	0.00502***
	(0.00002)	(0.00004)	(0.00002)	(0.00003)
Routine, 2004 x Trend		-0.00002*		-0.00003***
		(0.00001)		(0.00001)
Abstract, 2004 x Trend		0.00018***		0.00011***
		(0.00001)		(0.00001)
Human Capital and Demographics			X	X
Time Fixed-Effects	X	X	X	X
F- Statistic	3630	3570	7467	7354
R-Squared	0.18495	0.18517	0.32963	0.32973
Observations	2,003,557	2,003,557	2,003,557	2,003,557

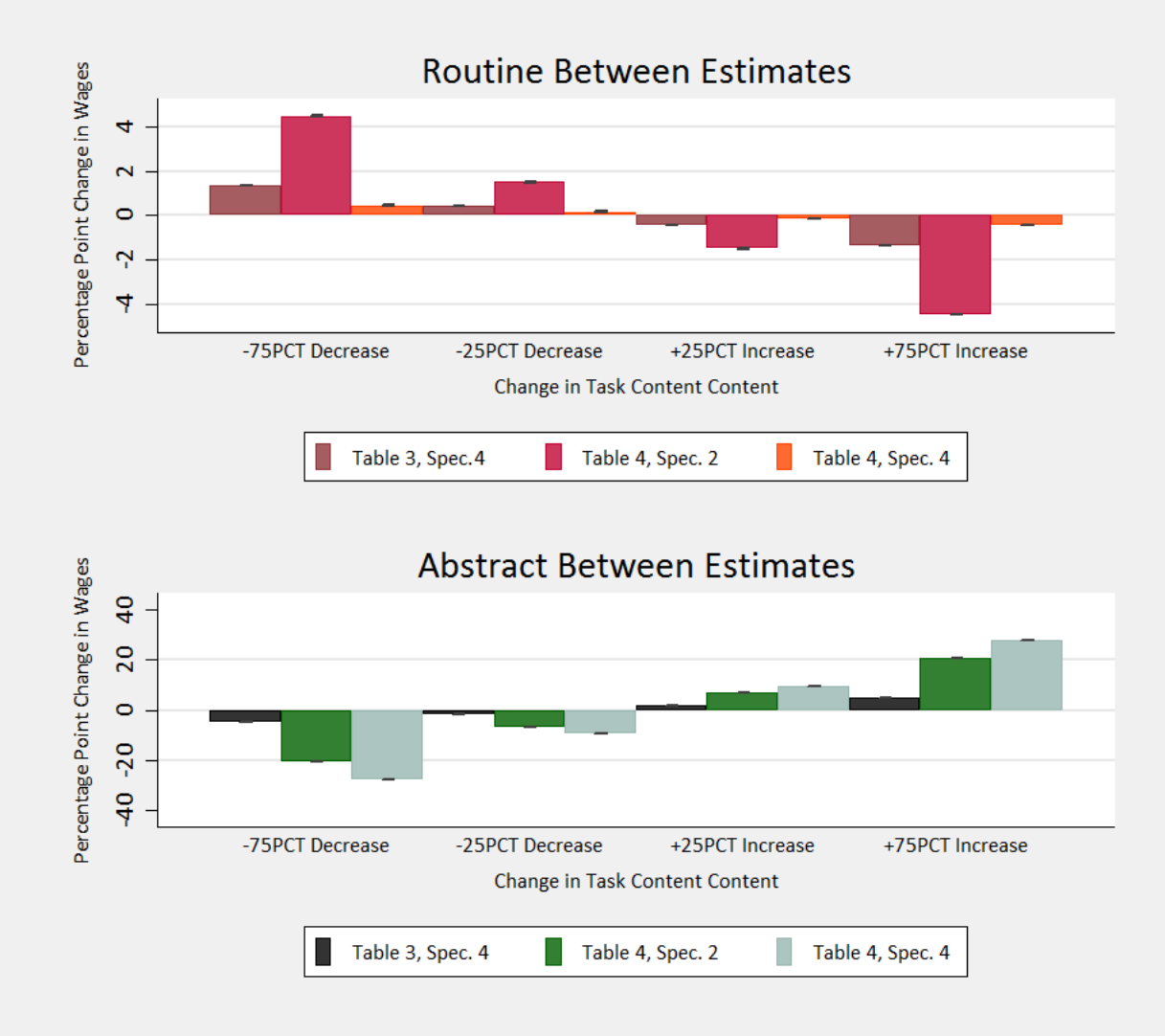
Note: The coefficients are presented above robust standard error where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.

Table 4: Regression of Wages on Variation in Task Content from Occupation Change

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Routine, 2004	0.00296***	0.00326***	0.00205***	0.00213***	0.00227***	0.00256***	0.00095***	0.00116***
	(0.00016)	(0.00023)	(0.00018)	(0.00026)	(0.00020)	(0.00033)	(0.00034)	(0.00040)
Abstract, 2004	0.01221***	0.01130***	0.01127***	0.01005***	0.01151***	0.01023***	0.00972***	0.00894***
	(0.00015)	(0.00021)	(0.00017)	(0.00023)	(0.00020)	(0.00030)	(0.00032)	(0.00037)
Routine, 2004 x Trend		-0.00010		-0.00001		-0.00008		-0.00010
		(0.00008)		(0.00009)		(0.00010)		(0.00030)
Abstract, 2004 x Trend		0.00046***		0.00062***		0.00056***		0.00113***
		(0.00008)		(0.00009)		(0.00010)		(0.00029)
Transition Type	E to U to E		E to E		E to E (Diff. Emp.)		E to E (Same Emp.)	
Time Fixed-Effects	X	X	X	X	X	X	X	X
F- Statistic	88	87	66	65	52	52	65	52
R-Squared	0.13	0.13	0.12	0.12	0.12	0.12	0.16	0.16
Observations	69,346	69,346	50,222	50,222	40,835	40,835	9,387	9,387

Note: The coefficients are presented above robust standard error where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.

