Job Tasks, Task-Specific Work Experience, and the Gender Wage Gap*

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Abstract

Taking advantage of unique longitudinal task data from the Berea Panel Study, we explore a task-specific experience channel through which gender differences in on-the-job human capital accumulation may arise. For a group of recent college graduates we find that, while the amount of general experience of men and women is indeed quite similar in the early portion of the career, a widening of the gender wage gap is created, in part, because gender differences in types of work experience increase over time. Importantly, the cumulative nature of the task-specific experience explanation implies that modest, constant yearly gender differences in current period tasks accumulate over time to create substantial gender differences in task-specific experience, which have meaningful effects on wages. A finding that substantial variation in tasks exists within college majors and that this variation is important for wage determination helps bolster the general motivation for task collection.

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1 Introduction

A comprehensive understanding of the gender wage gap must account for a well-recognized lifecycle pattern: the wages of male and female college graduates tend to be very similar at the start of the career, but diverge considerably over time (Bertrand, Goldin and Katz, 2010). Traditionally, of particular empirical importance for explaining this pattern is that substantial gender differences in general work experience arise over the early portion of the career (Blau and Kahn, 2017).

Pervasive evidence that general work experience is a strong predictor of wages suggests its importance in the accumulation of human capital through learning by doing (Becker, 1964). Then, the traditional, central role of gender differences in general work experience for explaining the gender wage gap raises a question of fundamental importance given that many policy issues relate to whether identical male and female workers receive the same pay for the same work: Does the substantial reduction in gender differences in general work experience for recent cohorts imply that a human capital explanation is no longer of substantial relevance for explaining the widening of the gender wage gap over the career?

Motivated directly by economic frameworks that recognize the multi-dimensional nature of skills (Keane and Wolpin, 1997; Heckman, Lochner and Taber, 1998), this paper takes advantage of unique new data to explore a "task-specific experience" channel through which differences in on-the-job human capital accumulation may remain very relevant.[1] For a group of recent college graduates we find that, while the amount of general experience of men and women is indeed quite similar in the early portion of the career, a widening of the gender wage gap is created, in part, because gender differences in types of work experience (i.e., task-specific experience) increase over time. Importantly, the cumulative nature of the task-specific experience explanation does not require large gaps in current period tasks to appear over time. Indeed, we find that modest, constant yearly gender differences in current period

[1] In Heckman, Lochner and Taber (1998), human capital is specific to education levels, and individuals invest in on-the-job training. In Keane and Wolpin (1997), skills are occupation-specific and human capital accumulates through learning-by-doing.

tasks accumulate over time to create substantial gender differences in task-specific experience, which have meaningful effects on wages.

Our ability to provide evidence about the importance of this channel comes from carefully characterizing how gender differences in task-specific experience, an intuitively appealing proxy for human capital accumulation, change over time. The data come from the Berea Panel Study (BPS), a longitudinal survey that followed respondents closely through the first ten years of their post-college lives. Motivated by the notion that, from the perspective of the theory of specific human capital, the task requirements of jobs are the primitive objects of interest for describing what takes place on jobs (Sanders and Taber, 2012), the BPS had a primary focus on the collection of task information. Unique features of the BPS task data address standard measurement difficulties that arise during the two parts of the process for constructing task-specific experience as of a particular point in the career: 1) characterizing the tasks a worker performed in the past and 2) aggregating these past tasks into a cumulative measure of total time spent on different tasks at each point in the career.

With respect to 1), while recent research that documents substantial variation in job tasks within, for example, occupations has stressed the conceptual importance of job-level information about job tasks, the BPS represents the first data where job-level task information is collected longitudinally for workers.[2] With respect to 2), the traditional measurement difficulty stems from the fact that available yearly task measures typically provide a qualitative view of task importance in each year; it is not 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, 2019*b*). To address this measurement

[2]Autor and Handel (2013) and Deming and Kahn (2018) find large variation in the tasks/skills required by jobs even within occupations.Even cross-sectional job-level task information is scarce. In research exploring the general benefits of task 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, and 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. The benefits of job-level task 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).

difficulty, the BPS collected explicit time allocation information, which produces quantitative task measures that are easily interpretable and conceptually appealing. These unique features allow us to construct six task-specific experience measures in the spirit of categories utilized in the Dictionary of Occupational Titles (DOT) 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 performing information, people, and objects tasks at high skill levels and at low skill levels. [3]

In the absence of longitudinal quantitative job-level task data, one can imagine alternative approaches for characterizing task-specific experience that might be feasible using standard data sources, although, in practice, there are well-known limitations of these approaches.[4,5] While a comparison of results obtained using different approaches may be of interest to a methodological literature interested in task-measurement, the BPS is not well-suited for this comparison because the most prominent potential alternative approach would involve imputing tasks on the basis of occupations, which are not observed in the BPS. However, given our substantive objective of providing what we believe is the first direct empirical evidence about the importance of the task-specific experience channel in determining the gender wage gap, what seems most important is that the quantitative, job-level longitudinal task data in the BPS allow us to characterize task-specific experience in the most conceptually appealing way currently possible.[6] From a substantive standpoint, it is not particularly relevant how much

[3]Cook et al. (2018) find that precisely measuring the work experience of Uber drivers is crucial for understanding gender pay gaps between drivers.

[4]Research examining the gender wage gap has often taken the approach of directly controlling for occupations (Black et al., 2008; Goldin and Katz, 2008; Goldin, 2014; Blau and Kahn, 2017). Extending the spirit of this approach to estimate models that contain occupation specific experience may, from a practical standpoint, require a non-trivial aggregation of occupations. For example, Sullivan (2010*a*) aggregates occupations into five categories, and Sullivan (2010*b*) uses eight aggregated occupations. Assigning tasks based on occupations may alleviate this dimensionality problem. However, this creates the earlier-discussed issue of how to aggregate yearly qualitative measures of task importance into a cumulative task-specific experience measure (Stinebrickner, Stinebrickner and Sullivan, 2019*b*).

[5]In the recent task-based literature, an external source such as the DOT (or newer ONET) would be used to assign tasks to jobs based on occupations.This approach is relevant because, while task information has traditionally not been collected in general surveys, a worker's occupation is typically observed (Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010; Autor and Handel, 2013). 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 (Black and Spitz-Oener, 2010; Bacolod and Blum, 2010; Yamaguchi, 2012, 2018; Beaudry and Lewis, 2014).

[6]Also bolstering the notion that our job-level task data are appealing, Goldin (2014) finds that the majority

results would change if task-specific measures were constructed using approaches that are less appealing from a conceptual standpoint.

