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Job Tasks and the Gender Wage Gap among College Graduates*

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Abstract

Gender differences in current and past job tasks may be crucial for understanding the gender wage gap. We use novel task data to address well-known measurement concerns, including that standard task measures assume away within-occupation gender differences in tasks. We find that unique measures of task-specific experience, in particular high-skilled information experience, are of particular importance for understanding the substantial widening of the wage gap early in the career. Highlighting the importance of these measures, traditional work-related proxies for gender differences in human capital accumulation are not informative because general work experience is similar by gender for our recent graduates.

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1 Introduction

A worker's productivity, and therefore wages, may depend on both the tasks the worker performs on her current job ("current tasks") and the tasks the worker performed in the past ("past tasks").[1] As such, accounting for gender differences in both current and past job tasks may be crucial for understanding a variety of issues related to the gender wage gap. Unfortunately, well-known measurement concerns arise when attempting to characterize these tasks. This paper provides new evidence about the role of current and past job tasks in determining the gender wage gap, taking advantage of unique job task data from the Berea Panel Study (BPS) that address these measurement concerns.

A traditional approach that recognizes the potential importance of gender differences in current tasks involves controlling for a worker's occupation (Black et al., 2008; Goldin and Katz, 2008; Goldin, 2014; Blau and Kahn, 2017). However, recent evidence suggests that this approach may have an important limitation. Goldin (2014) concludes that paying close attention to gender wage differentials that exist within occupations is of utmost importance for understanding the overall gender wage gap, stating that "The majority of the current (gender) earnings gap comes from within occupation differences rather than from between occupation differences. What happens within each occupation is far more important than the occupations in which women wind up."

A natural way to address this limitation is to explicitly characterize the tasks performed on individual jobs. Unfortunately, in practice, there exists a fundamental measurement difficulty that prevents the task-based approach from exploiting its advantage in this respect. For the purposes of characterizing tasks, what is typically observed in longitudinal surveys is only a worker's occupation. Thus, the task literature is typically forced to assign the same set of tasks to all jobs in a particular occupation using an external data source such as the DOT or the more recent ONET.[2] From a technical standpoint, substantial measurement error in current tasks

[1] The notion that productivity will depend directly on current tasks is supported empirically by a large literature that explores the existence of wage differentials across employers (Manning, 2003), industries (Gibbons and Katz, 1992), occupations (Heckman and Sedlacek, 1985), and worker skill levels (Acemoglu and Autor, 2011; Autor and Dorn, 2013) The notion that one's productivity today will also depend on past tasks is emphasized by the learning-by-doing model of human capital formation (Becker, 1964).

[2] Using occupation-level task information, several recent papers have demonstrated that the task-based approach can avoid the need to control for a large number of occupations and/or can provide an understanding of why the gender wage gap is related to occupations. Building on the framework of Autor, Levy and Murnane (2003), Black and Spitz-Oener (2010) find that a large fraction of the recent decline in the German gender wage gap can be attributed to

is likely to be created when a worker's current tasks are imputed solely on the basis of her occupation. The inherent concern in our substantive context is that if, as suggested by Autor and Handel (2013), measurement error in current tasks is correlated with gender, then a portion of the gender wage gap that should be attributed to differences in current tasks will incorrectly remain part of the unexplained portion of the gender wage gap.[3] This could lead to incorrect conclusions about a variety of important questions, such as whether men and women with similar human capital receive equal pay for equal work.

Related measurement concerns also arise when attempting to account for gender differences in past tasks, which may serve as useful proxies for gender differences in human capital accumulation. To summarize past tasks, it is natural to construct measures of task-specific work experience by adding up information about the tasks that a worker performed on her job in each past year. However, from a practical standpoint, the construction of these cumulative, task-specific experience measures is complicated by the fact that widely used data sources such as the DOT typically provide only qualitative measures of task importance in each year; it may not be obvious how to aggregate qualitative information, such as yearly survey questions about whether a particular task is "important" or not, into a measure describing the cumulative importance of a particular task up to any point in the career (Stinebrickner, Stinebrickner and Sullivan, 2017). Further, even putting this issue aside, the cumulative nature of the task-specific experience measures may further exacerbate the measurement error problems described in the previous paragraph given the strong persistence in workers' occupations over time.

This paper takes advantage of job task data that were collected with the explicit goal of addressing the measurement difficulties described above. The data come from the Berea Panel

relative task changes between men and women, with women shifting away from performing "routine" tasks. Bacolod and Blum (2010) find that large increases in the prices of cognitive and people skills (which women are well endowed with) combined with a decline in the price of manual skills (which men are well endowed with), can account for approximately twenty percent of the decline in the gender wage gap. Building on Yamaguchi (2012), Yamaguchi (2018) finds that a dramatic drop in the returns to motor skills can account for a major part of the narrowing U.S. gender wage gap between 1980 and 2000. In related work, Beaudry and Lewis (2014) use cross-city variation in the diffusion of personal computers to show that changes in skill prices can account for a substantial portion of the recent decline in the gender wage gap.

[3] Taking advantage of rare data in which tasks are observed at the level of individual jobs, Autor and Handel (2013) find that substantial variation exists in tasks within an occupation and that this variation is important for predicting wages, even after controlling for occupations. While whether a person is a Spanish-language speaker is the strongest predictor of tasks within occupations, evidence also exists of significant differences in tasks by gender within occupations. Further, the results in our paper suggest that even larger differences in tasks by gender might be found to exist within occupations in Autor and Handel (2013) if the Abstract category was disaggregated further to differentiate between Analytical and Interpersonal tasks.

Study (BPS), a longitudinal survey that followed respondents closely from the time of college entrance through the first ten years of their post-college lives (Section 2). Crucial for taking into account the possibility that gender differences in tasks may be present within occupations, the data represent a rare case where tasks are measured directly for a worker's actual job.[4] Perhaps just as importantly, the task data are unique in containing explicit time allocation information, which produces quantitative task measures that are easily interpretable and conceptually appealing. Specifically, in the spirit of the data that are available in the DOT, the task data allow us to characterize the percentage of one's time in her current job that is spent on high skilled information tasks, low skilled information tasks, high skilled people tasks, low skilled people tasks, high skilled objects tasks and low skilled objects tasks.[5] Further, the fact that the BPS is the only dataset where job-level task information is collected longitudinally, in conjunction with the time allocation feature of the data, allows us to compute six task-specific experience measures that serve as natural proxies for the human capital accumulated by a particular point in time - the cumulative amount of time that a person spent in the past on high skilled information tasks, low skilled information tasks, high skilled people tasks, low skilled people tasks, high skilled objects tasks and low skilled objects tasks.

Section 3 provides a descriptive view of gender differentials in wages and job tasks in the first ten post-college years. We first document an overall gender wage gap of seven percent. We then begin our investigation into the relevance of task-related explanations for the gender wage gap by providing a descriptive view of the (pooled) task data, which represents the first time that gender differences in job tasks have been documented using explicit time allocation information. We find substantial differences between the current period tasks performed by men and women. Men spend more time performing objects tasks at both a high skilled and low skilled level. Women spend more time performing people tasks at both a high skilled and low skilled level.

[4]The benefits of this type of data for studying the gender wage gap also motivates the work of Bizopoulou (2016), who studies nine European countries using cross-sectional data from the Program for the International Assessment of Adult Competencies (PIAAC). In terms of the scarcity of this type of data, Robinson (2018) uses the one year (1971) of CPS data in which an analyst assigned DOT tasks to jobs. Autor and Handel (2013) use individual level information collected as part of the Princeton Data Improvement Initiative. Black and Spitz-Oener (2010) make use of job level task information from the German Qualification and Career Survey, and then carry out their empirical analysis at the occupation level.

[5]The BPS data do not include occupation identifiers. The focus of the data on the collection of tasks measures is consistent with Sanders and Taber (2012), who note that, from the perspective of the theory of specific human capital, the primary usefulness of categorizing jobs by occupation is that occupations serve as observable proxies for the true task requirements of jobs.

However, for information tasks, men spend more time at a high skilled level, while women spend more time at a low skilled level. We note that our task-based approach is directly motivated by previous research that has stressed the importance of college major for understanding gender wage gaps (see, e.g., Altonji (1993); Grogger and Eide (1995); Black et al. (2008)), because college major likely affects wages, in large part, by influencing the types of jobs that one holds. Our descriptive evidence strengthens the motivation for the use of task data by showing that college major does seem to be an important determinant of gender differences in tasks, but that further gender differences in tasks are present conditional on major.

