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

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Existing empirical research on Skill Biased Technical Change has examined wage effects using constant measures of occupational task engagement. This analysis exploits temporal variation in task orientation within occupations and presents new evidence of wage effects for incumbent workers. We begin by constructing a synthetic panel of occupational task content using incumbent-updated data from archived releases of the *O*NET*. Wage effects are estimated using a model that includes individual, occupation, and job-spell fixed-effects. The results provide new evidence of a declining price for routine tasks and are robust to controlling for time invariant unobservables as well as instrumental variables estimation.

Existing empirical work on Skill Biased Technical Change (SBTC) has focused on examining changes to the wage distribution across occupations using fixed measures of task engagement. This analysis exploits temporal variation in task orientation within occupations and presets new evidence of wage effects for incumbent workers. Wage effects are estimated using a model that includes individual, occupation, and job-spell fixed-effects. Our findings provide new and substantive evidence that the return to middle-skills is decreasing even when we control for individual and job-spell fixed-effects. Instrumental variables estimation provides additional evidence that the findings, in regard to routine task engagement, are robust to controlling for time variant selection. Estimates of this type have previously been unavailable in the literature and are of particular interest because they provide a new perspective on the labor market dynamics associated with SBTC.

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The first section of this paper provides an introduction and overview of the relevant literature. The second section details an extension of the existing theory underlying the task-based approach and derives relevant implications. The third section provides descriptive statistics and details pertaining to the construction of the synthetic panel. The fourth section extends the theoretical model to an estimation strategy and presents the empirical results from our application. The fifth section contains a robustness check that relies on an instrumental variable approach. The sixth and final section summarizes our findings by providing some concluding remarks.

1. Motivating Literature

In describing why SBTC has resulted in some occupations becoming more automated than others, a recent paper by David Autor (2014) builds on existing work and outlines a compelling mechanism for observed changes in the labor market. In his 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. These tasks are less easily codified because they require frequent use of cognitive judgment or social interaction. Non-routine tasks, unlike routine tasks, utilize capital as a complement in production.

Autor's description of SBTC 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, he argues that these factors have displaced workers in occupations with a high degree of engagement in routine tasks while simultaneously increasing the demand for workers engaged in non-routine tasks. Empirical evidence of this predicted pattern of displacement and polarization has been prominently documented in works by Katz and Murphy (1992); Autor, Katz, and Krueger (1998); Autor, Levy, and Murnane (2003); Autor, Katz, Kearney (2005); Acemoglu and Autor (2011).

Acemoglu and Autor (2011) develop a comprehensive theoretical exposition of SBTC by detailing the dynamics of how tasks, skills, and wages might respond to evolving technology. A key component of their model is the 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, in contrast, are supplied by workers and accumulated through attainment of task-specific human capital. In their model, tasks and skills have an imperfect matching and are both necessary to complete production. The model articulates a fully developed supply and demand framework is used to derive comparative statics related to SBTC. This model has subsequently been expanded to accommodate empirical applications in a stream of literature that has become known as the task-based approach.

Firpo, Fortin, and Lemieux (2011), motivated by the model of Acemoglu and Autor (2011), develop a cross-sectional Roy model that is used 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 measures. The authors combine occupation-level task measures with self-reported task inputs and use the interaction to account for potential self-selection into occupations. Altonji, Kahn, and Speer (2014) use a similar framework to investigate the forces behind changes to the wage distribution across college graduates from different fields of study. All of these analyses have document polarization in employment and wages across occupations using the task-based approach.[1]

Much of the existing empirical work related to SBTC and wages has focused on examining differential returns to task engagement across occupations and the implication that technological change has had on the labor market. These analyses have examined temporal changes to employment and wages, using repeated cross-sectional data on workers, while holding constant reported measures of occupational task engagement. Assuming a constant distribution of occupational task engagement is a large assumption even in the short-run because firms often rapidly alter their capital investments and occupational task orientation is responsive to these changes in the production process. Further, a panel of occupational task engagement, unlike a single cross-section, is able to

1 Related work includes Blender (2007), Jensen and Kletzer (2010), Yamaguchi (2011), and Cortes et al. (2014; 2016);

incorporate individual and job-spell fixed-effects that control for sorting on unobserved heterogeneity. Gathmann and Schönberg (2010) and Spitz-Oener (2006) have documented evidence that skill-requirements and task engagement are changing within occupations over time. However, these papers do not explore how changes to task engagement affect the wage of incumbent workers, fully incorporate the modern task-based approach into their empirical analysis, or control for individual and job-spell fixed-effects.

Spitz-Oener (2006) examines changes in task engagement both within and across occupations over a twenty year period and asks how they are related to technological change. The author finds evidence that the most significant changes in skill engagement have occurred in occupations that have experienced a rapid adoption of computer technology since 1979. Relative to Spitz-Oener, our framework allows for task engagement to evolve over time which allows us to abstract from institutional factors like the decline of unionization by focusing on identification from variation in task engagement. However, unlike Spitz-Oener, our analysis goes beyond documenting occupational changes to task engagement and asks how these changes impact the wage of incumbent workers. Further, we analyze short-run variation in occupational task engagement from a synthetic panel where Spitz-Oener's task variation comes from four cross-sectional surveys occurring over a twenty year period. Our focus on short-run variation in task engagement provides additional confidence that institutional factors are not driving our results.

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. Using the same data as Spitz-Oener (2006), Gathmann and Schönberg allow for variation in task engagement both across occupations and within occupations over time. Following Gathmann and Schönberg, our analysis incorporates a distinction between task-specific and generalizable human capital. Rather than focusing on skill transferability, however, we make an important deviation from Gathmann and Schönberg by asking how changes to task engagement (within occupations) impacts the wage of incumbent workers. Further, we explore how these patterns relate to the theory of

SBTC and find evidence of a declining premium for routine task engagement even after controlling for unobserved individual heterogeneity.

Additional evidence that supports our approach of applying a fixed-effects model to understanding how wages evolve in response to changes in occupational task engagement can be found in recent work by Cortes et al. (2014; 2016). Cortes (2016) looks at employment transitions and wages for those that change occupations but relies on cross-sectional measures of task engagement. Cortes (2016) finds evidence that workers with high ability are more likely to switch into non-routine occupations and that workers with low ability have a higher probability of switching to occupations dominated by tasks considered non-routine manual. Additionally, 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. These dynamics indicate the presence of occupational selection in response to technological change based on both time variant and invariant factors like heterogeneous unobserved ability and expectations about the future of the labor market. Motivated by these findings, our analysis controls for both of these factors when asking how wages evolve in response to changes in occupational task engagement.

This analysis fills a significant gap in the literature by exploring wage effects associated with observed changes in task engagement within and across occupations using a model that accounts for unobserved heterogeneity. In this analysis, we begin by developing a synthetic panel of occupational task measures from 14 distinct releases of the *Occupational Information Network (O*NET*) workforce database. The synthetic panel is then used to build three task indices that are incorporated into a fixed-effect variant of the Roy-type from the task-based approach but where there is a distinction made between task-specific and generalizable human capital. Panel data on workers, matched to the task indices of their occupations, extends the existing literature by examining how the wages of incumbent workers are affected by changes to task engagement within occupations. The combined panel data on task measures and individual workers supports an analysis that controls for time-invariant unobserved heterogeneity associated with attributes of workers within occupations as well as specific jobs they hold. Estimates of this type have previously been unavailable in the literature and are of particular interest because they provide new evidence of the dynamics associated with SBTC.

2. Theoretical Framework

The theory presented in this section is motivated by the task-based models of the labor market that have increasingly been applied to understanding SBTC. Although the motivation and structure of the model is similar to Autor and Handel (2013), we include several key elements that differentiate our framework substantially.[2] Rather than focusing on an individual worker's production function, we begin by modeling production at the level of a representative firm. We assume that firm production takes a constant elasticity of substitution form where occupational production is treated as an intermediary good. As has been the standard approach in task-based models, we allow task premiums to vary across occupations and assume that this is the principal driver of occupational sorting.