We begin by providing new empirical evidence on gender differences in time spent on job tasks. Particularly noteworthy is the fact that men are 33 percent more likely than women to specialize in high skilled information tasks, such as analyzing data or using data analysis to make decisions. In contrast, women devote more time to working with people, and are fully 40 percent more likely than men to specialize in low skilled people tasks, such as following instructions or directly serving the needs of customers. Over time, both men and women tend to shift towards performing high skilled information and high skilled people tasks, and tend to shift away from performing low skilled people tasks. Suggesting that current period tasks alone may not be able to explain the widening of the gender wage gap, the sizes of these shifts are similar for men and women, so that gender differences in job tasks tend to remain quite constant over the early portion of the lifecycle that we study. However, importantly, these yearly differences produce substantial gender differences in accumulated experience performing different types of tasks. For example, nine to ten years after college graduation, men have spent 19 percent more time performing high skilled information tasks, while women have spent 23 percent more time performing low skilled people tasks.

Having established new facts about gender differences in job tasks, we examine the extent to which job tasks can account for the gender wage gap. Consistent with previous research, we find that the wage gap increases substantially over the first ten years after graduation, from very close to zero at the time of labor market entrance to approximately 22 percent by the end of the sample period. The novel job task measures are an important predictor of the gender wage gap. Controlling for both current tasks and the cumulative measures of past tasks (i.e., the task-specific experience measures) reduces the gender wage gap by 45 percent. In terms of understanding the substantial widening of the wage gap over the career, our regression specification is able to account for approximately 38 percent of the gender wage gap that exists in years 7 and 8 of the sample and 35 percent of the gender wage gap that exists in years 9 and

of the gender wage gap comes from within occupation differences.

10 of the sample, while also correctly predicting that there would not exist a substantial gender wage gap at the time of labor market entrance.

We find that the unique measures of task-specific experience, in particular high-skilled information experience, are of primary importance. The importance of the new task-specific experience measures is highlighted by the finding that, while general work experience (measured by years of work or total hours of work) is an important predictor of wages, it does not play a role in accounting for the gender wage gap for this group of recent college graduates.[7] Thus, our primary contribution comes from providing direct, empirical evidence that it may not be sufficient to characterize how much experience a worker has accumulated in the past - what type of experience the worker has accumulated may be of fundamental importance. While this finding is appealing given the recognition of the multi-dimensional nature of tasks, to the best of our knowledge this issue has received little attention in empirical analyses of the gender wage gap, presumably, in large part because of the lack of longitudinal task data that are ideal for measuring task-specific experience.[8]

From a conceptual standpoint, 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 may affect wages, in large part, by influencing the types of work that one performs (Black et al., 2008; Blau and Kahn, 2017).[9] We find substantial differences in job tasks even among men and women who share the same college major. These task differences are persistent over

[7]Our work relates to a model-based literature that explicitly describes how gender differences in the incentive to accumulate human capital may influence the gender wage gap (see, e.g., Erosa, Fuster and Restuccia (2002) and Bowlus (1997)). In one experiment, the former paper finds that, even holding employment (general work experience) constant between men and women, men accumulate nine percent more human capital by the age of 40. For their sample of workers from diverse educational backgrounds, they find evidence of gender differences in human capital accumulation arising because of gender differences in hours worked. In our college-educated sample, we find only small differences in hours worked. However, in the spirit of their paper, we are able to identify another source of gender differences in human capital accumulation - gender differences in the experience performing specific tasks.

[8]We note that the notion that skills are multi-dimensional in nature is of central important in the task literature, see, e.g., Poletaev and Robinson (2008), Autor and Handel (2013), Lise and Postel-Vinay (2019)

[9]The link between college major and tasks is relevant to a number of empirical questions. See, for example, Altonji, Kahn and Speer (2014), who employ a task-based approach to decomposing the causes of earnings inequality across college majors.

time, and a decomposition shows they account for a sizable fraction of the gender wage gap. Thus, our results strengthen the motivation for the use of task data, in the spirit of recent research showing that tasks vary substantially within occupations and that this variation is important for wage determination (Autor and Handel, 2013).[10]

As discussed in our conclusions, for a variety of reasons, including the reality that we are studying one school, our objective is not to provide general evidence about the importance of traditional variables, such as overall work experience or college major, in accounting for the gender wage gap. Nonetheless, the importance found for our unique task information conditional on these traditional variables provides a message of general importance - that misleading answers to important policy questions, such as whether (and to what extent) men and women with similar human capital receive equal pay for equal work, could potentially be obtained if one does not take into account the type of work experience that workers accumulate.

The question of whether (and to what extent) men and women with similar human capital receive equal pay for equal work is of interest, in part, because of its direct relevance for understanding the role of discrimination. From the standpoint of understanding the role of discrimination, the necessity of fully measuring gender differences in tasks depends critically on *why* gender differences in tasks exist. Consistent with sorting based on comparative advantage, we find positive selection into information tasks based on math ACT scores and negative selection into information tasks based on verbal ACT scores, even within majors. This finding that gender differences in tasks can seemingly not be attributed entirely to discrimination bolsters the cautionary message from our paper - that obtaining accurate conclusions about issues such as the quantitative role of discrimination in determining the gender wage gap may require careful attention to the longitudinal measurement of gender differences in tasks.

[10]From a conceptual standpoint, it is not clear whether a person's occupation or a person's major would tend to provide a more accurate view of what people do on their jobs. Workers with the same major may work in different occupations, but, within an occupation, workers with the same major may tend to do more similar things on their jobs than other workers.

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 has often been 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.[11]

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

[11] As shown in Table 1, each individual contributes an average of slightly more than six observations to the data. Based on regressions of sample attrition on our explanatory variables, attrition is unrelated to our key explanatory variables such as Gender, college GPA, and job tasks. Attrition is lower for professional and education majors, but the differences are not particularly large (empirical results available upon request).

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.

Berea is unique in certain ways that have been explored in previous work.[12] The presence of a mandatory work-study program at Berea is particularly noteworthy given the focus of this paper on the role of experience accumulated by workers after college. A possible concern might be that this program could potentially generate gender differences in the amount or type of work experience accumulated during college. However, mitigating the concern that there might exist gender differences in the amount of experience accumulated during college, Stinebrickner and Stinebrickner (2003b) finds that there exists little variation in work hours during the early portion of school; the mean and standard deviation of freshman weekly hours worked is 10.97 and 1.40. In later years, students have somewhat more flexibility in how many hours they work, but, because students cannot work full-time (and would typically not want to given the pay structure) and because students must work at least 10 hours per week, the variation in hours across students remains relatively small. Overall, it seems that the variation in work hours may be smaller at Berea than at many other schools, where some students work substantial hours, while other students do not work at all. Mitigating the concern that there might exist gender differences in the type of experience accumulated during college, all students are assigned to similar service/custodial jobs in the early portion of college. In later years, there is more flexibility in types of jobs, but many students continue to work in custodial/service jobs. The notion that the work-study program at Berea does not lead to im-

[12]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 (2019*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 (2019*a*) takes advantage of the BPS job task data to examine the labor market mechanisms generating the labor market returns to physical attractiveness.

Table 1: Descriptive Statistics by Gender

	Gender	
	Female	Male
	(1)	(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)
ACT verbal	24.283	22.157
	(4.357)	(4.234)
ACT math	22.341	22.173
	(3.963)	(4.313)
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	336	188
Ave. observations per person	6.14	6.27

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

portant gender differences in human capital at the time of graduation is bolstered directly by our finding that there does not exist a gender wage gap in the first years after graduation.