Section 3.2 describes how gender differences in wages and tasks evolve over the sample period. Consistent with previous research, we find that the wage gap increases substantially over the first ten years after graduation (Bertrand, Goldin and Katz, 2010), from very close to zero at the time of labor market entrance to approximately 22 percent by the end of the sample period. Our time varying task data allow us to provide descriptive evidence of relevance for two job-related mechanisms that could contribute to the observed time pattern. The first mechanism is that gender differences in current period tasks could change over time in a way that is beneficial to the wages of men. The second mechanism is that, even when gender differences in tasks are constant over time, persistent differences in current tasks could accumulate over time to produce gender differences in task-specific experience that are beneficial to the wages of men.

Section 4 uses a log-wage regression to quantify the role that gender differences in tasks play in generating the gender wage gap. We find that a statistically significant gender wage gap of 8.6 percent exists after controlling for our proxy for human capital at the time of entrance to the workforce, college GPA. The novel job task measures are an important determinant of the gender wage gap. Adding both the current task measures and the past task measures (i.e., the task-specific experience measures) as explanatory variables in the log-wage regression reduces the gender wage gap by a total of 45 percent. In terms of the relative importance of the current and past task measures for achieving this reduction, the regression results, combined with the descriptive task-performance results, suggest a relatively minor role for gender differences in current period tasks. This is the case because, while there exist substantial gender differences in current period tasks and while current period tasks are strongly related to wages, men do not tend to sort systematically into only the high paying tasks. For example, men spend more time performing the highest paying task (high skilled information), but also spend more time performing the lowest paying task (low skilled objects) and the third lowest paying task (high skilled objects). In contrast, the regression results and the task-performance results suggest a role for gender differences in task-specific experience; the extra experience that men obtain in high skilled information jobs is found to be extremely important for wages, and other types of task-specific experience have little effect. We find that adding college major and family information to our specifications has very little effect on the estimated importance of the task measures.[6]

Section 5 provides a more formal exploration of the findings from the wage regressions. We begin by showing that our regression specification that includes current tasks, task-specific experience, college GPA, and college major is able to account for approximately 36 percent of the gender wage gap that exists in years 7 and 8 of the sample and 26 percent of the gender wage gap that exists in years 9 and 10 of the sample, while also correctly predicting little difference in the wages of men and women at the beginning of the sample period. Highlighting the value of our longitudinal, quantitative task measures, the decompositions reveal that the task-specific experience variables account for virtually all of the "explained" portion of the gender wage gap in this specification.

Section 6 contains conclusions. For a variety of reasons, including the reality that we are studying students from one school, we do not believe that our comparative advantage is in trying to provide conclusive evidence about questions such as whether women with equal human capital receive equal pay for equal work. Rather, we believe that our main contribution comes from the important, general message that paying close attention to the measurement of job tasks may be crucial for future studies of the gender wage gap. For example, while differences in total work experience have traditionally been found to be an important proxy for gender differences in human capital accumulation (Light and Ureta, 1995; Black et al., 2008; Goldin, 2014; Blau and Kahn, 2017), we find that the males and females in our recent cohort of graduates work very similar amounts over the first ten years of their careers. This suggests that, without measures of task-specific experience of the type we propose here, researchers may increasingly find themselves without job-related information that can proxy for gender differences in human capital

[6]Recent work by Hotz, Johansson and Karimi (2017) uses matched worker-firm data from Sweden to provide new evidence on the role that family formation and firms play in accounting for gender differences in job characteristics and wages.

accumulation over the lifecycle, which represents one of the fundamental explanations for the overall gender wage gap and for the widening of the gender wage gap over time.

2 Data

This section provides general information about the Berea Panel Study (Section 2.1) and explains how job tasks are measured in this dataset (Section 2.2).

2.1 The Berea Panel Study

Designed and administered by Todd Stinebrickner and Ralph Stinebrickner, the Berea Panel Study (BPS) is a longitudinal survey, which was initiated to provide detailed information about the college and early post-college periods. The project involves surveying students who entered Berea College in the fall of 2000 and the fall of 2001 approximately sixty times from the time of college entrance through 2014. In this paper, we examine the earnings of graduates, by taking advantage of post-college surveys that were collected annually after students left school. More than ninety percent of all graduates completed one or more of these annual surveys, and the response rate on these surveys remained above eighty-two percent until 2011, before declining slightly. To avoid the need to impute crucial information, our analysis uses all yearly observations from the time of graduation until an individual first fails to complete a post-college survey. Our sample consists of 526 individuals who, on average, contribute 6.2 yearly observations to the data.

The survey data is merged with detailed administrative data. The administrative data provide basic demographic information. Of particular relevance, 64% of the sample is female. It also contains academic information. Cumulative grade point average (GPA), which is widely viewed as the best available proxy for human capital at the time of entrance to the workforce, has a mean (standard deviation) of 3.16 (0.46). As described in Section 3.1, the data also contain information about college major.

Important for the notion that the basic lessons from our study of one school are pertinent for thinking about what takes place elsewhere, Berea operates under a standard liberal arts curriculum, students at Berea are similar in academic quality to students at schools such as The University of Kentucky (Stinebrickner and Stinebrickner, 2008), and outcomes such as major choice at Berea are similar to those found in the NLSY by Arcidiacono (2004). However, even putting aside the obvious issue of data collection feasibility, there are benefits of studying one school. In particular, the ability to hold school quality constant is beneficial for a variety of reasons, including that it makes academic measures such as college GPA and major directly comparable across individuals.[7]

2.2 Measuring Job Tasks in the BPS

The task information associated with the job that a worker holds in a particular year comes from BPS survey Question C, which is shown in Appendix A. A unique component of the BPS task data is that the survey directly measures the time allocated to different job tasks by workers. Question C4 contains the time allocation questions that document the percentage of total work time that is spent on the people, information, and objects task categories. Questions C1, C2, and C3 contain the time allocation questions that document the percentages of time spent on each specific sub-task within the People, Information, and Objects task categories. Defining the first two sub-tasks (1 and 2) within each of the People (C1), Information (C2), and Objects (C3) task categories as low skilled and the last two sub-tasks (3 and 4) as high skilled, these questions allow us to compute the percentage of total work time in a year that is spent on each of the three task categories, at each of the two skill levels.[8]

In the remainder of the paper, where convenient, we abbreviate each task category as follows: people (P), information (I), and objects (O). In terms of notation, for each task k, $k \in (P, I, O)$, let $\tau^H(k)$ represent the fraction of time on-the-job (in a particular year) that a worker spends performing task k at a high skill level (H), and let $\tau^L(k)$ represent the fraction of time spent performing task k at a low skill level (L). The vector of the current tasks performed on a job in a particular year t is denoted by the six element vector $\mathbf{T}_t = \{\tau_t^H(P), \tau_t^L(P), \tau_t^H(I), \tau_t^L(I), \tau_t^H(O),$

[7] For previous work that has used the BPS to study issues in education, see Stinebrickner and Stinebrickner (2003*b*; 2003*a*; 2004; 2006; 2008*b*; 2008*a*; 2010; 2012; 2013; 2014). Stinebrickner, Stinebrickner and Sullivan (2018*b*) estimates the returns to current and past job tasks using the BPS job task data, and provides a detailed description of the task data. Stinebrickner, Stinebrickner and Sullivan (2018*a*) takes advantage of the BPS job task data to examine the labor market mechanisms generating the labor market returns to physical attractiveness.

[8] Relevant for whether survey respondents are able to understand the time allocation questions in Appendix A, these questions are similar in spirit to BPS questions that elicited beliefs (expectations) about grade performance (and other outcomes) by asking respondents to assign percent chances to a set of mutually exclusive and collectively exhaustive grade categories. As a result, respondents had received classroom training related to similar types of questions and had answered similar types of questions frequently in the past, with both exit interviews and internal consistency checks confirming a good understanding of these questions. See Stinebrickner, Stinebrickner and Sullivan (2017) for a more detailed description of the task data.