We begin in a similar fashion to Autor and Handel (2013) by assuming that workers have an endowment of j skills each period $\Phi_{t,i} = \{ \Phi_{t,i,1}, \Phi_{t,i,2}, \dots, \Phi_{t,i,j} \}$. Unlike Autor and Handel, we assume that a worker's endowment of skills correspond to a maximum possible level of task engagement $f_k(\Phi_{t,i}) \to \tau_{t,i,k}$ through a task-efficiency function. An individual acquires skills through task-specific human capital and combines them through the task-efficiency function to accomplish production. Task-specific human capital can be accumulated through some combination of occupational training and innate ability. The assumption of a task-efficiency function allows for occupational sorting based on education and ability as well as task premiums.

2 The model used by Autor and Handel (2013) has foundations in work by Autor, Levy, and Murnane (2003); Firpo, Fortin, and Lemieux (2011); Acemoglu and Autor (2011). As a result, the model presented herein can also be considered as having been inspired by these frameworks.

The production function for the aggregate economy takes a constant elasticity of substitution form represented in Equation 1.[3]

$$Y_t = \left[\sum_{s=1}^{N} \delta_s y_{t,s,i}^{\sigma}\right]^{\frac{1}{\sigma}} \quad (1)$$

The production function for a worker i in occupation s is represented in Equation 2 where $\tau_{t,s,k}$ represents the engagement in task k at time t for the representative worker employed in occupation s, $\lambda_{t,s,k}$ is a occupational output elasticity for engagement in task k, $h_{t,i}$ represents generalizable human capital (i.e. soft transferable skills),and $\eta_{t,i}$ represents an idiosyncratic error term.

$$y_{t,s,i} = l_{t,s,i} e^{[h_{t,i} + \sum_k \lambda_{t,s,k} \tau_{t,s,k} + \eta_{t,i}]} \quad (2)$$

The log marginal product of labor for worker i employed in occupation s at period t is shown in Equation 3.

$$ln(MPL_{t,s,i}) = ln(\delta_s) + (1-\sigma) ln\left(\frac{Y_t}{l_{t,s,i}}\right) + \sigma\left(h_{t,i} + \sum_k \lambda_{t,s,k} \tau_{t,s,k} + \eta_{t,i}\right) \quad (3)$$

Similar to Firpo et al. (2011) and Autor and Handel (2013), our model allows for output elasticity $\lambda_{t,s,k}$ to vary across occupations. Distinctly, however, we also allow output elasticity $\lambda_{t,s,k}$ to vary within occupations over time. The implication, in terms of the marginal product of labor, is that the wage premium associated with distinct tasks differs across and within occupations over time. This assumption is consistent with the idea that occupation-specific task premiums are driving selection. Although we assume that selection is driven principally by variation in task premiums across occupations, the task-efficiency function ensures that like workers (in terms of unobservables) sort into similar

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3 Although Equation 1 assumes that firms are homogenous across industries, our framework is amenable to including heterogeneous production structures. This assumption could be relaxed by differentiating the share parameter δ_s by industry either alone or in combination with σ the substitution parameter.

occupations. The combination of varying task premiums and an indirect mapping of skills to tasks, ensures that occupational selection and sorting occurs as a result of comparative advantage.

Following Autor and Handel (2013), we formalize this assumption through the maximization problem outlined in Equation 4.

$$\begin{aligned} y_{t,s,i} &= \max_{s}\left\{y_{t,1,i}, y_{t,2,i}, \dots, y_{t,s,i}\right\} = \max_{s}\left\{e^{\left[h_{t,i}+\sum_k \lambda_{t,s,k}\tau_{t,s,k}+\eta_{t,i}\right]}\right\} \\ &= \max_{s}\left\{e^{\left[h_{t,i}+\sum_k \lambda_{t,s,k} f_k(\Phi_{t,i})+\eta_{t,i}\right]}\right\} \end{aligned} \tag{4}$$

Autor and Handel (2013) utilize data on an individual's reported engagement in tasks at a single point in time. In this analysis, however, the data is obtained from aggregating task engagement measures by index (i.e. abstract, routine, and non-routine manual) within occupations at different points in 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 requirements necessary to produce a single unit of output. According to the maximization presented in Equation 3, an individual's task engagement will converge to the occupational requirements in equilibrium. This condition is reasonable if the cost associated with changing occupations is sufficiently high and firms can observe the production performance of each worker. The dynamics of 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. In equilibrium we expect that similar workers, in terms of skill endowments, sort into the same occupations due to these dynamics.

The SBTC literature associates occupations with a high degree of engagement in abstract tasks with employing more highly skilled workers. On the other hand, occupations with a high degree of engagement in (non-routine) manual and routine tasks employ more medium and low skilled workers. In the traditional SBTC model, capital is more easily substituted for routine occupations and complimentary to abstract occupations. In our model, variation in task k is shown to have an impact on the marginal product of labor $\frac{\partial MPL_{t,s,i}}{\partial \tau_{t,s,k}} = \lambda_{t,s,k}$ that is equal to the economy-wide output elasticity of that task. From

Equation 4, we interpret the sign of output elasticity to be positive for both abstract and non-routine manual tasks but negative for routine tasks. Taking this idea one step further, we would expect that a change in task orientation occurring within occupations (over time) to have similar wage effects to those described by SBTC across occupations at a fixed point in time.

We formalize this argument in Equation 5 by assuming that a worker is paid their marginal product and detail the log wage of worker *i* in occupation *s* at period *t*.

$$ln\left(w_{t,s,i}\right) = ln(\delta_s) + (1-\sigma)ln\left(\frac{Y_t}{l_{t,s,i}}\right) + \sigma\left(h_{t,i} + \sum_k \lambda_{t,s,k}\tau_{t,s,k} + \eta_{t,i}\right) \quad (5)$$

As can be seen in Equation 5, when $\lambda_{t,s,k} > 0$ (as in the case of abstract and non-routine manual tasks) a change in task engagement $\frac{\partial w_{t,s,i}}{\partial \tau_{t,s,k}} > 0$ is associated with an increase in wages either across occupations or within an occupation over time. In contrast, when $\lambda_{t,s,k} < 0$ (as in the case of routine tasks) a change in task engagement $\frac{\partial w_{t,s,i}}{\partial \tau_{t,s,k}} < 0$ is associated with a decline in the market wage. The previous statement holds as long as $\left(\frac{\sigma}{1-\sigma}\right) > 0$ when there is some degree of substitutability $\left(\frac{1}{1-\sigma}\right) > 1$ between different occupations.[4] Although presented in the context of a model with limited taxonomical scope, the assumption of substitutability between occupations is consistent with empirical work that has reported an elasticity of substitution in the range of $1.4 \approx \left(\frac{1}{1-\acute{\sigma}}\right) \approx 1.8$ (Katz and Murphy 1992; Autor, Katz, and Kearny 2008; Acemoglu and Autor 2011).

The implications from our model are intuitively appealing and provide the necessary structure for identification in empirical applications. An occupation that is observed to experience an increased level of engagement in routine tasks would be decreasing in worker's marginal product of labor. We would expect this to occur as the task

4 If we assume Cobb-Douglas production where substitutability between occupations is unit elastic $\left(\frac{1}{1-\sigma}\right) = 1$ then $\frac{\partial w_{t,s,i}}{\partial \tau_{t,s,k}} = 0$ for all tasks. If, however, there is some degree of complementarity between occupations $\left(\frac{1}{1-\sigma}\right) < 1$ we would expect that $\frac{\partial w_{t,s,i}}{\partial \tau_{t,s,k}} < 0$ for abstract and non-routine manual tasks but that $\frac{\partial w_{t,s,i}}{\partial \tau_{t,s,k}} > 0$ for those considered routine.

accomplished by the occupation become more easily codified and are substituted for capital in the production process. If workers are paid their marginal product, we would expect wages to decline both across occupations and within occupations over time. In contrast, an occupation with an increasing engagement in abstract (i.e. non-routine) tasks is assumed to be reorienting production towards more tacit forms of knowledge.

3. Data Overview

The data used in this analysis combines a panel of individuals and their work activities with a synthetic panel of occupational task measures. 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 stretched from October 2003 to December 2007 and the 2008 panel contains 16 waves that stretched from May 2008 to November 2013. A synthetic panel of occupational task measures was constructed from 14 archived versions of the *O*NET* production database released between April 2003 (*O*NET* 5) and July 2014 (*O*NET* 19). The synthetic panel of *O*NET* task measures was linked to the *SIPP* panel by occupation code and aggregated at annual intervals.