Figure 2: Coefficient Estimates using Between Occupation Variation in Task Content



Note: Lines represent a 95% confidence interval of the coefficient estimates and bars are ordered as described in the legend.

Table 5: Regression of Wages on Variation in Task Content within Occupations

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)
Routine	0.00105***	0.00126***	0.00066***	0.00078***
	(0.00011)	(0.00011)	(0.00010)	(0.00011)
Abstract	-0.00040***	-0.00018*	-0.00028***	-0.00012
	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Routine x Trend		-0.00011***		-0.00008***
		(0.00001)		(0.00001)
Abstract x Trend		0.00002*		0.00004***
		(0.00001)		(0.00001)
Human Capital and Demographics			X	X
Occupation Fixed-Effects	X	X	X	X
Time Fixed-Effects	X	X	X	X
F- Statistic	125	124	2512	2475
R-Squared	0.29	0.29	0.39	0.39
Observations	2,003,557	2,003,557	2,003,557	2,003,557

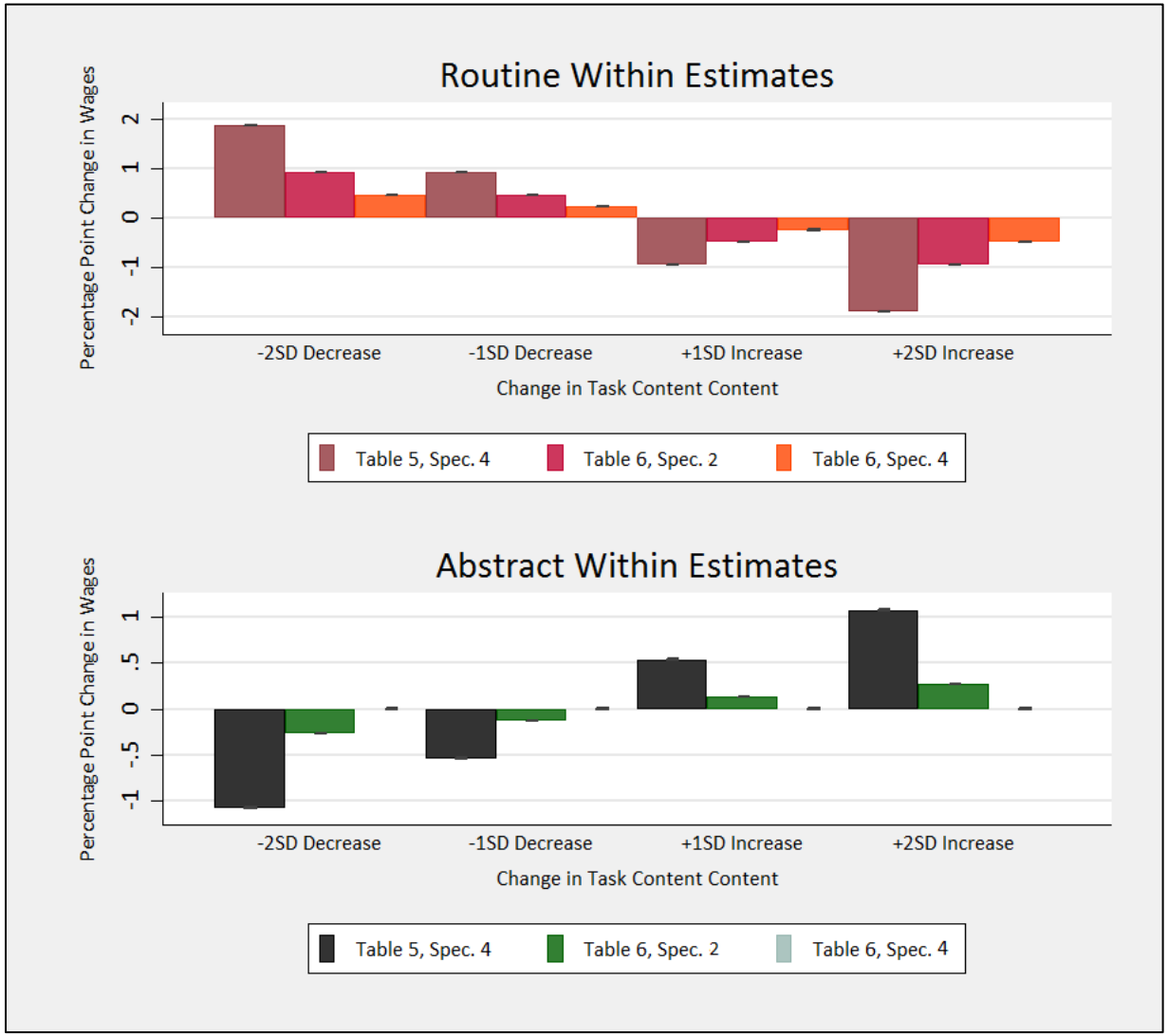
Note: The coefficients are presented above standard error clustered on occupations where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on individuals.

Table 6: Regression of Wages on Variation in Task Content within Occupations Controlling for Unobserved Heterogeneity

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)
Routine	-0.00019*	-0.00009	-0.00035***	-0.00030***
	(0.00010)	(0.00010)	(0.00006)	(0.00006)
Abstract	0.00042***	0.00048***	0.00227***	0.00225***
	(0.00009)	(0.00009)	(0.00005)	(0.00005)
Routine x Trend		-0.00004***		-0.00003**
		(0.00001)		(0.00001)
Abstract x Trend		-0.00001		0.00003***
		(0.00001)		(0.00001)
Occupation Fixed-Effects	X	X	X	X
Individual-Employer Fixed-Effects			X	X
Individual Fixed-Effects	X	X		
Time Fixed-Effects	X	X	X	X
F- Statistic	304	301	180	177
R-Squared	0.03	0.03	0.01	0.01
Observations	2,003,557	2,003,557	2,003,557	2,003,557

Note: The coefficients are presented above standard errors clustered on individuals where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.