Table 1: Descriptive Statistics by Gender

	Gender	
	Female (1)	Male (2)
Log-wage†	2.563	2.629
	(0.614)	(0.659)
College GPA	3.228	3.088
	(0.428)	(0.465)
Has children	0.316	0.255
	(0.465)	(0.436)
Employed	0.849	0.909
	(0.358)	(0.288)
Weekly hours	38.594	41.425
	(10.600)	(10.497)
College Major		
Humanities	0.221	0.222
Professional	0.220	0.167
Business	0.114	0.188
Science and Math	0.125	0.183
Social Science	0.139	0.099
Agriculture	0.072	0.089
Education	0.108	0.051
Number of people	337	189
Ave. observations per person	6.14	6.27

Major entries are means, standard deviations in parentheses.
† Wages converted to 2005 dollars using the CPI.

$\tau_t^L(O)\}$. For each worker, summing a particular task variable in $\mathbf{T}_t$ over time, after weighting by hours worked, provides a measure of task-specific work experience at each point of the career - the number of full-time work years spent performing the particular task as of time t.[9] We denote the vector of task-specific experience measures at time t as $\boldsymbol{E_t} = \{e_t^H(P), e_t^L(P), e_t^H(I), e_t^L(I), e_t^H(O), e_t^L(O)\}$.

[9]Specifically, the cumulative amount of time that individual i at time t has spent performing each of the three tasks (people, information, objects) at each skill level (high (H) and low (L)) in the past is given by $e_t^s(k) = \sum_{j=1}^{t-1} \tau_j^s(k)\omega_j^s(k)$, $s \in (H,L)$, $k \in (P,I,O)$, where $\tau_j^s(k)$ is the fraction of time that individual i spends performing task k at skill level s in time j and $\omega_j^s(k)$ is a weight derived from the hours that person i works in time j. The hours weight is $\omega_j^s(k) = hours_j/40$, where $hours_j$ represents the hours worked per week by worker i on her job at time j. The weights are normalized in this manner so that $\omega_j^s(k) = 1$ indicates that a worker works a forty hour week. We make use of the hours data based on the premise that the amount of learning-by-doing depends on the time allocated to each task, rather than simply the percentage of time spent on each task. For example, 1.30 would mean that a worker has spent a total of 1.30 years or, equivalently, approximately 2704 hours (1.30 x 52$\times$(work weeks)$\times$40(hours per week)) performing high skilled people tasks as of time t.

3 Gender Differences in Wages and Tasks: Descriptive Evidence

This section characterizes the gender wage gap for our sample and provides new descriptive evidence about gender differences in tasks. In Section 3.1, we pool observations over the entire sample period. In Section 3.2, we exploit the panel nature of the BPS data to examine how gender differences in wages and tasks change over time.

3.1 Pooling Observations over Time: Gender Differences in Wages and Tasks

This subsection takes advantage of the pooled sample of 3,271 yearly observations that is obtained by combining all observations for all sample members over the full sample period.

3.1.1 The Gender Wage Gap

Hourly wages are constructed from Survey Question D2 (Appendix A), which gave respondents flexibility over whether earnings were reported for an hourly, weekly, monthly, or yearly period, and Survey Question D1, which elicited a worker's hours in a typical week. Pooling observations across the entire sample period, Column 1 of Table 1 shows that the mean log hourly wage for females is 2.563 (in 2005 dollars), while Column 2 shows that the mean log hourly wage for males is 2.629 (in 2005) dollars. Thus, there exists an overall gender wage gap of approximately seven percent.[10]

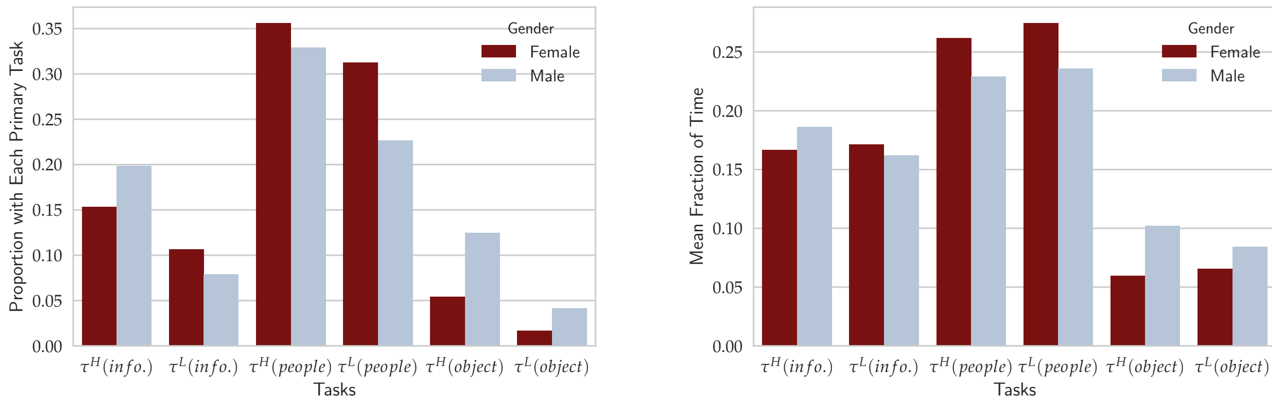
3.1.2 Gender Differences in Job Tasks

We begin our investigation into the relevance of task-related explanations for the gender wage gap by providing a descriptive view of the (pooled) task data. This descriptive analysis represents the first time that gender differences in job tasks have been documented using explicit time allocation information.

We begin with a descriptive view of the current task vector $\mathbf{T}_t$ that is appealing in its simplicity. Specifically, in each year, we characterize the "primary task" for each job as the task on which a worker spends the most time. Figure 1a depicts the proportion of jobs in the sample that have each of the six possible primary tasks, and shows strong evidence of gender differences in

[10] Table 1 also shows that employment rates are quite high for both men and women, which suggests that selection into employment is unlikely to be a major concern in this particular context. See Olivetti and Petrongolo (2008) for an analysis of selection into employment and gender wage gaps across different countries.

