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Computerization of White Collar Jobs

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ABSTRACT

We investigate the impact of computerization of white-collar jobs on wages and employment. Using online job postings from 2007 and 2010–2016 for office and administrative support (OAS) jobs, we show that when firms adopt new software at the job-title level they increase the skills required of job applicants. Furthermore, firms change the task content of such jobs, broadening them to include tasks associated with higher-skill office functions. We aggregate these patterns to the local labor-market level, instrumenting for local technology adoption with national measures. We find that a 1 standard deviation increase in OAS technology usage reduces employment in OAS occupations by about 1 percentage point and increases wages for college graduates in OAS jobs by over 3 percent. We find negative wage spillovers, with wages falling for both workers with no college experience and college graduates. These losses are in part driven by high-skill office occupations. These results are consistent with technological adoption inducing a realignment in task assignment across occupations, leading office support occupations to become higher skill and hence less at risk from further automation. In addition, we find that total employment and wages per population increase with technological adoption, indicating average gains from computerization that are unequally distributed across the labor market.

JEL Classification Codes: J23, J24, J31, O33

Key Words: computerizations, job postings, office and administrative, task content, technology adoption, skill, wages

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1 Introduction

For centuries, advances in labor-saving technology have been met with fear that such technology will eliminate jobs. In the computer era, seminal work by Autor, Levy, and Murnane (2003) clarified that certain jobs are most at risk from technology, in particular so-called *routine* jobs which are made up of tasks most easily substituted for by computers. As Acemoglu and Autor (2011) show, these jobs neatly correspond to occupations that have experienced employment and wage declines in recent decades—in particular sales, office and administrative support (OAS), production, and operators. Projecting forward, headline-grabbing articles such as Frey and Osborne (2015) have predicted that 47 percent of all jobs could become automated in coming decades, contributing to popular anxiety and calls for preemptive policies such as universal basic income to combat *technological unemployment* (Keynes, 1930). Although recent work by Acemoglu and Restrepo (2017) on the effect of industrial robots suggests these fears are warranted in manufacturing, little is known about how firms and local labor markets adjust in response to the computerization of white-collar jobs.

In this paper, we investigate the role of technological adoption in a large class of routine jobs: office and administrative support (OAS) occupations. From a peak of over 16 percent of all employment in 1980, the OAS employment share has steadily fallen each year to its current level of below 13 percent.[1] This nonetheless represents a larger share of employment than does manufacturing. At the same time, these jobs have become increasingly reliant on personal computers; for instance, according to O*NET 86% of administrative assistants report using e-mail every day.[2]

We use over eight million detailed job ads from 2007 and 2010–2016 to observe how firms change the task content and requirements within positions in conjunction with the adoption of software. We find that the task content of jobs changes when firms adopt

[1]Source: 1980 Census, 2015 American Communities Survey. Retrieved from IPUMS. See Figure 1.
[2]See National Center for O*NET Development (2017).

technology, resulting in office and administrative support jobs becoming more highly skilled and encompassing cognitive tasks that are less at risk of computerization. In particular, we find an increase in tasks assigned to OAS jobs that are associated with finance, accounting, legal, and management jobs.

We then construct indices of technological intensity, allowing us to measure the effect of technological adoption on employment and wage outcomes in the local labor market. By constructing a Bartik-style instrument using national technology adoption and historic employment patterns, we find that a 1 standard deviation increase in technology usage in a local labor market leads to a 1.0 percentage point decrease in OAS employment and a 2.5 percentage point increase in the share of OAS employed persons with a college degree. Furthermore, we find that technology adoption increases wages for OAS workers with a college degree by more than 3 percent for each unit increase in technology, while wage changes for non–college graduates are negative but not statistically distinct from zero. These local labor-market effects of technological adoption are consistent with the upskilling we observe in the individual job-posting data.

Despite the reduction in employment in OAS occupations, we find that overall employment per population increases in commuting zones, and that there are larger increases in technology adoption: a 1-unit increase in technology leads to a 1.0 percentage point increase in the employment-to-population ratio and a 1.2 percentage point increase in the female employment-to-population rate. We do find negative wage spillovers for non-OAS workers, with a 1 standard deviation increase in OAS technology adoption associated with a 1 percent decrease in wages for college graduates and a 4 percent decrease for non–college graduates.

We investigate which occupations are affected by the spillovers in OAS technological change. We find the increases in employment are broad based–however, with larger effects for white-collar occupations. We find the largest wage losses are in ”pink collar” occupations—that is, occupations in which the majority of workers are female without a college degree. This is consistent with increased competition for these pink-collar jobs as the employment opportunities in OAS jobs decline for workers without college degrees. In addition, we see wage losses in white-collar occupations. We see some evidence that this may be driven by the occupations in which OAS workers are increasingly performing tasks, such as legal occupations and business occupations. Finally, we see large increases in employment in computer-related occupations, which is consistent with the increased use of software requiring additional technical support.

The software that is adopted by OAS workers has elements of both factor-augmenting and task-substituting technological change. To test which feature is dominant, we draw from Acemoglu and Autor (2011), who show that factor-augmenting technological change should lead to relative wage gains for middle-skill occupations, while task-substituting technological change should lead to relative wage losses. We find that OAS workers' wages rise compared with both noncollege and college workers, indicating the factor-augmenting features of OAS software adoption appear to be dominant. This may explain our divergent results from Acemoglu and Restrepo (2017), who find negative employment and wage effects due to the adoption of task-substituting industrial robots. In addition, the fact that we see larger gains for college-educated OAS workers suggests that this technological change is also skill-biased among OAS workers.

In aggregate, we find that type of technology adopted by OAS workers leads to a positive effect on the local labor market, with rising employment and increasing wages per population. However, these gains are concentrated in women with college degrees, who capture all of the employment gains and none of the wage losses. On the other hand, wage losses are largest for women without college degrees, while men with and without college degrees also experience losses. Although we do see substantial decreases in employment in OAS occupations, as the task content of these jobs becomes less routine and more cognitive, we expect that the employment share will stabilize and these occupations will remain an important segment of the labor market for years to come.

2 Related Literature

Our focus on office and administrative support jobs is linked to the routine-biased technological change hypothesis (RBTC), an idea popularized by Autor et al. (2003). These authors (and the extensive follow-up literature) argue that computers are best suited to replace tasks that can be described as "routine"; thus, the falling price of computing power has allowed firms to substitute technology for workers who specialize in these tasks. Although the RBTC hypothesis operates at the task level, the bulk of research in this area has focused on occupation-level predictions. For instance, work by Goos and Manning (2007) and Goos, Manning, and Salomons (2014) provides broad international evidence of falling employment in occupations that primarily perform routine tasks. Recent evidence from Jaimovich and Siu (2012) finds this process accelerates during recessions.

The evidence on the "intensive margin" of polarization—that is, changes in the task content of jobs, is less developed. Autor et al. (2003) show some evidence of this, finding a drop in the importance of cognitive routine skills in occupations with increased use of computers. Autor and Handel (2013) show that cross-sectional variation in tasks within occupation is predictive of wage variation. In this paper, we are able to directly capture the intensive margin by measuring changes in technology usage at the firm-job-title level. That is, we can observe the adoption of technology for a particular position within the firm, and observe how this adoption is associated with changes in worker skill requirements as well as the job tasks listed in the job ad. Moreover, we can connect this routine-biased technological change within firms to changing employment patterns at the local level.

The key mechanism that we observe, that technology adoption is associated with increasing demand for education at the position level, is consistent with a large literature linking technology to skill. This is related to the skill-biased technological change hypothesis (SBTC), which argues that the rise of computers in the workplace in the 1980s was responsible for increases in the returns to education over the same time period.[3] Although certain

[3]See, for instance, Krueger (1993). See also Machin and Van Reenen (2008) for an international per-

features of the changing shares of employment and wage inequality are more consistent with routine-biased technological change (see Card and DiNardo (2002) and Goos and Manning (2007) for discussion), we find a similar pattern of educational upskilling in response to technological change as observed in the original SBTC literature. This nuanced perspective is consistent with Ben-Ner and Urtasun (2013), who find heterogeneity across occupations in the effects of computerization on worker skill.