Figure 3: Coefficient Estimates using Within Occupation Variation in Task Content



Note: Lines represent a 95% confidence interval of the coefficient estimates and bars are ordered as described in the legend.

Table 7: Regression of Wage Residuals on Variation in Task Content from Occupation Change

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Routine, 2004	0.00233***	0.00215***	0.00150***	0.00130***	0.00171***	0.00166***	0.00049*	0.00040
	(0.00014)	(0.00021)	(0.00016)	(0.00024)	(0.00019)	(0.00031)	(0.00030)	(0.00035)
Abstract, 2004	0.00671***	0.00614***	0.00601***	0.00527***	0.00618***	0.00549***	0.00493***	0.00415***
	(0.00014)	(0.00019)	(0.00016)	(0.00022)	(0.00018)	(0.00028)	(0.00028)	(0.00033)
Routine, 2004 x Trend		0.00010		0.00011		0.00003		0.00025
		(0.00007)		(0.00008)		(0.00010)		(0.00027)
Abstract, 2004 x Trend		0.00028***		0.00037***		0.00029***		0.00113***
		(0.00007)		(0.00008)		(0.00009)		(0.00027)
Transition Type	E to U to E		E to E		E to E (Diff. Emp.)		E to E (Same Emp.)	
Human Capital and Demographics (Wage Res.)	X	X	X	X	X	X	X	X
Time Fixed-Effects	X	X	X	X	X	X	X	X
F- Statistic	29	28	21	21	16	16	23	23
R-Squared	0.04	0.04	0.04	0.04	0.04	0.04	0.07	0.07
Observations	69,346	69,346	50,222	50,222	40,835	40,835	9,387	9,387

Note: The coefficients are presented above robust standard error where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.

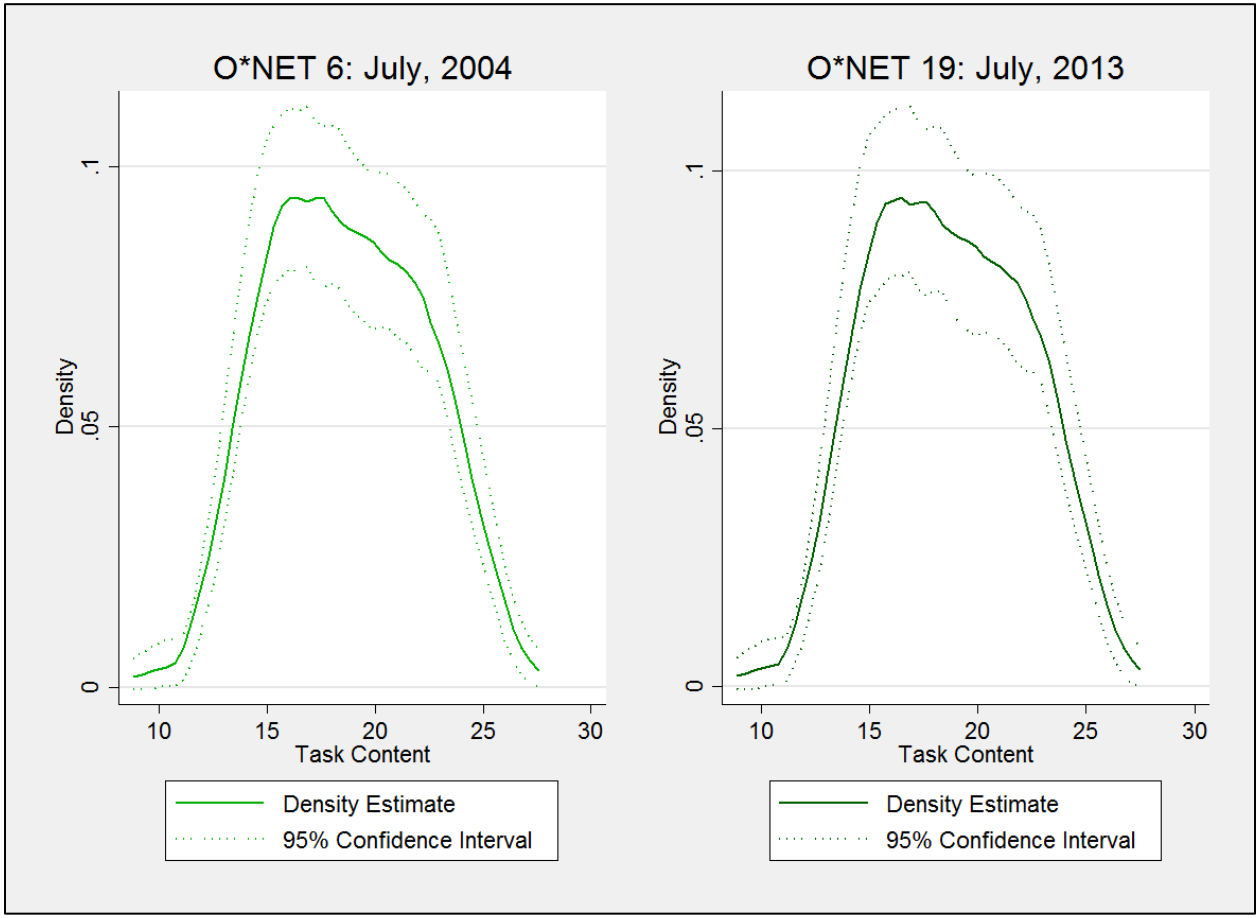
Table 8: Regression of Wage Residuals on Variation in Task Content within Occupations Controlling for Unobserved Heterogeneity