Figure 1: Mean Job Tasks by Gender



(a) Primary Tasks by Gender

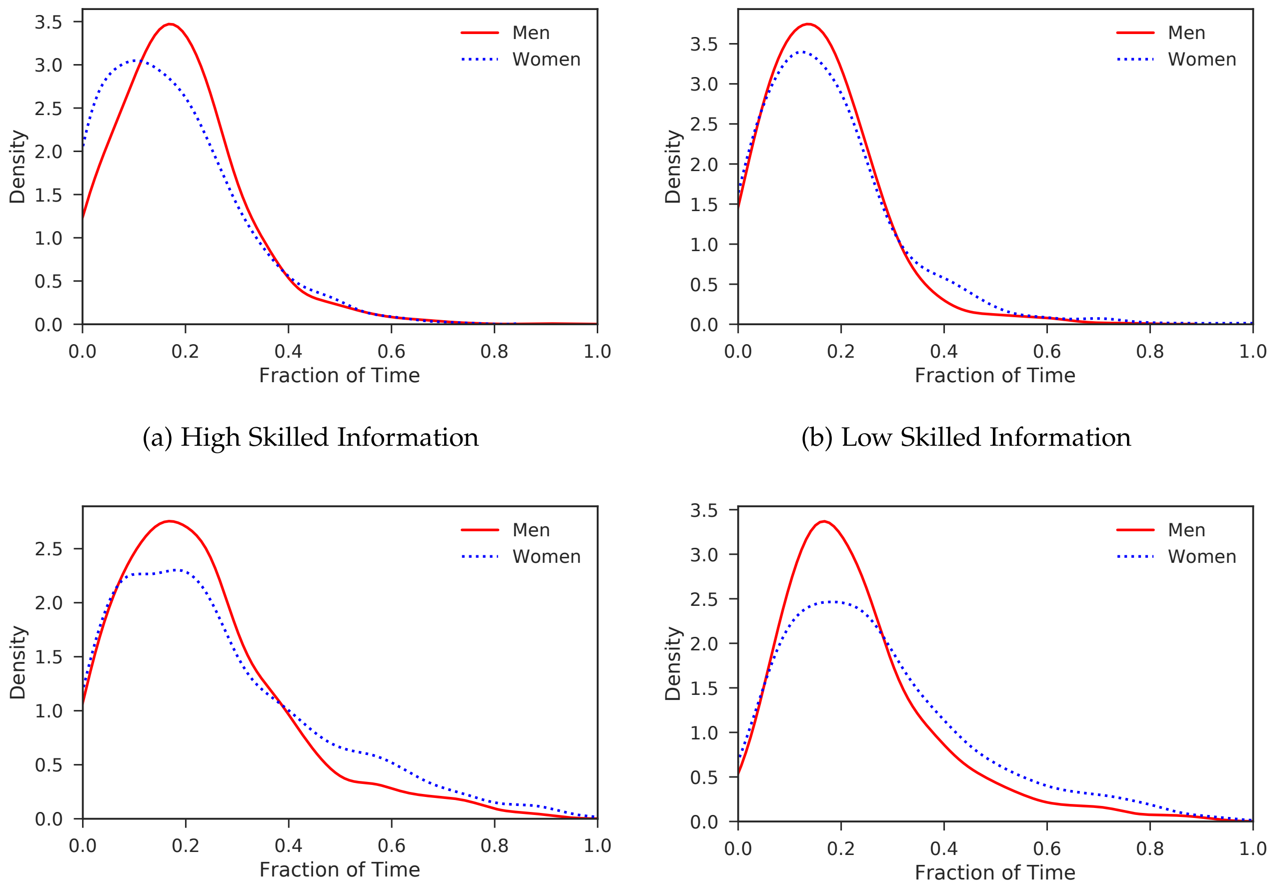
(b) Time Spent on Tasks by Gender

job tasks. Men are over twice as likely to hold a job with a primary task of high-skilled objects (0.125 vs. 0.054, t-stat from test of equality = 7.128) and over twice as likely to hold a job with a primary task of low-skilled objects (0.042 vs. 0.017, t-stat=4.265). Women are 8.2 percent more likely to hold a job with a primary task of high-skilled people (0.356 vs. 0.329, t-stat=1.537) and 37.8 percent more likely to hold a job with a primary task of low-skilled people (0.313 vs. 0.227, t-stat=5.167). However, for information tasks, men are 30 percent more likely to hold a job with a primary task of high-skilled information (0.199 vs. 0.153, t-stat=3.259), but women are 35 percent more likely to hold a job with a primary task of low-skilled information (0.107 vs. 0.079, t-stat=2.55).

While the primary task measures provide a convenient way to view the data, they do not summarize all of the information contained in $\mathbf{T}_t$. Figure 1b shows the mean task fraction separately for males and females. This figure shows that the conclusions about gender differences from the task fractions are qualitatively the same as those from the primary task measures. Women spend more time interacting with people and performing low skilled information tasks, while men spend more time on objects tasks and performing high skilled information tasks. The additional information conveyed by Figure 1b illustrates quantitatively, in fraction of time units, how men and women spend their time on the job. The wage regressions in the remainder of the paper utilize the full set of task fractions in $\mathbf{T}_t$.

Figure 2 moves beyond simple comparisons of mean tasks by showing kernel density estimates of the distribution of job tasks by gender. In the interest of brevity, we omit the objects

Figure 2: The Distribution of Current Period Tasks by Gender: Kernel Density Estimates



(a) High Skilled Information

(b) Low Skilled Information

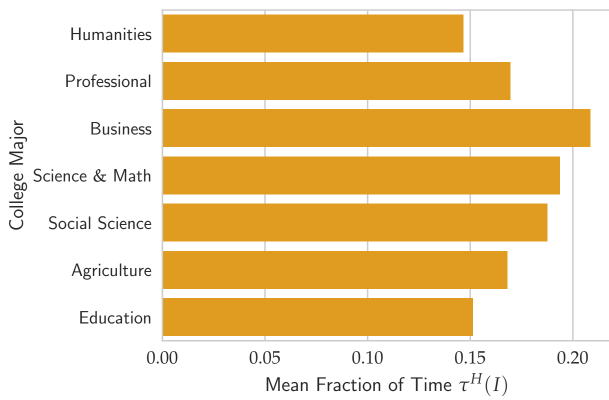
(c) High Skilled People

(d) Low Skilled People

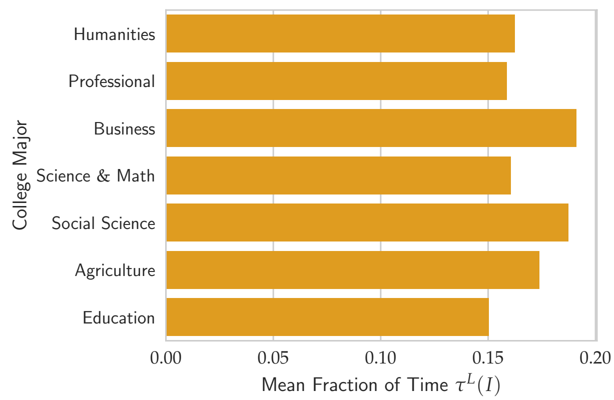
task densities because they are not particularly informative, given the low levels of objects tasks performed by women. Panel (a) of the figure shows that women are more likely to perform low levels of high skilled information tasks, but the right tail of the distribution looks similar for men and women. Panel (d) shows that both men and women are similarly unlikely to hold jobs where no time is occupied by low skilled people tasks ($\tau^L(P) = 0$). However, the right tail of the density shows that women are consistently more likely to perform large amounts of low skilled people tasks.

Existing research finds college major to be very important for understanding gender wage gaps (see, for example, Altonji (1993); Grogger and Eide (1995); Black et al. (2008)). Our task-based approach is directly motivated by this previous research because college major likely affects wages, in large part, by influencing the types of jobs that one holds. In the remainder of this

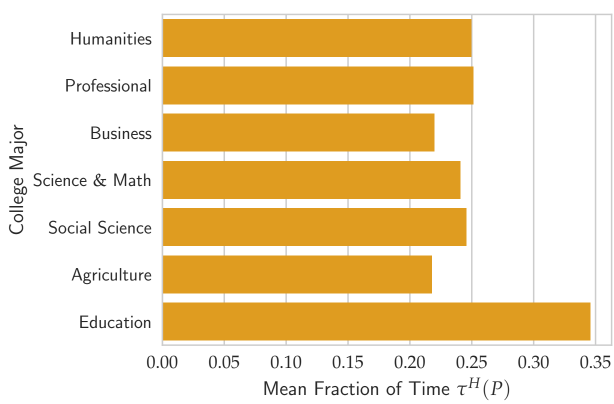
Figure 3: Mean Tasks by College Major



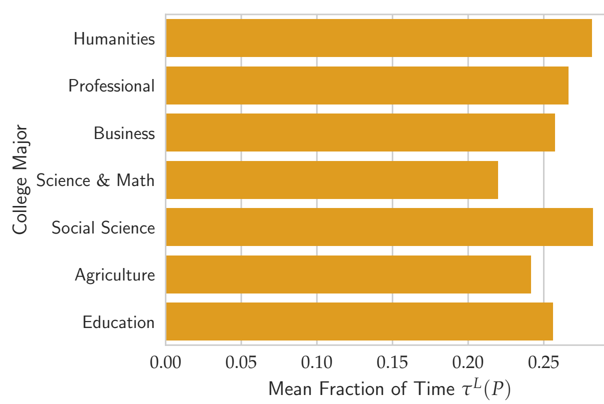
(a) High Skilled Information



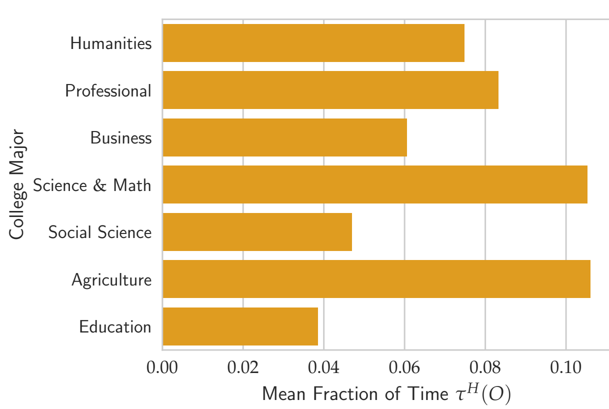
(b) Low Skilled Information



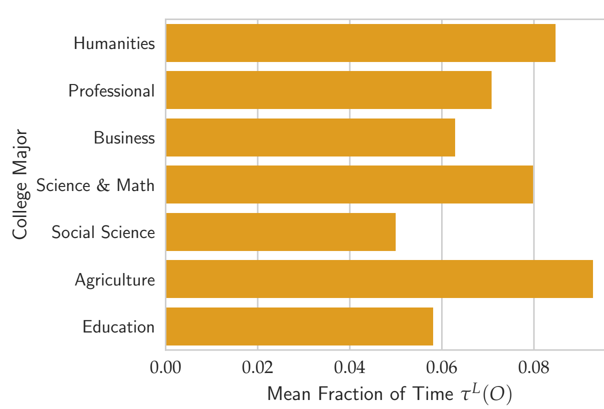
(c) High Skilled People



(d) Low Skilled People



(e) High Skilled Objects



(f) Low Skilled Objects

subsection, we provide some descriptive evidence that college major is indeed a determinant of tasks, and, in the context of a discussion of the potential role of major, note some potentially important features of the task information. We return to issues related to college major in Section 4.1 and Section 5, where we examine whether conclusions about the importance of tasks and conclusions about the gender wage gap are sensitive to whether college major is included, along with our task information, in our empirical specifications.