Our project also relates to a recent working paper by Acemoglu and Restrepo (2017), who investigate the role of industrial robots on local labor-market outcomes. Unlike software, which is typically operated by workers within the occupation, the industrial robots Acemoglu and Restrepo (2017) focus on typically completely replace jobs performed by low-skill manufacturing workers. In contrast to our finding that OAS software depresses wages but increases aggregate employment levels, Acemoglu and Restrepo (2017) find industrial robots decrease both employment and wages. These heterogeneous results suggest that the impact of technology on labor markets may differ based on characteristics of the jobs and the technology. We discuss this in more detail in Section 4.

Finally, our paper contributes to a growing literature using job postings as a source of labor market data. These papers include Kuhn and Shen (2013), Marinescu and Wolthoff (2015), and Marinescu (2017). Several papers use the same source of data we employ, online job postings collected by Burning Glass Technologies: Rothwell (2014), Modestino, Shoag, and Ballance (2016), Modestino, Shoag, and Ballance (2015), and Hershbein and Kahn (2018).

3 Background on OAS Occupations

Office and administrative support (OAS) occupations are a major occupational category as defined by the Standard Occupational Classification Policy Committee (*2010 SOC User Guide*, 2010). These occupations include secretaries and administrative assistants, financial

spective.

clerks, schedule and dispatching workers, and other related categories. See Table A.4 for a list of occupational categories and employment shares.

As discussed in the introduction, OAS occupations experienced a rapid growth in employment in the post-war era, growing from less than 12 percent of all employment in the United States in 1950 to a peak of nearly 17 percent by 1980. However, after 1980, the employment share suffered a precipitous decline. By 2016, the employment share had fallen to a level last seen in 1960. Figure 1 illustrates this trend. What changed for OAS workers in the 1980s? Notably, the mass adoption of personal computers for office workers. The share of secretaries using a computer at work rose from 46 percent in 1984 to 77 percent by 1989 (Krueger, 1993).

Over the same time period, education levels rose substantially for all workers; Figure 2 shows the share of workers with college degrees among OAS and non-OAS workers. In the 1950 census, less than 1 percent of OAS workers had college degrees. This increased to 21 percent by 2015. The trend for OAS workers has mirrored those for non-OAS workers, suggesting that rising education levels alone cannot explain the fall in employment share for OAS workers. Nonetheless, we will show there is a relationship between technological adoption and demand for education, at both the firm and local labor-market levels.

Thus, there have been three simultaneous macroeconomic trends for OAS workers: 1) falling employment levels since 1980, 2) rising computer use through the 1980s and 1990s and continued adoption of new software through 2016, and 3) rising educational levels. In the next section, we investigate the theoretical underpinnings of technological change to see how these trends may be connected.

4 Theory and Testable Predictions

Before measuring how office-support software has impacted OAS jobs and the labor market, we want to provide a framework of how to conceptualize such technological change.

In particular, we draw on the task perspective of technology popularized by Autor et al. (2003) to connect technological adoption to changes in how tasks are performed within jobs. We then link these task changes to changes in wages and employment in the broader labor market.

Since our research design examines how task and technology changes within individual job postings, we need a framework that can explain how software operated by individuals employed in OAS occupations can change these jobs. Empirically, the most frequent type of technology we observe in OAS job postings is office software, such as Microsoft Word and Excel. When word-processing software first entered the market, it resulted in massive productivity improvements over typewriters, leading to the end of the once ubiquitous secretarial pool.

Software availability and proficiency continues to improve the productivity of office support workers. For instance, mastering mail merge can allow an office worker to automate mass mailings, freeing up time for other tasks or allowing the employer to reduce OAS headcount. However, such proficiency requires training and general computer literacy. Thus, technology adoption tends to go hand in hand with education. We expect to see that firms that increase demand for software usage in OAS jobs will also increase requirements for education and other skills.[4]

In order to understand how such technology may change the task assignment to jobs, as well as wages and employment, we turn to a model developed by Acemoglu and Autor (2011) to explain changing wage and employment patterns for workers employed in middle-skill occupations. Suppose the economy consists of three types of workers: low-skill, middle-skill, and high-skill, all of whom compete in a competitive labor market for a continuum of tasks. Each type of worker has a comparative advantage for a range of tasks, and the authors show that tasks can be ordered in such a way that each type of worker will specialize in a compact set of tasks, ordered by skill level. In this case, OAS workers would be classified as being in

[4] See (Downey, 2019) for the related phenomenon of technology allowing for a job to be performed by a lower-skill worker.

middle-skill occupations.

There are two ways in which technological change can affect the labor market: 1) factor-augmenting and 2) task-replacing technological change. Factor-augmenting technological change increases these workers' productivity across all tasks. In this case, such technological change for middle-skill occupations should broaden the set of tasks performed by middle-skill workers and increase wages for middle-skill workers compared to both low- and high-skill workers.[5]

On the other hand, if software serves to replace tasks in the middle-skill task range, the predictions are different. Although the task measure should again broaden, wages for middle-skill workers are predicted to fall compared to both low- and high-skilled workers.[6] Why the difference in predicted effect on wages? In the case of factor-augmenting technological change, the measure of tasks performed by middle-skill workers increases relative to low- and high-skill workers, while in the case of task-replacing technological change, the total amount of tasks performed by middle-skill workers decreases. Thus, the net effect on wages will depend on whether enough tasks are added in the process of task-broadening to counteract the reduction in routine tasks that are replaced by technology.

In the case of software adopted by OAS occupations, both factor-augmenting and task-replacing technological change is likely at play. As discussed above, OAS workers who can successfully operate software are likely more productive than those that do not use software, leading to productivity improvements across a variety of tasks. However other basic office-support tasks are functionally automated by modern office software. Thus, whether we see relative wages increase or decrease for OAS workers will depend on which feature of the technological change dominates. We test this directly in Section 7.5.

Regardless of the nature of the technological change, the Acemoglu and Autor (2011) framework predicts that technological change for office support workers will lead workers to perform a broader variety of tasks. In addition, even if employers reduce headcount, the

[5] See Acemoglu and Autor (2011) Proposition 2.

[6] See Acemoglu and Autor (2011) Propositions 3 and 4.

lumpiness of work hours will lead employers to find additional tasks to fill their remaining workers' schedules. Thus, we predict that employers that adopt technology will increase the number of tasks demanded of OAS workers.

What types of tasks do we expect employers to add? This depends on the tasks for which OAS workers are the closest substitutes for other workers. Although Acemoglu and Autor (2011) argue that middle-skill workers are closer substitutes for low-skill workers, OAS may be closer substitutes for high-skill workers. If employers increase skill requirements, the new OAS employees will be increasingly qualified for higher-skill tasks. In particular, since OAS employees are by definition in support occupations, these more-skilled OAS employees will be able to take on tasks from other white-collar occupations. This is an empirical question we can directly address by examining which tasks are added to job advertisements in conjunction with the increases in technology demanded.

How might broad-based technology adoption affect wages for OAS workers? At a particular firm, wages are likely to be most affected by whether the job becomes higher-skill or lower-skill. If, as we suspect, firms upskill in conjunction with technological adoption, this should lead to an increase in observed wages in order to attract talent. In the labor market as a whole, there are several opposing pressures on OAS wages. First, the factor-augmenting components of the technological change should increase demand for OAS workers and, in particular, skilled OAS workers, leading to upward wage pressure. In addition, any local multiplier from the increased productivity should generally increase labor demand and wages. However, the task-substitution components of technological change will decrease demand for OAS employment and accordingly provide downward wage pressure. Thus, the effect of technological adoption on wages will depend on which of these factors is dominant.

We can also examine which non-OAS workers are likely to be affected by spillovers from OAS technological adoption. There are three main dynamics at play: task competition, labor-supply competition, and local productivity effects. As the tasks assigned to OAS workers broaden in response to technological change, this may reduce demand for the occupations that previously performed these tasks, reducing employment as well as wages.

On the other hand, as would-be OAS workers move into other occupations, this should lead to competition in labor supply for these jobs. This should lead to an increase in employment and a decrease in wages. Which jobs are likely to be affected? Since OAS workers are predominantly female and lack college degrees, we expect to see this effect concentrated in jobs with similar profiles, such as health care support and food preparation occupations.

Finally, if the adoption of technology serves as a productivity boost, local labor markets that adopt such technology may see broad increases in economic activity, leading to increases in labor demand. This will depend on the relative magnitude of the direct decrease in OAS employment compared with the diffuse increase in economic activity. In addition, we expect to see positive employment effects for the computer tech occupations that maintain the new technology.