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)
Routine	-0.00048***	-0.00042***	-0.00034***	-0.00038***
	(0.00010)	(0.00010)	(0.00006)	(0.00006)
Abstract	0.00053***	0.00054***	0.00195***	0.00191***
	(0.00009)	(0.00009)	(0.00005)	(0.00005)
Routine x Trend		-0.00001		0.00002*
		(0.00001)		(0.00001)
Abstract x Trend		-0.00003***		0.00003***
		(0.00001)		(0.00001)
Human Capital and Demographics (Wage Res.)	X	X	X	X
Occupation Fixed-Effects	X	X	X	X
Person-Employer Fixed-Effects			X	X
Person Fixed-Effects	X	X		
Time Fixed-Effects	X	X	X	X
F- Statistic	216	214	36	36
R-Squared	0.02	0.02	0.01	0.01
Observations	2,003,557	2,003,557	2,003,557	2,003,557

Note: The coefficients are presented above standard errors clustered on individuals where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.

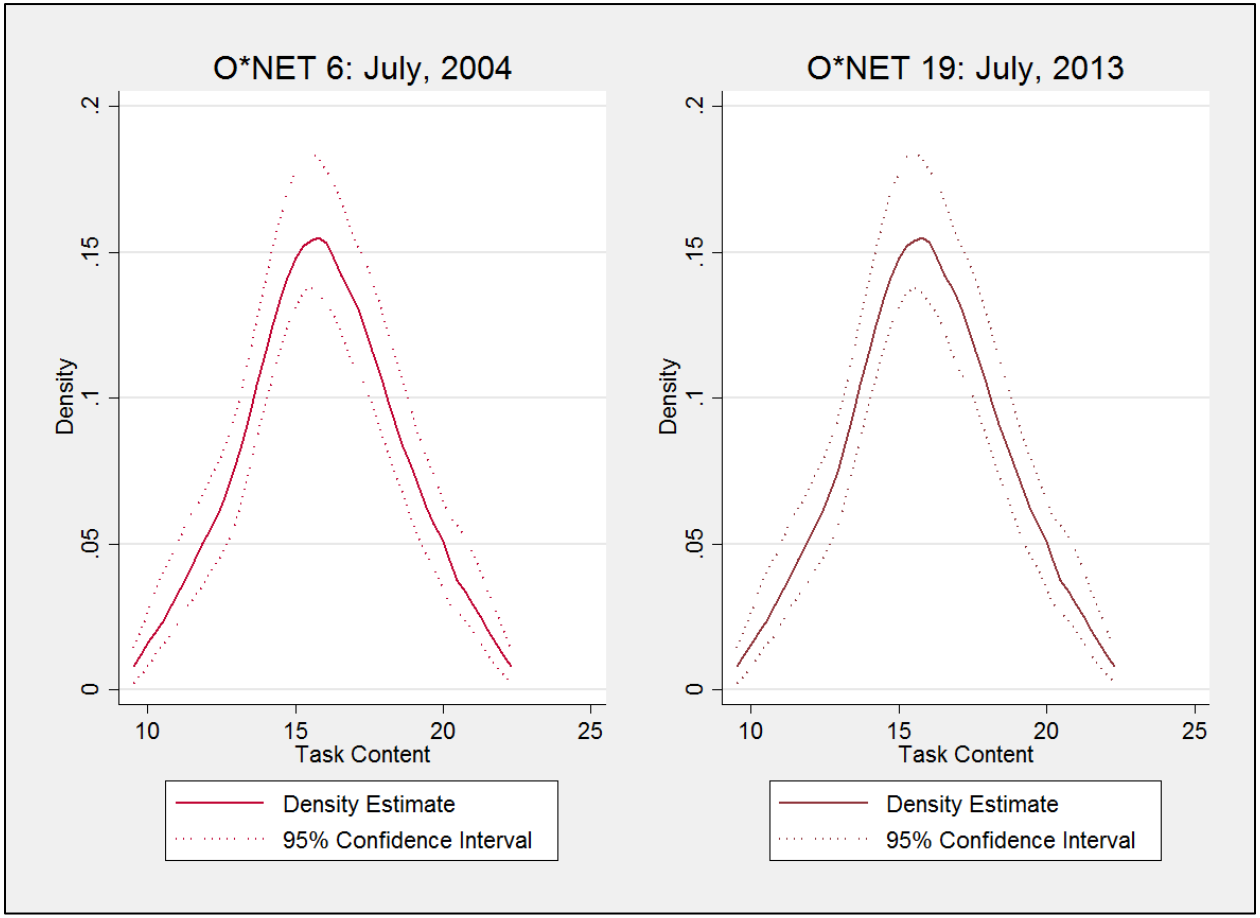
Technical Appendix

Figure A.1: Kernel Density Estimates of Abstract Task Index, 2004-13



Note: Density estimates are estimated using the change in task content across 91 occupations at the 3-digit SOC level from 2004 to 2013 with an Epanechnikov kernel and optimal bandwidth selection.

Figure A.2: Kernel Density Estimates of Routine Task Index, 2004-13



Note: Density estimates are estimated using the change in task content across 91 occupations at the 3-digit SOC level from 2004 to 2013 with an Epanechnikov kernel and optimal bandwidth selection.