Table 1 shows sizable gender differences in college major. We group the full set of majors at Berea into seven categories: Humanities, Professional, Business, Science/Math, Social Sciences, Agriculture/Physical Education, and Education.[11] Of note, men are 50 percent more likely to major in Science/Math and 65 percent more likely to major in Business. On the other hand, women are 32 percent more likely to have a Professional major, 40 percent more likely to have a Social Science major, and over twice as likely to have an Education major.

Figure 3 provides evidence that these gender differences in college major are indeed related to the gender differences in tasks seen in Figure 1. Figure 1 showed that men are more likely than women to hold jobs that require more high skilled information tasks, more high skilled objects tasks, and more low skilled objects tasks. Figure 3, when viewed along with the gender differences in college major in Table 1, shows that men are more likely to choose the two majors with the largest amounts of high skilled information tasks (Business, Science/Math), are more likely to choose the two majors with the largest amounts of high skilled objects tasks (Agriculture, Science/Math), and are more likely to choose the major with the largest amount of low skilled objects tasks (Agriculture). Figure 1 showed that women are more likely than men to hold jobs that require more high skilled people tasks, more low skilled people tasks, and more low skilled information tasks. Figure 3, along with Table 1, shows that women are more likely to choose the two majors with the largest amounts of high skilled people tasks (Education, Humanities), are more likely to choose the two majors with the largest amounts of low skilled people tasks (Social Science, Humanities), and are more likely to choose the major with the second largest amount of low skilled information tasks (Social Science).

While the results in the previous paragraph indicate that information abut college major can be successful in capturing some gender differences in types of work, an important advantage of our task data comes from its ability to also capture any gender differences in types of work that

[11]Humanities includes Art, English, Foreign Languages, History, Music, Philosophy, Religion, and Theater Professional includes Nursing, Industrial Arts, Industrial Technology, Child Development, Dietetics, Home Economics, and Nutrition. Science/Math includes Biology, Chemistry, Computer Science, Physics, and Math. Social Sciences includes Economics, Political Science, Psychology, and Sociology.

Figure 4: Gender Gap in Mean Tasks by College Major

exist within a major. Figure 4 provides evidence that this is important, by showing the gender gap in job tasks conditional on college major. Figure 1 showed that men are more likely than women to hold jobs that require more high skilled objects tasks, low skilled objects tasks, and high skilled information tasks. Figure 3 showed that this is due, in part, to men tending to choosing majors that require more of these tasks. However, Figure 4 shows that this is also due, in part, to men spending more time on these tasks conditional on their major. For example, looking across the seven panels, men perform more high skilled objects tasks than women in each of the seven major groups (the sixth entry in each panel), perform more low skilled objects tasks in each of the seven major groups (seventh entry), and perform more high skilled information tasks in five of the seven major groups (first entry). Similarly, examining the tasks that women were found to be more likely to perform (Figure 1), we see that women perform more high skilled people tasks in six of the seven major groups (third entry), perform more low skilled people tasks in five of the seven major groups (fourth entry), and perform more low skilled information tasks in four of the seven major groups (second entry).

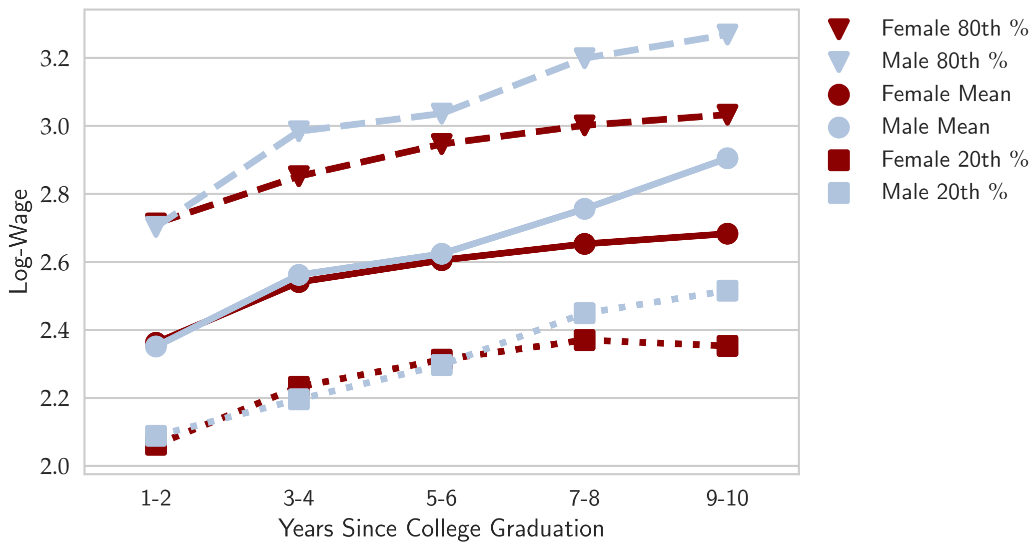
We stress that the exact numbers in the two previous paragraphs will depend on a variety of factors, including the extent to which majors are aggregated into groups. Nonetheless, the general message from these paragraphs - that majors are likely important determinants of gender differences in tasks, but that further gender differences in tasks are likely to be present conditional on major - serves as a strong motivation for our collection and use of task data. Related to this point, the (individual-level) task measures are also important because, unlike static variables such as college major, they are able to capture changes in types of work over time. This type of dynamic consideration is the focus of the next subsection.

3.2 Dynamics: Gender Differences in Wages and Tasks Over Time

3.2.1 The Rising Gender Wage Gap Over the Career

Figure 5 shows how male and female wages change over time. A striking feature of the data is that male and female wages are identical at the start of the career across the 20th percentile, 80th percentile, and mean. However, pooling observations over the full sample period masks important dynamics in the gender wage gap. Although males and females have very similar wages at the time of labor market entrance, wages diverge substantially in later years, with the

Figure 5: Log-Wages by Gender and Time



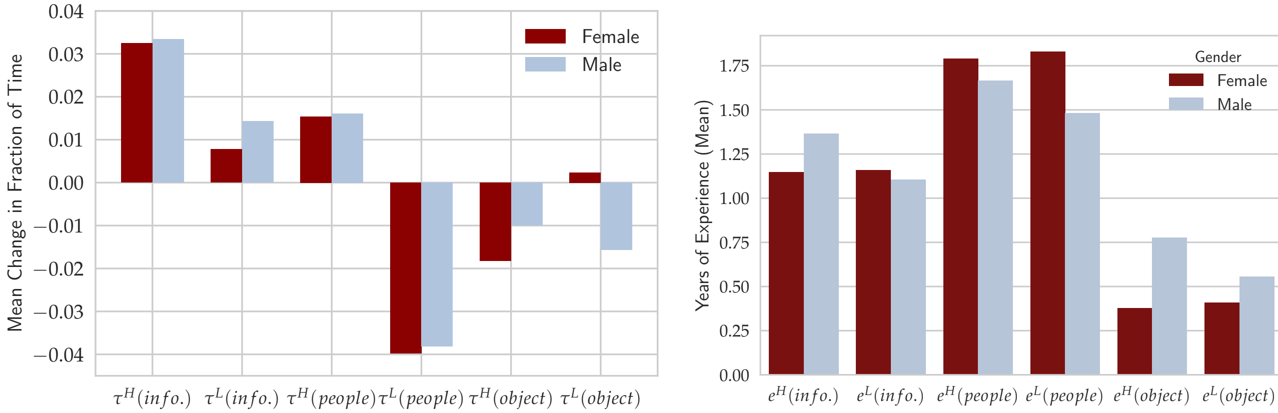
gender wage gap at the end of the sample period reaching 16.2 percent at the 20th percentile, 22 percent at the mean, and 23.6 percent at the 80th percentile. At the 80th percentile of the wage distribution, the gender wage gap arises early in the career during the third and fourth years after college graduation. In contrast, at the mean and 20th percentiles, male and female wages diverge later.