The synthetic *O*NET* panel allows us to exploit variation in task engagement reported by incumbent workers within occupations over time. The advantage of creating a synthetic panel of task engagement from the *O*NET*, rather than using the *German Qualification and Career Survey,* is that it allows us to focus on short-run changes in task engagement. Focusing on short-run changes in task engagement ensures that our identification strategy produces results that are abject of any occupation-specific institutional changes like the decline of unionization. In addition, we are able to focus our analysis on the United States where there has been a more pronounced polarization of the wage distribution than Western Germany.[5]

Combining the synthetic *O*NET* panel with the *SIPP* allows us to apply an estimation procedure that controls for individual fixed-effects and includes an instrumental variable

5 Spitz-Oener (2006; p. 240) cites Gottschalk and Smeeding (1997) as providing evidence that wage trends in Germany have different substantially from other western countries. Further, Spitz-Oener acknowledges that differences in the rate of unionization may be playing a role in these developments and that SBTC might manifest in Europe as unemployment rather than wage declines due to these differences. These two factors support our short-run analysis using the O*NET rather than a long-run analysis using German data where unionization and institutional factors might conflate our findings.

approach. Fixed-effects estimation allows us to ask how variation in task engagement affects the wage of incumbent workers while controlling for time invariant selection on unobserved heterogeneous ability. Our robustness check using instrumental variables, further controls for time variant selection based on expectations about technological adoption across occupations. This section begins by describing the construction of the synthetic *O*NET* panel and presenting relevant descriptive statistics. Next, we discuss our use of the *SIPP* by presenting descriptive statistics from the panel alone as well as descriptives from combining it with the synthetic *O*NET* panel.

Synthetic Panel of Occupational Task Measures

The first version of the *O*NET* database was constructed as a prototype to replace the existing *Dictionary of Occupation Titles (DOT)* (NRC 2010). Unlike the *DOT*, the *O*NET* was created with the goal of having the underlying measures populated by a survey of incumbent workers rather than analyst observations. The completed database was released in June 2002 (*O*NET* 4) with the initial measures having been populated by job analysts who assigned values to the *O*NET* survey questions by referencing the *DOT* releases from the 1980s. As a result, the initial release of the *O*NET* database was composed entirely of a new rating system applied to old data by analysts using judgment-based methods, as opposed to personal observations of jobs by incumbent workers. The *O*NET* surveys were administered to random samples of workers in an average of 110 different target occupations beginning in 2002. Each of the 14 subsequent releases (*O*NET* 5 to 19) contained updated data on an average of 110 occupations.[6] As of the latest release (*O*NET* 19), there have been a total 589 7-digit occupations that have been updated at least twice using surveys of incumbent worker. Changes in the underlying engagement of

6 The O*NET selects occupations to be updated 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 (Tippins & Hilton 2010, p. 5). The result is that occupations are sometimes selected for updates on the basis of relative employment size, demand, or changes in occupational engagement. Aggregating task measures from a 7-digit to a 3-digit SOC taxonomy using employment weights alleviates concern related to measurement error. The 7-digit occupations updated in each of the O*NET releases are distributed relatively evenly across the 3-digit SOC taxonomy. Assuming occupations are chosen for an update based on employment size and changes to engagement, the 3-digit aggregate measures will minimize measurement error and capture the underlying temporal variation.

these 589 occupations constitute the primary source of variation that we exploit in our synthetic panel and the subsequent empirical analysis.

We constructed the synthetic panel by first combining incumbent-updated measures from the work context and activity sections of each *O*NET* release. The value of each occupational task measure was linearly trended between the earliest and latest incumbent update. Values outside the earliest and latest incumbent update were then imputed using the closest incumbent-updated value. The occupations were then aggregated from a 7-digit to a 3-digit SOC taxonomy using a rolling 3-year national employment weight constructed from *the Occupational Employment Statistics*. Aggregating to a less detailed SOC taxonomy was necessary to ensure a sufficiently large and robust sample was available in the *SIPP* panel. In addition, the less detailed taxonomy helped alleviate potential measurement error and selection related to the update schedule. [7]

Using the synthetic panel of task measures, we follow Autor and Handel (2013) by constructing three broad categories that describe the bundle of tasks performed by an individual working in a given occupation. The advantage of using the synthetic panel of task measures is that, unlike Autor and Handel, our task indices vary both across occupations and within occupations over time. The abstract task index describes an occupation's degree of engagement in complex analytical or interpersonal decision-making. In contrast, the routine task index describes an occupation's engagement in cognitive or manual tasks that follow explicit and easily codified rules. The third task index, non-routine manual, describes an occupation's engagement in tasks that require irregular physical movement or spatial orientation. Table 1 presents the *O*NET* variables that underlie each of the three task indices.[8]

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7 Our use of employment weights also alleviates problems concerning changes to the SOC taxonomy throughout the analysis period. Specifically, we accomplish this by matching occupation codes in the SIPP to those in the synthetic 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.

8 The three task indices differ slightly in their composition than those constructed by Autor and Handel (2013). Specifically, we replace Manual Dexterity and Spatial Orientation from the non-routine manual task index with Handling & Moving Objects and Performing General Physical Activities. These measures were the only drawn from the work ability portion of O*NET database which is not updated by a survey of incumbent workers. In addition, we replace Importance of Being Exact or Accurate and Importance of Repeating the Same Tasks from the routine cognitive task index with Processing Information and Frequency of Decision Making. These two measures were replaced because a principal components analysis of the routine task index indicated the presence of a strong secondary component driven by these two measures. In contrast, the abstract and non-routine manual indices were driven by a single component as was the routine task index once these measures were replaced.

Table 1

Cross-Occupation Descriptive Statistics for Variables Included in the Task Indices

Task Index		Task Measure	Mean (Std. Dev.) O*NET 5 (April, 2003)	Mean (Std. Dev.) O*NET 19 (July, 2014)
Abstract	Analytical	Analyzing Data or Information	3.0 (0.8)	3.1 (0.8)
		Thinking Creatively	3.1 (0.7)	3.3 (0.7)
		Interpreting the Meaning of Information for Others	3.0 (0.9)	3.0 (0.9)
	Interpersonal	Establishing and Maintaining Interpersonal Relationships	3.1 (0.9)	3.2 (0.9)
		Guiding, Directing, and Motivating Subordinates	2.5 (0.9)	2.6 (1.0)
		Coaching and Developing Others	2.1 (1.0)	2.2 (1.0)
Routine	Cognitive	Processing Information*	2.6 (0.8)	2.8 (0.7)
		Frequency of Decision Making*	2.8 (0.7)	3.0 (0.7)
		Structured versus Unstructured Work*	3.8 (0.5)	3.9 (0.5)
	Manual	Controlling Machines and Processes	3.3 (0.8)	3.3 (0.8)
		Spend Time Making Repetitive Motions	2.9 (0. 7)	3.0 (0.6)
		Pace Determined by Speed of Equipment	3.0 (0.6)	3.1 (0.6)
Non-Routine Manual		Handling and Moving Objects	2.0 (0.8)	2.0 (0.8)
		Performing General Physical Activities	1.0 (0.4)	1.0 (0.4)
		Operating Vehicles, Mechanized Devices, or Equipment	1.1 (0.5)	1.1 (0.4)
		Spend Time Using Your Hands to […] Control or Feel Objects	2.3 (0.6)	2.2 (0.7)

* The measure was reversed before being included in the requisite task index.

In our construction of the three task indices, we utilize the important and level measures for variables from the work activity category of the *O*NET* database. We follow Blinder (2007) and Firpo et al. (2011) by assigning a Cobb-Douglas weight of two thirds to importance and a weight of one third to the level measures. The context measure was used for variables that come from the work context category in the *O*NET* database. The value of task index k in time period t for occupation s is created according to Equation 6.[9]

$$\tau_{t,s,k} = \sum_{j \in k}^{k} \left(LV_{t,s,j}^{1/3} \; IM_{t,s,j}^{2/3} + CX_{t,s,j} \right) \tag{6}$$

The specific tasks that an occupation accomplishes in the production process are assumed to interact in a complex and unobservable manner. Although the *O*NET* database provides a detailed summary of various task measures that describe an occupation's productive activities, these measures do not fully detail individual tasks. As a result, the three indices should not be considered the fraction of time that an occupation spends engaged in specific tasks from each of the respective categories. The task indices can, however, be considered as a proxy for the output elasticity term $\lambda_{t,s,k}$ in Equations 2-5 that describes an occupation's task engagement relative to other occupations and itself over time.