Figure A.3: Histogram of Average Occupational Sample Size of Incumbent-Updated Survey Data in the *O*NET* Panel

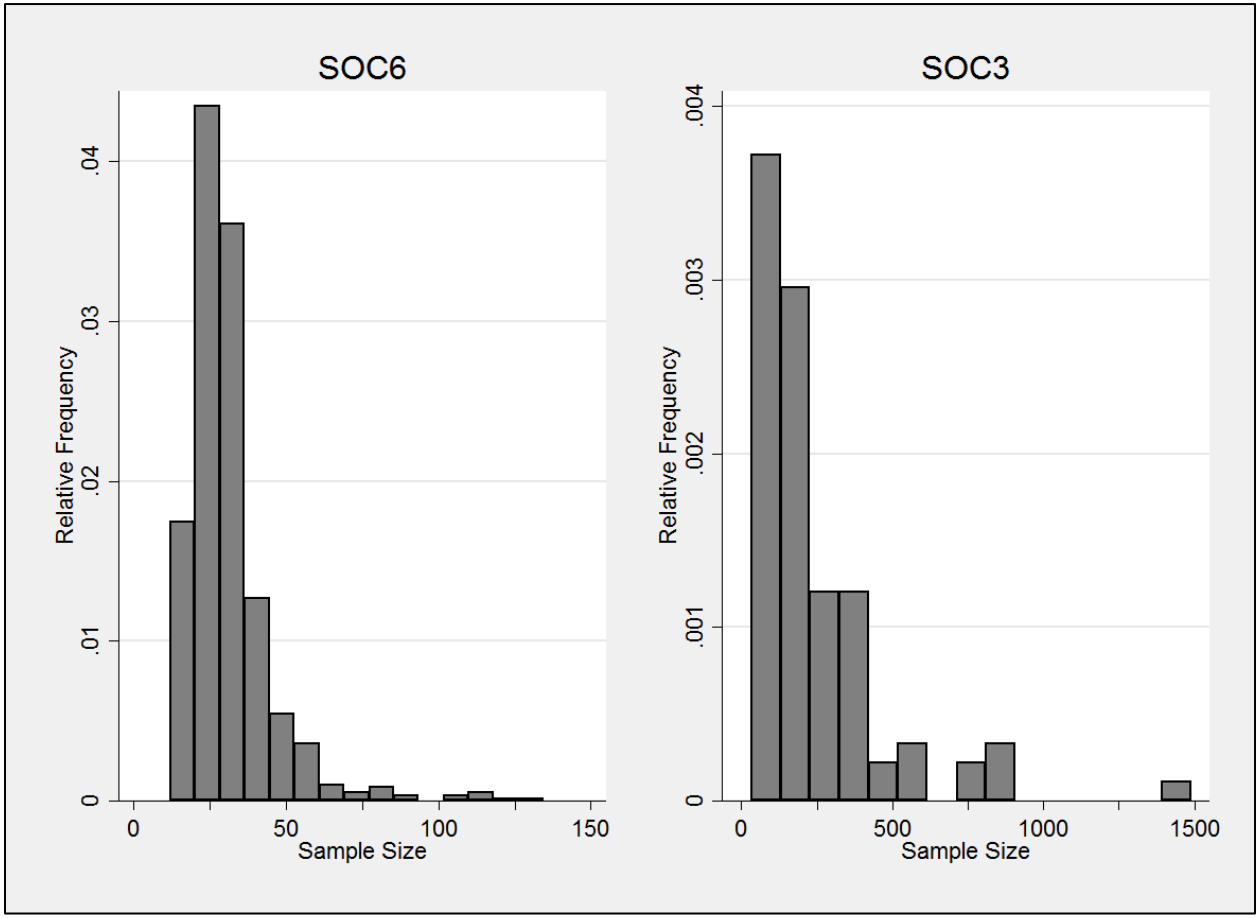


Figure A.4: Histogram of Average Occupational Sample Size of Incumbent-Updated Survey Data in the *SIPP* Estimation Sample