3.2.2 Task Dynamics by Gender

The large increase in the gender wage gap over the career highlights the value of time varying variables that could potentially account for some portion of this feature of the data. We use the longitudinal element of the job task data to examine two job-related mechanisms that could potentially contribute to the widening gender wage gap shown in Figure 5. The first mechanism is that current period tasks $\mathbf{T}_t$ could change differentially by gender. The second mechanism is that, even if gender differences in tasks are constant over time, persistent differences in current tasks could accumulate over time to produce gender differences in task-specific experience $\boldsymbol{E}_t$.

Speaking to the issue of whether or not male and female job tasks diverge over time, Figure 6a shows the mean change in current period job tasks $(\mathbf{T}_t)$ from years 1-2 to years 9-10. While this figure provides clear evidence that current tasks change for both men and women over the career, the changes tend to be quite similar for men and women. As one example, between the first two years and the last two years of the sample period, the average fraction of time spent on high

Figure 6: Mean Changes in Tasks over Time and Task Specific Experience



(a) Changes in Tasks: Years 1-2 to Years 9-10

(b) Task Specific Experience in Years 9-10

skilled information tasks increases by approximately 0.034 for both men and women. Similarly, both men and women tend to move away from performing low skilled people tasks over time, but both groups have a mean decrease of nearly 0.04.

Figure 6b shows the average values of the task-specific experience variables in the last two years of the sample period, separately by gender. The figure shows that persistent differences in mean job tasks by gender translate into sizable gender differences in accumulated time performing job tasks by the end of the sample time frame. Focusing on the three largest differences, men accumulate an extra 0.217 of a year (19 percent more) of high skilled information experience and an extra 0.397 of a year (104 percent more) of high skilled objects experience, but women accumulate an extra 0.346 of a year of low skilled people experience than men. These differences at the end of the sample period, along with the fact that, by definition, there exist no gender differences in task-specific experience at the beginning of the sample period, suggest the promise of the task-specific experience information to simultaneously account for the lack of a gender wage gap at the beginning of the sample period, and the substantial gender wage gap that develops over time (Figure 5). However, the extent to which these patterns are accounted for in practice depends on the quantitative relationship between each type of task-specific experience and wages. We turn to this question in the next section.

4 Empirical Analysis of the Gender Wage Gap

Section 3 detailed gender differences in current period tasks and task-specific experience. In this section we use a regression framework to explore the role that these differences play in generating the gender wage gap.

4.1 Regression Estimates of the Gender Wage Gap

Table 2 shows different specifications of a log-wage regression. Column 1 of Table 2 controls for college GPA, our measure of human capital at the time of entrance to the workforce. The estimated coefficient on the female dummy variable in this specification indicates a gender wage gap of 8.6 percent conditional on college GPA, with a test of the null that there exists no gender wage gap having a t-statistic of 2.21. Controlling for college GPA *increases* the gender wage gap over the unconditional wage gap of 6.6 percent described earlier because, as seen in the first row of Table 1, women have significantly higher college grades than men.

Studies relying on standard data sources use measures of total work experience as a proxy for gender differences in human capital accumulation over the lifecycle (Light and Ureta, 1995; Black et al., 2008; Goldin, 2014; Blau and Kahn, 2017). Following in this tradition, Column 2 of Table 2 adds a variable measuring years of work experience to the specification in column 1. While work experience is strongly related to wages, controlling for it does not alter the estimated gender wage gap of 8.6 percent found in column 1. This is the case because, for our recent cohort of college graduates, the labor market experiences of males and females are similar across many traditionally measured dimensions. For example, Table 1 shows that both men and women have high employment rates (90.9 percent men, 84.9 percent women) and both men and women tend to be working full-time (average hours for men 41.42, average hours for women 38.59). Given that both men and women are strongly attached to the labor market, years of work experience is effectively uncorrelated with gender. This suggests that, when using standard data sources, researchers may increasingly find themselves without job-related information that can proxy for gender differences in human capital accumulation over the lifecycle.

Column 4 of Table 2 adds both current job tasks, $\mathbf{T}_t$, and task-specific experience, $\boldsymbol{E}_t$, as explanatory variables. We find that, together, these task measures play a substantial role in determining the gender wage gap. Specifically, column 4 shows that holding current and past

Table 2: Log-Wage Regression: The Gender Wage Gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.086	-0.086	-0.072	-0.047	-0.048	-0.032	-0.025
	(0.039)	(0.038)	(0.036)	(0.035)	(0.034)	(0.038)	(0.039)
College GPA	0.151	0.149	0.108	0.098	0.120	0.119	0.098
	(0.041)	(0.041)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Female×Child						-0.064	-0.085
						(0.066)	(0.069)
Child						0.063	0.089
						(0.053)	(0.055)
Experience		0.054					
		(0.005)					
Current Tasks ($\mathbf{T}_t$)							
High skilled info. ($\tau^H(I)$)			1.102	0.744	0.696	0.699	0.746
			(0.128)	(0.112)	(0.109)	(0.110)	(0.113)
Low skilled info. ($\tau^L(I)$)			0.203	0.171	0.162	0.162	0.171
			(0.135)	(0.126)	(0.126)	(0.126)	(0.126)
High skilled people ($\tau^H(P)$)			0.349	0.306	0.321	0.322	0.307
			(0.104)	(0.101)	(0.103)	(0.104)	(0.101)
High skilled objects ($\tau^H(O)$)			0.165	0.075	0.027	0.030	0.078
			(0.159)	(0.154)	(0.152)	(0.152)	(0.154)
Low skilled objects ($\tau^L(O)$)			-0.325	-0.343	-0.319	-0.319	-0.343
			(0.187)	(0.163)	(0.158)	(0.158)	(0.162)
Task-Specific Experience ($\boldsymbol{E}_t$)							
High skilled info. ($e^H(I)$)				0.192	0.176	0.174	0.188
				(0.035)	(0.036)	(0.036)	(0.036)
Low skilled info. ($e^L(I)$)				-0.016	-0.004	-0.008	-0.021
				(0.041)	(0.040)	(0.040)	(0.041)
High skilled people ($e^H(P)$)				0.009	0.009	0.008	0.008
				(0.017)	(0.017)	(0.017)	(0.018)
Low skilled people ($e^L(P)$)				0.019	0.016	0.017	0.020
				(0.025)	(0.024)	(0.024)	(0.025)
High skilled objects ($e^H(O)$)				0.076	0.065	0.065	0.076
				(0.054)	(0.054)	(0.054)	(0.054)
Low skilled objects ($e^L(O)$)				-0.029	-0.009	-0.017	-0.040
				(0.070)	(0.061)	(0.061)	(0.068)
College Major Dummies	no	no	no	no	yes	yes	no
R^2	0.014	0.059	0.070	0.112	0.139	0.140	0.113
N	3271	3271	3271	3271	3271	3271	3271

Notes: All regressions include a constant. Coefficients on current tasks ($\mathbf{T}_t$) are measured relative to the omitted category of low skilled people ($\tau^L(P)$). Standard errors clustered by person. "College Major Dummies" indicates dummy variables for the major categories: Humanities, Professional, Business, Science and Math, Social Sciences, Physical Education and Agriculture, and Education.

tasks constant leads to a 45 percent reduction in the gender wage gap, from 8.6 percent (column 1) to 4.7 percent (column 4). With a t-statistic of -1.34 on the female dummy variable, the null hypothesis of a zero wage gap is not rejected at conventional significance levels after accounting for the fact that men and women perform different job tasks.