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 to-

tal 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.[13]

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 $\mathbf{T_t} = \{\tau_t^H(P), \tau_t^L(P), \tau_t^H(I), \tau_t^L(I), \tau_t^H(O), \tau_t^L(O)\}$. 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.[14] We denote the vector of task-specific experience measures at time t as $\boldsymbol{E_t} = \{e_t^H(P), e_t^L(P), e_t^H(I), e_t^L(I), e_t^H(O), e_t^L(O)\}$.

[13]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 (2019*b*) for a more detailed description of the task data.

[14]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(work weeks)×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

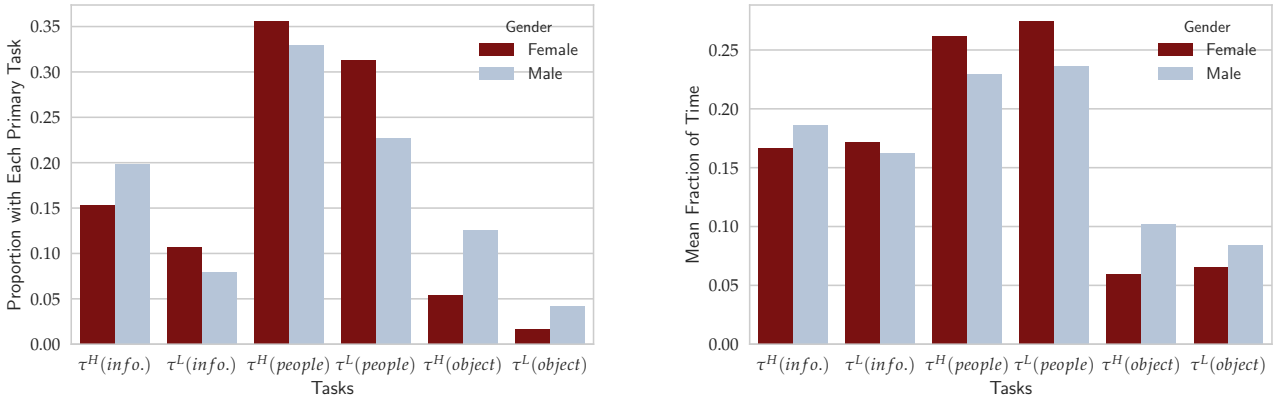
Hourly wages are constructed from Survey Question D2 (Appendix A), which gave respondents flexibility over whether earnings were reported for an hourly, weekly, monthly, or yearly period, and Survey Question D1, which elicited a worker's hours in a typical week. Pooling observations across the entire 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.[15]

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 task data, with our analysis representing the first time that gender differences in job tasks have been documented using explicit time allocation information. We first provide 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

[15] 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



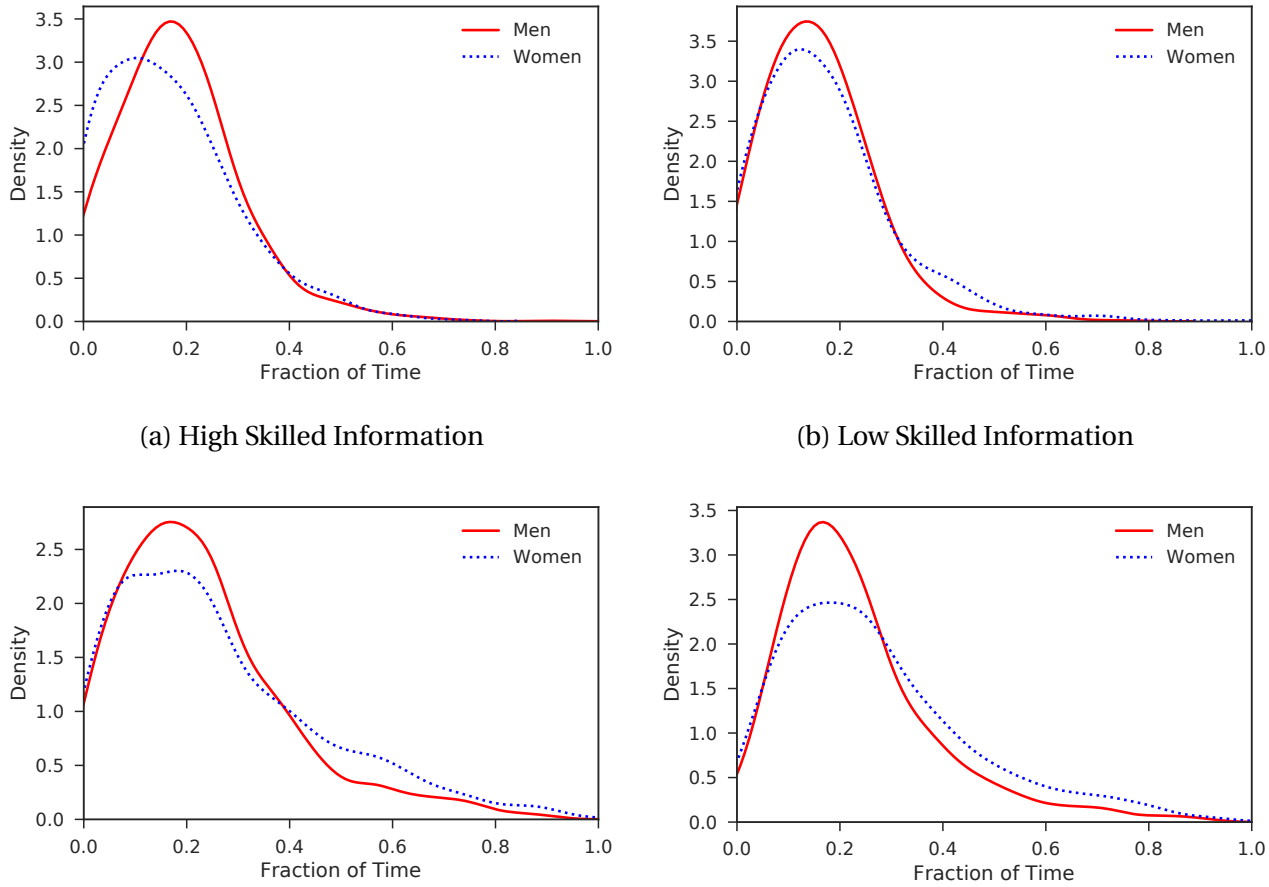
(a) Primary Tasks by Gender

(b) Time Spent on Tasks by Gender

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 job tasks. Three features of the male-female comparison are immediately apparent: (1) women tend to specialize in interpersonal tasks, (2) women tend not to specialize in objects tasks, (3) while, overall, women are (roughly) as likely as men to specialize in information tasks, their focus within this category is much more likely be on low-skilled tasks. More specifically: (1) women are 8.2 percent more likely than men to hold a job with a primary task of high-skilled people (0.356 vs. 0.329, t-stat from test of equality=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), (2) 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=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), (3) 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 differ-

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

ences 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 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 per-

form 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.

