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Abstract

At the heart of the Skill Biased Technical Change literature is a discussion of the temporal impact of technological change on wages. The narrative describes technological change as allowing for the increased codification of routine tasks which enables capital to become more easily substituted for occupations with a high degree of engagement in these tasks. Existing empirical analyses have focused on the impact of SBTC by examining repeated cross-sections of individuals using constant measures of occupational task requirements. This approach is unable to explore how wages respond to the time variant components of occupational task requirements. This analysis expands the existing literature by examining wage effects using a panel of occupational task requirements constructed from 19 releases of the O*Net database. The panel of occupational task requirements is combined with a micropanel of workers and used to estimate the returns to differential task requirements both within and across occupations. These estimates confirm previous empirical findings that have relied on repeated cross sections but show that controlling for individual fixed effects reduces the magnitude of estimates across occupations. In addition, the analysis develops a structurally derived fixed effects model that helps to provide evidence that the same wage effects are absent for changes to tasks within occupations. The within occupation estimates do, however, illustrate how cross-occupational dynamics and employment transitions might be playing a role in the observed cross-sectional estimates.

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I. Introduction

Over the last thirty years, the productivity of labor has increased drastically due to a technological paradigm shift that has been realized across all economic sectors. The modern U.S. labor market is often categorized as a knowledge intensive economy that relies heavily on an ever-increasing supply of human capital. The Skill Biased Technological Change (SBTC) hypothesis suggests that transformative technological innovations act as a substitute for low skilled (routine) labor and a complement to high skilled (non-routine) labor. The SBTC hypothesis suggests that the increased demand for highly educated workers has been the result of technological advances created by Schumpeter's Gale. The SBTC hypothesis relies on this narrative to explain observed growth in the wage differential between college educated and non-educated workers. The SBTC hypothesis links the increased demand for college educated workers in non-routine occupations to the observed polarization of the wage distribution. Existing empirical work on SBTC has provided extensive evidence confirming the implications of the theoretical exposition.

Autor (2014) provides a description of SBTC that outlines the dominant view that those tasks following explicit rules are more easily codified by technology. The codification of these tasks allows for them to be more easily substituted for capital in the production process. In contrast, human tasks that require judgment and tacit forms of knowledge are less easily codified. Instead, workers engaged in these tasks utilize capital to complement their efforts in the production process. Autor’s SBTC narrative suggests that the falling price of computing power is the primary driving force behind observed changes to the labor market. More specifically, the falling price of computing power is believed to have displaced workers with codifiable knowledge accomplishing explicit routine tasks while at the same time increasing the demand for workers with tacit knowledge accomplishing non-routine tasks.

The existing empirical work on SBTC has focused on examining differential returns to task requirements across occupations. These analyses have examined temporal changes to employment and wages while holding constant occupational task content. Although assuming a constant distribution of task content across occupations is realistic in the very short-term, the assumption becomes increasingly problematic with a longer time horizons. The assumption is problematic because of the possibility that significant changes to task content have occurred within occupations at differing rates. The absence of a panel of occupational task requirements has prevented economists from controlling for these dynamic effects. This analysis will expand the existing empirical literature related to the labor market impact of SBTC by assess cross-sectional and within occupation wage effects using such a panel. This empirical strategy allows for the reassessment of previous cross-sectional findings by accounting for occupational sorting on time invariant factors by applying a model with individual fixed effects.

This empirical analysis takes a task based approach to defining routine and non-routine labor in a similar fashion as many previous works on SBTC (Autor et al. 2003; Acemoglu and Autor 2011; Firpo et al 2011; and Autor and Handel 2013). As mentioned, these empirical studies have only examined these effects at the extensive margin using a cross-sectional or repeated cross-sectional analysis. Firpo et al. (2011), though asking a different question than is asked in this analysis, apply repeated cross-sections but assume a fixed level of occupational task engagement over time. Autor and Handel (2013) use a single cross section and utilize self-reported task engagement as the primary source of variation. In this analysis, we seek to explore whether these findings can be replicated using a model that allows occupational task engagement to vary but assuming an economy-wide wage premium. In addition, we control for individual fixed effects that may account for heterogeneous ability and cross-occupational sorting.

The findings from this analysis indicate that a large portion of the findings at the extensive margin may be driven by changes in occupational task requirements rather than differences in task premiums across occupations. The results also demonstrate that sorting of workers plays a key role in driving cross-sectional patterns. Estimates of this type have previously been unavailable in the literature. Although the analysis does not find wage effects after accounting for individual fixed effects, the author concludes that this may be due to nominal wage rigidities that cause technological change to manifest as employment transitions rather than through a worker's wage. These findings are of particular interest because they provide a new an interesting perspective on SBTC that has been previously unexplored.

II. Literature Review

The existing empirical work on SBTC has utilized repeated or single cross-sections of both workers and occupational task requirements. This analysis expands that body of literature by utilizing an individual panel of workers in combination with a panel of occupational task requirements. The resulting analysis allows occupational task requirements to evolve over time while accounting for individual heterogeneity and potential cross-occupation sorting based on unobserved ability. The motivation and many of the estimation equations used in the analysis are drawn from existing empirical works on SBTC but have been enhanced to accommodate panel data. As a result, it is important to understand the evolution of the SBTC theory and the empirical works that have preceded this analysis.

One of the most important works examining the empirical implications of SBTC was authored by Katz and Murphy in 1992. Katz and Murphy utilized a supply and demand framework to assess the change in patterns of wage differentials from 1932 through 1987. The authors combined 25 March releases of the Current Population Survey (CPS) and divided the sample into 320 subgroups by gender, level of education, and work experience. The authors found that the acceleration in the demand for highly skilled labor drove the major changes seen in the wage structure during the period. The conclusion the authors reach was that the changes to overall wage structure were significantly more favorable to college educated workers and that this was the primary force behind the increase in the supply of graduates.

Katz and Murphy's analysis is still extremely relevant to the literature for several important reasons. The author's acknowledgement that a significant change had occurred in the demand for specific occupations and industries helped pave the way for the task based analysis at the forefront of the literature today. In addition, they also discuss how these demand changes required a higher level of education than was previously necessary. This finding is synonymous with the observations discussed in the literature and widely accepted by modern labor economists.

Related work by Autor, Katz, and Krueger (1998) on SBTC began by empirically estimating the impact of technological change on the labor market. The authors did this by measuring the degree of computerization at the industry and occupation level. The authors' use a methodological framework over a significantly long timeframe while accounting for shifts in both supply and demand. They find that supply changes and the wage differential for college educated workers from 1940 to 1996 indicate a strong acceleration in the demand for skilled labor. The authors report that industries and occupations with a high degree of computer usage have expanded their demand for skilled labor as measured by the education level of the requisite workforce.

Autor continued his work using computerization as a proxy for technological change in 2003 with coauthors Levy and Murnane. The authors argue that computer capital can substitute for workers performing routine cognitive and manual tasks while complimenting workers performing non-routine tasks. They assume these tasks are imperfectly substitutable and find evidence of noticeable changes in the labor market as computerization increases. The author's combine the task input data from the 1960 to 1998 Dictionary of Occupational Titles (DOT) with a panel constructed from repeated cross-sections of the Census and Current Population Survey. The authors find that within industry, occupation, and educational groups have seen reduced demand for labor associated with routine tasks but increased demand for non-routine labor.

Autor and his coauthors identify two sources of variation in the interaction between task content and computer usage (Autor et al. 2003, p. 1292). They refer to the two sources of variation as the intensive and extensive margin. The extensive margin refers to cross-occupational observed changes in the distribution of employment over time holding task content fixed. The intensive margin, on the other hand, refers to within-occupational observed changes in the distribution of employment over time allowing task content to vary. Although the authors pay a considerable amount of detail to the intensive margin, they do not apply a fixed effects model account for unobserved ability or occupational sorting because of their repeated cross-sectional data.

The most important contribution of Autor et al. (2003) is the authors' fully developed argument that computer capital acts as a substitute for workers completing routine tasks and a complement for workers completing non-routine tasks that involve making uncertain decisions or communication. As has become the generally accepted narrative on SBTC, the authors posit that routine and non-routine labor are imperfectly substitutable with each other and capital. The authors attribute changes in the composition of job tasks and increased computerization to a reduced demand for routine tasks and an increased demand for non-routine labor.

In the paper, the authors translate shifts in the demand for specific tasks to changes into shifts in the demand for educated labor (as a proxy for relevant skills). They find that their model explains 60 percent of the growth of college educated labor from 1970-98. Much of the subsequent empirical work on SBTC has expanded on the 2003 work by Autor, Levy, and Murnane while still making use of the distinction between routine and non-routine labor. This clear distinction between routine and non-routine labor, as it relates to technological change, persists through the remainder of Autor's work (2011, 2012, 2013a, 2013b, 2014) on SBTC and has become a concept that is generally accepted in the literature today.

Christina Gathmann and Uta Schonberg (2010) make a significant contribution to the SBTC literature by examining employment dynamics using a panel constructed from German administrative records on individual workers. Specifically, the authors investigate the transferability of skills across occupations. They find that individuals are more likely to move to occupations with similar task requirements. The authors' findings indicate that the distance between the task content of an occupation and a workers individual's accumulated task-specific human capital is critical in the likelihood of selection into occupations with vastly different task content. The author's findings are in stark contrast to traditional models of labor mobility and human capital accumulation where path dependence is assumed to be nonexistent. Concluding the paper, the authors advocate for a task-based approach where skills are transferable across occupations and have an imperfect matching to task engagement.