A natural question is whether the reduction in the gender wage gap between column 1 and column 4 is primarily due to the inclusion of $\mathbf{T}_t$ or $\boldsymbol{E}_t$. In Section 5 we use a decomposition to formally examine this issue. Here we explore what the estimates in Table 2 suggest about what we might expect. We begin by considering the importance of gender differences in current period tasks. Column 4 shows that current period tasks have important effects on wages. For example, perhaps most notably, with current task variables measured in fraction of time units, the coefficient of 0.744 on $\tau^H(I)$ indicates that shifting 10 percent of work time $(\triangle\tau^H(I) = 0.10)$ from low skilled people tasks (the omitted category) to high skilled information tasks is associated with a 7.4 percent increase in wages. Then, the partial effect of men spending more time performing high skilled information tasks in the current period (Figure 2) is to reduce the gender wage gap. However, this reduction in the gender wage gap will be offset, to some extent, by the fact that men also spend more time performing the lowest-paying task (low skilled objects) and by the fact that women spend more time performing the second and third highest-paying tasks (high skilled people, low skilled information).

The previous paragraph suggests that gender differences in task-specific experience may play the more important role in the reduction of the gender wage gap seen between column 1 and column 4. Before turning to the decomposition in Section 5 to examine this formally, we examine why the coefficients associated with $\boldsymbol{E}_t$ in column 4 suggest this might be the case. The most noteworthy result is the strong positive relationship between accumulated time spent performing high skilled information tasks and wages. Specifically, the coefficient of 0.192 on $e^H(I)$ implies that performing one extra full year of high skilled information tasks in the past increases the predicted current wage by 19.2 percent. The remaining task-specific experience coefficients are much smaller in magnitude, and not statistically different from zero at conventional levels. Thus, task-specific experience may influence the gender wage gap because, as described in Section 3.2, males accumulate substantially more high skilled information experience, and the other types of task-specific experience do not have an important effect on wages.

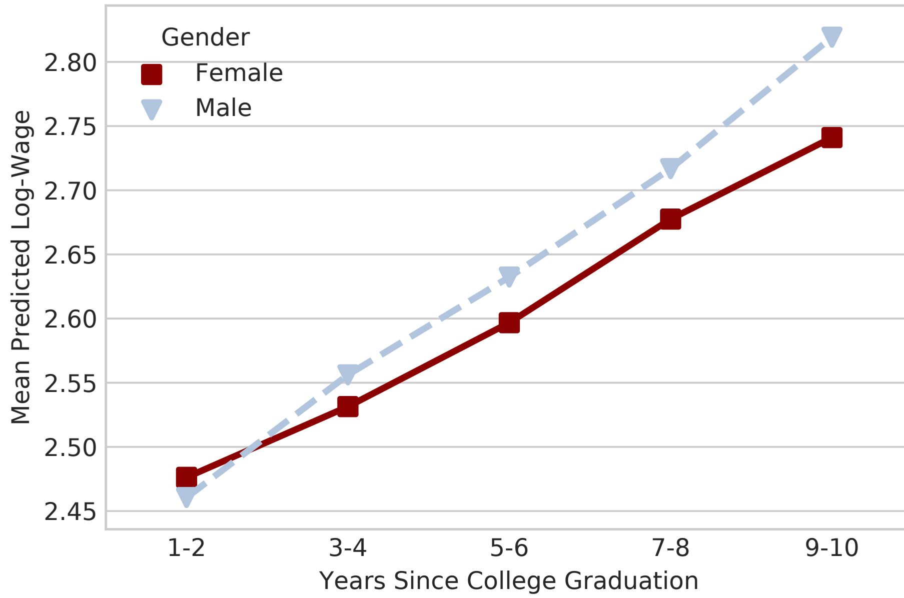
Our task-based approach of estimating specifications that include (current and past) tasks, but not college major, is natural if a student's college major tends to affect her wages, in large part, by influencing the types of jobs she holds. Nonetheless, because there are a variety of reasons that college major could have a direct effect on wages, it is worthwhile to confirm that the effects of gender differences in tasks on the gender wage gap do not change substantially when we add controls for college major variables to our regression. That this is the case is seen in Column 5 of Table 2, which shows that controlling for major leads to virtually no change in the estimated coefficient on Female (-0.047 in column 4, -0.048 in column 5). Furthermore, the estimated coefficients on $\mathbf{T}_t$ and $\boldsymbol{E}_t$ change very little when the major variables are added. The decomposition in Section 5 examines the role of major more formally, with the discussion being relevant for understanding why the estimated female coefficient remains essentially unchanged between columns 4 and 5. The decomposition also examines the role of fertility, which has been found in the past to be a strong predictor of the gender wage gap. As can be seen in columns 6 and 7, adding a time-varying variable that indicates whether a person has at least one child does not influence the estimated effects of the task variables, but does lead to a further reduction in the estimated female coefficient.

5 Accounting for the Gender Wage Gaps: Predictions and Decompositions

5.1 Prediction

Figure 7 shows mean predicted wages of males and females over time. These predictions are based on the specification in Column 6 of Table 2, which includes current period tasks, task-specific experience, GPA, college major, and the time-varying indicator of whether a person has at least one child. Comparing Figure 7 to the middle (mean) set of lines in Figure 5 reveals that these variables are able to correctly predict that virtually no gender wage gap exists at the beginning of the sample period, and that a wage gap develops over time. Together, these variables predict a gender wage gap of 3.9 percent in years 7-8 of the sample period, out of a total gender wage gap of 10.3 percent in this period. Together, these variables predict a gender wage gap of 7.8 percent in years 9-10 of the sample period, out of a total gender wage gap of 22.2

Figure 7: Predicted Log-Wages by Gender and Time



Notes: Predicted log-wages are based on the regression in Column 6 of Table 2.

percent in this period.

5.2 Decomposing Sources of the Gender Wage Gap

This section performs decompositions to determine the relative ability of job tasks, proxies for human capital accumulated during college, and fertility to account for the gender wage gap. Motivated by the importance of understanding why the gender wage gap widens substantially over time, we focus on the latter stages of the sample period when the gender wage gap is largest. The last row of panel A of Table 3 shows the total gender wage gap of 10.3 percent in years 7-8 and the total gender wage gap of 22.2 percent in years 9-10, which were noted in the previous subsection. The decomposition in Panel A is based on the specification shown in column 5 of Table 2, which includes the task measures, college GPA, and college major. The decomposition in Panel B is based on the specification shown in column 6, which also controls for fertility.

Given that we are particularly interested in determining the extent to which our unique task information can account for the gender wage gap, two facts established earlier in the paper are particularly relevant. First, although gender differences in job tasks are persistent over time, current-period tasks do not change differentially for men and women over the career (Sec-

Table 3: Regression Decomposition of Gender Wage Gap

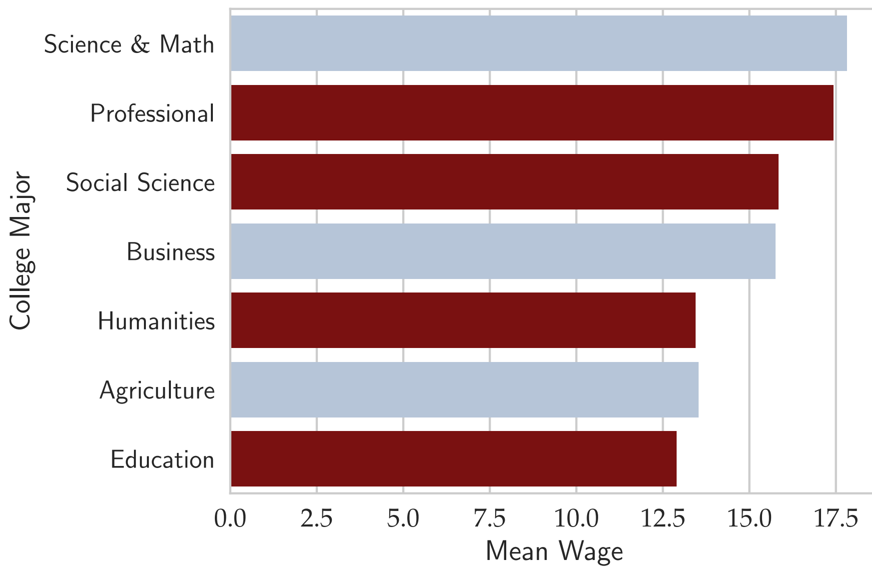
	Mean $log(wage)$ Gap	
	Years 7-8	Years 9-10
	(1)	(2)
Panel A: Human Capital Specification		
GPA and College Major	0.013	0.009
Current Tasks $(\mathbf{T}_t)$	0.007	-0.001
Task-Specific Experience $(\boldsymbol{E}_t)$	-0.037	-0.057
Total Gender Gap	-0.103	-0.222
Panel B: Full Specification		
GPA and College Major	0.013	0.009
Current Tasks $(\mathbf{T}_t)$	0.007	-0.002
Task-Specific Experience $(\boldsymbol{E}_t)$	-0.036	-0.055
Child	-0.023	-0.031
Total Gender Gap	-0.103	-0.222