5 Measuring Technology from Job Postings

Our job-posting data come from a company called Burning Glass. As access to and use of the Internet have grown, online job advertisements have become a common way to fill vacancies. Burning Glass is one of several companies that track these vacancies by scraping job information from roughly 40,000 online job boards and company websites. Burning Glass then parses the job posts and removes duplicate postings to create labor market data that can be analyzed by researchers. We use data from 2007 and from 2010 to 2016.

These data have several advantages over other data sets. The first advantage of the Burning Glass data is that they contain information on labor demand, which is sparse. Other commonly used data sets, such as the census, the American Community Survey, and the Current Population Survey, only include information on completed matches rather than on the original vacancy postings. Another advantage of the Burning Glass data set is that it is large. The database covers approximately 145 million openings that were posted in calendar years 2007 and 2010–2016. A third advantage of these data is that they contain a much wider set of information than is available in many other data sets. In addition to containing information such as the education and experience requirements and the occupation of the job, Burning Glass also parses the skills and tasks listed, which is especially important for our purposes. For a majority of the observations, the data contain the advertising firm's name, which allows us to examine within-firm changes.[7]

Despite the advantages of these data, two issues should be kept in mind. First, while the data set aims to be a near-census of online job ads, online job ads are not representative of all vacancies. Compared to the Job Openings and Labor Turnover Survey (JOLTS), which is a survey of a representative sample of employers, data from online postings tends to overrepresent computer, management, and business occupations and underrepresent health care support, transportation, maintenance, sales, and food service workers. Second, the use of online job postings continues to rise throughout the years of the data, so the number and types of jobs that appear in the data change over time. These issues mean the data are not good for estimating economy-wide trends in occupational demand; however, they are less problematic for our purpose because our empirical strategy controls for various fixed effects, including year-month and employer-commuting-zone fixed effects.

We draw on two Burning Glass data sets to create our analysis data set. The first is ad-level data that contain education requirements, experience requirements, SOC codes, the posting date, the county, and firm name for each ad. The second data set contains other elements of ads, including specific skill and task requirements of the job, as well as a unique identifier for matching these elements to each ad in the primary data set. We match O*NET information to this element-level data set (described below), collapse the data set to the ad level, and then merge it with the main ad-level data set.

For our analysis, we focus on the 15,452,623 advertisements in OAS occupations. Among

[7] Many of the ads without firm name are from the temporary-help sector. Burning Glass does not list the names of temporary-help firms and instead leaves the ad's firm name blank.

those ads, we restrict attention to the 8,589,664 advertisements that contain the firm name.

5.1 Measuring Technology

Although Burning Glass Technologies processes the job ad's raw text into more than 12,000 phrases, these phrases are largely unstructured. In order to identify technologies and classify them into categories, we use O*NET data on job characteristics. O*NET is a project of the Department of Labor to provide regularized data on occupations in the United States.

An advantage of O*NET is that it links commercial technology names to categories of technology and then further links those categories to specific occupations. For instance, using the O*NET database, we can see that secretary occupations often use Excel, which is categorized as "spreadsheet software," as is Corel QuattroPro. According to O*NET, there are 85 categories of technology used by OAS workers. These map to 8,425 specific technology names in the O*NET technology database. After performing a fuzzy-text match with the phrases in the Burning Glass data, which we then confirm by hand, we generate a master list of 821 brand names and generic names (e.g., spreadsheet software) that are classified into 69 technology categories. Appendix Table A.1 describes these data.

5.2 Measuring Skills and Tasks

We focus on two types of measures of changing labor demand. First, we use data scraped by Burning Glass on educational requirements in job ads. Only about 50 percent of OAS job ads include educational requirements, so we include measures of any educational requirement as well as "requires high school" and "requires college" as possible outcome variables. In addition, we measure requirements for previous relevant job experience. We use two measures, an indicator for including any experience requirement, as well as the number of years of required experience. These variables are described in Table A.5.

The second focus of labor demand is measuring changes in the task content of the job. We measure this by assigning the top 1,000 phrases that appear in OAS job ads to several specific categories. Appendix Table A.2 shows examples of each category of task. First, we isolate tasks that are associated with lower-skill office support tasks such as typing, data entry, and use of office equipment. We further subdivide this category into six subcategories: 1) basic administrative assistance tasks, 2) tools, 3) physical tasks, 4) mail, 5) routine accounting, and 6) clerking tasks. The second group of tasks are those that are associated with other office function tasks. These include the following six categories: 1) legal, 2) logistics, 3) human resources, 4) marketing, 5) sales/customer service, and 6) accounting/finance. Finally, we isolate tasks that are associated with higher-level skills. These are grouped into four categories: 1) writing, 2) research, 3) management, and 4) other cognitive. These variables are described in Table A.6.

5.3 Classifying Occupations

In order to capture spillovers from office support occupations to other occupations, we use census data from 2000 to classify occupations into four categories based on the share female and share with a college degree, as illustrated in Figure 7. In particular, occupations with fewer than 40 percent of workers having a college degree are defined to be blue-collar occupations if the occupations were majority male in 2000 and pink-collar if the occupations were majority female in 2000. Similarly, occupations with over 40 percent holding a college degree are defined to be white-collar, which we again divide into white-collar male and white-collar female. By this classification, OAS occupations would be considered pink-collar, although we exclude it from the category to estimate spillovers.

6 Within Job Posting Results

We begin by examining how employers change other aspects of job requirements when they adopt technology. We first focus on two measures of skill requirements: 1) educational requirements and 2) experience requirements. We then turn to changes in the required tasks.

6.1 Econometric Specification

Our goal in this section is to examine the relationship between the intensity of technology demanded with the skills and tasks of the job. We first examine the cross-sectional relationship between average technology intensity and job characteristics within OAS job postings. In particular, we estimate the following equation:

$$y_{ict} = \alpha + \gamma_t + \gamma_c + \beta \text{Tech}_{ict} + \epsilon_{ict} \tag{1}$$

where i indexes the ad, c indexes the commuting zone, t indexes the year and month the ad was listed, and y is a measure of skill or other job characteristics. Tech counts the number of technologies listed in the job ad as described in Section 5.1. Commuting zones are geographic areas, defined as sets of counties within which individuals commonly commute (Tolbert & Sizer, 1996).

We include two sets of fixed effects. γ_t is a vector of year-month indicator variables which control for cyclicality or seasonality in job-posting characteristics. γ_c is a vector of commuting zone indicator variables which control for time-invariant differences in job-posting characteristics across geographic regions. These specifications are estimated using 15,452,623 OAS job postings.

Although specification 1 allows us to show the cross-sectional relationship between technology intensity and job posting characteristics, we are also interested in how these measures co-move within firms and within jobs in firms. Thus, we also estimate panel specifications in which we restrict our analysis to jobs that have been posted more than once. In order to identify repeat postings, first we identify firms using firm name and commuting zone. We then identify jobs using job titles within firms. Thus, our panel data is at the firm name $\times$ commuting zone $\times$ job-title level. This leaves us with 5,261,935 observations in the panel sample.

Defining firms at the firm-location level ensures we do not treat all establishments of a national chain as being the same. Instead, we allow the requirements (for example) for a Facebook administrative assistant in Seattle to differ from those of a Facebook administrative assistant in Austin, thus ensuring that we are not simply measuring various locations with different requirements hiring at different times.

We estimate three specifications using the panel data. First, we include the same fixed effects from Equation 1. This tells us whether our panel sample is similar to the larger data set. Second, we replace the commuting zone fixed effects γ_c with firm fixed effects γ_{fc}. Third, we replace the firm fixed effects with firm-job-title fixed effects γ_{fcj}.

The job-title-level fixed effect allows us to measure changes in job characteristics within specific jobs. That is, we measure how the skill requirements in Executive Assistant III jobs at Facebook in Seattle change when technology intensity changes. However, it is possible that technological adoption may change how tasks are allocated across the firm. For instance, if the employer reduces headcount in OAS jobs, that emloyer may reduce the breadth of job titles or introduce new job titles. Thus, the firm-location-level specification measures changes across office-support jobs within a location.