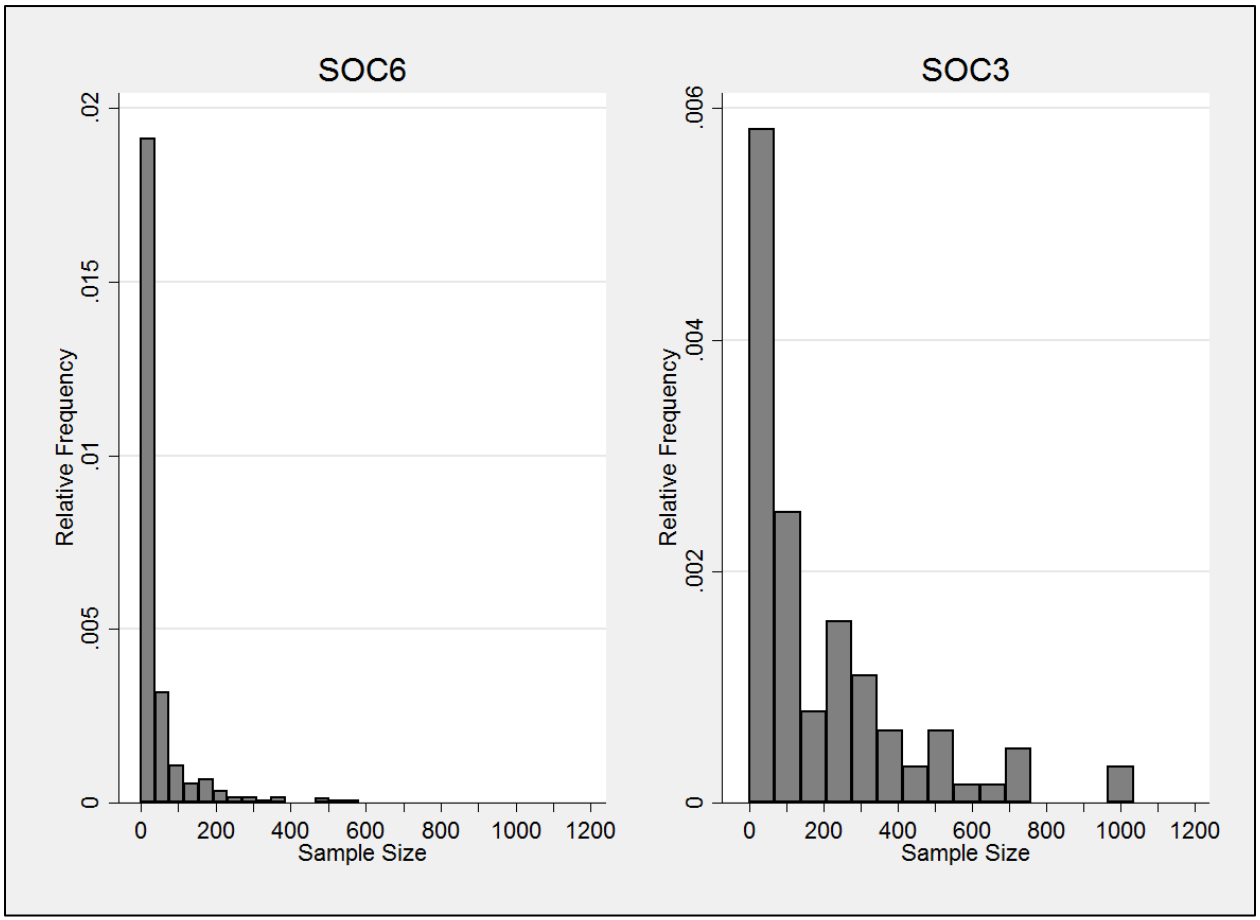


Table A.1: Regression of Wage Residuals on Variation in Task Content across Initial Occupation

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)
Routine, 2004	0.00158***	0.00164***	0.00116***	0.00105***
	(0.00002)	(0.00004)	(0.00002)	(0.00004)
Abstract, 2004	0.00966***	0.00918***	0.00408***	0.00394***
	(0.00002)	(0.00004)	(0.00002)	(0.00003)
Routine, 2004 x Trend		-0.00002*		0.00004***
		(0.00001)		(0.00001)
Abstract, 2004 x Trend		0.00018***		0.00005***
		(0.00001)		(0.00001)
Human Capital and Demographics (Wage Res.)			X	X
Time Fixed-Effects	X	X	X	X
F- Statistic	3630	3570	820	807
R-Squared	0.18	0.19	0.05	0.05
Observations	2,003,557	2,003,557	2,003,557	2,003,557

Note: The coefficients are presented above robust standard error where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.

Table A.2: Regression of Wage Residuals on Variation in Task Content within Occupations

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)
Routine	0.00105***	0.00126***	0.00038***	0.00039***
	(0.00011)	(0.00011)	(0.00010)	(0.00011)
Abstract	-0.00040***	-0.00018*	0.00003	0.00004
	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Routine x Trend		-0.00011***		-0.00000
		(0.00001)		(0.00001)
Abstract x Trend		0.00002*		-0.00000
		(0.00001)		(0.00001)
Human Capital and Demographics (Wage Res.)			X	X
Time Fixed-Effects	X	X	X	X
Occupation Fixed-Effects	X	X	X	X
F- Statistic	125	124	1	1
R-Squared	0.29	0.29	0.13	0.13
Observations	2,003,557	2,003,557	2,003,557	2,003,557

Note: The coefficients are presented above standard error clustered on occupations where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on individuals.

Table A.3: Regression of Wages on Variation in the Upper and Lower Bounds of Task Content across Initial Occupation

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)
Routine, 2004 (Upper Bound)	0.00365***	0.00388***	0.00236***	0.00249***
	(0.00003)	(0.00004)	(0.00003)	(0.00004)
Abstract, 2004 (Upper Bound)	0.01297***	0.01258***	0.00778***	0.00749***
	(0.00002)	(0.00004)	(0.00002)	(0.00004)
Routine, 2004 (Upper Bound) x Trend		-0.00009***		-0.00005***
		(0.00001)		(0.00001)
Abstract, 2004 (Upper Bound) x Trend		0.00014***		0.00011***
		(0.00001)		(0.00001)
Human Capital and Demographics			X	X
Time Fixed-Effects	X	X	X	X
F- Statistic	4365	4294	7917	7797
R-Squared	0.22	0.22	0.34	0.34
Observations	2,003,557	2,003,557	2,003,557	2,003,557
Routine, 2004 (Lower Bound)	0.00028***	0.00015***	0.00045***	0.00041***
	(0.00002)	(0.00004)	(0.00002)	(0.00003)
Abstract, 2004 (Lower Bound)	0.00913***	0.00844***	0.00518***	0.00478***
	(0.00002)	(0.00003)	(0.00002)	(0.00003)
Routine, 2004 (Lower Bound) x Trend		0.00005***		0.00001
		(0.00001)		(0.00001)
Abstract, 2004 (Lower Bound) x Trend		0.00025***		0.00015***
		(0.00001)		(0.00001)
Human Capital and Demographics			X	X
Time Fixed-Effects	X	X	X	X
F- Statistic	3454	3399	7369	7260
R-Squared	0.17	0.17	0.33	0.33
Observations	2,003,557	2,003,557	2,003,557	2,003,557

Note: The coefficients are presented above robust standard error where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.