Gathmann and Schonberg make substantial contributions towards investigating the effects of SBTC that occur at the intensive margin. The task indices they develop, however, are collected at the individual worker level but are comparable to those developed by Autor and others. The paper does not focus on the wage effects resulting from SBTC at the intensive margin but, rather, with skill transferability. The concluding statement of the paper that advocates on behalf of a task-based approach that allows for cross-occupation transferability can be considered a precursory motivation for the application of Roy models seen in much of the later literature.

Acemoglu and Autor's (2011) develop the most comprehensive theoretical exposition available about the relationship between SBTC, job content, and wages. A key part of their theoretical model relies on a distinction between employers' demand for tasks and workers' supply of skills. The model assumes a production function consisting of routine and non-routine labor. In the context of the model, labor can be thought of as a bundle of tasks differing across occupational categories. Skills supplied, in contrast, are accumulated through a workers attainment of human capital (education) and have an imperfect matching to tasks.

Acemoglu and Autor introduce technological change through shocks to factor productivity. The differing substitution parameter on these two types of labor demanded is what determines the magnitude and direction of the demand shifts. Workers are assumed to attain skills through education and then sort into different jobs based on task requirements. Their model articulates a fully developed supply and demand framework that can be used to derive comparative statics related to SBTC. This model has been used extensively in subsequent work on SBTC and expanded to accommodate empirical applications.

Firpo et al (2011). Develop a particularly notable work motivated heavily by the 2011 paper by Acemoglu and Autor. The author's utilize a cross-sectional Roy model to estimate the return to tasks across occupations. The application of a Roy model to a SBTC framework helps accommodate the proposed model described in the conclusion to Gathmann et al. (2010). The authors utilize a set of task indices updated from Autor et al. (2003) and augmented to utilize the O*Net database of occupational characteristics. The analysis applies this framework to repeated cross-sections of the CPS using a single release of the O*Net database. The authors assess how occupational tasks have contributed to changes in the wage distribution observed over the last two decades. The authors find that this model helps to explain much of the polarization reported in other empirical works on SBTC.

Firpo et al. (2011) include a passage that notes how their framework would be applicable to panel data. The authors posit that panel data could help shed light on how an individual workers' wage responds to changes in occupational task requirements and account for possible occupational sorting. The estimation equation used in this analysis is an extension of the model presented in Firpo (2011) while making several important additions to their analysis. In our analysis, the model is applied to a panel of workers as suggested by Firpo and his coauthors. This is accomplished by including a panel of occupational characteristics that measures the changing nature of task requirements over time. The use of panel data allow both for the role of unobserved, fixed-individual attributes, in explaining cross-sectional patterns of wage dispersion to be explored as well as the role of sorting of individuals through jobs over time. Prior analyses based on single or repeated cross-sections were limited to speculation about these factors and could not assess the effect of evolving occupational task requirements.

As mentioned, a set of task indices motivated by Autor et al. (2003) is used by Firpo et al. (2011); Autor and Handel (2013) refine these measures significantly in a more recent paper. In this most recent empirical assessment of the returns to differential occupational tasks, a survey of self-reported employment characteristics is used in conjunction with a single release of the O*Net economy-wide database of occupational characteristics. They apply a Roy model in the analysis that is motivated, in part, by the discussion presented in Acemoglu and Autor (2011) and refined by Firpo et al. (2011). The authors combine occupation-level task measures with self-reported task inputs and use the interaction to account for potential self-selection. Autor's self-selection refers to the comparative advantage that occurs when workers with high ability related to observed task measures sort into occupations with a higher wage premium for those tasks. Autor and Handel (2013) accomplish this by using a self-reported panel of workers with a Roy model.

Motivating this analysis is the goal of refining previous empirical works as well as exploring the effect of evolving task requirements on wages across and within occupations. As has been outlined most prominently by Autor et al. (2003), capital is substitutable for routine tasks because they are more easily codified. In contrast, capital is complementary to non-routine tasks that require tacit forms of knowledge. It seems natural to assume that over time technological change allows for capital to substitute for a greater degree of tasks that had been previously been considered non-routine. More specifically, technological change enhances the ability of capital to substitute for non-routine tasks by allowing for tacit knowledge to become increasingly codified. These effects describe a process that we would expect to be playing an important role on wages both within and across occupations.

III. Empirical Methods

The primary estimation equation used in this analysis takes the form of a Roy-type Model adapted from previous cross-sectional approaches used to estimate the effects of SBTC (Firpo at al. 2011; Autor and Handel 2013). The estimation equation was adjusted so that it could accommodate panel data and individual fixed effects. In addition, generalizable human capital was introduced as a total factor productivity term in the underlying production function. Again, the use of a fixed effects model with an individual level panel helps us to abstract from problems of occupational sorting and individual heterogeneity. In addition, combining our individual panel with the panel of occupational task requirements lets us investigate how individual wages respond to changes in occupational task requirements.

The production function necessary to accommodate these goals begins with a Cobb-Douglas framework seen in Equation 2. As mentioned previously, Autor and Handel (2013) use individual reported survey data to estimate a similar cross-sectional model and contrast those results with ones obtained from a single release of the O*Net database. Firpo et al. (2011), however, also use a similar estimation equation with a single release of the O*Net database but do so only using cross-sectional estimates. The estimation equation that follows is an extension of the model presented in Firpo et al. (2011) as well as Autor and Handel (2013) with several important alterations. These models both allow task premiums to vary across occupations and, as a result, are difficult to apply when the concern is with varying levels of task engagement within occupations.

We amend the model used by Firpo et al. (2011) and Autor et al. (2013) but restrict our examination to economy-wide task premiums rather than allowing them to vary by occupation. Instead, we allow for mean levels of task engagement to vary across and within occupations over time but examine only the cross-occupation premium paid for each task cluster. The distinction here is subtle because the resulting wage and employment implications will likely be quite similar. These cross-sectional estimates investigate changes in wages and employment while holding task requirements constant. As a result, the variation comes principally from changing premiums associated with task clusters that differ across occupations. In contrast, we hold premiums constant across occupations but allow the task requirements themselves to vary. Put differently, we investigate how wages react to changes in the way workers within occupations accomplish production.

We begin by presenting the basic components of the model applied by Autor et al. (2013) to examine differential task premiums using a cross-sectional survey of workers with self-reported levels of task engagement. Autor et al. (2013) begin by assuming that workers have an endowment of skills $\Phi_i = \left\{ \Phi_{i,2},\ \Phi_{i,2}, \dots,\ \Phi_{i,k} \right\}$ that represents a vector of task efficiencies. In this model, each element of Φ_i is a strictly positive number that measures the efficiency of a worker *i* at a task *k* and where a worker can perform $\Phi_{i,k}$ units of a given task *k* per period. Autor et al. (2013) describe the skill endowment as representing a stock of human capital resulting from a combination of education and innate ability.

The production function for worker *i* in occupation *s* is represented in Equation 1.

$$Y_{i,s} = exp\left(\alpha_s + \sum_k \lambda_{s,k}\phi_{i,k} + \mu_i\right) \tag{1}$$

Assuming workers are paid their marginal product, the resulting log wage equation from Autor and Handel's model is detailed in Equation 2.

$$w_i = \alpha_s + \sum_k \lambda_{s,k}\phi_{i,k} + \mu_i \tag{2}$$

The key assumption of the Autor's model is that workers take the production structure as given. Workers sort into occupations based on the associated task premiums that will maximize their output and resulting wage. This assumption is represented through the maximization problem outlined in Equation 3.

$$Y_i = \max_s\{Y_{i,1}, Y_{i,2}, \ldots, Y_{i,K}\} = \max_s\{\alpha_s + \ \Phi_i\Lambda_s{}'\} \tag{3}$$

The model used in this analysis is constructed in a similar fashion but has several key differences that allows us to control for time variant sorting based on unobserved heterogeneous ability that may be contributing to results estimated across occupations. Firpo et al. (2011) and Autor et al. (2013) and allow the task premiums to $\lambda_{s,k}$ vary across occupations and use this as the basis for how individuals sort into occupations. In this analysis, we are principally concerned with how variation in task content across and within occupations affects an individual's wage. Although we support the traditional SBTC narrative that suggests that task premiums vary across occupations, we assume that the 'law of one price' will hold across occupations for the premium associated with differing task clusters in an effort to make our estimation more tractable.

In a similar fashion as Autor et al. (2013), we begin by assuming that workers have an endowment of *j* skills each period $\Phi_{t,i} = \{\ \Phi_{t,i,1},\ \Phi_{t,i,2}, \ldots,\ \Phi_{t,i,j}\}$. However, unlike Autor, we also assume that a worker's endowment of skills correspond to a maximum possible level of task engagement $f\big(\Phi_{t,i}\big) \rightarrow \mathrm{T}_{\mathrm{t,i,k}}$ through an efficiency function. An individual acquires skills through task-specific human capital and combines them through the efficiency function to accomplish tasks. Task-specific human capital can be accumulated through some combination of education and innate ability. The assumption of an efficiency function allows for occupational sorting based on education and ability but accommodates our assumption that the 'law of one price' holds across occupations for premiums associated with differing task clusters. Another way to think about our 'law of one price' is that our model estimates the mean premium across all occupations for differing task clusters.