6.2 Upskilling Results

We begin by estimating the relationship between technology intensity and skill demand, focusing on education and experience requirements. In Table 1, we report the technology coefficients from estimating the four variations of Equation (1) described in the previous section. In Panel A, we see that a little over half of job ads list an education requirement. However, one additional technology listed is associated with a 6 percentage point increase in the likelihood the job ad includes an explicit education requirement, which corresponds to an 11 percent increase over the mean. When we control for firm fixed effects, we see the effect falls to about 7 percent, indicating that a portion of the cross-sectional effect is due to the fact that the firms that list more technology are more likely to list educational requirements. However, in Column (4), we see that within job titles the effect size is larger than in the cross-sectional estimates, suggesting that firms are likely increasing skill requirements when they increase technological intensity.

In Panel B, we restrict our analysis to job ads that mention an educational requirement, and we estimate the relationship between technological intensity on the likelihood the job ad requires a high school diploma. Some 67 percent of job ads that list an educational requirement specify a high school diploma. Here we see the relationship is negative for all four specifications. In contrast, in Panel C we estimate the relationship for requiring a college degree, which comprises 24 percent of job postings that list an education requirement. Here we see the effect is positive across all specifications.

In both Panel B and Panel C, the effect size is substantially larger in the cross-section than for the within-firm and within-job-title specifications. This indicates that most of the cross-sectional relationship is driven by differences across firms and job titles in the likelihood of requiring a high-school or college diploma. Nonetheless, the coefficients are still statistically significant for the within-firm and within-job-title specifications.

In Panels D and E, we turn to experience requirements. Some 42 percent of OAS job ads specify an experience requirement, which corresponds to an average of one year of required experience (with missing coded as zero). In the cross-section, job ads that specify one additional technology are 17 percent more likely to list an experience requirement, which corresponds to 0.3 years of additional required experience. Within firms and within job title there remains a robust relationship, with an increase of about 0.2 years in required experience within firms and job titles. This is consistent with firms increasing experience requirements at the same time as increasing demand for technology.

These results suggest that increasing the technology requirements for a job is associated with increasing the education and experience requirements for that job. However, if firms that adopt technology also increase skill requirements for unrelated reasons, we would erroneously estimate a positive relationship between technology and skill demand. To consider the possibility of pre-existing trends, we estimate models that more carefully consider the timing of the education and experience changes relative to technology adoption.

In order to capture the specific moment that the firm increased technology demand, we restrict our sample to ads from firms that hired OAS occupations in 2007 and 2010 but did not list technology as a requirement for any of their OAS jobs. Of the 8,589,664 OAS ads that contain employer names, 1,098,781 meet this criterion.

We then estimate models of the following form:

$$y_{ifmt} = \alpha + \gamma_t + \gamma_{fm} + \sum_{k=-1}^{k=2} \beta_k \text{Tech}_{fmt} + \epsilon_{ifmt} \tag{2}$$

where k is the number of calendar years from the year in which the firm began asking for technology for the position. We consider the relationship between technology and education/experience two years before technology adoption ($k = -2$), the year before technology adoption ($k = -1$), the year of technology adoption ($k = 0$), the year after technology adoption ($k = 1$), and more than one year after technology adoption ($k = 2$). Each β_k estimate can be interpreted as the association between asking for technology and the dependent variable at each point in time relative to the association between being at least two years from asking for technology and the dependent variable.

Figure 3 plots estimates of the β coefficients from Equation (2) along with their 95 percent confidence intervals. The results indicate that firms that will adopt technology do ask for more education in previous years, but demand for education increases substantially in the year of technology adoption, persisting up to two years after adoption. While Figure 3 provides evidence that firms may be likely to list experience the year before asking for technology, the coefficient approximately doubles as firms begin asking for technology.

In conclusion, in this section we have shown that increasing technology usage in office support jobs and increasing educational attainment are directly linked within firms. As firms adopt new technology, they increase their demand for skills. In the case of education, this appears to happen simultaneously with technology adoption, and skill requirements remain elevated for up to two years after the adoption of technology. This is consistent with technological change that is complementary with skill, in which technology allows workers to specialize in aspects of the job that produce a higher return to skill.

6.3 Task Broadening

Next we investigate how the tasks associated with OAS jobs change when firms increase their demand for technology. So far we have documented that technology adoption is associated with increased demand for education and experience. There are a few ways in which technology adoption may change how firms assign tasks to OAS workers. Mechanically, if the technology reduces the time spent on certain tasks, then there will be more time to spend on other tasks. Thus, we would expect the set of tasks demanded to either shift, broaden, or change in time intensity. Since our task information is derived from the job ad, we cannot observe changes in the time usage associated with tasks. However, we can observe whether certain tasks disappear from the job description or whether new tasks are added in.

Since we already saw that technology adoption is associated with increased skill demand, this may lead to complementarities between technology, worker skill, and tasks. In particular, employing higher-skill workers in OAS occupations means firms may find they are able to reassign higher-skill tasks to these workers. Thus, in this section we investigate whether the introduction of technology is associated with changes in the presence of three broad categories of tasks in the job description. First, we examine routine tasks, which are more standard to OAS occupations and are more likely to be replaced by technology. Second, we examine tasks that are associated with other white collar occupations, to see if tasks are shifted between job categories. Finally, we examine whether other broad higher-skill tasks are added to job ads.

In particular, in Table 2, we replicate the methodology from Equation 1; however now the dependent variable is the count of how many tasks of a specific type are included in the job ad. For these specifications, we report estimates for the cross-sectional specification, in

Appendix Table A.11 we report coefficients from the within-job-title specification.

In Panel A of Table 2 we see that, instead of reducing demand for routine tasks, job ads that list more technology are more likely to demand tasks in these categories. We see the biggest effect for clerking tasks, which include tasks such as file management, record keeping, and data management. However, we also see positive coefficients for more basic administrative-assistant tasks, which include tasks such as typing, copying, and clerical duties. Thus, it does not appear that technology adoption allows firms to remove these less-skilled tasks from their job ads. Nonetheless, we do not see an increase in the tasks involving a physical routine that some office support workers are asked to perform (including tasks such as cleaning, equipment maintenance, and materials moving).

In Panel B we examine how the adoption of technology is associated with changes in tasks for particular office functions. Here we see robust positive coefficients for legal, accounting and finance, logistics, and human-resources tasks, but a negative correlation for sales and marketing. These results suggest that firms are increasingly asking office support workers to perform tasks that are more typically performed by individuals with more specialized job titles, such as paralegals or accountants. This is consistent with technology making it possible for firms to shift tasks down the hierarchy to the newly upskilled support workers.

In Panel C, we directly test whether firms are demanding higher-level tasks from their office support workers. Here we see a strong positive relationship between technology demand and management, cognitive, and research tasks. We interpret these results as evidence of a broadening task space for office support workers. Far from performing the routine and repetitive tasks of previous generations, office support jobs increasingly demand that individuals perform a broad variety of tasks, including lower-skill tasks (answering phones, typing, mailing) as well as legal research, writing, and data analysis.

In order to more systematically examine how the tasks of OAS job ads vary with technology intensity, we next create a list of tasks that are associated with specific occupational groups. In particular, we use the four types of occupations defined in Section 5.3: pink-collar, blue-collar, male white-collar, and female white-collar. For each set of occupations, we capture the first 100 phrases that are not technology and are unique across the occupations, and we define those phrases as core to the occupation group. Appendix Table A.3 provides examples of these tasks. In Table 3, we again estimate the four specifications that build off of Equation 1.

On average, there is the most overlap in tasks between OAS job ads and job ads for pink-collar occupations: the average job ad contains 0.3 tasks from the pink-collar list, such as food preparation or retail sales. In contrast, the average job ad only includes 0.13 tasks associated with female-dominant white-collar occupations and 0.09 tasks associated with male-dominant white-collar occupations. Blue-collar occupations exhibit the smallest overlap with OAS jobs, with the average OAS job ad listing 0.07 of these tasks.

In Panels A and B, we estimate the relationship between technology intensity and blue-collar and pink-collar tasks, respectively. In the cross section, job ads that request more technology include fewer tasks from both of these lower-skill occupation groups. However when we look within job titles in column (4), we see the relationship becomes positive, indicating that within jobs, increases in technology demand are associated with small increases in blue-collar and pink-collar tasks. In column (4) we see that increases in OAS technology are associated with larger increases for pink-collar (0.05) than for blue-collar (0.08) tasks.