Table A.4: Regression of Wages on Variation in the Upper and Lower Bounds of Task Content from Occupation Change

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Routine, 2004 (Upper Bound)	0.00296***	0.00326***	0.00205***	0.00213***	0.00227***	0.00256***	0.00095***	0.00116***
	(0.00016)	(0.00023)	(0.00018)	(0.00026)	(0.00020)	(0.00033)	(0.00034)	(0.00040)
Abstract, 2004 (Upper Bound)	0.01221***	0.01130***	0.01127***	0.01005***	0.01151***	0.01023***	0.00972***	0.00894***
	(0.00015)	(0.00021)	(0.00017)	(0.00023)	(0.00020)	(0.00030)	(0.00032)	(0.00037)
Routine, 2004 (Upper Bound) x Trend		-0.00010		0.00001		-0.00008		-0.00010
		(0.00008)		(0.00009)		(0.00010)		(0.00030)
Abstract, 2004 (Upper Bound) x Trend		0.00046***		0.00062***		0.00056***		0.00113***
		(0.00008)		(0.00009)		(0.00010)		(0.00029)
Transition Type	E to U to E		E to E		E to E (Diff. Emp.)		E to E (Same Emp.)	
Time Fixed-Effects	X	X	X	X	X	X	X	X
F- Statistic	88	87	66	65	52	52	65	52
R-Squared	0.13	0.13	0.12	0.12	0.12	0.12	0.16	0.16
Routine, 2004 (Lower Bound)	0.00296***	0.00326***	0.00205***	0.00213***	0.00227***	0.00256***	0.00095***	0.00116***
	(0.00016)	(0.00023)	(0.00018)	(0.00026)	(0.00020)	(0.00033)	(0.00034)	(0.00040)
Abstract, 2004 (Lower Bound)	0.01221***	0.01130***	0.01127***	0.01005***	0.01151***	0.01023***	0.00972***	0.00894***
	(0.00015)	(0.00021)	(0.00017)	(0.00023)	(0.00020)	(0.00030)	(0.00032)	(0.00037)
Routine, 2004 (Lower Bound) x Trend		-0.00010		0.00001		-0.00008		-0.00010
		(0.00008)		(0.00009)		(0.00010)		(0.00030)
Abstract, 2004 (Lower Bound) x Trend		0.00046***		0.00062***		0.00056***		0.00113***
		(0.00008)		(0.00009)		(0.00010)		(0.00029)
Transition Type	E to U to E		E to E		E to E (Diff. Emp.)		E to E (Same Emp.)	
Time Fixed-Effects	X	X	X	X	X	X	X	X
F- Statistic	88	87	66	65	52	52	65	52
R-Squared	0.13	0.13	0.12	0.12	0.12	0.12	0.16	0.16
Observations	69,346	69,346	50,222	50,222	40,835	40,835	9,387	9,387

Note: The coefficients are presented above robust standard error where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.

Table A.5: Regression of Wages on Variation in the Upper and Lower Bounds of Task Content within Occupations

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)
Routine (Upper Bound)	0.00105***	0.00126***	0.00066***	0.00078***
	(0.00011)	(0.00011)	(0.00010)	(0.00011)
Abstract (Upper Bound)	-0.00040***	-0.00018*	-0.00028***	-0.00012
	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Routine (Upper Bound) x Trend		-0.00011***		-0.00008***
		(0.00001)		(0.00001)
Abstract (Upper Bound) x Trend		0.00002*		0.00004***
		(0.00001)		(0.00001)
Human Capital and Demographics			X	X
Occupation Fixed-Effects	X	X	X	X
Time Fixed-Effects	X	X	X	X
F- Statistic	125	124	2512	2475
R-Squared	0.29	0.29	0.39	0.39
Observations	2,003,557	2,003,557	2,003,557	2,003,557
Routine (Lower Bound)	0.00105***	0.00126***	0.00066***	0.00078***
	(0.00011)	(0.00011)	(0.00010)	(0.00011)
Abstract (Lower Bound)	-0.00040***	-0.00018*	-0.00028***	-0.00012
	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Routine (Lower Bound) x Trend		-0.00011***		-0.00008***
		(0.00001)		(0.00001)
Abstract (Lower Bound) x Trend		0.00002*		0.00004***
		(0.00001)		(0.00001)
Human Capital and Demographics			X	X
Occupation Fixed-Effects	X	X	X	X
Time Fixed-Effects	X	X	X	X
F- Statistic	125	124	2512	2475
R-Squared	0.29	0.29	0.39	0.39
Observations	2,003,557	2,003,557	2,003,557	2,003,557

Note: The coefficients are presented above standard error clustered on occupations where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on individuals.

Table A.6: Regression of Wages on Variation in the Upper and Lower Bounds of Task Content within Occupations Controlling for Unobserved Heterogeneity

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)
Routine (Upper Bound)	0.00105***	0.00126***	0.00066***	0.00078***
	(0.00011)	(0.00011)	(0.00010)	(0.00011)
Abstract (Upper Bound)	-0.00040***	-0.00018*	-0.00028***	-0.00012
	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Routine (Upper Bound) x Trend		-0.00011***		-0.00008***
		(0.00001)		(0.00001)
Abstract (Upper Bound) x Trend		0.00002*		0.00004***
		(0.00001)		(0.00001)
Human Capital and Demographics			X	X
Occupation Fixed-Effects	X	X	X	X
Time Fixed-Effects	X	X	X	X
F- Statistic	125	124	2512	2475
R-Squared	0.29	0.29	0.39	0.39
Observations	2,003,557	2,003,557	2,003,557	2,003,557
Routine (Lower Bound)	0.00105***	0.00126***	0.00066***	0.00078***
	(0.00011)	(0.00011)	(0.00010)	(0.00011)
Abstract (Lower Bound)	-0.00040***	-0.00018*	-0.00028***	-0.00012
	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Routine (Lower Bound) x Trend		-0.00011***		-0.00008***
		(0.00001)		(0.00001)
Abstract (Lower Bound) x Trend		0.00002*		0.00004***
		(0.00001)		(0.00001)
Human Capital and Demographics			X	X
Occupation Fixed-Effects	X	X	X	X
Time Fixed-Effects	X	X	X	X
F- Statistic	125	124	2512	2475
R-Squared	0.29	0.29	0.39	0.39
Observations	2,003,557	2,003,557	2,003,557	2,003,557

Note: The coefficients are presented above standard errors clustered on individuals where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.