The production function for a worker *i* in occupation *s* is represented in Equation 4 where $L_{t,s,i} = \{1,0\}$ is a binary choice variable representing the decision of individual *i* to work in an occupation *s* at time *t*.

$$Y_{t,i} = \mathrm{A}_s \Psi_t \prod_{k=1}^{K} \mathrm{T}_{t,s,k}{}^{\lambda_{t,k}} L_{t,s,i}\, e^{\mu_{t,i}} \tag{4}$$

The resulting log wage equation from our model is detailed in Equation 5.

$$w_{t,i} = \alpha_s + \psi_t + \sum_{k} \lambda_{t,k} \tau_{t,s,k} + \mu_{t,i} \tag{5}$$

In our model, unlike that of Firpo et al. (2011) and Autor et al. (2013), we hold constant output elasticity $\lambda_{t,k}$ (i.e. the wage premium associated with each task) across occupations rather than allowing it to vary across occupations. We make this alteration so that we may ask whether changes in occupational task requirements have an impact on wages across occupations. As mentioned, we have also altered Autor's model by including an efficiency function that maps skills to occupational tasks. In doing this, we have assumed that sorting across occupations occurs through skill-task efficiency and that similarly skilled workers sort into occupations where the task requirements align with their skill. This assumption is represented through the maximization problem outlined in Equation 6.

$$Y_i = \max_s\{Y_{i,1}, Y_{i,2}, \dots, Y_{i,s}\} = \max_s\left\{\mathrm{A}_{t,s}\prod_{k=1}^{K}\mathrm{T}_{t,s,k}{}^{\lambda_{t,k}}L_{t,s,i}e^{\mu_i}\right\} = \max_s\left\{\mathrm{A}_{t,s}\prod_{k=1}^{K}f\left(\Phi_{t,i,k}\right)^{\lambda_{t,k}}L_{t,s,i}e^{\mu_i}\right\} \qquad (6)$$

Autor and Handel (2013) utilize data on an individual's reported engagement in tasks $\mathrm{T}_{s,i}$ at a single point in time. In this analysis, however, the data is obtained from aggregating task engagement measures by cluster across occupations at different periods of time. The level of occupational task engagement can be thought of as the mean level of task engagement across individuals working in a given occupation or, put differently, the occupational production requirements necessary to produce a single unit of output. According to the maximization presented in Equation 6, we must assume that in equilibrium an individual's task engagement will converge to the occupational requirements. This condition will hold if the cost associated with changing occupations is sufficiently high and firms can observe the production performance of each worker.

The dynamics necessary for mean task convergence

Imagine that the marginal product of labor for worker *i* were less than the mean level for a comparable worker in the same occupation $w_{t,i}\left(\mathrm{T}_{t,i,1}, \mathrm{T}_{t,i,2}, .., \mathrm{T}_{t,i,k}\right) < w_{t,s}\left(\mathrm{T}_{t,s,1}, \mathrm{T}_{t,s,2}, .., \mathrm{T}_{t,s,k}\right)$ but that the wage rate received by worker *i* is equal to the mean occupational level $\widetilde{w}_{t,i} = w_{t,s}$ but greater than their actual marginal product of labor. In this case, the worker is over paid relative to other comparable workers who are a better match to the task requirements of occupation *s*. Although the firm is assumed to only observe, $\mathrm{T}_{t,s,k}$ rather than $\mathrm{T}_{t,i,k}$ at the time an employment arraignment begins, convergence to a mean level of task engagement requires that eventually $\mathrm{T}_{t,i,k}$ is perfectly observable to the employer. We assume convergence to mean levels of task engagement across occupations which implies that worker *i* will be replaced by the firm for another worker *j* who has a comparative advantage in occupation *s* shown through $Y_{t,i}(\mathrm{T}_{t,i,1}, \mathrm{T}_{t,i,2}, .., \mathrm{T}_{t,i,k}) < Y_{t,j}(\mathrm{T}_{t,s,1}, \mathrm{T}_{t,s,2}, .., \mathrm{T}_{t,s,k})$.

In contrast, imagine that the marginal product of labor for worker *i* were more than the mean level for a comparable worker in the same occupation $w_{t,i}(\mathrm{T}_{t,i,1}, \mathrm{T}_{t,i,2}, .., \mathrm{T}_{t,i,k}) > w_{t,s}(\mathrm{T}_{t,s,1}, \mathrm{T}_{t,s,2}, .., \mathrm{T}_{t,s,k})$ but that the wage rate received by worker *i* is equal to the mean occupational level $\widetilde{w}_{t,i} = w_{t,s}$. In this case, the worker is under paid relative to other comparable workers who are a better match to the task requirements of occupation *s*. Although the worker is assumed to imperfectly observe, $\mathrm{T}_{t,s,k}$ at the time an employment arraignment begins, convergence to a mean level of task engagement requires that eventually$\mathrm{T}_{t,i,k}$ is perfectly observable to the worker. Again, we assume convergence to mean levels of task engagement across occupations which implies that the worker *i* will seek employment in another occupation *r* where they have comparative advantage shown through $Y_{t,i}(\mathrm{T}_{t,i,1}, \mathrm{T}_{t,i,2}, .., \mathrm{T}_{t,i,k}) > Y_{t,j}(\mathrm{T}_{t,s,1}, \mathrm{T}_{t,s,2}, .., \mathrm{T}_{t,s,k})$.

The dynamics of mean task convergence indicate that, in equilibrium, the expected level of task engagement for any given worker is equivalent to the occupational requirements in that period. This condition implies that the endowment of skills across any given worker in an occupation are, on average, equivalent as a result of task efficiency maximization. The implication is that we assume that workers seek to maximize tasks but that, through the task efficiency mapping, they are constrained by their skill endowment. In equilibrium we expect that similar workers, in terms of skill endowments, sort into the same occupations due to these dynamics.

Estimating the economy-wide returns to tasks

The production function from Equation 4 can be further amended to accommodate generalizable human capital. We differentiate generalizable human capital with occupation-specific human capital that, along with ability, determines an individual's skill endowment. Unlike occupation-specific human capital, we consider generalizable human capital to be soft-skills that make a worker more productive in any occupation. We assume that generalizable human capital enters the production function as total factor productivity and show the amended production function in Equation 7.

$$Y_{t,i} = \mathrm{A}_s \Psi_t H_{t,i} \prod_{k=1}^{K} \mathrm{T}_{t,s,k}{}^{\lambda_{t,k}} L_{t,s,i} e^{\mu_{t,i}} \tag{7}$$

In Equation 8, we specify that generalizable human capital term is a function of individual ability (Δ_i), education ($E_{t,i}$), and experience ($EXP_{t,i}$).

$$H_{t,i} = \Delta_i E_{t,i}{}^{\beta_1} EXP_{t,i}{}^{\beta_2} EXP_{t,i}{}^{2\beta_3} \tag{8}$$

Assuming that workers are paid the marginal product for their occupation, the resulting log wage equation for an individual in occupation *s* at time *t* is seen in Equation 9. In Equation 9, the output elasticity of each task can be interpreted as an economy-wide premium that the worker receives for engagement is each requisite task.

$$w_{t,i} = \alpha_s + \psi_t + h_{t,i} + \sum_k \lambda_{t,k} \tau_{t,s,k} + \mu_{t,i} \tag{9}$$

The primary estimation equation used in the empirical analysis is derived from Equation 9 and shown in Equation 10. It now becomes clear that generalizable human capital takes a Mincerian form.

$$w_{t,i} = \alpha_s + \delta_i + \psi_t + \beta_1 e_{t,i} + \beta_2 exp_{t,i} + \beta_3 exp_{t,i}{}^2 + \sum_k \lambda_{t,k} \tau_{t,s,k} + \mu_{t,i} \tag{10}$$

Although, our analysis is conducted using several distinct estimation procedures, Equation 10 serves as the backbone of our empirical methodology. We make minor modifications to Equation 10 throughout the analysis by including various fixed effects to identify the source and magnitude of the variation. Recall that we assume that the 'law of one price' applies to the premium associated with each distinct task-cluster. This assumption differentiates our model from previous cross-sectional applications that have applied a similar estimation procedure but allowed the task premium to vary across occupations. As discussed previously, the motivation for our framework is to analytically inquire whether changes in occupational task requirements create observable changes in an individual's wage.

IV. Data Overview and Descriptive Statistics

The data used in the analysis combines a panel of individuals and their work activities with a panel of occupational task requirements. The advantage of this combination is that it allows us to extend the analysis presented in previous empirical studies on SBTC (Firpo et al. 2011; Autor et al. 2013). The individual level panel helps account for sorting across occupations by allowing us to apply a fixed effects model that accounts for heterogeneous ability levels. The panel of occupational task requirements, on the other hand, allows for an analysis of wage effects within occupations. Specifically, we ask how an individual's wages are impacted by evolving occupational task requirements. Combining these two panels, and creating the variable of interest, requires some particular attention.

The Survey of Income Program Participation (SIPP) was used to construct the individual panel. 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 has the necessary components to conduct this analysis. The SIPP has detailed occupational codes, frequent interviews, and a large sample. Compared to the Current Population Survey, its main advantage is its longitudinal nature that allows job changes and individuals 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 occupational codes are 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.

The 2004 and 2008 SIPP panels were combined to create an unbalanced panel of approximately two million observations. Specifically, the combined panel spanned the period from February 2004 through December 2012 with some months missing due to breaks in the survey. The sample was restricted to prime working age individuals between 25 and 55 years old who were not in the military. The combined panels have a total of 61,606 individuals observed on average 29 times each for a total of 2,397,907 observations.[†] The descriptive statistics for variables used in the empirical analysis are presented in Table 1.