3.2 Dynamics: Gender Differences in Wages and Tasks Over Time

This section documents the rising gender wage gap over the first ten years of the career, and then shows how the job tasks performed by men and women change over the same time frame.

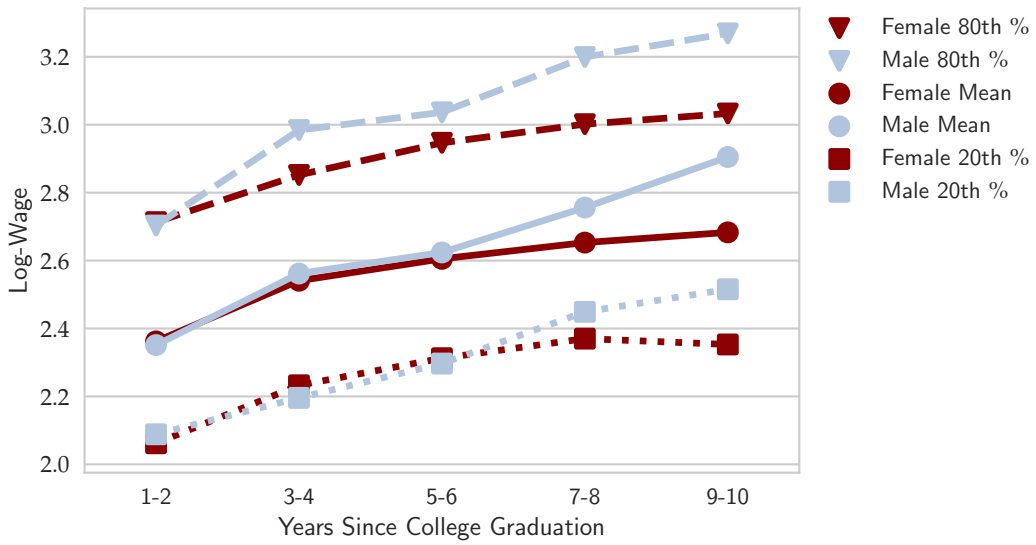
3.2.1 The Rising Gender Wage Gap Over the Career

Figure 3 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. Although males and females have very similar wages at the time of labor market entrance, wages diverge substantially in later years, with the 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 3. The first mechanism is that, over time, current period tasks ($\mathbf{T}_t$) could change differentially by gender.

Figure 3: Log-Wages by Gender and Time

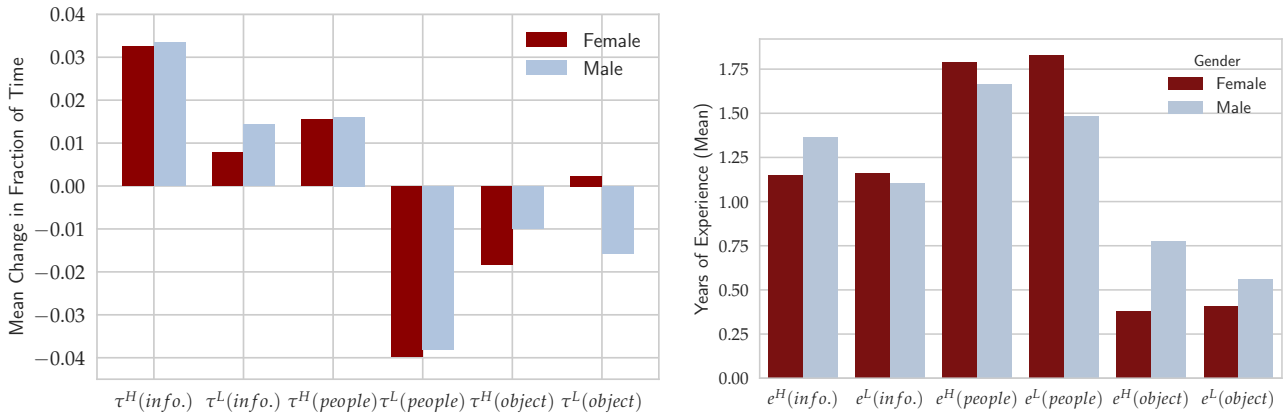


The second mechanism is that, even if gender differences in tasks are stable over time, persistent differences in current tasks could accumulate over time to produce gender differences in task-specific experience ($\boldsymbol{E_t}$).

Speaking to the issue of whether or not male and female job tasks diverge over time, Figure 4a 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 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 4b 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,

Figure 4: 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

but women accumulate an extra 0.346 of a year (23 percent more) of low skilled people experience than men.[16] 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 data 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. 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 4.1 presents regressions that show how controlling for current and past job tasks affects the estimated gender wage gap. Section 4.2 discusses the role of college major in accounting for the gender wage gap, and also provides new evidence on variation in job tasks both across and within college majors.

[16]These three differences are each statistically significant at the 5 percent level.

4.1 Job Tasks and 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 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 very strongly related to wages (t-statistic greater than 10.0), 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.[17]

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

[17]We also estimated a version of the model in Column 2 of Table 2 where experience is measured in hours, rather than years, to control for gender differences on the intensive margin of labor supply. In this model, the coefficient on the Female variable is -0.0761 with a standard error of 0.038. In these data, variation in cumulative hours worked cannot account for the gender wage gap.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.086	-0.086	-0.072	-0.047	-0.048	-0.032	-0.025	-0.053
	(0.039)	(0.038)	(0.036)	(0.035)	(0.034)	(0.038)	(0.039)	(0.035)
College GPA	0.151	0.149	0.108	0.098	0.120	0.119	0.098	0.121
	(0.041)	(0.041)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.040)
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	0.695
			(0.128)	(0.112)	(0.109)	(0.110)	(0.113)	(0.110)
Low skilled info. ($\tau^L(I)$)			0.203	0.171	0.162	0.162	0.171	0.149
			(0.135)	(0.126)	(0.126)	(0.126)	(0.126)	(0.136)
High skilled people ($\tau^H(P)$)			0.349	0.306	0.321	0.322	0.307	0.317
			(0.104)	(0.101)	(0.103)	(0.104)	(0.101)	(0.106)
High skilled objects ($\tau^H(O)$)			0.165	0.075	0.027	0.030	0.078	0.099
			(0.159)	(0.154)	(0.152)	(0.152)	(0.154)	(0.154)
Low skilled objects ($\tau^L(O)$)			-0.325	-0.343	-0.319	-0.319	-0.343	-0.324
			(0.187)	(0.163)	(0.158)	(0.158)	(0.162)	(0.172)
Task-Specific Experience ($\boldsymbol{E}_t$)								
High skilled info. ($e^H(I)$)				0.192	0.176	0.174	0.188	0.180
				(0.035)	(0.036)	(0.036)	(0.036)	(0.034)
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)	
Non high skilled info.†								0.012
								(0.008)
College Major Dummies	no	no	no	no	yes	yes	no	yes
R^2	0.014	0.059	0.070	0.112	0.139	0.140	0.113	0.138
Observations	3,271	3,271	3,271	3,271	3,271	3,271	3,271	3271
Individuals	526	526	526	526	526	526	526	525

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.