Table A.7: Regression of Wages on Variation in 5-Digit SOC Task Content across Initial Occupation

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)	(5)	(6)
Routine, 2004	-0.00033***	-0.00002	-0.00195***	-0.00157***	-0.00040***	-0.00012***
	(0.00002)	(0.00004)	(0.00002)	(0.00004)	(0.00002)	(0.00003)
Abstract, 2004	0.00890***	0.00847***	0.00789***	0.00756***	0.00525***	0.00502***
	(0.00002)	(0.00003)	(0.00002)	(0.00003)	(0.00002)	(0.00003)
Routine, 2004 x Trend		-0.00012***		-0.00014***		-0.00010***
		(0.00001)		(0.00001)		(0.00001)
Abstract, 2004 x Trend		0.00016***		0.00012***		0.00009***
		(0.00001)		(0.00001)		(0.00001)
Human Capital Controls					X	X
Demographic Controls			X	X	X	X
Time Fixed-Effects	X	X	X	X	X	X
F- Statistic	3388	3333	5138	5057	6774	6672
R-Squared	0.19	0.19	0.27	0.27	0.33	0.33
Observations	1,828,445	1,828,445	1,828,445	1,828,445	1,828,445	1,828,445

Note: The coefficients are presented above robust standard error where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.

Table A.8: Regression of Wages on Variation in 5-Digit SOC Task Content from Occupation Change

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Routine, 2004	0.00132***	0.00100***	0.00067***	0.00024	0.00091***	0.00056**	-0.00035	-0.00058
	(0.00014)	(0.00020)	(0.00016)	(0.00023)	(0.00018)	(0.00029)	(0.00031)	(0.00036)
Abstract, 2004	0.01102***	0.01029***	0.01041***	0.00942***	0.01063***	0.00960***	0.00911***	0.00848***
	(0.00013)	(0.00018)	(0.00014)	(0.00020)	(0.00017)	(0.00026)	(0.00027)	(0.00031)
Routine, 2004 x Trend		0.00017**		0.00024***		0.00016		0.00041
		(0.00007)		(0.00008)		(0.00009)		(0.00028)
Abstract, 2004 x Trend		0.00036***		0.00049***		0.00043***		0.00090***
		(0.00007)		(0.00007)		(0.00009)		(0.00024)
Transition Type	E to U to E		E to E		E to E (Diff. Emp.)		E to E (Same Emp.)	
Time Fixed-Effects	X	X	X	X	X	X	X	X
F- Statistic	90	89	69	68	55	54	53	51
R-Squared	0.13	0.13	0.13	0.13	0.13	0.13	0.17	0.17
Observations	69,517	69,517	50,036	50,036	40,578	40,578	9,458	9,458

Note: The coefficients are presented above robust standard error where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.

Table A.9: Regression of Wages on Variation in 5-Digit SOC Task Content within Occupations

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)	(5)	(6)
Routine	0.00071***	0.00098***	0.00041***	0.00055***	0.00044***	0.00061***
	(0.00009)	(0.00010)	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Abstract	0.00016**	0.00012	0.00026***	0.00020***	0.00025***	0.00019***
	(0.00008)	(0.00008)	(0.00007)	(0.00007)	(0.00007)	(0.00007)
Routine x Trend		-0.00012***		-0.00007***		-0.00008***
		(0.00001)		(0.00001)		(0.00001)
Abstract x Trend		0.00004***		0.00005***		0.00005***
		(0.00001)		(0.00001)		(0.00001)
Demographics					X	X
Human Capital			X	X	X	X
Occupation Fixed-Effects	X	X	X	X	X	X
Time Fixed-Effects	X	X	X	X	X	X
F- Statistic	125	124	1440	1419	1840	1815
R-Squared	0.34	0.34	0.40	0.40	0.42	0.42
Observations	1,836,469	1,836,469	1,836,469	1,836,469	1,836,469	1,836,469

Note: The coefficients are presented above standard error clustered on occupations where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on individuals.

Table A.10: Regression of Wages on Variation in 5-Digit SOC Task Content within Occupations Controlling for Unobserved Heterogeneity

Dependent: Log Monthly Wage	(1)	(2)	(3)	(4)

Routine	-0.00021**	0.00003	-0.00075***	-0.00072***
	(0.00010)	(0.00010)	(0.00006)	(0.00006)
Abstract	0.00011	0.00017**	0.00193***	0.00192***
	(0.00007)	(0.00008)	(0.00005)	(0.00005)
Routine x Trend		-0.00010***		-0.00002
		(0.00001)		(0.00001)
Abstract x Trend		-0.00003***		0.00001
		(0.00001)		(0.00001)
Occupation Fixed-Effects	X	X	X	X
Individual-Employer Fixed-Effects			X	X
Individual Fixed-Effects	X	X		
Time Fixed-Effects	X	X	X	X
F- Statistic	146	146	157	155
R-Squared	0.04	0.04	0.01	0.01
Observations	2,003,557	2,003,557	2,003,557	2,003,557

Note: The coefficients are presented above standard errors clustered on individuals where significance is represented by * if p ≤ .1, ** if p ≤ .05, and *** if p ≤ .01. Results are generally robust to clustering on occupations.