Table 1

Descriptive Statistics from Combined 2004 and 2008 SIPP Panels

	Period	N	n	T-bar
Sample Characteristics	10/2003-11/2012	2,397,907	81,606	29
	Sample		BLS	
2-Digit SOC	22		22	
3-Digit SOC	85		94	
	Mean		Std. Dev.	
Hourly Wage	$14.7		$51.7	
Log Hourly Wage	2.8		0.6	
Age	40.2		8.8	
Years of Education	14.9		3.3	
Usual Weekly Hours Worked	35.7		16.4	
Occupational Experience	13.7		55.1	
	Hourly		Salaried	
Mean Hourly Wage	$14.7		$15.2	
Type of Worker	53.8%		46.2%	
	Male		Female	
Sex	50.2%		49.8%	
	2004		2008	
Panel	51.0%		49.0%	
	Less than High School	High School	College	Post-college
Education	9.9%	28.1%	29.7%	32.3%
	Caucasian	African American	Asian or Pacific Islander	American Indian
Race	77.6%	13.4%	4.2%	4.8%

† These figures vary based on the specification used in each part of the analysis. This is due to unreported occupational codes and other factors.

The dependent variable, average hourly wage from primary employment, was reported in the SIPP for non-salaried employees. Although the average hourly wage was not directly reported for salaried employees, it was estimated by dividing the total earned income for the observation month by the number of weeks worked in the month and the number of usual hours worked per week. The characteristics of each individual's primary job were the only ones utilized in the analysis. Any information on an individual's secondary job as well as information pertaining to self-employed individuals was disregarded.

The panel of occupational task requirements was constructed using several releases of the O*Net developer database. The data from the O*Net database were combined with several releases of the Occupational Employment Statistics (OES) national employment estimates. Specifically, a total of 14 releases of the O*Net database spanning from November 2003 through July 2013 were combined with 12 releases of the OES estimates from November 2003 to May 2012. The OES employment figures were used only to weight the O*Net task requirements so that they could be utilized at different occupational aggregation levels.[‡] The O*Net task variables were weighted using the OES employment estimates in an effort to alleviate any potential measurement error in the original task requirements.

The variables used in the primary analysis align with the indices created by Autor and Handel (2013). The task indices should not be thought of as specific tasks. Rather, these indices can be thought of as measuring the mean level of occupational engagement in task clusters. These clusters are characterized by utilizing similar processes to accomplish their goals. An example of this might be dealing with vendors outside of a company as compared to dealing with subordinates. These two activities are certainly considered distinct tasks with differing goals but would both be considered

[‡] A more detailed exposition of the data aggregation process is outlined in the appendix.

part of the interpersonal task cluster. As previously mentioned, prior analyses utilized only a single release of the O*Net database and could not assess the degree to which individual wages respond to changes in occupational task requirements.

The task indices used by Autor and Handel (2013) include tasks considered abstract, routine, and non-routine manual. The motivation behind these indices is based in how inherently codifiable the tasks are and how technology interacts with workers engaged in them. We would expect workers employed in occupations that can be characterized by high levels of engagement in abstract tasks to have higher relative wages. This is because, according to the SBTC theory, the tasks that characterize these occupations would be complementary to new technology and increase demand. The same would be true for occupations characterized by high levels of engagement in non-routine manual tasks while the reverse would be true for routine tasks. The Autor et al. (2013) task cluster definitions in the context of their layout in the O*Net database is displayed in Table 2.

Table 2

O*Net Variables Included in the Task Indices

O*Net Survey Variable	Autor at al. (2013) Task Indices				
	Abstract		Routine		Non-routine
	Analytical	Interpersonal	Cognitive	Manual	Manual
O*Net: Abilities					
Spatial Orientation					X
Manual Dexterity					X
O*Net: Work Activities					
Analyzing Data or Information	X				
Thinking Creatively	X				
Controlling Machines and Processes				X	
Operating Vehicles, Mechanized Devices, or Equipment					X
Interpreting the Meaning of Information for Others	X				
Establishing and Maintaining Interpersonal Relationships		X			
Guiding, Directing, and Motivating Subordinates		X			
Coaching and Developing Others		X			
O*Net: Work Context					
Spend Time Using Your Hands to Handle, Control, or Feel Obj., Tools, or Controls					X
Spend Time Making Repetitive Motions				X	
Importance of Being Exact or Accurate			X		
Importance of Repeating Same Tasks			X		
Structured versus Unstructured Work			X		
Pace Determined by Speed of Equipment				X	

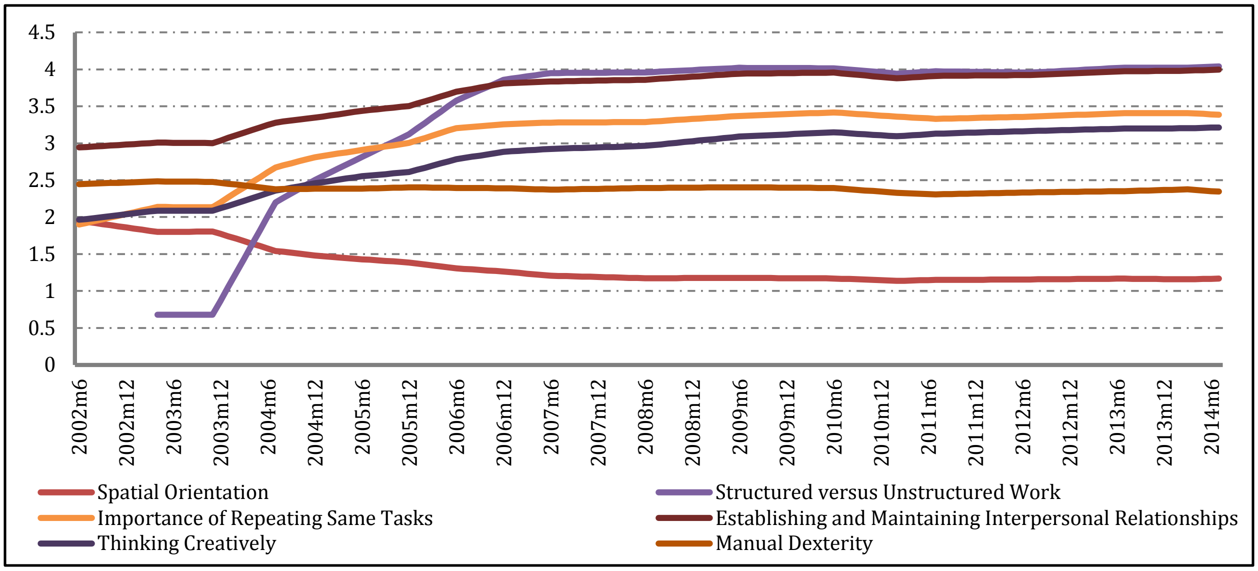
Autor (2013) outlines the need for a shared definition of task measures. Specifically, he argues that comparing the contributions of new analyses becomes increasingly difficult without consistent measures of task engagement. It is with this notion in mind that we adopt the most recent definitions used by Autor et al. (2013) for the primary variable of interest in our analysis. A large contribution of our analysis comes from our emphasis on presenting temporal sources of variation that occur within occupations. A consistent measure of tasks between our work and previous empirical applications helps to provide the necessary foundation for our contribution.

The importance of constructing a panel of occupational task measures is illustrated in Figure 1 where the weighted cross-occupational average of six of the total 16 components that underlie Autor's three task indices is presented from 2002 through 2013.[§] The measures presented in Figure 1 are from 19 distinct releases of the O*Net database and have been weighted based on 6-digit employment averages for the period. The variables were linearly trended on a monthly basis between each of the O*Net releases. Figure 1 illustrates that, over the long-run, the way that occupations accomplish production is changing and that the components underlying each of Autor's task indices are experiencing different patterns of growth. A single cross-sectional release of occupational task measures is unable to capture the dynamics underlying this process and is unable to explore how these dynamics might be playing a role in determining wage effects within and across occupations.

[§] Figures that display all of the 16 components disaggregated by each of Autor's task indices are contained in the appendix.

Figure 1

Weighted Cross-Occupation Average for Select Components of the Autor's Task Indices, 2002-13



Blinder (2007) and Firpo et al. (2011) assign a Cobb-Douglas weight of 2/3 to importance and 1/3 to level. Autor and Handel (2013), however, only rely on the level component of the O*Net measures. In our construction of these measures, we utilize only the level category for work abilities and activities while the context category was the only used for the work context variables.[**] Following Autor and Handel (2013) we use the first component from a principal components analysis to create each of the three task indices at the 2 and 3-digit SOC aggregation level.

One particular concern with the task indices might be cross-correlation between the components. Table 3 reports the results from a cross-sectional regression of the bivariate relationships between each of the indices. The sign and magnitude of the coefficients on these estimates are as we would expect. In addition, the signs indicate a relationship between the variables that align with the relationship espoused by Acemoglu and Autor (2011).

[**] The level and context categories have similar meanings across the broader O*Net task groupings.

Table 3

Cross-sectional Regressions of Bivariate Relationships between O*Net Indices

	(1)	(2)	(3)	(4)	(5)	(6)
LHS:	Non-routine Manual	Abstract	Routine	Non-routine Manual	Abstract	Routine
Abstract	-0.51***			-0.62***		
	(0.00)			(0.00)		
Routine		-0.19***			-0.21***	
		(0.00)			(0.00)	
Non-routine Manual			0.43***			0.28***
			(0.00)			(0.00)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
SOC Level	3	3	3	2	2	2
R-squared	0.32	0.35	0.69	0.37	0.32	0.63

V. Estimation Results

We first present a cross-sectional regression using an identical set of variables as that used by Autor and Handel (2013). Autor and Handel utilize this framework with a single release of O*Net data as well as with a survey of self-report task engagement. As mentioned previously, the task indices presented were created from the panel of O*Net database releases rather than a single release of that data and are reported at the occupation level. In the context of our model, an individual worker's relative wage is a function of a vector of human capital covariates ($h_{t,i}$), engagement in specific tasks ($\tau_{t,s,k}$), a vector of person-level covariates ($x_{t,i}$), and a time fixed effect (ψ_t). The estimation equation used in the cross-sectional estimates can be seen in Equation 11.

$$w_i = \psi_t + \beta_m h_i + \sum_k \lambda_k \tau_{s,k} + \beta_n x_{t,i} + t + \mu_i \tag{11}$$

Table 4 reports the result of a pooled cross-section of the three task indices regressed on log wages. The first specification shows the results for the control values alone. The second and third specification are built using the three task indices aggregated at the 3-digit SOC level while the fourth and fifth utilize the 2-digit aggregation level. Again, the coefficients on the cross-sectional regressions in Table 4 represent the relative return of the three task indices across occupations from 2004-12.