The overall variation in each of the three task indices across the panel is displayed graphically in Figure 1. Rather than weighting the O*NET measures from a 7-digit to a 3-digit SOC taxonomy as is done in the remainder of the empirical analysis, we use the employment weights to create a cross-occupation measures of each task index. As can be seen below, there has been a substantial increase abstract task engagement across occupations from 2003 to 2014 (*O*NET* 5 to 19). In contrast, engagement in routine tasks has decreased slightly over the same period. Similarly, engagement in non-routine manual tasks has experienced a modest increase. Although the cross-occupation routine and non-routine manual task indices show very little variation over time, the occupation-specific measures show distinct and varying rates of growth within occupations over time.[10]

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9 As mentioned, only those measures from the work activity and ability categories contain a value for both level and importance. In contrast, the context measure is only available for variables from the work context category. As a result, a measure $j \in k$ from the context category would have $LV_{t,s,j}^{1/3} \; IM_{t,s,j}^{2/3} = 0$ and a variable from the activity or ability category would have $CX_{t,s,j} = 0$. In addition, we account for changes in the SOC taxonomy by matching occupation codes in the SIPP to those in the synthetic 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, higher level task measures provide an accurate imputation.
10 A more detailed graphical presentation of the variation in 2-digit SOC occupations can be seen in Appendix Figures 1,2, and 3. We omit the 3-digit counterpart of these figures because they are difficult to interpret visually.

Figure 1

Cross-Occupation Variation in Task Indices

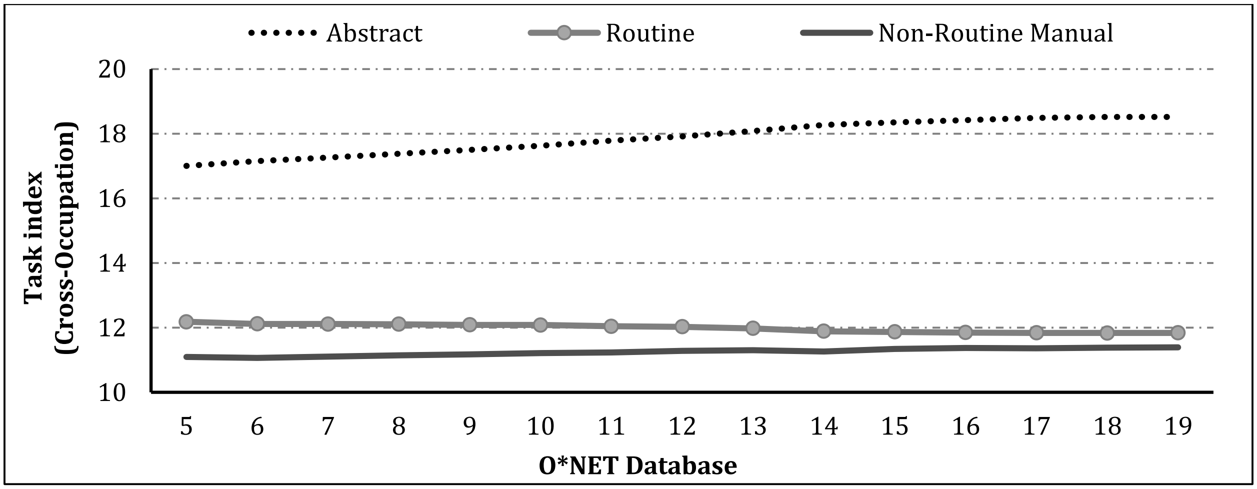


Table 2 presents descriptive statistics from the synthetic *O*NET* panel for each of the three task indices at the 3-digit SOC taxonomy. The standard deviation and bounds of the growth rate across the synthetic panel illustrates the substantial variation in these measures over time. The highest growth of engagement in abstract tasks was observed in the Fire Fighting and Prevention Workers (56.7%) while the most significant decline was seen in the Animal Care and Service Workers (17%). Engagement in routine tasks grew most significantly in Supervisors of Farming, Fishing, and Forestry Workers (23%) and experienced the largest decline in Other Healthcare Practitioners and Technical Occupations (16.2%). The greatest increase in non-routine manual task engagement was seen in Supervisors of Installation, Maintenance, and Repair Workers (26.9%) while the greatest decrease could be observed in Mathematical Science Occupations (15.4%).

Table 2
Descriptive Statistics for Task Indices at the 3-Digit SOC Taxonomy

		Abstract	Routine	Non-Routine Manual
O*NET 5 (April, 2003)	Mean (Std. Dev.)	18.2	11.9	11.5
		3.4	2.8	3.2
	Min	11.7	6.2	5.1
	Max	26.3	18.2	17.1
O*NET 19 (July, 2014)	Mean (Std. Dev.)	19.0	12.0	11.7
		3.2	2.8	3.3
	Min	13.3	6.4	5.4
	Max	25.9	17.9	17.7
Growth Rate 5-19	Mean (Std. Dev.)	5.6%	0.4%	2.6%
		10.9%	6.4%	8.2%
	Min	-17.0%	-16.2%	-15.4%
	Max	56.7%	23.0%	37.7%

Survey of Income Program Participation

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. 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*.

The 2004 and 2008 SIPP panels are combined to create an unbalanced panel of approximately three million observations. The combined panels span the period from October 2003 through November 2013 with some months in 2007 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 111,494 individuals observed on average 30 times each for a total of 3,366,682 observations.[11] Employment information is reported in the *SIPP* under four distinct classifications: primary employment, secondary employment, primary self-employment, and secondary self-employment. All information for each of an individual's employment arraignments is recorded separately within each classification. Although an individual's occupation is recorded for secondary employment and self-employment, only the information recorded under an individual's primary employment arraignment was used for this analysis.[12] Relevant descriptive statistics from the SIPP are presented in Table 1 where hourly wage is from primary employment alone.

Table 3

Descriptive Statistics from the Combined 2004 and 2008 *SIPP* Panel

Period	Observations	Individuals	T-bar
10/2003- 11/2013	3,366,682	111,494	30
2004 Panel		2008 Panel	
42.6%		57.4%	
Hourly Wage	14.7		
	(51.6)		
Age	40.4		
	(8.9)		
Years of Education	13.6		
	(2.7)		
Experience	9.8		
	(47.5)		
Less than High School	High School	Some College	College or Post-College
10.4%	25.7%	25.8%	38.3%
White	Black	Asian	Other
79.1%	12.6%	4.5%	3.9%
Male		Female	
45.7%		54.3%	

Hourly wage was obtained from an individual's primary employment arraignment in the *SIPP*. Average hourly wage is reported directly in the *SIPP* for non-salaried

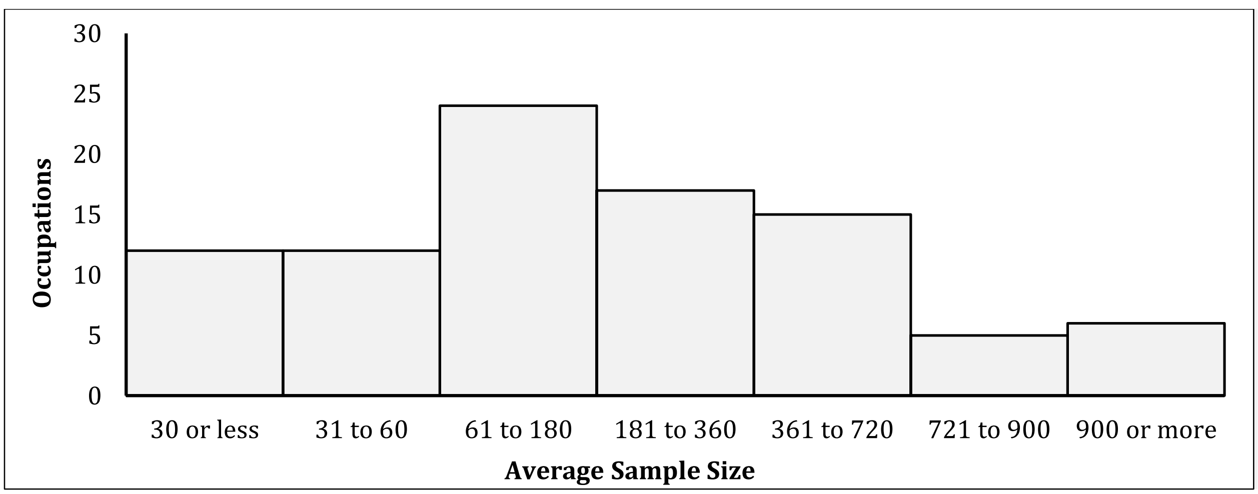
11 These figures vary based on the specification used in each part of the analysis. This is due to unreported occupational codes and other factors that cause observations to be omitted. On average, the effective sample size used in the empirical analysis contains approximately 26,599 individuals and 372,388 observations.