† Non high skilled info experience is the sum of all task specific experience variables excluding $e^H(I)$. Specifically, it is defined as $e^L(I) + e^H(P) + e^L(P) + e^H(O) + e^L(O)$.

predicting the gender wage gap. Specifically, column 4 shows that holding current and past 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 (t-statistic of 6.64) 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 1) 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, with a t-statistic of 5.48, 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.

4.2 College Major, Tasks, and the Gender Wage Gap

College major has played a central role in the study of gender wage gaps (see, for example, Altonji (1993), Grogger and Eide (1995), and Black et al. (2008)). In Section 4.2.1, we describe our measure of college major and examine gender differences in major. In the interest of providing a better understanding of the determinants of gender differences in tasks, in Section 4.2.2, we examine the relationship between college major and gender differences in both current tasks and task-specific experience. In Section 4.2.3, we explore the implications of including college major in our wage regressions.

4.2.1 Gender differences in major

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.[18] 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.

4.2.2 The relationship between college major and gender differences in tasks

Providing evidence that major and job tasks are related, Figure 5 documents considerable variation in mean tasks across majors. For example, panel (a) shows that Business majors spend

[18]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.

over 33 percent more time performing high skilled information tasks compared to Humanities majors. Panel (c) shows that Education majors spend approximately 50 percent more time on high skilled people tasks compared to Science/Math majors. There is also some evidence that men and women are systematically sorting into majors in ways that are related to job tasks. For example, focusing again on the three largest differences in Figure 4b, men are more likely to choose the two majors with the largest amounts of high skilled information tasks (Business, Science/Math) and the two majors with the largest amounts of high skilled objects tasks (Science/Math, Agriculture). However, women are more likely to choose the major with the largest amount of low skilled people tasks (Social Science).

However, while gender, college major, and job tasks are related, we find that substantial gender differences in job tasks remain even after conditioning on college major. For example, again focusing on the three tasks with the largest gender gaps shown in Figure 4b, Panel A of Figure 6 shows that female Social Science majors spend 21 percent less time (0.016 measured in fraction of time units) on high skilled information tasks and 125 percent less time on high skilled objects tasks, and instead spend 28 percent more time on low skilled people tasks. Interestingly, the gender differences in tasks present within the Social Science major are representative of common patterns seen across the range of majors at Berea. Men spend more time on high skilled information tasks in five out of the seven majors and on high skilled objects tasks in all seven majors, while women spend more time on low skilled people tasks in five out of the seven majors.

The substantial within-major variation in job tasks performed by men and women accounts for a large fraction of gender disparities in task-specific work experience. Decomposing the three largest differences in task specific experience shown in Figure 4b, we find that 89 percent of the gender gap in high skilled information experience at the end of the sample period is due to within major gender differences, 93 percent of the gender gap in high skilled objects experience is due to within major gender differences, and 95 percent of the gender gap in low skilled people experience is due to within major gender differences.

4.2.3 Including college major in the wage regressions

Column 5 of Table 2 shows estimates from a specification that adds dummy variables for the college majors. Not surprisingly, we find that majors are important for wage determination; four out of the six college major dummies are significantly related to wages at the 5 percent level, and the R^2 increases by approximately 25 percent when college major is added (column 5 vs. column 4).[19]

A comparison of columns 4 and 5 of Table 2 shows that the estimated coefficients on $\mathbf{T}_t$ and $\boldsymbol{E}_t$ change very little when the major variables are added and 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). This suggests that the decrease in the gender wage gap between columns 2 and 4 of Table 5 is not being driven by a correlation between tasks and omitted major.[20]

The fact that major tends to not have a substantial effect on the gender wage gap at Berea arises because, at least at Berea, women are not systematically choosing the majors that pay the least conditional on tasks. For example, as can be seen from Table 1 and Footnote 19, while men are more likely than women to choose the majors with the second and third highest hourly wages conditional on tasks (Science/Math and Business), women are more likely than men to choose the first and fourth highest paying majors conditional on tasks (Professional and Social Science). This pattern of major choice may be different at other schools, highlighting the reality that there are a variety of reasons that college major could have a different (conditional) effect on the gender wage gap at other schools. As a result, it would not seem appropriate to conclude that major does not generally matter after conditioning on tasks. However, what is important here is that our findings highlight the importance of task information for understanding issues related to the gender wage gap. More generally, the finding that variation in tasks exists within majors and that this variation is important for wage determination helps bolster the motivation for task collection from research such as Autor Handel (2013),

[19]The estimated major coefficients from the regression shown in column 5 of Table 2, with t-statistics in parentheses, are as follows: Professional, 0.25 (4.6), Science/Math, 0.20 (3.6), Business, 0.12 (2.1), Social Science, 0.11 (2.0), Agriculture, -0.03 (-0.4), Education, -0.2 (-0.4).

[20]Appendix B confirms this. Controlling for college major, but not tasks, leads to only a 0.006 log-point decrease in the gender wage gap, compared to the specification shown in column 1 of Table 2.

who show that tasks vary substantially within occupations and that this variation is important for wage determination.