Table 4

Cross-sectional Regressions of Standardized Log Hourly Wage on O*Net Task Indices

LHS: Standardized Wage	(1)	(2)	(3)	(4)	(5)
Abstract		0.45***	0.27***	0.41***	0.24***
		(0.00)	(0.00)	(0.00)	(0.00)
Routine		-0.32***	-0.16***	-0.13***	-0.04***
		(0.00)	(0.00)	(0.00)	(0.00)
Non-routine Manual		0.15***	0.08***	0.10***	0.05***
		(0.00)	(0.00)	(0.00)	(0.00)
Less Than High School	-0.36***		-0.28***		-0.32***
	(0.00)		(0.00)		(0.00)
Some College	0.20***		0.13***		0.13***
	(0.00)		(0.00)		(0.00)
College	0.69***		0.48***		0.48***
	(0.00)		(0.00)		(0.00)
Post-college	1.17***		0.92***		0.92***
	(0.00)		(0.00)		(0.00)
Age	0.09***		0.09***		0.09***
	(0.00)		(0.00)		(0.00)
Sq(Age)	-0.00***		-0.00***		-0.00***
	(0.00)		(0.00)		(0.00)
Female	-0.36***		-0.35***		-0.37***
	(0.00)		(0.00)		(0.00)
African American	-0.23***		-0.18***		-0.20***
	(0.00)		(0.00)		(0.00)
American Indian	0.00		0.02***		-0.03***
	(0.00)		(0.01)		(0.00)
Asian or Pacific Islander	-0.10***		-0.06***		-0.09***
	(0.00)		(0.00)		(0.00)
Full-time > 35 Hours	0.25***		0.16***		0.20***
	(0.00)		(0.00)		(0.00)
Part-time	-0.10***		-0.10***		-0.12***
	(0.00)		(0.00)		(0.01)
Time FE	Yes	Yes	Yes	Yes	Yes
SOC Level	N/A	3	3	2	2
R-squared	0.28	0.17	0.32	0.13	0.30

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: The results presented cluster standard errors at the individual level. The results are also robust to clustering at the occupation level.
Note 3: The total number of observations is N= 800,966 with the 3-digit specifications and N= 1,306,568 with the 2-digit specifications.

The specification without controls and at the 3-digit level estimates that a one standard deviation increase in the abstract task index results in a 45 percent standard deviation increase in the log of hourly wage. After adding controls to the 3-digit specification, we see that the coefficient on the abstract task index drops to .27 but remains statistically significant in both specifications. Similarly, the coefficient is .41 and statistically significant at the 2-digit level but drops to .24 when the controls are added. The results indicate that as the mean level of engagement in abstract tasks increases across occupations, it is matched by an increase in the relative wage level.

At the 3-digit level and without controls, we can interpret a one standard deviation increase in the routine task index as resulting in 32 percent standard deviation decrease in the log of hourly wage. After adding controls to the 3-digit specification, we see that the coefficient on the routine task index drops in magnitude to .16 but remains statistically significant in both specifications. Similarly, the coefficient is .13 and statistically significant at the 2-digit level but drops to .04 when the controls are added. The results indicate that as the mean level of engagement in routine tasks increases across occupations, it is matched by a decrease in the relative wage level.

Again, we can interpret a one standard deviation increase in the non-routine manual task index as resulting in 15 percent standard deviation decrease in the log of hourly wage when estimated without controls and at the 3-digit level. After adding controls to the 3-digit specification, we see that the coefficient on the routine task index drops in magnitude to .08 but remains statistically significant in both specifications. Similarly, the coefficient is .10 and statistically significant at the 2-digit level but drops to .05 when the controls are added. The results indicate that as the mean level of engagement in non-routine manual tasks increases across occupations, it is matched by an increase in the relative wage level.

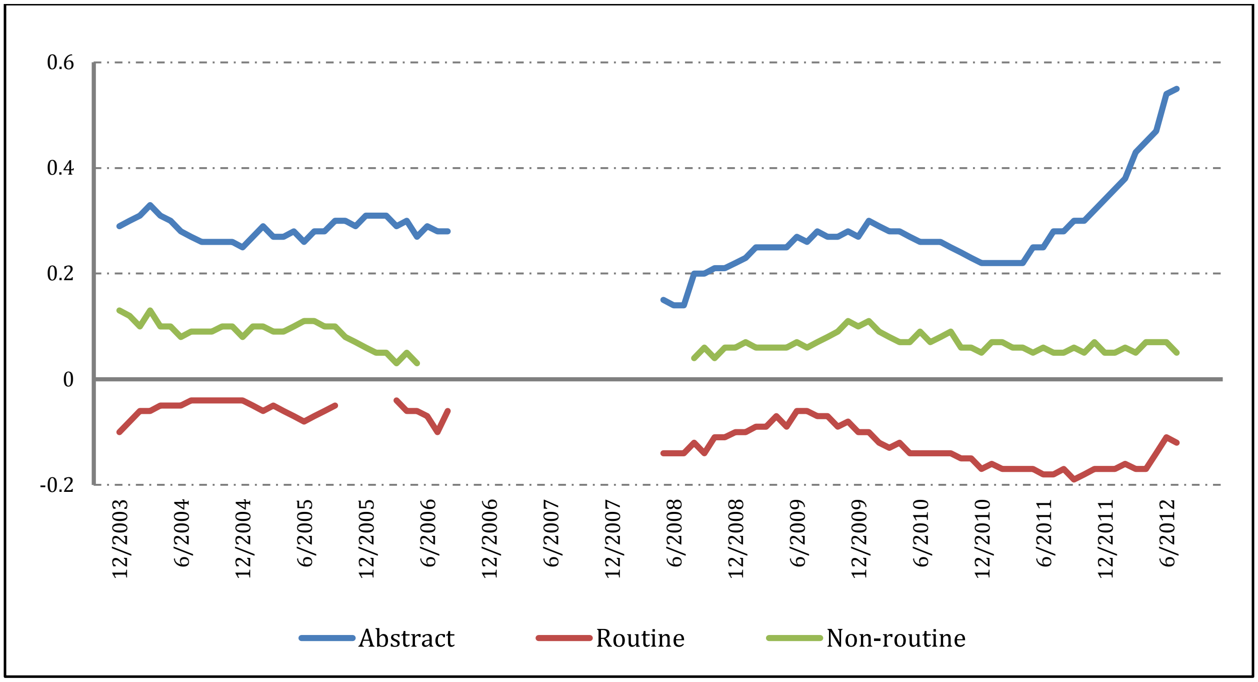
The results align quite well with the theoretical motivation outlined by Acemoglu and Autor (2011). As expected, task requirements that necessitate a worker engage in activities that are not easily codifiable cannot be substituted for capital in the production process. The result is that these occupations, whether they require high cognitive ability (Abstract) or simply irregular movements and decision making (Non-routine Manual), have experienced a significant demand shift that has resulted in changes to the wage distribution. This demand shift is the result of changing occupational task requirements driven by technological progress that has occurred over the last half century.

The results in Table 4, however, are merely cross-sectional and presented only for descriptive purposes. It is unclear that where the variation is coming from in the results obtained from the pooled cross-section. It could be that variation in wages is coming from variation in task engagement across occupations, through changes occurring within occupations over time, or from both these sources. The analysis will address both of these sources of variation individually using a panel data models that can identify the direction and source.

The same cross-sectional regression presented in Equation 1 was also applied at each observation month in the panel. The results of this rolling cross-sectional regression are presented in Figure 2. It is clear from the rolling cross-section that the relative return to the three task indices vary drastically over time. It also appears that these returns are responsive to fluctuations in the business cycle. As is illustrated in Figure 2, it is difficult to determine the true returns from the three task indices using a cross-sectional approach because we cannot distinguish between changing occupational task requirements and labor market fluctuations.

Figure 2

Rolling Cross-sectional Regressions of Standardized Log Hourly Wage on O*Net Task Indices



Note 1: The coefficients are only presented when they were found to have a p-value that was at least the .1 level of significance.
Note 2: The sample was restricted to individuals who remained in the entire sample to alleviate any potential attrition bias.
Note 3: Observations were eliminated after the eighth wave of the 2004 panel because the sample size was considerably reduced due to federal budget cuts and the sample size became a problem when accounting for attrition bias.

The structural model constructed in Equation 10 is used as the basis for estimating the between and within estimator. The results of these two models are presented in Table 5. The between estimator examines only cross-sectional variation of occupational task engagement while the within estimator relies on the time series variation of these measures. The first and second specifications estimate the between effects at the 3 and 2-digit SOC level. The third and fourth specifications, on the other hand, estimate the within effects at the 3 and 2-digit SOC level. The contrast between these two estimation procedures help to identify the direction of the variation within the panel.