We see larger effects for tasks from male-dominant white-collar occupations in Panel C. Ads that include one additional OAS technology list 0.06 additional white collar male tasks, which is an increase of almost 60 percent. Even once we control for firm location or for job title, we see this effect size is quite robust, indicating this relationship is largely a within-job phenomenon. For female-dominant white-collar occupation tasks, the relationship is also strong within job title, falling from 0.04 to 0.03.

Thus, we see here that in the cross section, OAS job ads that ask for more technology are more likely to ask for tasks from white-collar occupations, and less likely to ask for tasks from blue- or pink-collar occupations. Although within jobs we see an increase in tasks from all four categories with technology increases, the effect size is substantially larger for pink- and white-collar tasks, with the largest effects for tasks in male-dominant white-collar occupations. We will return to these occupational categories when examining the effect of technology adoption on local labor-market outcomes.

Appendix Table A.10 is constructed similarly to Table 3; however, it instead focuses on tasks from specific occupations: management, business, legal, and sales. The results in Appendix Table A.10 indicate that requiring technology is associated with also being more likely to ask for skills that are prevalent in other occupations, which confirms the main analysis.

6.4 Discussion

Thus, within firms we find three processes occurring simultaneously: 1) adoption of technology, 2) changing skill demands, and 3) broadening the task content of jobs. Although we show that many of the changes in skill and task demand occur after the adoption of technology, we cannot rule out alternative causal pathways. For instance, increasing education of the labor force may allow firms to both adopt technology (if the new workers have computer skills) and add increasingly high-skill tasks to the job description. In addition, our job-posting data does not include salary information, so we cannot examine how these changes are associated with wages. Thus, in the next section, we turn to a local labor-market approach in which we use an instrumental variable approach to determine the effect of technology usage in the local area on labor-market outcomes for office support workers as well as spillovers to the rest of the labor market.

7 Local Labor Markets and Technology

In the previous section, we established that firms add additional skill requirements in conjunction with introducing new technology to job ads. Although this indicates how firms would like to staff these changing occupations and is consistent with aggregate educational trends for OAS workers, we would like to directly test whether these changes in job postings affect local labor-market outcomes. In this section we introduce our methodology for measuring the effect of technological adoption on local labor-market outcomes and then test the labor-market effects for OAS and other workers.

7.1 Measuring Local Technology Exposure

In the previous section we showed that requesting technology in job ads is correlated with upskilling and changing task requirements at the position level. In order to measure the effect of technological adoption on local labor markets, we need to aggregate our measure. We construct the following exposure measure for each local labor market g and year t:

$$\text{Exposure}_{gt} = \sum_{o} \frac{L_{ogt}}{L_{gt,\text{OAS}}} \text{Tech}_{ogt} \tag{3}$$

where Tech_{ogt} represents the average number of OAS software types per job ad for OAS occupation o in region g and year t. The number of OAS software types is constructed following the methodology outlined in Section 5.1. In order to aggregate from the occupation level to the local labor-market level, we weight each occupation-level measure by the share of local employment in OAS occupations ($L_{gt,\text{OAS}}$) in occupation o (L_{ogt}). This ensures that the intensity measure is not mechanically determined by changes in the level of OAS employment.

Why do we believe this is a good measure of local technology adoption for OAS workers? First, since employers use job ads to communicate with potential employees, it is likely to be accurate. Second, since we draw from over eight million job ads with detailed geographic information, we have enough data to construct commuting-zone-by-detailed-occupation-level measures.

The accuracy of this measure depends on how well it approximates the actual technology usage of ongoing employment. There are several reasons why the measure may fail to accurately reflect usage. First, since the measure is derived from job postings, it reflects technology demand for new hires, which may differ systematically from technology demand for ongoing positions. This means our estimates are more heavily weighted toward high-growth and high-turnover employers who may systematically use different technology than low-growth and low-turnover employers. Second, employers may underreport technology usage. This could be the case if employers either assume all applicants will have proficiency with a technology or if they expect to train hires in a technology. In these cases, our measures may be an underestimate of true technology usage. Third, it is possible that employers could overreport technology usage, for instance if they strategically include a technology in their job ads as a signal to potential applicants. We believe systematic underreporting is more likely than systematic overreporting, leading our job-ad-based measure to be an underestimate of true technology usage.

In Figure 4, we plot the 2016 exposure measure for each commuting zone, defined as in Equation 3. Here the darkest regions show the most technology-intensive one-sixth of commuting zones, in which nearly one type of technology was requested per job ad in 2016. Thus, although technology intensity in job ads has been increasing, there are still many postings that do not list any technology in 2016.

In Figure 5, we show how the change in OAS share of the local employment correlates with the change in the local technology intensity measure between 2007 and 2016. The technology intensity measure has been normalized so 1 unit is 1 standard deviation in 2007 and the size of each circle corresponds to population in 2007. Here we see a negative relationship with a slope of 0.3, indicating that commuting zones with a 1-unit-larger increase in the intensity measure have three-tenths of a percentage point larger decrease in the OAS share of employment.

However, there are several reasons why this raw correlation may be misleading. The decision of an individual firm to adopt new technology depends on local conditions. An optimizing firm will weigh the benefit of available technology against the costs associated with implementation. These will depend on product market competition and demand, as well as wages in the local labor market and the availability of talent. As we saw in the job-posting data, software adoption for office support workers is associated with an increase in demand for skill. Employers in regions in which college-educated workers are relatively scarce may find it more costly to upskill their labor force, which in turn could make the decision to adopt new technology relatively more costly. Furthermore, a negative local labor-market shock will depress economic outcomes and may also induce (or inhibit) technological adoption, which would then produce a spurious relationship between economic outcomes and technological adoption. On the product market side, the extent of market competition may influence a firm's decision to adopt technology. Thus, local labor-market and product-market conditions will directly effect firms' decisions about technology adoption.

To address these endogenity issues, we take advantage of three features of the market for OAS software. First, software is not typically geographically specific. Instead, it is available nationwide and has one price nationally. For instance, the dominant software for OAS workers, Microsoft Office, can be purchased online and downloaded anywhere, with pricing only depending on enterprise size, not location or industry. Thus the cost of adopting such software should not vary systematically with local labor-market conditions.

Second, the current share of OAS workers is in part related to historical industry development. In Table 4, we report example industries that had the highest and lowest shares of OAS employment in 2000. Some industries are diffuse, such as the U.S. Postal Service and physicians' offices. Others are geographically concentrated, such as insurance and banking. Industries that employ relatively few OAS workers range from the geographically diffuse service-sector industries to the relatively geographically specific, such as agricultural production. Thus we can take advantage of the fact that local labor markets are likely to be more exposed to OAS technological change because of the historical geographic dispersion of industries.

Third, there is heterogeneity within OAS occupations in the extent to which new software is relevant to jobs. Table 6 shows the largest 10 occupations, which collectively make up 77 percent of OAS employment in 2016. Here we see important variation between occupations. Occupations such as administrative assistants, office clerks, and bookkeepers tend to be more technologically intensive in 2007 and also see larger increases in average technology demanded between 2007 and 2016. In contrast, occupations such as customer service representatives, stock clerks, and tellers tend to be less technologically intensive in 2007 and see smaller increases in technology demanded between 2007 and 2016.

These three features of the market for OAS software mean that a portion of the local exposure to technological change will be due to the historical industry mix of the local labor market rather than current labor-market conditions. Thus, we can construct an instrument to isolate this variation in order to capture the causal effect of technological change on local labor markets.

In particular, for each narrowly defined occupation, we measure the average number of types of software requested nationally in job ads in a given year, excluding the commuting zone of interest. We then aggregate this occupational measure to the region-year level using the local labor-market industry mix in 2000. Specifically, we first construct the occupational distribution of employment for each industry in 2000 using nationwide data. We then construct a predicted local occupational share based on the industry share of employment in the local labor market in 2000:

$$\text{Instrument}_{gt} = \sum_{o} \sum_{i} \frac{L_{ig,2000}}{L_{g,2000}} \frac{L_{io,2000}}{L_{i,2000}} \text{Tech}_{o \neg gt} \tag{4}$$

Figure 6 illustrates the relationship between this constructed instrument and our endogenous technology measure. Here we see that most commuting zones experience a substantial increase in predicted technology use as well as the endogenous technology measure between 2007 and 2016. Furthermore, we see that there is a positive correlation between these two measures.