5 Accounting for the Gender Wage Gaps: Predictions and Decompositions

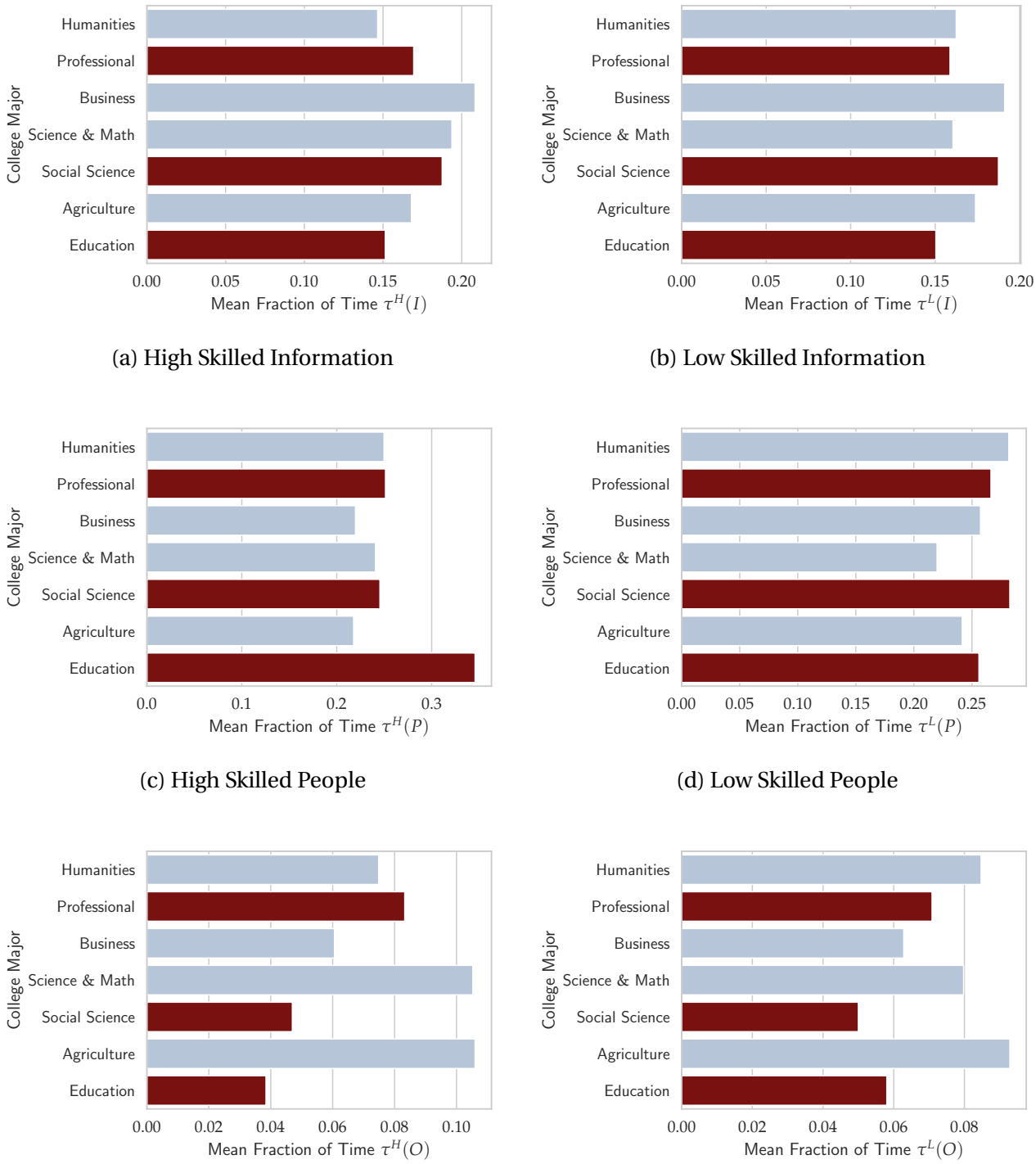
5.1 Prediction

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 a time-varying indicator of whether a person has at least one child. Comparing Figure 7 to the middle (mean) set of lines in Figure 3 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 (i.e., 38% of the total). 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 percent in this period (i.e., 35% of the total).

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 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 is based on the specification shown in column 8 of Table 2. This specification imposes the restriction that the coefficients on the task-specific experience