Table 5

Between and Within Effects Regressions of Standardized Log Hourly Wage on O*Net Task Indices

LHS: Standardized Wage	(1)	(2)	(3)	(4)
Abstract	0.41***	0.37***	0.16***	0.16***
	(0.01)	(0.01)	(0.01)	(0.01)
Routine	-0.30***	-0.09***	-0.13***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)
Non-routine Manual	0.21***	0.16***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Years of Education	0.07***	0.08***	0.06***	0.06***
	(0.00)	(0.00)	(0.01)	(0.01)
Age	0.08***	0.08***	0.09***	0.10***
	(0.00)	(0.00)	(0.01)	(0.01)
Sq(Age)	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
SOC Level	3	2	3	2
Within R-squared	0.08	0.08	0.08	0.08
Between R-squared	0.21	0.20	0.21	0.20
Overall R-squared	0.20	0.19	0.20	0.19

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: The results presented cluster standard errors at the individual level. The results are also robust to clustering at the occupation level.
Note 3: The total number of observations is N= 800,966 with the 3-digit specifications and N= 1,306,568 with the 2-digit specifications.

The first and second specification in Table 5 report that a one standard deviation difference in the abstract index between occupations corresponds with a 0.41 standard deviation increase in the log of hourly wages at the 3-digit SOC level and a 0.37 standard deviation increase at the 2-digit SOC level. These specifications report that as engagement in the routine index between occupations increases by one standard deviation, wages decrease by 0.30 standard deviations at the 3-digit SOC level and 0.09 standard deviations at the 2-digit SOC level. A one standard deviation difference in the level of engagement in the non-routine manual index corresponds with a 0.21 increase in wages at the 3-digit SOC level and a 0.16 increase in wages at the 2-digit SOC level. The between occupation variation observed in our panel corresponds with the SBTC hypothesis where occupations with engagement in less easily codified tasks are characterized by relatively higher wages because of historic and current trends in technological progress.

The third and fourth specification in Table 5 report the within estimator for the same variables. At first glance, these specifications seem to indicate that, after accounting for heterogeneous ability, the direction of the variation from changing task requirements within occupations is consistent with the estimates across occupations. Although the magnitude of these estimates are tempered, the results seem to indicate that an individual's wages may respond to evolving occupation levels of task engagement. It is possible, however, that these within estimates are driven solely by individuals changing occupations as our specification does not properly account for individuals whose level of task engagement changes because they obtained a new occupation. Specifically, we raise the possibility that the within estimator specification presented in Table 5 may be picking up cross-sectional variation from individuals changing occupations.

We further investigate the possibility that our initial within estimator specifications were picking up cross-sectional variation from individuals changing occupations in Table 6. Table 6 reports the results of eight distinct fixed effects specifications that help to identify the source of variation presented in Table 5.[††]. The individual fixed effects shown in Table 6 control for individual heterogeneity while the occupation fixed effects control for individuals changing occupations within our sample. Additionally, we add employer fixed effects to control for changes in an individual's wage that may arise from switching employers.

[††] The specifications were also run with the standard errors clustered at each requisite occupation level. The results were consistent with those presented in Table 5 and have been omitted for parsimony.

Table 6

Fixed effects Regressions of Standardized Log Hourly Wage on O*Net Task Indices

LHS: Standardized Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abstract	0.16***	-0.01	0.16***	0.00	0.16***	-0.01	0.16***	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Routine	-0.13***	0.00	-0.13***	0.00	-0.08***	-0.01	-0.08***	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Non-routine Manual	0.05***	-0.01	0.05***	-0.01	0.05***	0.03**	0.05***	0.03*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Years of Education	0.06***	0.05***	0.06***	0.05***	0.06***	0.06***	0.07***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	0.09***	0.09***	0.10***	0.09***	0.10***	0.09***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sq(Age)	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	No	Yes	No	Yes
Employer FE	No	No	Yes	Yes	No	No	Yes	Yes
SOC Level	3	3	3	3	2	2	2	2
Within R-squared	0.08	0.10	0.08	0.10	0.08	0.09	0.08	0.10
Between R-squared	0.21	0.30	0.22	0.30	0.20	0.27	0.21	0.27
Overall R-squared	0.20	0.28	0.21	0.29	0.19	0.25	0.20	0.25

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: The results presented cluster standard errors at the individual level. The results are also robust to clustering at the occupation level.
Note 3: The total number of observations is N= 800,966 with the 3-digit specifications and N= 1,306,568 with the 2-digit specifications.

The nuances of these fixed effects and the insight they afford are important for understanding how workers and firms respond to technological change. The first and fifth specifications presented in Table 6 include only individual fixed effects and are the same as those presented in Table 5. Again, individual fixed effects help create control for unobserved ability bias and estimate the impact of changing occupational task requirements within occupations. The second and sixth specifications include occupation fixed effects that control for individuals who change occupations and account for any remaining cross-sectional variation in the within estimate from Table 5. The third and seventh specifications include the employer fixed effects that control for changes in an individual's wage that might arise from changing employers. Finally, the fourth and eighth specifications include all three fixed effects together.

The second and sixth specification presented in Table 6 includes both an individual and occupation fixed effect. This fixed effect controls for each individual in the sample separately for each occupation they are observed working. Although this specification limits the variation more than the individual fixed effects alone, it still suffers from an inability to control for individuals changing employers while working in the same occupation. The coefficients reported in the second and sixth specifications becomes completely insignificant.

The second and sixth specifications from Table 6 indicate that, in the short-run, an individual's wage is not affected by within occupation changes to the level of engagement in easily codifiable tasks. According to the results in Table 6, we would expect an increase in the mean level of engagement in easily codfiable tasks to have no statistically significant impact on wages for those individuals who remained in the same occupation. It appears that the within estimator reported in the third and fourth specification of Table 5 and in the first and fifth specification of Table 6 is being completely driven by cross-sectional variation. Specifically, the variation identified in these specifications was being driven solely by individuals changing occupations.

The third and seventh specifications presented in Table 6 include an employer fixed effect along with an individual fixed effect but not an occupation fixed effect. The occupation fixed effect controls for each individual in each employer (but not each occupation) that they are observed working in the sample. This specification limits the variation by observing only changes in wages that come from an individual in the same employer during the period but allows for variation from individuals who change occupations within the same employer. Interestingly, the coefficients change back to those observed with individual fixed effects and indicate that individuals changing employers within the same occupation is having little effect on our results.

The fourth and eighth specifications presented in Table 6 include both an occupation and employer fixed effect along with individual fixed effects. These specification controls for each individual in each employer that they are observed working in the sample and each occupation that they are employed. This specification limits the variation by observing only changes in wages that come from an individual in the same occupation and employed at the same employer during the period. Again, the coefficients become statistically insignificant when the occupation fixed effects are added.

As discussed previously, the SBTC hypothesis describes technology as being complementary to non-routine labor that relies on tacit knowledge and a substitute for routine labor defined by easily codifiable tasks. . The SBTC hypothesis tells us that new technology can more easily substitute (or compliment) for routine (non-routine) tasks. As a result, we would expect to see an individual's wage respond to occupational changes in relative levels of task engagement. We would also expect for the wage of occupations with increasing levels of engagement in routine tasks to decrease. In contrast, we would expect the wage of occupations with increasing levels of engagement in non-routine tasks to increase In the short-run, however, we do not observe that within occupation changes task engagement corresponds with changes to an individual's relative wage.

We have been careful in the above descriptions to include the "short-run" caveat to all of our findings. We did this because one might be concerned that our analysis focuses on immediate wage responses. The literature, however, is rich with analyses that provide evidence that wages suffer from short-run rigidities. Along these lines, it seems plausible that our findings are restricted by our focus on immediate responses and cannot fully capture any impact. Further, the evidence presented in Table 5 and 6 shows that there are observed wage effects from people changing occupations. Although it could be that our inclusion of individual fixed effects simply eliminated all of the variation observed in the cross-section, it is plausible that the cross-sectional results are driven by employment transitions. More specifically, we postulate that we are unable to observe wage effects within occupations because changes in task engagement manifest through employment transitions due to nominal wage rigidities.

Imagine that engagement in routine tasks increases for a particular occupation over time. It seems logical to infer that something about that occupations way of accomplishing production has changed. The SBTC hypothesis would lead us to believe that labor in this occupation engages in tasks that are more easily codified as a result of the occupation becoming more routine. Initially, we would have expected to see the changes occurring within occupations to result in the same wage effects that have been observed across occupations. Although our findings did not yield these results, it is possible that nominal wage rigidities and section on time variant unobservable are driving these results. The fact that we are able to observe within variation using the specification that includes individuals who change occupations is particularly interesting. This finding seems to indicate that a smaller but observable effect appears through wage differentials across occupations resulting from employer-to-employer transitions but not within occupation.

VI. Robustness Checks

The results presented in this analysis indicate an interesting new story about the impact of technological change. These results, however, require additional empirical inquiry. The purpose of this section is to present several robustness checks as well as an alternative estimation equation that serve to verify the results from the original analysis. The initial specification indicates that using an individual level panel in conjunction with a panel of occupational task requirements provides additional insight into the nature and impact of SBTC on wages. The robustness checks presented in this section add a level of validity to the findings from the original analysis and verify the hypothesis discussed in that requisite section.

This section details the results from two different robustness checks on the original specification and estimation equation. The first robustness check extends the original monthly interval between observations from a single month to eight months. The second test involves using a forward rolling three month average of an individual's hourly wage as the dependent variable rather than the observed monthly wage that was used in the original analysis. The robustness checks provide results that verify the findings presented in the original analysis and reported in Table 6. A third robustness check that does not rely on the original specification is also included. Instead, we develop an alternative task index that evaluates the level of codifiability rather than using the three task indices from Autor et al. (2013)

Table 7 presents the results using the same empirical model and specifications used to produce the results reported in Table 6. The only distinction between the two tables is interval between observations. Each respondent in the SIPP is interviewed every four months and asked to report information about the current (referred to as the reference month) and past months income and earnings. Table 7 limits the observations to only those that occurred every second reference month. The results presented in Table 7 indicate that those seen in Table 6 are robust and not driven by recall bias or any other misspecification. These results provide further evidence of the hypothesis suggested in the original analysis and reported in Table 6.