12 An expanded version of this analysis could also utilize secondary employment as well as self-employment.

employees but is not reported for salaried employees. An hourly wage was calculated for salaried employees by dividing total earned income in the observation month by the reported number of weeks worked in that month and the usual hours worked per week. The average hourly wage reported in Table 1 contains both the directly reported figures for non-salaried employees as well as the imputed values for salaried employees. References to hourly wage in the remainder of this analysis will indicate the combined reported and imputed values.

An individual's occupation, as it pertains to their primary employment arraignment, is reported in the *SIPP* at the detailed 6-digit SOC taxonomy. There were 455 distinct 6-digit SOC occupations reported by respondents in the SIPP under the primary employment arraignment category. The empirical estimation in this paper utilized only a 3-digit rather than the more detailed 6-digit SOC taxonomy because a less detailed coding schema helped to alleviate issues related to measurement error in the task indices. In addition, the less detailed 3-digit SOC taxonomy ensured a larger and more robust sample size in the *SIPP* panel. The average sample size in the *SIPP* (across all periods) for each 3-digit SOC occupation is shown graphically in Figure 1.[13]

Figure 2
Average Sample Size in the *SIPP* by 3-digit SOC Occupation



13 The 12 occupations with a sample size that was less than 30 individuals on average per period were distributed evenly across major 2-digit occupations. The 2 and 5-digit SOC level was also used as a robustness check on our empirical findings at the 3-digit level. The confirmation of our estimates at these alternative aggregation levels was sufficiently convincing that there was no sample selection occurring within the SIPP panel.

The distribution of educational attainment relative to the distribution of each task index across 3-digit SOC occupations is presented for employed individuals in Table 4. As can be seen in the table below, occupations with higher engagement in abstract tasks are dominated by highly educated individuals. In contrast, highly routine occupations are dominated by individuals with lower levels of education. However, occupations in the middle of the routine task distribution employ individuals from across the educational distribution. Similarly, occupations with a high level of engagement in non-routine manual tasks are also dominated by individuals with low levels of education. Unlike occupations dominated by routine tasks, those ranging from the middle to the bottom of the non-routine manual distribution employ individuals from across the educational distribution. The distribution of educational attainment by occupation corresponds to that described in previous works on SBTC.

Table 4
Educational Distribution by Task Index Distribution at the 3-Digit SOC level

		Years of Education (Quintiles)		
		1	3	5
Abstract (Quintiles)	1	56.50%	18.20%	1.50%
	3	31.10%	28.40%	3.70%
	5	12.70%	13.20%	28.80%
Routine (Quintiles)	1	12.70%	13.50%	25.30%
	3	28.70%	25.90%	4.90%
	5	62.50%	18.60%	1.00%
Non-Routine Manual (Quintiles)	1	18.10%	18.20%	17.40%
	3	29.30%	19.40%	11.40%
	5	56.60%	22.90%	0.90%

4. Empirical Analysis

This section details the methodology and results from an empirical analysis using our combined synthetic panel. We begin by amending the theoretical model outlined in Section 2 to accommodate empirical estimation. As mentioned in the introduction, our estimation procedure includes controls for individual, occupation, and job-spell fixed-effects. Each of the fixed-effects included in our estimation controls for a different level of unobserved heterogeneity. We accomplish this by expanding the existing task-based approach to accommodate panel data.

We begin by transforming Equation 5 into Equation 7 where we have assumed that generalizable human capital is a function of α_i heterogeneous individual ability, $e_{t,i}$ formalized education, and $x_{t,i}$ workforce experience.

$$ln(w_{t,s,i}) = ln(\delta_s) + (1-\sigma)ln\left(\frac{Y_t}{l_{t,s,i}}\right) + \sigma\left(h_{t,i}(\alpha_i, e_{t,i}, x_{t,i}) + \sum_k \lambda_{t,s,k}\tau_{t,s,k} + \eta_{t,i}\right) \quad (7)$$

Motivated by Gathmann and Schönberg (2010), we include generalizable human capital directly in our estimation equation. We assume that occupation-specific human capital is captured through task engagement $\sum_k \lambda_{t,s,k}\tau_{t,s,k}$ and that workers within occupations are similar in terms of their occupation-specific training. In terms of generalizable skills that are portable across occupations, however, we assume that workers differ within occupations and that these differences are driven by workforce experience as well as formalized schooling. As such, we include generalizable human capital as a total factor productivity term.

Moving to a reduced form framework, we convert Equation 7 into Equation 8 and assume that generalizable human capital takes a Mincerian form. Further, we aggregate $\sum_k \lambda_{t,k}\tau_{t,s,k}$ into three indices measuring engagement in $A_{t,s}$ abstract, $R_{t,s}$ routine, and $M_{t,s}$ non-routine manual tasks.

$$w_{t,s,i} = \alpha_i + Y_t + \beta_1 e_{t,i} + \beta_2 x_{t,i} + \beta_3 x_{t,i}^2 + p_A A_{t,s} + p_R R_{t,s} + p_M M_{t,s} + \eta_{t,i} \quad (8)$$

The individual fixed-effects α_i in Equation 8 captures time-invariant unobserved ability as well as the occupation-specific wage premium δ_s when these fixed-effects are expanded to occupation and job-spell. Applying increasingly more restrictive fixed-effects helps to isolate the variation in our task indices and reduce wage volatility from employment-to-employment transitions. Additionally, job-spell fixed-effects are appropriate if changes in task engagement are also predictive of transitions to non-employment or across states of employment. Although our initial estimates contain results that include individual and occupation fixed-effects, it is for this reason that we focus primarily on specifications with job-spell fixed-effects.

We interpret the value obtained from the synthetic *O*NET* panel for each task index as representing $\lambda_{t,k}\tau_{t,s,k}$ where the task input $\tau_{t,s,k}$ has been normalized to unity across occupations. As such, the coefficient on each of our three task indices from Equation 8 represents the price differential for engagement in abstract, routine, and non-routine tasks. In estimates of between-effects, we interpret this coefficient as representing the average wage differential between occupations of differing levels of engagement.[14] In contrast, we interpret the coefficient obtained from a within-effects regressions as representing the trajectory of each task's price. According to the comparative statics Acemoglu and Autor (2011) outline for the model of middle skill replacing technological change, we would expect the coefficient from the within-effects regression to be positive for abstract tasks (corresponding with high skills), negative for routine tasks (corresponding with medium skills), and exhibit little variation for non-routine manual tasks (corresponding with low skills). The author's attribute the declining return to middle skills to an increasing substitutability between technological capital and routine tasks in production.