Figure 5: Mean Tasks by College Major



(a) High Skilled Information

(b) Low Skilled Information

(c) High Skilled People

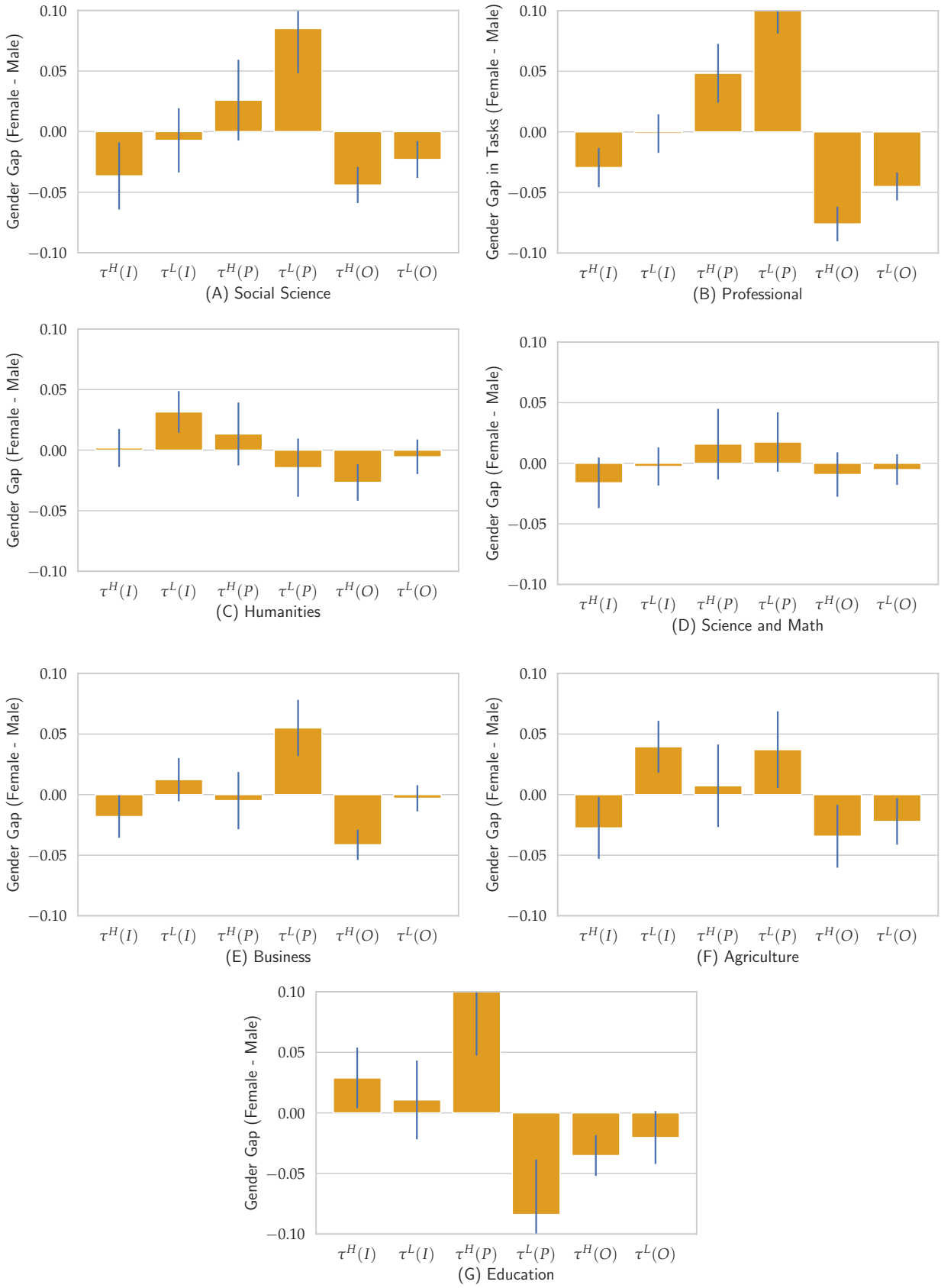
(d) Low Skilled People

(e) High Skilled Objects

(f) Low Skilled Objects

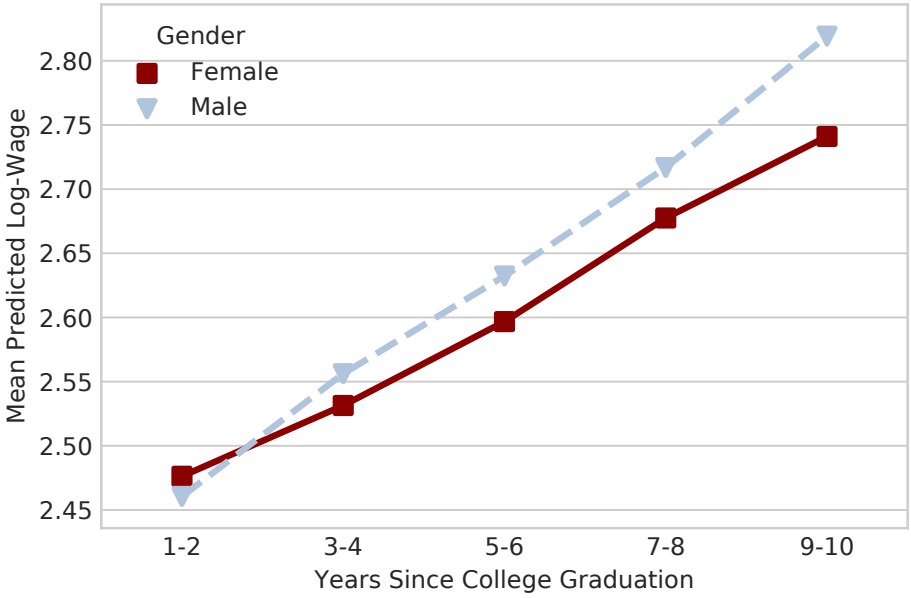
Notes: Dark shaded bars (red) are predominantly female majors, Light shaded bars (grey) are predominantly male majors. Summary statistics for college major by gender are shown in Table 1.

Figure 6: Mean Gender Gap in Tasks by College Major



Notes: Bars represent differences in mean tasks between genders (Female - Male). Vertical lines show 90 percent confidence intervals.

Figure 7: Predicted Log-Wages by Gender and Time



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

variables, except for high skilled information experience, are equal. Based on these estimates, one year of high skilled information experience is associated with an 18 percent increase in wages. This parameter is precisely estimated, with a t-statistic of 5.29. In contrast, the coefficient on cumulative experience performing all other tasks is only 0.012, and is not statistically different from zero at conventional levels.

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 (Section 3.2.2). Second, men do not strictly work in jobs with the highest-paying tasks (Figure 1 and Section 4.1). 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 (0.004 log-points) and years 9-10 (-0.005 log-points).

Table 3: Regression Decomposition of Gender Wage Gap

	Mean log(wage) Gap	
	Years 7-8	Years 9-10
	(1)	(2)
GPA and College Major	0.013	0.009
Current Tasks ($\mathbf{T}_t$)	0.004	-0.005
High Skilled Information Experience $\left(e^H(I)\right)$	-0.025[‡]	-0.039[#]
Non High Skilled Information Experience[†]	-1.11×10^{-4}	-2.49×10^{-4}
Total Gender Gap	-0.103	-0.222

Notes: Entries are mean log-wage differences (Female - Male). The decomposition is based on the estimates from specification (8) in Table 2.
[†] Non high skilled info experience is the sum of all task specific experience variables excluding $e^H(I)$. Specifically, it is defined as $e^L(I)+e^H(P)+e^L(P)+e^H(O)+e^L(O)$.
[‡] The bootstrapped standard error for this predicted value is 0.013.
[#] The bootstrapped standard error for this predicted value is 0.022.

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 high skilled information 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. Specifically, the first column shows that gender differences in high skilled information experience predict a gender wage gap of 2.5 percent in years 7-8, or 24 percent of the total gender wage gap in that period. The second column shows that gender differences in high skilled information experience predict a gender wage gap of 3.9 percent in years 9-10, or 17.5 percent of the total gender wage gap in that period. Although it is uncommon in the literature to present standard errors for this type of wage decomposition, we bootstrapped standard errors for the $e^H(I)$ component because these results are of primary importance. The standard errors are 0.013 for years 7-8 and 0.022 for years 9-10, so both predictions are statistically different from zero at the 10 percent level.[21] The fourth row of the table shows that gender differences in experience performing tasks other than high skilled

[21]When the data is pooled over all four years (years 7-10), the contribution of $e^H(I)$ is -0.03, with a standard error of 0.016. The total gender wage gap in years 7-10 is -0.15

information make a negligible contribution to the gender wage gap.[22]

As alluded to earlier in the paper, simple descriptive evidence suggests 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 cannot account for the male-female wage differential.

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 a time-varying 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 8, in Appendix B, the task information predicts more of the gender wage gap than the children information.

5.3 Accounting for the Gender Gap in High Skilled Information Experience

Our results show that gender disparities in experience performing high skilled information tasks can account for a sizable fraction of the gender wage gap that arises in the latter survey years. In this section, we provide new evidence on *why* men and women might persistently perform different levels of high skilled information tasks. Specifically, viewing ACT scores as a measure of pre-college mathematical and verbal ability, we investigate the extent to which these attributes can account for gender gaps in high skilled information tasks.

Column 1 of Table 4 shows an OLS regression of the amount of high skilled information

[22] Like much other work in this literature (Black et al., 2008; Blau and Kahn, 2017), our focus is on the extent to which gender wage differences can be predicted by gender differences in explanatory variables. Nonetheless, it is perhaps natural to wonder how decomposition results would change if the Table 2 coefficients were allowed to be different for men and women, as in an Oaxaca-Blinder decomposition. Unfortunately, in practice, we find that difficulties related to precision arise in this type of specification because of our relatively small sample size. For example, the largest total predicted difference between men and women arises due to the College GPA term. This occurs largely because the estimated coefficient on College GPA for women (0.145) is substantially larger than the estimated coefficient on College GPA for men (0.063). Unfortunately, it is hard to know how to interpret this result (and the decomposition obtained using this result) because the difference in these estimates is not close to being statistically significant at traditional levels. However, of value for bolstering our primary finding in the paper, in this specification, we find that differences in task-specific experience continue to be important for explaining the gender wage gap. For example, we find that the predicted wages of men would fall by about 0.06 (compared to 0.039 in Table 3) if men had the same amount of high skilled information experience as women.

Table 4: Regression of High Skilled Information Experience in Year 9 on ACT Scores ($e^H(I)$)

	(1)	(2)
Female	-0.186	-0.196
	(0.082)	(0.083)
ACT math[&]	0.122	0.091
	(0.042)	(0.044)
ACT verbal[&]	-0.170	-0.128
	(0.044)	(0.048)
College GPA[&]		0.068
		(0.042)
College Majors		
Business		0.514
		(0.136)
Education		0.145
		(0.144)
Science and Math		0.219
		(0.131)
Professional		0.244
		(0.118)
Social Science		0.129
		(0.135)
Agriculture		0.348
		(0.155)
R^2	0.074	0.120
N	357	357

Notes: All regressions include a constant. Humanities is the omitted college major. Observations are from survey year 9.
[&] ACT scores and college GPA are standardized.