Notes: Entries are mean log-wage differences (Female - Male). Panel A is based on the estimates from specification (5) in Table 2. Panel B is based on the estimates from specification (6) in Table 2.

tion 3.2.2). Second, men do not strictly work in jobs with the highest-paying tasks (Figure 1). Taken together, these two features of the data suggest that current period tasks are not likely to account for the substantial gender wage gap present at the end of the sample period. This conjecture is confirmed by the second row of Table 3, which shows that the portion of the log-wage gap explained by "current tasks" is very close to zero in both years 7-8 (0.007 log-points) and years 9-10 (-0.001 log-points).

In contrast, the descriptive evidence presented in Section 3.2.2, which shows that men accumulate substantially more high-skilled information experience, combined with the regression results presented in Section 4.1, which show that this type of experience is strongly related to wages, suggest that task-specific experience is likely to play a large role in the prediction of the substantial gender wage gap at the end of the sample period. This is confirmed by the the third row of Table 3, Panel A. Specifically, the first column shows that gender differences in task-specific experience predict a gender wage gap of 3.7 percent in years 7-8, or 36 percent of the total gender wage gap in that period. The second column of Panel A shows that gender differences in task-specific experience predict a gender wage gap of 5.7 percent in years 7-8, or 26 percent of the total gender wage gap in that period.

Figure 8: Mean Wages by College Major



Notes: Dark shaded bars (red) are predominantly female majors, Light shaded bars (grey) are predominantly male majors. Wages in 2005 dollars.

In terms of the roles played by other variables in our specification, given that much previous research has carefully documented the central importance of family information in determining the gender wage gap (Goldin, 2014; Blau and Kahn, 2017), we view the inclusion of the children variable as being most valuable for providing some context for considering the importance of our task information. As seen by comparing the third and fourth rows of Table 3, the task information predicts more of the gender wage gap than the children information.

As alluded to earlier in the paper, simple descriptive evidence suggest that academic variables are unlikely to account for the gender wage gap in our data. Demonstrating that this is the case, the first row of Table 3 shows that together, college major and GPA account for only a small share of the male-female wage differential. As a bit of an aside, the reason that major does not play a large role in our data is that women are not systematically choosing the lowest paying majors. Figure 8 shows mean wages by college major, and the bars are shaded to indicate majors that are majority female (shaded red or dark) versus majors that are majority male (shaded grey or light).[12] As is clear in the figure, there is no clear evidence that men and women are differentially

[12]The exact gender composition of each major is shown in Table 1. It is worth noting that the Humanities major is only very slightly majority female: 22.1 percent male versus 22.2 percent female.

sorting into high or low paying majors. Of course, the role that major plays in determining the gender wage gap will depend critically on the particular set of majors a school offers. As such, we do not feel that our data are particularly well-suited for providing evidence about the role of college major, per se, in determining the gender wage gap. Rather, the primary reason for controlling for major in our specifications is to ensure that the estimates we obtain for the unique task information are not arising spuriously, for some reason, due to their relationship with college major.[13]

6 Conclusions

This paper describes the potential conceptual importance of the unique task data from the Berea Panel Study for understanding the gender wage gap. In practice, this information is found to be important for prediction of the gap, with the additional experience that men accumulate in high skilled information tasks playing a particularly central role.

One prominent question in the literature studying the gender wage gap is whether men and women with similar human capital receive equal pay for equal work. It may be tempting to conclude that this is the case for our sample because Column 6 of Table 2 reveals that controlling for time-varying task and family variables, along with college academic variables, lead to a reduction of the gender wage gap to only 3.2 percent (t-stat = 0.842). However, the dynamics of the gender gap suggest that this conclusion is perhaps not warranted. The gender wage gap is widening substantially by the end of the sample period and the unexplained portion of the gap is also increasing over time.

Regardless, for a variety of reasons, including the reality that we are studying students from one school, it was not the objective of this paper to provide conclusive evidence about these types of questions. Rather, we believe that our main contribution comes from the message that paying close attention to the measurement of job tasks may be crucial for future studies of the gender wage gap. For example, we find that, while general work experience is an important predictor of wages, it plays no role in the prediction of the gender wage gap for our recent cohort of graduates. As a result, measures of task-specific experience may be crucial for proxying for

[13] The concern here would be that, in a specification without college major, tasks, which are correlated with college major, could potentially pick up any direct effects that majors might have on wages.

gender differences in human capital accumulation over the lifecycle. Indeed, without these types of measures, researchers may have limited job-related options for explaining the gender wage gap, in general, and the widening of the gender wage gap over time, in particular.

Appendix A: Survey Questions

Question C: How does your JOB1 require you to relate to PEOPLE, INFORMATION, and OBJECTS?

- Question C1: Below are 4 ways that you may interact with PEOPLE on a job.

  1. Following instructions from others such as supervisors or directly serving the needs of customers or animals.
  2. Persuading others about a company product/service or point of view (e.g. sales) or entertaining others.
  3. Supervising others or instructing/teaching others.
  4. Exchanging ideas/information/opinions or negotiating with others to make decisions or formulate policies.

  – Think about the TOTAL time that you spend **interacting with PEOPLE** as part of your JOB1. Indicate what percentage of the total time is spent interacting in each of the four ways. **Note:** Each percentage should be between 0 (the item plays no role) and 100 (all interactions are from the one item) **and the four items should sum to 100.**

- Question C2: Below are 4 ways that you may interact with INFORMATION on a job.

  1. Entering data; typing documents written by others; posting information etc.
  2. Gathering or classifying information/data and performing simple calculations using data.
  3. Analyzing data/information.
  4. Using data analysis done by yourself/others to develop knowledge/solutions and make important decisions.

  – Think about the TOTAL time that you spend **interacting with INFORMATION** as part of your JOB1. Indicate what percentage of the total time is spent interacting in each of the four ways. **Note:** Each percentage should be between 0 (the item plays no role) and 100 (all interactions are from the one item) **and the four items should sum to 100.**

- Question C3: Below are 4 ways that you may interact with OBJECTS on a job.

  1. Working with or moving objects or operating a machine in a way that requires only a small amount of judgment.
  2. Working with or moving objects or operating a machine in a way that requires a moderate amount of judgment.
  3. Working with or moving objects or operating a machine in a way that requires a large amount of judgment.
  4. Working with or moving objects in a way that judgment is extremely important; or having full responsibility for planning or setting up machines or processes.

- Think about the TOTAL time that you spend **interacting with OBJECTS** as part of your JOB1. Indicate what percentage of the total time is spent interacting in each of the four ways. **Note:** Each percentage should be between 0 (the item plays no role) and 100 (all interactions are from the one item) **and the four items should sum to 100.**

- Question C4: Now think about your TOTAL job responsibilities on your JOB1. Indicate the percentage of your responsibilities that involve interacting with PEOPLE, INFORMATION, and OBJECTS, respectively. Each percentage should be between 0 and 100 and the three percentages should sum to 100.

Question D: Hours and Earnings for JOB1

- Question D1: How many hours do you typically work each week in your JOB1?

- Question D2: Approximately how much do you earn in your JOB1? NOTE: Please indicate both a dollar amount and whether this amount is your pay per hour, per day, per week, per month, per year etc. For example, if you earn $8.50 an hour, please write $8.50 per hour. If you earn $30,000 per year, please write $30,000 per year.

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