Table 5 contains between-effects estimates of the wage premium for different levels of task engagement obtained from applying Equation 8 to our data. The coefficient on each of the variables obtained from the between-effects estimation captures cross-sectional variation across occupations. The between-effects estimator from the first specification is obtained using individual fixed-effects while the second and third use occupation-spell and job-spell fixed-effects. In each of these specifications, an increase of one standard deviation (3.3) in the abstract task index across occupations is associated with a wage premium of between 17.8 and 18.8 log points. In contrast, a one standard deviation (2.8) increase

14 The between-effects estimates regress the mean of each variable within each fixed-effect. Since our task variables are occupational means (i.e. they are not individually reported), the coefficients can be interpreted as the effect from variation across occupations.

across occupations in the routine task index is associated with a 7.8 log point wage penalty. An increase of one standard deviation (3.3) in the non-routine manual task index, on the other hand, is associated with a wage premium of between 8.9 and 9.9 log points. Each of the estimates was found to be highly statistically significant regardless of the fixed-effect used in the estimation. The sign and magnitude of the estimates for the abstract and routine task indices match those obtained by Autor and Handel (2013) using the *PDII* dataset. Although the non-routine manual task index is different in sign that previous estimates using the *PDII*, we believe that our estimates align well with theoretical exposition of SBTC.

Table 5
Cross-Sectional Regression of Log Wages on Task Indices

	Between-Effect Estimates		
	(1)	(2)	(3)
Abstract	0.057***	0.052***	0.054***
	(0.001)	(0.001)	(0.001)
Routine	-0.028***	-0.027***	-0.027***
	(0.002)	(0.001)	(0.001)
Non-Routine Manual	0.030***	0.027***	0.029***
	(0.001)	(0.001)	(0.001)
Years of Education	0.064***	0.063***	0.061***
	(0.001)	(0.001)	(0.001)
Age	0.047***	0.046***	0.045***
	(0.002)	(0.002)	(0.002)
Age-squared	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Time FE	Yes	Yes	Yes
Individual FE	Yes	No	No
Occupation-Spell FE	No	Yes	No
Job-Spell FE	No	No	Yes
Effective Sample Size	333,542	357,635	367,517

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value ≤ .1, ** represents a p-value ≤ .05, and *** represents a p-value ≤ .01 significance.
Note 2: The results are presented with standard errors clustered on individuals but the overall results are robust to clustering on occupations.
Note 3: The task indices and fixed-effects were aggregated to a 3-Digit SOC taxonomy but the results are robust to estimation at a 2 and 5-Digit SOC taxonomy.
Note 4: The results were robust to estimation using only data after 2008 when almost all O*NET occupations had been updated at least once.

Table 6 contains a traditional fixed-effects estimate of the wage premium for different levels of task engagement obtained from applying Equation 8 to our data. As discussed previously, we interpret the sign of the coefficient under each specification as representing the economy-wide change in the return from engagement in each type of task.

The observed coefficient can also be interpreted as changes in the return to low, medium, and high skilled labor input. The first specification in Table 6 controls for unobserved individual heterogeneity using individual fixed-effects and finds statistical significance in each of the task indices. The specification using individual fixed-effects contain variation in task engagement from within occupations for those individuals who remain in the same occupation. However, the specification also contains cross-sectional variation in task engagement for those individuals who change occupations.

Table 6

Fixed-Effects Regression of Log Wages on Task Indices

	Fixed-Effect Estimates		
	(1)	(2)	(3)
Abstract	0.017***	0.001	0.011***
	(0.001)	(0.003)	(0.002)
Routine	-0.013***	-0.005	-0.017***
	(0.002)	(0.008)	(0.004)
Non-Routine Manual	0.004***	-0.004	-0.002
	(0.001)	(0.007)	(0.003)
Years of Education	0.015***	0.008***	0.010***
	(0.002)	(0.002)	(0.002)
Age	0.051***	0.037***	0.036***
	(0.003)	(0.003)	(0.004)
Age-squared	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Time FE	Yes	Yes	Yes
Individual FE	Yes	No	No
Occupation-Spell FE	No	Yes	No
Job-Spell FE	No	No	Yes
Effective Sample Size	333,542	357,635	367,517

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value ≤ .1, ** represents a p-value ≤ .05, and *** represents a p-value ≤ .01 significance.
Note 2: The results are presented with standard errors clustered on individuals but the overall results are robust to clustering on occupations.
Note 3: The task indices and fixed-effects were aggregated to a 3-Digit SOC taxonomy but the results are robust to estimation at a 2 and 5-Digit SOC taxonomy.
Note 4: The results were robust to estimation using only data after 2008 when almost all O*NET occupations had been updated at least once.

We eliminate the second source of variation by controlling for occupation-spell fixed-effects (i.e. a fixed effect for an individual in each occupation) in the second specification.[15] Although the second specification loses statistical significance for each task index, we attribute this result to additional noise from individuals experiencing

15 The results from Table 6 using occupation-spell fixed effects match those obtained from including occupation dummy variables.

employment transitions in response to changes in task engagement.[16] The third and most restrictive specification includes a job-spell fixed-effect for each individual in each job that they hold. The statistical significance for two of the three task indices returns in the third specification. Although the remainder of this analysis will focus on results obtained from this last specification, the fifth section of the paper includes the first two specifications in our robustness check using instrumental variable estimation.

According to the third specification, the wage premium for engagement in abstract tasks (i.e. the return to high skills) is observed to have experienced a statistically significant increase over the period. In contrast, the premium associated for engagement in routine tasks (i.e. the return to middle skills) has declined substantially over the same period. The premium for non-routine manual tasks (i.e. the return to low skills) has remained constant throughout the period. These differential changes to the skill premium match the predictions and empirical observations detailed most prominently by Acemoglu and Autor (2011). To our knowledge, these estimates represent the first empirical evidence of SBTC that controls for unobserved individual heterogeneity and illustrates these theoretical predictions using the task-based approach.

The SBTC narrative states that 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 technology in production. In order to test whether we can observe the presence of task replacing technology, we append Equation 8 to include an index for occupational technology adoption.[17] Table 7 presents the results from including the technology adoption index into our model with job-spell fixed effects. The cross-sectional variation from the between-effects estimator reveals that an increase in the routine task index is associated with an increase wages but its interaction with technology adoption has a negative coefficient. Similarly, the fixed-effects estimate illustrates that the return to routine tasks (i.e. the return to middle skills) is actually increasing except in occupations where there is a corresponding increase in the adoption of technological capital.

16 Evidence of this can be found in the data and is detailed by Ross (2015) and Cortes (2016).
17 The index for technology adoption includes the degree of automation and interacting with computers measures from the O*NET database.

Table 7
Cross-Sectional Regression of Log Wages on Task Indices and Technology Adoption

	Between-Effect Estimate	Fixed-Effect Estimate
	(1)	(2)
Abstract	0.042***	0.006***
	(0.001)	(0.002)
Routine	0.124***	0.033***
	(0.003)	(0.010)
Technology Adoption	0.532***	0.172***
	(0.007)	(0.024)
Routine x Technology Adoption	-0.034***	-0.011***
	(0.001)	(0.002)
Non-Routine Manual	0.071***	0.011***
	(0.001)	(0.003)
Years of Education	0.063***	0.010***
	(0.001)	(0.002)
Age	0.042***	0.036***
	(0.001)	(0.004)
Age-squared	-0.000***	-0.000***
	(0.000)	(0.000)
Time FE	Yes	Yes
Individual FE	No	No
Occupation-Spell FE	No	No
Job-Spell FE	Yes	Yes
Effective Sample Size	367,517	367,517

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value ≤ .1, ** represents a p-value ≤ .05, and *** represents a p-value ≤ .01 significance.
Note 2: The results are presented with standard errors clustered on individuals but the overall results are robust to clustering on occupations.
Note 3: The task indices and fixed-effects were aggregated to a 3-Digit SOC taxonomy but the results are robust to estimation at a 2 and 5-Digit SOC taxonomy.
Note 4: The results were robust to estimation using only data after 2008 when almost all O*NET occupations had been updated at least once.

5. Instrumental Variables

This section presents a robustness check with instrumental variables that confirms the results presented in Section 4. The fixed-effects wage model presented in the previous section controls for unobserved heterogeneous ability. Specifically, the fixed-effects control for endogeneity in those estimates if we believe that occupational choice (i.e. selection) is driven by time-invariant factors like unobserved heterogeneous ability or specific attributes of individuals within jobs or occupations. It is plausible, however, that sorting across occupations also occurs as a result of expectations about occupational task engagement in future periods. As a robustness check on our initial findings, we construct three instruments for each of the task indices and apply two stage least squares with fixed-effects.