Table 7

Fixed effects Regressions of Standardized Log Hourly Wage on O*Net Task Indices with a Eight Month Interval between Observations

LHS: Standardized Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abstract	0.16***	0.00	0.16***	0.00	0.16***	-0.02	0.16***	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Routine	-0.13***	-0.00	-0.13***	-0.00	-0.08***	0.02*	-0.08***	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Non-routine Manual	0.05***	-0.02	0.05***	-0.01	0.06***	-0.01	0.06***	-0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Years of Education	0.06***	0.05***	0.06***	0.05***	0.07***	0.07***	0.07***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	0.09***	0.09***	0.10***	0.09***	0.09***	0.09***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age-squared	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual-Occupation FE	No	Yes	No	Yes	No	Yes	No	Yes
Individual-Job FE	No	No	Yes	Yes	No	No	Yes	Yes
SOC Level	3	3	3	3	2	2	2	2
Within R-squared	0.09	0.11	0.09	0.12	0.09	0.11	0.09	0.11
Between R-squared	0.21	0.29	0.21	0.29	0.20	0.26	0.20	0.26
Overall R-squared	0.20	0.28	0.21	0.29	0.19	0.25	0.20	0.25

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: The results presented cluster standard errors at the individual level. The results are also robust to clustering at the occupation level.
Note 3: Each observation is limited to the reference month and reported at eight month intervals. The results are also robust to a four and twelve month interval.
Note 4: The total number of observations is N= 199,311 with the 3-digit specifications and N= 325,018 with the 2-digit specifications.

Another alternative specification is reported in Table 8 using the same empirical model and specifications used to produce the results reported in Table 6. The only distinction between the two tables is the dependent variable. The standardized log of each individual's hourly wage during each period is used as the dependent variable in the original analysis. In Table 8, the same specifications are estimated using a forward rolling 3-month average of each individual's hourly wage. The results in Table 8 are, again, quite similar to that presented in Table 6. The results presented in Table 8 indicate that those seen in Table 6 are not driven by an immediate or temporary drop in earnings caused by an employment transition. However, Table 8 indicates that the overall pattern and hypothesis presented in the original analysis are robust to this alternative specification.

Table 8

Fixed effects Regressions of Standardized 3 Month Average of Log Hourly Wage on O*Net Task Indices

LHS: Standardized Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abstract	0.15***	0.00	0.15***	0.00	0.15***	-0.00	0.15***	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Routine	-0.12***	0.00	-0.12***	0.00	-0.08***	-0.01	-0.08***	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Non-routine Manual	0.05***	-0.01	0.05***	-0.01	0.06***	0.02	0.06***	0.02
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Years of Education	0.06***	0.06***	0.06***	0.06***	0.07***	0.07***	0.07***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	0.10***	0.10***	0.11***	0.11***	0.10***	0.10***	0.11***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age-squared	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual-Occupation FE	No	Yes	No	Yes	No	Yes	No	Yes
Individual-Job FE	No	No	Yes	Yes	No	No	Yes	Yes
SOC Level	3	3	3	3	2	2	2	2
Within R-squared	0.06	0.08	0.06	0.08	0.06	0.08	0.07	0.08
Between R-squared	0.22	0.30	0.23	0.30	0.21	0.27	0.21	0.28
Overall R-squared	0.21	0.29	0.21	0.29	0.20	0.26	0.21	0.26

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: The results presented cluster standard errors at the individual level. The results are also robust to clustering at the occupation level.
Note 3: The results are presented with the standardized forward rolling 3-month average log hourly wage as the dependent variable. The results are also robust when a 6-month average log hourly wage is used as the dependent variable.
Note 4: The total number of observations is N= 800,966 with the 3-digit specifications and N= 1,306,568 with the 2-digit specifications.

The third robustness check we provide involves replacing the three task indices used in the original analysis with a single task index created from a larger swatch of O*Net variables. The O*Net variables included in this index are used to proxy for occupational engagement in non-routine (i.e. tacit or not easily codified) tasks and outlined in Table 8. Unlike the indices used in the primary analysis, this variable attempt to abstain from making any distinctions between manual and cognitive labor. In addition, the variable of interest was constructed using exploratory factor analysis rather than principal components. The single strongest factor driving the index was the only one selected for inclusion in the robustness check. This factor was assumed to represent technological change driving changes in occupational task engagement.

Table 8

O*Net Variables Included in the non-routine Task Index

O*Net Survey Variable	Autor's Task Indices	Non-routine Task Index
O*Net: Abilities		
Deductive Reasoning		X
Inductive Reasoning		X
Spatial Orientation	X	
Manual Dexterity	X	
O*Net: Work Activities		
Getting Information		X
Judging the Qualities of Things, Services, or People		X
Analyzing Data or Information	X	
Making Decisions and Solving Problems		X
Thinking Creatively	X	X
Updating and Using Relevant Knowledge		X
Controlling Machines and Processes	X	
Operating Vehicles, Mechanized Devices, or Equipment	X	
Interpreting the Meaning of Information for Others	X	X
Establishing and Maintaining Interpersonal Relationships	X	
Guiding, Directing, and Motivating Subordinates	X	
Coaching and Developing Others	X	
O*Net: Work Context		
Spend Time Using Your Hands to Handle, Control, or Feel Obj., Tools, or Controls	X	
Spend Time Making Repetitive Motions	X	
Frequency of Decision Making		X
Freedom to Make Decisions		X
Degree of Automation		X
Importance of Being Exact or Accurate	X	
Importance of Repeating Same Tasks	X	X
Structured versus Unstructured Work	X	X
Pace Determined by Speed of Equipment	X	X

The results reported in Table 9 replicate the specification discussed in Table 6. These results, though constructed from a significantly different set of O*Net variables, align quite well with those discussed in the primary analysis with Autor's task indices. These results, albeit different in magnitude, are similar in pattern to those shown in the original analysis and reported in Table 6. They are as we might expect given the previous discussion about the effect of changing task requirements within occupations. The alternative specification provides additional evidence that our initial findings are robust to alternative specification. The results also seem to indicate that the index creates a viable proxy for the level of occupational engagement in non-routine tasks and can help evaluate the degree of codifiability across occupations.

Table 9

Fixed Effects Regressions of Standardized Log Hourly Wage on O*Net non-routine index

LHS: Standardized Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-routine	0.14***	-0.01	0.14***	-0.01	0.15***	-0.01	0.15***	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Years of Education	0.06***	0.05***	0.06***	0.05***	0.06***	0.06***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	0.10***	0.09***	0.10***	0.09***	0.10***	0.09***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age-squared	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual-Occupation FE	No	Yes	No	Yes	No	Yes	No	Yes
Individual-Job FE	No	No	Yes	Yes	No	No	Yes	Yes
SOC Level	3	3	3	3	2	2	2	2
Within R-squared	0.08	0.10	0.08	0.10	0.08	0.10	0.08	0.10
Between R-squared	0.21	0.30	0.21	0.30	0.21	0.27	0.21	0.27
Overall R-squared	0.20	0.28	0.20	0.29	0.20	0.25	0.20	0.25

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value of .1, ** represents a p-value of .05, and *** represents a p-value of .01 significance.
Note 2: The results presented cluster standard errors at the individual level. The results are also robust to clustering at the occupation level.
Note 3: The total number of observations is N= 800,966 with the 3-digit specifications and N= 1,306,568 with the 2-digit specifications.

VII. Conclusions

According to a narrative of SBTC provided in many works by David Autor but most recently in 2014, those tasks that follow explicit rules are easily codified and substituted for machinery in the production process. In contrast, human tasks that require judgment and tacit forms of knowledge utilize capital as a compliment in the production process. Autor's SBTC narrative suggests that the falling price of computing power is the primary driving force behind observed changes to the labor market. More specifically, the falling price of computing power is believed to have displaced workers with codifiable knowledge accomplishing explicit routine tasks while at the same time increasing the demand for workers with tacit knowledge accomplishing non-routine tasks.

It follows from the SBTC narrative that as technological change increases computing power, capital should more easily able to substitute for routine labor in the production process. More specifically, SBTC effects within occupations would result from previously non-routine tasks become relatively more routine as technology evolves and codifies those processes. We might expect to observe wage effects from evolving task requirements within occupations that are similar to those observed across occupations. This analysis sought to further investigate these effects by establishing a panel of occupational task requirements and matching this panel with a panel of individual workers.

The SBTC hypothesis corresponds well with the results seen in portions of the analysis. Specifically, the cross-sectional results from the between estimator mirror those reported in previous empirical investigations into the wage impacts of SBTC across occupations. We are unable, however, to find results for changes to task requirements occurring within occupations and illustrate that changes to occupational task requirements have very little impact on an individual's wage in the short-run. Rather, we find that all of the variation is being driven by those individuals who change occupations within and across employers.

The results for our within estimator (without occupation fixed effects) were driven by workers changing occupations. This finding provides us with the insight necessary to formulate a new hypothesis. We postulate that changes to the level of occupational task engagement manifest, in the short-run, through employment transitions rather than wages. It seems possible that workers (and firms) respond to changes in the way occupations accomplish production by changing jobs or occupations rather than renegotiating their current employment contract.