For all specifications, we normalize each technology measure by the 2007 distribution, so the interpretation of each coefficient is the relationship between a 1 standard deviation increase in technology intensity in 2007. Since our panel is short, we use the level of technology usage each year and include commuting-zone fixed effects. Finally, to partially avoid the confounding effects of national economic trends such as the Great Recession and general changes in labor-force participation and educational attainment, we include year fixed effects. Thus the estimates will be based on heterogeneity between commuting zones in their increase in technology usage since 2007.

In Table 5, we estimate the first-stage specification, regressing the endogenous technology measure on the instrument. In the first column, we show that there is a robust relationship between the instrument and the endogenous technology measure, with a 1.00 unit increase in predicted technology adoption associated with a 0.25 unit increase in the endogenous measure. In addition, the F-statistic shows the instrument is strong.

One concern with using the distribution of industries and occupations in 2000 is that the computerization of the OAS workforce was already well underway at that time and thus the industry distribution in the commuting zone may already reflect changes in response to technological adoption. To address this we construct an alternative instrument that uses the 1970 industry distribution for each commuting zone and the 1970 nationwide occupational distribution by industry. However, by virtue of using a more historical industry distribution, this measure may have a weaker relationship with the contemporaneous technology measure. In the second column of Table 5, we see that the relationship is indeed slightly weaker, but not statistically different from the point estimate for the 2000 instrument. This instrument also is quite strong, with an F-statistic of 314. Thus, for our two-stage least squares estimates, we will produce estimates using both instruments.

7.2 Local Labor Market Methodology

Our local labor-market data comes from the American Community Survey of the census, retrieved from the IPUMS data repository (Sobek et al., 2010) in the years for which we have job-posting data from Burning Glass (2007, 2010–2016). We restrict our analysis to the working-age population (15–65). We aggregate employment and wage data to the commuting-zone level, as defined by Tolbert and Sizer (1996).[8] Summary statistics of our main variables of interest are reported in Appendix Table A.7.

Our specifications are primarily two-stage least squares. Specifically, we estimate the following:

$$Y_{gt} = \alpha_g + \gamma_t + \beta \text{Exposure}_{gt} + \epsilon_{gt} \tag{5}$$

where Exposure_{gt} is defined by Equation 3 and instrumented by the expression in Equation 4. For ease of interpretation, both measures are normalized to be mean 0 and standard deviation 1 in 2007. Thus units are in terms of standard deviations in the 2007 technology distribution. All specifications include commuting-zone (α_g) and year (γ_t) fixed effects. Estimates are weighted by the contemporaneous working-age population in the commuting zone, and standard errors are clustered at the state level to allow for spatial correlation across commuting zones.[9]

In addition, we construct demographically adjusted measures, in which we hold fixed the demographic mix of a commuting zone in 2000. In particular, we create cells based on sex (male, female), race (white, nonwhite), education (high school graduate or less, some college, bachelor's degree or more), and age (under 30, 30–40, over 40). This allows us to see how changes in the dependent variables are due to changes in the demographic characteristics of the commuting zone.

[8] We follow Autor and Dorn (2013) in mapping from Census MSAs to commuting zones.

[9] For commuting zones that span state boundaries we assign the commuting zone to the state that contributed the largest share of the commuting zone's population in 2000.

7.3 Effect of Technology Adoption on OAS Workers

In Table 7, we begin by examining the effect of technology exposure on the OAS share of employment and population, as well as the share of OAS workers with a college degree. In Panel A, we report the ordinary least squares estimate, in which we directly regress the outcome variables on the endogenous technology measure. In Panels B and D, we report the reduced-form estimates, in which we regress the outcome variables on the 2000 and 1970 instruments, respectively. Finally, in Panels C and E we report the two-stage least squares estimates.

In column (1) of Table 7, we see that there is a modest negative relationship between endogenous technology usage and the OAS share of employment; however, once we implement the two-stage least squares procedure, the effect of a 1 standard deviation increase in technology adoption is between 0.9 (1970 instrument) and 1.0 (2000 instrument) percentage points. Over our time period, OAS occupations account for 13 percent of employment; thus, our estimates correspond to about a 7 percent decrease in OAS employment share for a 1 standard deviation increase in technology adoption.

Since the employment share could be affected by changes in OAS employment or changes in labor force participation, in column (2) we estimate the effect of technology adoption on the share of OAS employment per population. Again we see a robust negative effect, with a reduction in OAS employment share of between 0.45 and 0.58 percentage points. These results indicate that larger increases in technology exposure lead directly to a reduction in employment in OAS occupations.

In column (3) of Table 7, we turn to the educational composition of the OAS workforce. In Section 6.1, we saw that as firms begin to ask for new technology, they are likely to demand more educational attainment from their workers. Here we see that these firms appear to be successful: a 1 standard deviation increase in technology exposure leads to between a 2.5 and 2.8 percentage point increase in the college share of OAS employment, depending on the instrument. Over our time period, 15 percent of OAS workers have a college degree.

Thus, a 1 standard deviation increase in technology exposure leads to an increase of over 16 percent in the share of OAS workers with college degrees. These results indicate that the patterns we saw in Section 3, namely the falling OAS employment share and rising share of OAS workers with college degrees, can be explained in part by technological adoption.

Next, we want to examine the impact of technology adoption on the wages earned by OAS employees. Because of limitations in the job-posting data, we were unable to see how individual firms' wages vary as technology usage changes over time. As discussed in Section 4, the effect of increased technological adoption on wages for OAS workers is ambiguous and depends on how much the technological change induces a reduction in demand for OAS workers, as well as the extent to which employers engage in skill upgrading. As we saw in Table 7, demand for OAS employment falls and the college share of employment increases with technological adoption, which should have offsetting effects on wages.

Here we look at log annual wages, deflated to 2007 prices. In column (1) of Table 8, we focus on wages for all OAS workers. We see a positive point estimate for both two-stage least squares estimates; however, the coefficients are not statistically distinct from zero. In columns (2) and (3), we separately estimate the effect of technology on wages for college-educated and non-college-educated OAS workers, respectively. Here we see wage increases of between 3.4 and 3.8 percent for college-educated OAS workers, while wage estimates for non-college-educated workers are negative but close to zero and not statistically significant. In column (4), we show that the point estimates for the demographically adjusted wage measures are similar to the estimates in column (1), indicating that the increase in wages is not due to changing demographic composition.

The fact that wages increase for college graduates suggests that the returns from productivity improvement and broadening task responsibilities are primarily accruing to more-educated OAS workers. For OAS workers without a college degree, the suggestive negative point estimates are consistent with these workers absorbing more of the reduction in demand for OAS employment, which prevents wages from rising as they do for the more educated workers.

7.4 Spillovers

Next we turn to spillovers from OAS employment to the rest of the local labor market. We begin by investigating the effect of OAS technology adoption on labor-force participation. Recall from the previous section that a 1 unit increase in technology adoption is associated with about a 0.5 percentage point decrease in OAS employment share per population. Thus, if there are no spillovers, we would expect this to lead directly to a reduction in the employment-to-population ratio. However, as discussed in Section 4, there may be further spillovers if technological adoption increases productivity and leads to local multipliers.

In Table 9, we see that this indeed is the case. In particular, in the two-stage least squares estimates in Panels C and E, the employment-to-population ratio increases by about 1 percentage point for both the 2000 and 1970 instruments. This indicates that employment in non-OAS occupations must increase by about 1.5 percentage points in order to compensate for the employment losses in OAS occupations.

In columns (2) and (3) of Table 9, we show the effect of OAS technology adoption on the female and male employment-to-population ratios, respectively. Since OAS occupations are predominantly female (over 70 percent for this time period), the effect of the reduction in OAS employment is unlikely to be equal across genders. Nonetheless, we see in Panels C and E that the effect of OAS technology adoption increases female labor-force participation rates somewhat faster than the overall increase in total labor-force participation. Thus, it appears that women who would have been employed in OAS occupations are finding employment elsewhere. Finally, in column (3), we see that the male employment-to-population ratio rises as well, albeit somewhat more slowly than the female employment-to-population ratio. Even though women are more affected by the reduction in OAS employment, we see a larger positive effect on their employment rates.

Next we turn to wage spillovers. As discussed in Section 4, the predicted effect of OAS technology adoption on wages for non-OAS workers is ambiguous, due to several offsetting effects. On the one hand, the increased labor demand we saw in Table 9 suggests wages should rise. On the other, increased task competition and labor-supply competition may reduce wage growth. These offsetting factors may also have different effects on different populations.