Motivated by Bartik (1991) and Card (2001), we construct instruments for each of our three task indices that take a similar form. The instruments rely on exogenous shocks to task engagement by interacting cross-occupational task engagement in period t with the relative occupation-specific level of task engagement in a base year. The data used for the base year was collected in the year 2000 and was obtained from the third release of the *O*NET* database. The measures in this release of the *O*NET* database rely on analyst assessments rather than surveys of incumbent workers. As before, we follow Blinder (2007) and Firpo et al. (2011) by assigning a Cobb-Douglas weight of two thirds to importance and a weight of one third to level categories. We also maintain the structure of our synthetic panel by weighting the *O*NET* measures and aggregating to a 3-digit SOC level. The explicit form of the instrument used for each of the task indices can be seen in Equation 9.[18]

$$\hat{\boldsymbol{\tau}}_{t,s,k} = \sum\nolimits_{j\in k}^{k} \left(\left(\boldsymbol{LV}_{t,j}^{1/3}\ \boldsymbol{IM}_{t,j}^{2/3} \times \frac{\boldsymbol{LV}_{00,s,j}^{1/3}\ \boldsymbol{IM}_{00,s,j}^{2/3}}{\boldsymbol{LV}_{00,j}^{1/3}\ \boldsymbol{IM}_{00,j}^{2/3}} \right) + \left(\boldsymbol{CX}_{t,j} \times \frac{\boldsymbol{CX}_{00,s,j}}{\boldsymbol{CX}_{00,j}} \right) \right) \tag{9}$$

The results from the first stage of our instrumental variable estimation are presented in Table 8. The first column contains estimates with individual fixed-effects while the second include occupation and job-sell fixed-effects. The first panel contains the first stage results for the abstract index while the second and third contain results for the routine and non-routine manual index. The third column includes controls for job-spell fixed-effects and contains results that are consistent with our expectations of a viable first stage with sufficiently strong instruments.

18 As before, those measures from the work activity and ability categories contain a value for both level and importance. In contrast, the context measure is only available for variables from the work context category. As a result, a measure $j \in k$ from the context category would have $LV_{t,s,j}^{1/3}\ IM_{t,s,j}^{2/3} = 0$ and a variable from the activity or ability category would have $CX_{t,s,j} = 0$.

Table 8
First Stage Fixed-Effects Regression of Task Indices on Instrumental Variables

	Fixed-Effect Estimates		
	(1)	(2)	(3)
	1st Stage: Abstract		
Abstract	0.321***	-0.755***	0.346***
	(0.003)	(0.021)	(0.007)
Routine	-0.260***	4.225***	-0.242***
	(0.009)	(0.196)	(0.026)
Non-Routine Manual	0.043***	-0.769***	0.083***
	(0.043)	(0.093)	(0.018)
R-square	0.714	0.3884	0.674
F-stat	2871	686	768
	1st Stage: Routine		
Abstract	-0.004**	-0.034***	-0.009*
	(0.002)	(0.011)	(0.005)
Routine	0.928***	0.739***	0.895***
	(0.009)	(0.078)	(0.025)
Non-Routine Manual	0.201***	-0.478***	0.200***
	(0.006)	(0.042)	(0.018)
R-square	0.765	0.051	0.739
F-stat	3252	100	415
	1st Stage: Non-Routine Manual		
Abstract	0.036***	-0.089***	0.025***
	(0.002)	(0.015)	(0.005)
Routine	0.285***	1.574***	0.203***
	(0.007)	(0.109)	(0.020)
Non-Routine Manual	0.732***	-0.261***	0.753***
	(0.005)	(0.044)	(0.014)
R-square	0.75	0.139	0.696
F-stat	2888	259	417
Time FE	Yes	Yes	Yes
Individual FE	Yes	No	No
Occupation-Spell FE	No	Yes	No
Job-Spell FE	No	No	Yes
Effective Sample Size	333,493	357,567	367,447

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value ≤ .1, ** represents a p-value ≤ .05, and *** represents a p-value ≤ .01 significance.
Note 2: The results are presented with standard errors clustered on individuals but the overall results are robust to clustering on occupations.
Note 3: The task indices and fixed-effects were aggregated to a 3-Digit SOC taxonomy but the results are robust to estimation at a 2 and 5-Digit SOC taxonomy.
Note 4: The results were robust to estimation using only data after 2008 when almost all O*NET occupations had been updated at least once.

Table 9 contains second stage estimates of wage effects using the instruments in models containing fixed effects for individuals, occupations, and job-spells. As mentioned, these estimates control for possible time time variant selection based on expectations about the future of the labor market. Specifically, the instrumental variables help control for endogeneity if we believe that individuals have expectations about how task engagement might evolve over time. The results from the third specification using job-spell fixed-effects indicate that only the coefficient on the routine task index remains statistically significant using this methodology.

Table 9
Instrumental Variable Fixed-Effects Regression of Log Wages on Task Indices

	Fixed-Effect Estimates		
	(1)	(2)	(3)
Abstract	0.013***	-0.013	0.006
	(0.002)	(0.029)	(0.004)
Routine	-0.016***	0.145	-0.027***
	(0.004)	(0.101)	(0.008)
Non-Routine Manual	0.005**	-0.091	0.003
	(0.002)	(0.272)	(0.005)
Years of Education	0.016***	0.008***	0.010***
	(0.002)	(0.002)	(0.002)
Age	0.052***	0.037***	0.036***
	(0.003)	(0.004)	(0.004)
Age-squared	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Time FE	Yes	Yes	Yes
Individual FE	Yes	No	No
Occupation-Spell FE	No	Yes	No
Job-Spell FE	No	No	Yes
Effective Sample Size	333,493	357,567	367,447

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value ≤ .1, ** represents a p-value ≤ .05, and *** represents a p-value ≤ .01 significance.
Note 2: The results are presented with standard errors clustered on individuals but the overall results are robust to clustering on occupations.
Note 3: The task indices and fixed-effects were aggregated to a 3-Digit SOC taxonomy but the results are robust to estimation at a 2 and 5-Digit SOC taxonomy.
Note 4: The results were robust to estimation using only data after 2008 when almost all O*NET occupations had been updated at least once.

6. Conclusions

In this study, a theoretical model of occupational production is developed and used to derive comparative statics related wages. This model is used as the basis for estimating how the wages of incumbent workers respond to changes in occupational task engagement. We construct a synthetic panel of occupational task engagement and attached it to panel data on workers. This data allows us to explore the source of wage premiums for routine and non-routine tasks while controlling for individual, occupation, and job-spell fixed-effects. This methodology is an important contribution to the existing literature because it allows estimates to control for time invariant unobservable. In addition, the application of ten year worth of task data ensures that the variation in wages is unlikely to be driven by institutional factors.

Cross-sectional estimates confirm prior findings in terms of the ordering of the coefficients. Within-effects estimates demonstrate that cross-section of task measures cannot fully capture the dynamics of evolving occupational wage premiums. The within-effects estimates from our fixed-effects model reduce the magnitude of cross-sectional estimates and provide new and more robust evidence of a declining premium for routine tasks and middle skilled labor. Further, we provide insight into how this declining task price interacts with technology adoption. Estimates using a robustness check with instrumental variables confirms that the price for routine tasks is declining by additionally controlling for time variant unobservables.

Although we are unable to find confirmation of our estimates related to abstract and non-routine tasks, we believe this may be due to effects operating through a different channel. Specifically, we believe that changes in task engagement may also be predictive of employment transitions. Additional research using this methodology might focus specifically on effects associated with these dynamics rather than wages.