The results presented in this analysis offer new insight into the mechanisms through which SBTC impacts workers. Specifically, we find that occupational sorting does impact the coefficients on each of the task indexes and utilizing individual fixed affects reduces the magnitude of previous estimates. In addition, we find that wages do not respond in the short-run to changes in task requirements within occupations. Further, this analysis provides the foundation for further empirical exploration into potential employment transitions and long-term within occupation wage impacts resulting from evolving task requirements. These areas would benefit from additional empirical exploration and build upon the work presented in this analysis.

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Appendix

Individual Worker Panel: Survey of Income Program Participation

The Survey of Income Program Participation (SIPP) was used to construct the individual panel in the analysis. 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 has the necessary components to conduct this analysis. The SIPP has more detailed occupational codes, more frequent interviews, and a larger sample compared to the Current Population Survey and the Panel Study of Income Dynamics. Although the occupational codes are similar to that reported in the National Longitudinal Survey of Youth, the SIPP has much more frequent interviews and a larger sample.

The 2004 and 2008 SIPP panels were combined to create an unbalanced panel of approximately two million observations. Specifically, the combined panel spanned the period from February 2004 through December 2012 with some months missing due to breaks in the survey. The sample was restricted to prime working age individuals between 25 and 55 years of age who were not in the military. The combined panels had a total of 61,606 prime working age individuals observed on average 29 times each for a total of 2,397,907 observations.

The dependent variable, average hourly wage from primary employment, was reported in the SIPP for non-salaried employees but was not directly reported for salaried employees. The average hourly wage for salaried employees was generated by dividing the total earned income for the observation month by the number of weeks worked in the month and the number of usual hours worked. The characteristics of each individual's primary job were the only ones utilized in the analysis. Any information on an individual's secondary job as well as information pertaining to self-employed individuals was not included in the analysis.

Occupational Task Requirement Panel: Occupational Information Network and Occupational Employment Statistics

The panel of occupational task requirements was constructed using several releases of the O*Net developer database. The data from the O*Net database were combined with several releases of the Occupational Employment Statistics (OES) national employment estimates. Specifically, a total of 18 releases of the O*Net database spanning from November 2003 through July 2013 were combined with 12 releases of the OES estimates from November 2003 to May 2012. The OES employment figures were used only to weight the O*Net task requirements so that they could be utilized at different occupational aggregation levels.

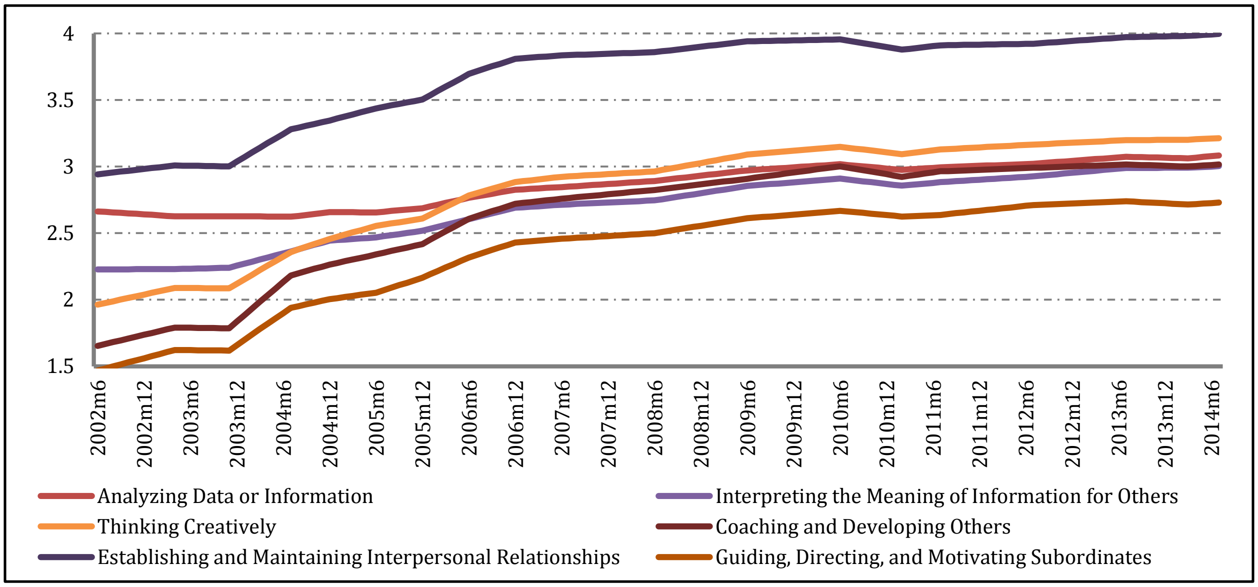
The O*Net data was only available at the 7-digit Standard Occupation Classification (SOC) level but the OES data was available to the 6-digit SOC level. However, there were only a very small number of occupations that actually extended beyond the 6-digit to the 7-digit SOC level in the O*Net data. In the small number of cases where 7-digit SOC detail was present, the requisite data values were simply averaged to create a 6-digit SOC occupation. The O*Net task variables were weighted using the OES employment estimates in an effort to alleviate any potential measurement error in the original task requirements.

Matching the OES data with the O*Net data proved difficult as the release months were different across datasets and variable over time. To overcome this issue, the 6-digit national OES data was first combined to form a panel with observations corresponding to the 14 release dates. Employment was then trended by occupation to form monthly estimates between the actual OES release months. Those months from the newly formed OES trend estimates that matched the O*Net release months were combined upwards to create a 5,4,3, and 2-digit version of the original O*Net panel. These higher level versions of the O*Net panel were then again trended monthly to create a panel that corresponded with the dates of the individual level SIPP panel and then normalized at each period.

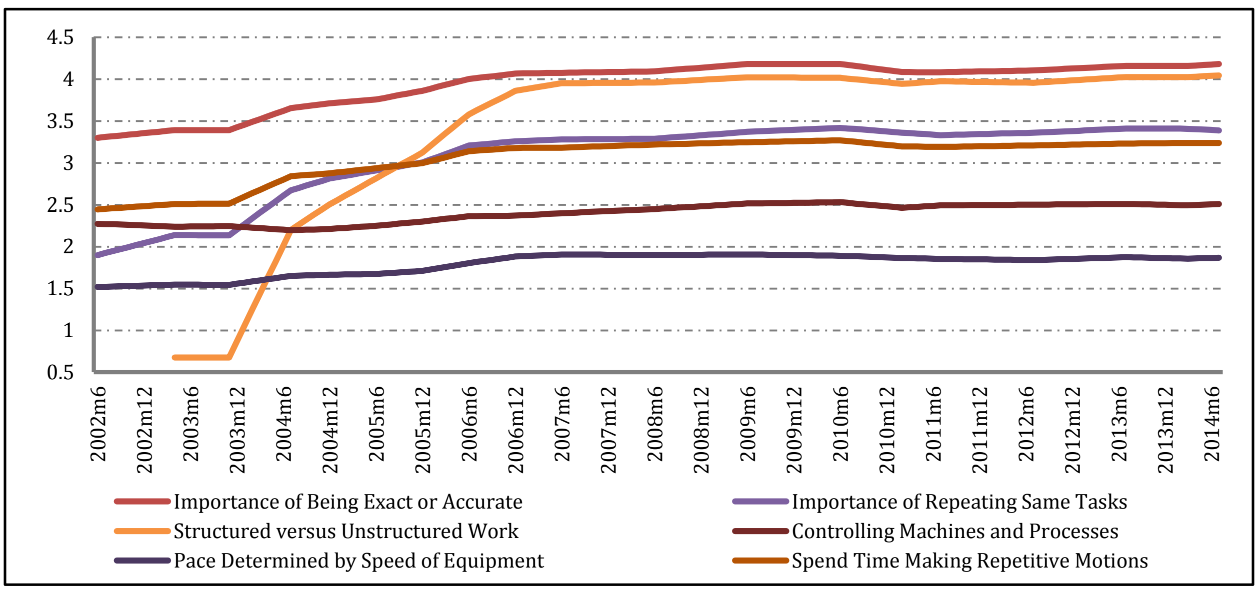
The variables used in the primary analysis align with the index created by Autor and Handel (2013). In addition to reproducing the Autor's task indices, a task index was also created that serves as a proxy for the level of capital intensity within an occupation. The "Capital Intensity" index was used as a robustness check on the findings from applying Autor's task indices on our data. Although Blinder (2007) and Firpo et al. (2011) assign a Cobb-Douglas weight of 2/3 to importance and 1/3 to level, we utilize only the level category for work abilities and activities while the context category was the only used for the work context variables.

Reconstructing the O*Net panel at a less detailed occupational level, that is creating the 5,4,3, and 2-digit panels by weighting the 6-digit O*Net panel by the OES and aggregating upwards, has the advantage of mitigating the potential effects of sampling and measurement error in the original survey. Each of these less detailed SOC panels were then trended between the O*Net release dates to create a panel with monthly observations to match the SIPP panel. The data across occupations for each month in the 5,4,3, and 2-digit panel was left in raw form. Following Autor and Handel (2013) we use principal components analysis to create each of the three task indices at the 2 and 3-digit SOC aggregation level. The components included in the final indices were chosen using Kaiser's stopping rule where only components with eigenvalues over one were included. The "Capital Intensity" index, however, was created using exploratory factor analysis rather than principal components. Only the single strongest factor was included in this variable as it was considered to be driven by (if not itself representing) technological change.

Appendix Figure 1
Weighted Cross-Occupation Average for Components of the Abstract Task Index 2004-13



Appendix Figure 2
Weighted Cross-Occupation Average for Components of the Routine Task Index 2004-13



Appendix Figure 3

Weighted Cross-Occupation Average for Components of the Non-routine Manual Task Index 2004-13