In Columns (1) and (2) of Table 10, we examine the effect of technological adoption on log annual wages for all workers and log annual wages per population, respectively. Here we see there may be a small negative effect on wages overall, but once we account for the increase in the labor-force participation rate, wages per population appear to increase by 1–2 percentage points, depending on the choice of instrument; however, this is only marginally significant. In column (3), we restrict the analysis to only non-OAS workers, which shows a marginally significant negative effect of about 1 percent losses.

Next we separate estimates for college-educated workers and those without college degrees in columns (4) and (5), respectively. Here, we see a 2.3 percent loss using the 2000 instrument and a nonsignificant 1.0 percent loss using the 1970 instrument. However, the two measures are in concordance for the effect of OAS technology on non-OAS workers without a college degree: both estimates report a 4 percent wage loss for these workers for each unit increase in OAS technology usage. Finally, in column (5) we calculate the demographically adjusted wage changes for non-OAS workers, which are very similar to the estimates from column (3), indicating that the changes in wages we observe are within demographic cells rather than due to changing demographic composition within commuting zones.

Thus, although the effect of OAS technology adoption on average wages in the commuting zone is close to zero, we see relatively large losses for non-OAS workers that are both college graduates and non–college graduates. This is in contrast with the direct effect on OAS wages, over 3.5 percent wage growth for college graduates and imprecisely estimated negative wage growth for non–college graduates.

Next, we want to investigate the effect of OAS technological adoption on the college share of the labor force. In Table 11, we first reproduce the results from Table 7 that show that a 1 unit increase in OAS technology usage leads to a 2.5 to 2.8 percentage point increase in the share of OAS workers with a college degree. In Column (3) we investigate the effect of OAS technological adoption on the share of non-OAS workers with a college degree. Here we see a smaller positive effect, an increase of around 1.2 to 1.6 percentage point. Why might technological adoption by one occupation lead to spillovers in other occupations? As fewer workers can be hired into OAS occupations without a college degree, this could prompt more individuals to go to college and then find jobs in other fields. In addition, as employers increase technology usage in OAS jobs, they may also increase technology usage across the firm, leading to stepped-up skill demand for other occupations.

How much of the increase in the college share of employment can be explained by rising educational attainment in the commuting zone? In columns (2) and (4), we replicate the estimates from columns (1) and (3), respectively, but now include contemporaneous measures of the share of the population in the commuting zone with a college degree. Now we see that the effect of technology on the college share of OAS employment that is not accounted for by increasing college attainment is about 1 percentage point. That is, the share of OAS employment with a college degree is increasing substantially faster than the overall increase in college attainment. On the other hand, if we examine the estimates for non-OAS workers, we see that their college share decreases by about 0.9 of a percentage point with a 1 unit increase in OAS technology, indicating these occupations are upskilling more slowly than would be expected, given the general increase in college attainment. Since increased educational attainment is a possible response to the increase in technology adoption, our preferred estimates do not include these contemporaneous education controls.

7.5 Distinguishing between Models of Technological Change

In Section 4, we showed that the effect of technological change on wages for middle-skill workers depended on whether the technological change can be characterized as factor-augmenting or task-substitution. In particular, Acemoglu and Autor (2011) find that factor-augmenting technological change increases middle-skill workers' wage premium, while task-substitution technological change decreases the wage premium. As we saw in Section 6, since technological change leads to large decreases in OAS employment as well as increases in wages for college-educated OAS workers, there is reason to believe that both features are at play. In this section, we directly test how the ratio of OAS wages to other workers' wages changes with the adoption of technology.

In order to connect the empirical results to the theory, we compare three groups of workers: 1) non-OAS workers without a college degree, 2) OAS workers, and 3) non-OAS workers with a college degree. These groups correspond to the low-, middle- and high-skill groups from the theory, respectively. In columns (1) and (2) of Table 12, we see that an increase in technology exposure increases the OAS wage premium at a rate of about 5 percent compared to non-college-educated workers and a rate of about 3 percent compared with college-educated workers. This is consistent with the factor-augmenting model of technological change, with an increase in OAS workers' productivity compared with other groups. Although we believe both types of technological change are at play, this suggests that the factor-augmenting effects dominate.

In columns (3) and (4), we restrict the OAS group to noncollege and college, respectively. Here we see that the OAS wage premium is smaller among noncollege OAS workers but still about 2 percent. In contrast, the OAS wage premium is larger for college-educated OAS workers, with a premium of between 5 and 6 percent depending on the specification. These patterns are consistent with technology adoption allowing the productivity of college-educated OAS workers to increase rapidly compared with other college-educated workers. In contrast, while the wage premium is still positive for non-college-educated OAS workers, the smaller magnitude is consistent with these workers being less able to benefit from the productivity improvements of new software.

The fact that we see a larger wage premium for OAS workers among college-educated workers than non-college-educated workers is consistent with what we found in Section 6, namely that the OAS task space appears to be broadening into higher-skill tasks rather than lower-skill tasks. In contrast to the hypothesis in Acemoglu and Autor (2011), that technological change is leading middle-skill occupations to become increasingly low-skill, we find the opposite for OAS occupations.

7.6 Occupational Spillovers

Next, we want to investigate how these employment and wage spillovers are distributed between other occupations. In Table 13, we investigate how the main results for employment and wages differ across these four categories. All estimates are two-stage least squares, using the 2000 instrument. In Panel A, we see that all groups have positive point estimates for the increase in employment per population. This indicates that the spillover employment growth appears to have a broad basis in commuting zones that adopt more technology. However, we see the largest increases for white-collar occupations, in particular female white-collar occupations. In Panel B, we investigate how the increase in the share with a college degree varies across occupation groups. Here we see that all groups are increasing their share with a college degree except for pink-collar occupations, which appear to be increasingly concentrated among less-educated workers.

In Panels C through F, we examine wages. Here, we see divergent patterns across the occupations. While the male-dominated occupations see modest wage losses of about 2 percent, pink-collar occupations experience the largest losses, with decreases of 6 percent. On the other hand, female white-collar occupations show no wage losses. When we separate these wage changes into college and noncollege subgroups, we see losses of 1–2 percent across groups for college graduates and losses of between 2 and 5 percent for non–college graduates. Finally, in Panel F, we show that demographically adjusted wage results are similar to the results in Panel C, indicating that wage changes cannot be explained by compositional changes in the demographics of the commuting zone.

These results indicate that OAS technological change has divergent spillover effects on different segments of the labor force. OAS occupations are most similar to other pink-collar occupations, which are increasingly concentrated with noncollege workers. This group experiences the smallest increase in employment, which likely contributes to the large wage losses experienced by this group. In contrast, white-collar female occupations see the largest increase in employment and no wage losses in aggregate.

The two male-dominated occupation groups, blue-collar and white-collar male, are likely to experience less labor-supply competition from would-be OAS workers. This is consistent with the negligible effects on employment and wages we see for blue-collar occupations. However, several white-collar male occupations perform tasks that are increasingly found in the OAS job descriptions, such as management and legal occupations. This may contribute to the wage losses we see for these groups.

In Appendix Table A.8, we separate each of these groups of occupations into major SOC categories. Here we see a substantial increase in employment for computer and math occupations, which is consistent with an increase in demand for technology workers to maintain new software.

7.7 Effects by Subpopulation

In the previous section, we saw that workers in pink-collar occupations experienced the largest wage losses with technological change, suggesting that women without a college degree likely experience the biggest negative effects from OAS technology adoption. In this section, we directly investigate the effect of technological change on women and men with and without a college degree.

In the first column of Table14, we show the change in the employment-to-population ratio for each of these four demographic subgroups. Coefficients are estimated using two-stage least squares and the 2000 industry-weighted instrument. Here we see that the increase in the E/pop ratio from Table 9 is primarily driven by female college graduates, who have an increase of 2.2 percentage points, compared with other groups, which are close to 0.

In the second column of Table 14, we measure the effect on real annual wages. Consistent with Table 13, wage losses are largest for women without a college degree, who have losses of about 5 percent. Men without a college degree have losses of about 3 percent, while men with college degrees have losses of 2.3 percent. These point estimates are somewhat larger than the occupation-based estimates from Table 13. Finally, women with a college degree have a point estimate of 0.5 percent, which is not statistically different from 0 and is consistent with the 0 effect we saw in Table 13 for female-dominant white-collar occupations.