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Technical Appendix (Online Publication Only)

Figure A.1
Variation in the Abstract Task Index at the 2-Digit SOC Taxonomy

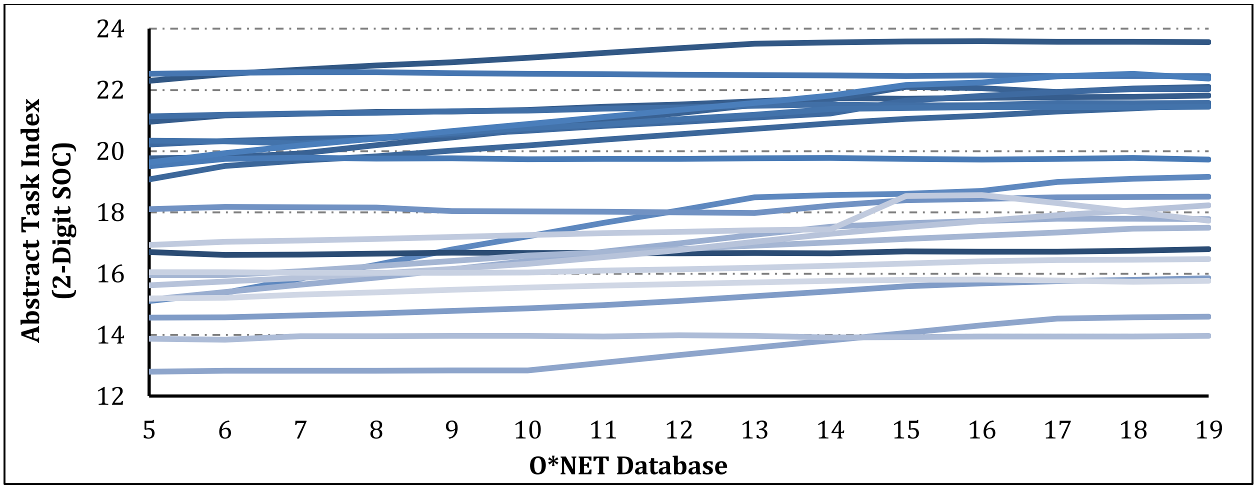

Figure A.2
Variation in the Routine Task Index at the 2-Digit SOC Taxonomy

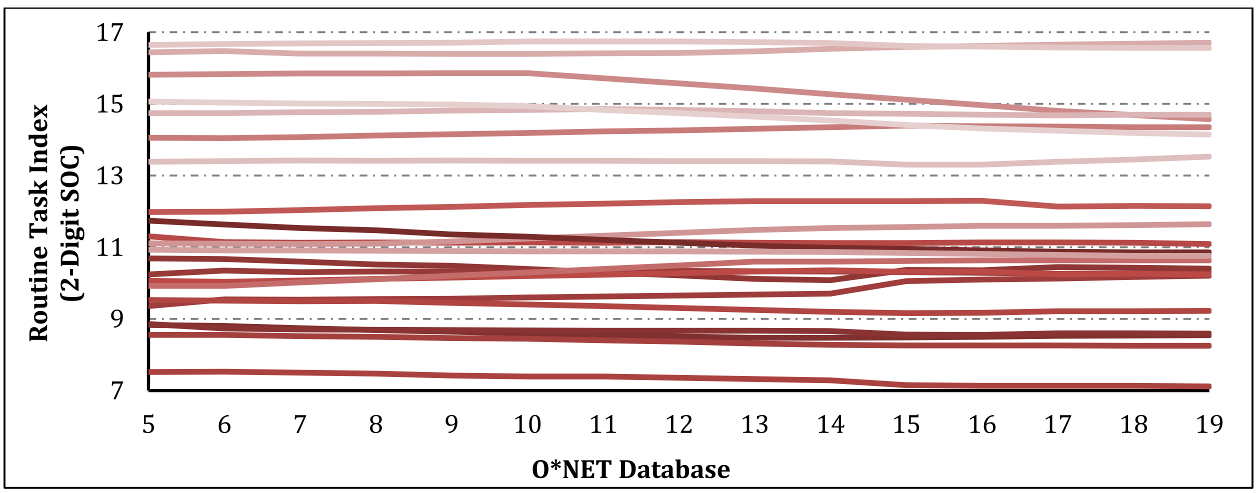

Figure A.3

Variation in the Non-Routine Manual Task Index at the 2-Digit SOC Taxonomy

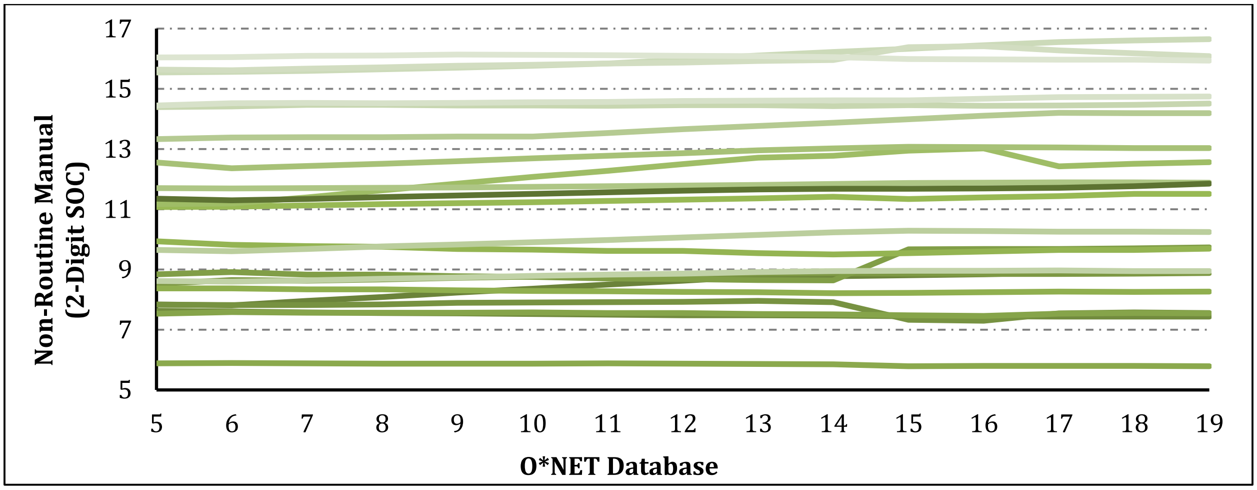

Table A.1

Fixed-Effects Regression of Log Wages on Task Indices, 2-Digit SOC Taxonomy

	Fixed-Effect Estimates		
	(1)	(2)	(3)
Abstract	0.020***	-0.009	0.013***
	(0.001)	(0.006)	(0.003)
Routine	-0.012***	-0.024**	-0.018***
	(0.003)	(0.011)	(0.005)
Non-Routine Manual	0.007***	0.014	0.005
	(0.002)	(0.010)	(0.004)
Years of Education	0.016***	0.006***	0.010***
	(0.002)	(0.002)	(0.002)
Age	0.052***	0.040***	0.036***
	(0.003)	(0.003)	(0.004)
Age-squared	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Time FE	Yes	Yes	Yes
Individual FE	Yes	No	No
Occupation-Spell FE	No	Yes	No
Job-Spell FE	No	No	Yes
Effective Sample Size	333,573	352,976	367,556

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value ≤ .1, ** represents a p-value ≤ .05, and *** represents a p-value ≤ .01 significance.
Note 2: The results are presented with standard errors clustered on individuals but the overall results are robust to clustering on occupations.
Note 3: The results were robust to estimation using only data after 2008 when almost all O*NET occupations had been updated at least once.

Table A.2

Fixed-Effects Regression of Log Wages on Task Indices, 5-Digit SOC Taxonomy

	Fixed-Effect Estimates		
	(1)	(2)	(3)
Abstract	0.015***	0.003	0.011***
	(0.001)	(0.002)	(0.002)
Routine	-0.006***	-0.004	-0.011***
	(0.002)	(0.006)	(0.003)
Non-Routine Manual	-0.003***	-0.008	-0.008***
	(0.001)	(0.005)	(0.003)
Years of Education	0.014***	0.007***	0.010***
	(0.002)	(0.002)	(0.002)
Age	0.050***	0.036***	0.036***
	(0.003)	(0.004)	(0.004)
Age-squared	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Time FE	Yes	Yes	Yes
Individual FE	Yes	No	No
Occupation-Spell FE	No	Yes	No
Job-Spell FE	No	No	Yes
Effective Sample Size	321,621	346,230	353,772

Note 1: The coefficients are presented along with their level of significant. A coefficient concatenated with * represents a p-value ≤ .1, ** represents a p-value ≤ .05, and *** represents a p-value ≤ .01 significance.
Note 2: The results are presented with standard errors clustered on individuals but the overall results are robust to clustering on occupations.
Note 3: The results were robust to estimation using only data after 2008 when almost all O*NET occupations had been updated at least once.