Table 5: Regression Decomposition of the Gender Gap in High Skilled Information Experience ($e^H(I)$)

	(1)[&]	(2)[#]
Years 7-8		
Total Gap in $e^H(I)$	-0.149	-0.149
Percentage of gap accounted for by ACT scores	43.2%	30.2%
Years 9-10		
Total Gap in $e^H(I)$	-0.242	-0.242
Percentage of gap accounted for by ACT scores	31.6%	24.2%

[&] Notes: Decomposition in column (1) is based on a regression of $e^H(I)$ on verbal and math ACT scores. This specification is shown in column 1 of Table 4

[#] Decomposition in column (2) is based on a regression of $e^H(I)$ on verbal and math ACT scores, college major dummies, and college GPA. This specification is shown in column 2 of Table 4

Separate regressions are run for each year (7,8,9,10).

experience ($e^H(I)$) accumulated as of the 9th survey year on gender and ACT scores. The estimates show that ACT scores are strong predictors of the amount of time a person will spend working with information and data at a high skilled level over the career. A one standard deviation increase in math ACT score is associated with a 0.122 increase in $e^H(I)$, and the t-statistic is 2.90. To put the magnitude of this estimate in context, note that the average worker accumulates 1.13 full-time years of experience performing high skilled information tasks by year 9. The positive relationship between math ACT score and tendency to perform quantitative information and data tasks is consistent with the hypothesis that workers sort into job tasks based on their ability to perform them. Turning to verbal ACT scores, a one standard deviation increase in verbal ACT score is associated with a 0.17 *decrease* in high skilled information experience, and the t-statistic is -3.86. This result is consistent with the idea that workers with high verbal ability do not have a comparative advantage performing quantitatively oriented data tasks, so they sort into other types of job tasks. Column 2 of Table 4 shows that ACT scores continue to be an important predictor, even when we also control for college major and college GPA.

Turning to the magnitude of gender differences in ACT scores, Table 1 shows that on, average, women score approximately one-half of a standard deviation higher on the verbal ACT

than men, and also have a very slight edge on the math ACT (0.04 standard deviations). Table 5 quantifies how much of the gender gap in mean $e^H(I)$ can be accounted for by gender differences in ACT scores. This decomposition is based on the models shown in Table 4, estimated separately for each year. Column 1 shows that gender differences in ACT scores can account for 43.2 percent of the gender gap in $e^H(I)$ in years 7-8 of the sample, and 31.6 percent of the gap in years 9-10. Column 2 of Table 5 shows that ACT scores still account for a large fraction of the gender gap in $e^H(I)$, even after conditioning on college GPA and major

Taken as a whole, these results show that gender differences in verbal and mathematical aptitude at college entry can predict a substantial fraction of the differential sorting of men and women into high skilled information tasks that occurs later in the career.[23] In the final section, we comment on the broader implications of this finding for research on the gender wage gap that attempts to determine the role of discrimination.

6 Conclusions

This paper takes advantage of unique new data to explore a task-specific experience channel through which differences in on-the-job human capital accumulation may remain very relevant even in the absence of gender differences in general work experience. For a group of recent college graduates we find that, while the amount of general experience of men and women is indeed quite similar in the early portion of the career, a widening of the gender wage gap is created, in part, because gender differences in types of work experience (i.e., task-specific experience) increase over time. Importantly, the cumulative nature of the task-specific experience explanation implies that modest, constant yearly gender differences in current period tasks accumulate over time to create substantial gender differences in task-specific experience, which have meaningful effects on wages.

From a methodological standpoint, the finding that variation in tasks exists within college

[23] An important issue regarding ACT scores is whether these variables have a direct effect on wages, or if they instead affect wages only indirectly through their relationship with other explanatory variables, such as job tasks. Table 7 in Appendix B shows that when ACT verbal and math scores are added to our primary wage regression specification, both coefficients are small in magnitude and not statistically different from zero.

majors and that this variation is important for wage determination helps bolster the general motivation for task collection from research such as Autor and Handel (2013), who show that tasks vary substantially within occupations and that this variation is important for wage determination. The central role of the cumulative task-specific experience measure in our analysis highlights the importance of previously unavailable longitudinal task data, as well as the benefits of the time-allocation feature of the task measures in the Berea Panel Study.

A prominent policy question, which is directly related to important issues such as discrimination, is whether men and women with similar human capital receive equal pay for equal work. Our findings have a direct bearing on this question. Our characterization of a largely unexplored channel through which gender differences in human capital may arise provides a cautionary note about the difficulty of answering this question. However, we feel that substantial caution is needed when moving beyond this cautionary note to interpret specific results. As one example, Column 6 of Table 2 reveals that controlling for time-varying task and family variables, along with college academic variables, leads to a reduction of the gender wage gap to only 3.2 percent (t-stat = 0.842). However, a conclusion that male and female graduates at Berea do receive equal pay for equal work may not be warranted because 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.

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.

Appendix B: Additional Regression Results

Table 6: Log-Wage Regression: College Major

	(1)
Female	-0.080
	(0.037)
College GPA	0.176
	(0.042)
College Major	
Business	0.224
	(0.060)
Education	0.042
	(0.061)
Agriculture	0.045
	(0.072)
Science and Math	0.277
	(0.057)
Professional	0.325
	(0.055)
Social Science	0.194
	(0.060)
R^2	0.054
N	3271

Notes: All regressions include a constant. Humanities is the omitted college major.

Table 7: Log-Wage Regression: Including ACT Scores

	(1)	(2)
Female	-0.050	-0.047
	(0.035)	(0.035)
College GPA	0.121	0.131
	(0.040)	(0.044)
ACT math (standardized)		-0.004
		(0.019)
ACT verbal (standardized)		-0.009
		(0.021)
Current Tasks ($\mathbf{T}_t$)		
High skilled info. ($\tau^H(I)$)	0.690	0.691
	(0.111)	(0.111)
Low skilled info. ($\tau^L(I)$)	0.171	0.171
	(0.128)	(0.128)
High skilled people ($\tau^H(P)$)	0.323	0.322
	(0.105)	(0.105)
High skilled objects ($\tau^H(O)$)	0.065	0.067
	(0.149)	(0.149)
Low skilled objects ($\tau^L(O)$)	-0.336	-0.333
	(0.160)	(0.160)
Task-Specific Experience ($\boldsymbol{E}_t$)		
High skilled info. ($e^H(I)$)	0.150	0.148
	(0.033)	(0.033)
Low skilled info. ($e^L(I)$)	0.008	0.009
	(0.040)	(0.040)
High skilled people ($e^H(P)$)	0.013	0.013
	(0.017)	(0.017)
Low skilled people ($e^L(P)$)	0.015	0.015
	(0.025)	(0.025)
High skilled objects ($e^H(O)$)	0.049	0.048
	(0.053)	(0.053)
Low skilled objects ($e^L(O)$)	0.008	0.011
	(0.059)	(0.059)
College Major Dummies	yes	yes
R^2	0.1268	0.1271
Observations	3192	3192
Individuals	509	509

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.

Table 8: Additional Regression Decomposition of Gender Wage Gap

	Mean $log(wage)$ Gap	
	Years 7-8	Years 9-10
	(1)	(2)
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). The decomposition is based on the estimates from specification (6) in Table 2.

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