Thus, consistent with technological change inducing employers to increase demand for college degrees, we see that women with college degrees capture all of the employment increases and are insulated from the wage losses. On the other hand, wage losses are relatively diffuse across the other three demographic groups, with somewhat larger negative effects for women without a college degree. This is consistent with the education results from Table 13, which showed decreasing college share for pink-collar occupations, suggesting women without college degrees are increasingly segregated into low-wage service and caring occupations.

7.8 Alternative Specifications

In this section, we explore how sensitive our results are to alternative specifications. In Table 15, we show that our results are robust to a variety of alternative specifications, including using a technology measure based on adoption of Microsoft Office, including a variety of time-varying commuting-zone-level controls, and dropping the most technology-intensive commuting zones or the least technology-intensive commuting zones. We show that our results are qualitatively similar if we do not weight; however, the point estimates for wage spillovers are somewhat smaller. Our results are not robust to dropping the largest 10 percent of commuting zones; in this case, we no longer have a valid first-stage relationship between the endogenous technology measure and the instrument.

In Table 16, we instead run our specifications using stacked long differences, measuring the changes from 2007 to 2012 and 2012 to 2016 and including commuting-zone and period fixed effects. Here we find results that are qualitatively similar but less precise.

8 Conclusions

In this paper, we have demonstrated that technology adoption is associated with increasing skill requirements within positions for office-support workers. We find that firms that adopt new software technology begin asking for higher levels of education and experience. We find that the job descriptions change, with firms increasingly listing tasks associated with other office occupations and higher-skill tasks. Nonetheless, we do not find a reduction in lower-skill or traditional office support tasks, suggesting that these jobs are spanning a widening task space. As we find that these occupations are increasingly performing high-skill tasks that are difficult to replace with technology, we conclude that office support jobs are likely to remain an important segment of the labor market for the foreseeable future.

We then link this firm-level behavior to local labor markets, and we find that commuting zones that increase technology usage have reduced employment in OAS occupations and an increased share of OAS workers with college degrees. Our results are consistent with technology that allows OAS workers to replace some tasks with technology, resulting in a labor market with a smaller number of OAS workers who specialize in higher-return skills. Consistent with this, we find robust wage growth for college-educated OAS workers but no positive wage effect for OAS workers without college degrees. Despite our finding that technology leads to substantial reductions in OAS employment, we find that the local employment-to-population ratio increases, indicating would-be OAS workers find employment elsewhere.

In contrast to Keynes's prediction of technological unemployment, our results indicate that adoption of OAS software benefits local labor markets, weakly increasing wages per population and employment per population. Nonetheless, certain segments do experience negative consequences. These losses are concentrated in women without a college degree and college-educated white-collar workers.

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Figure 1: OAS Share of Employment, Census/ACS

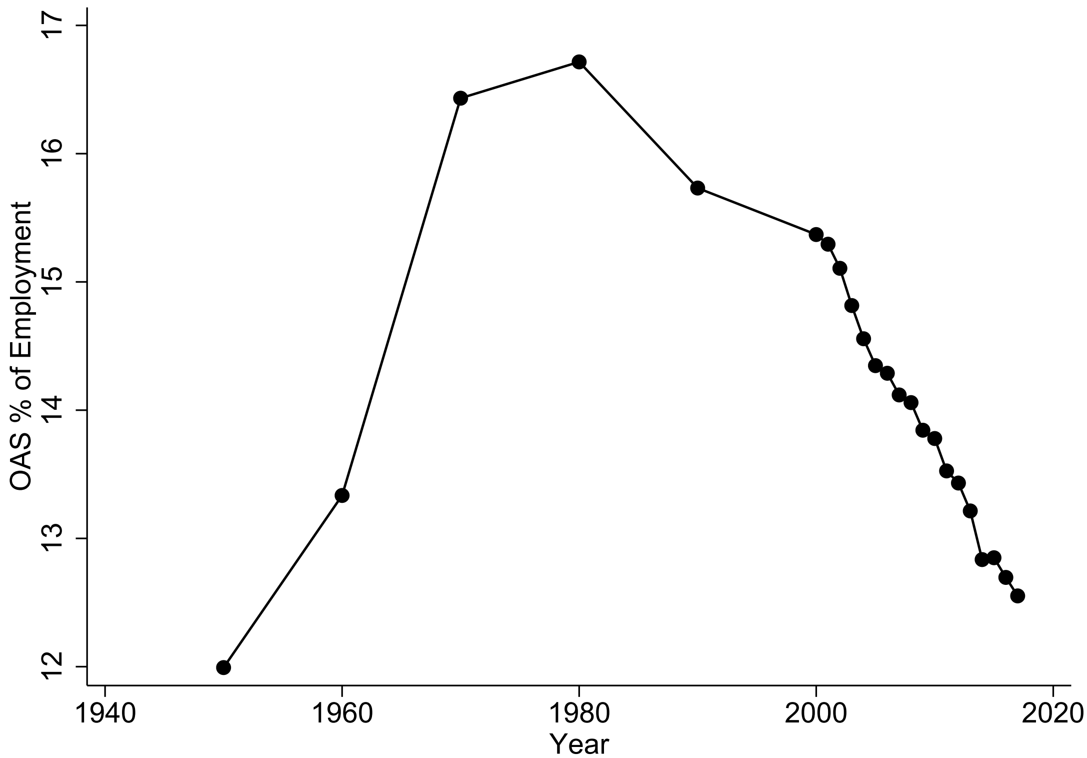


Figure 2: Share of OAS and Non-OAS Workers with A College Degree

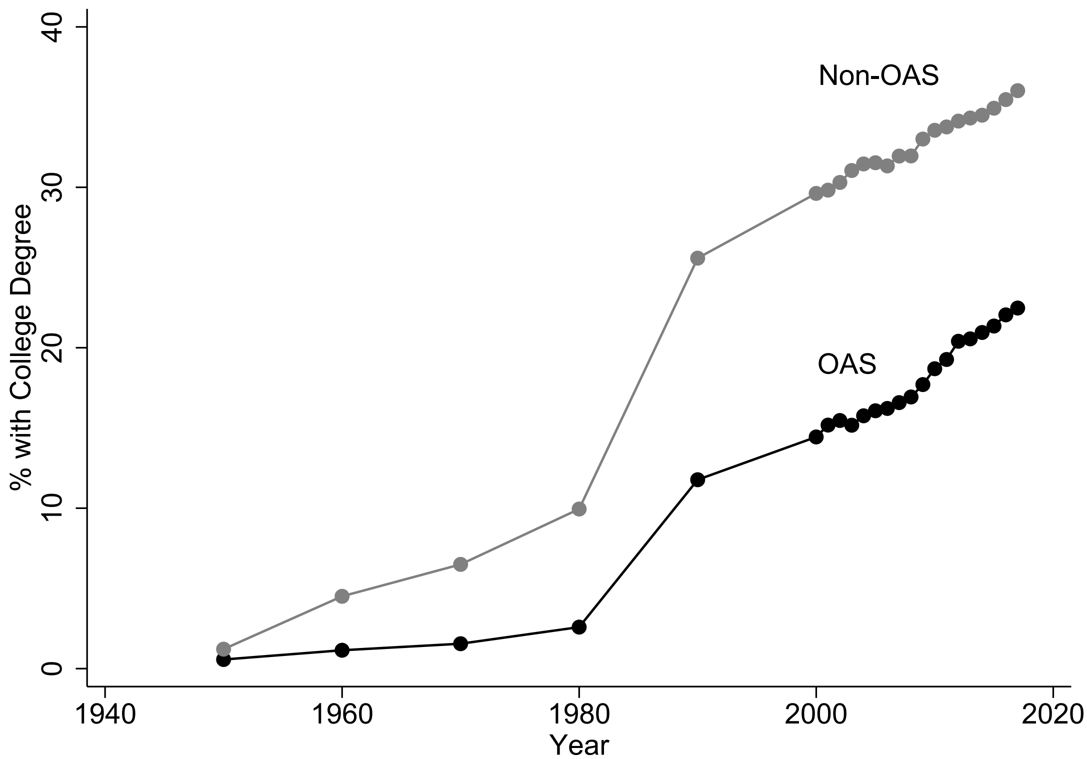
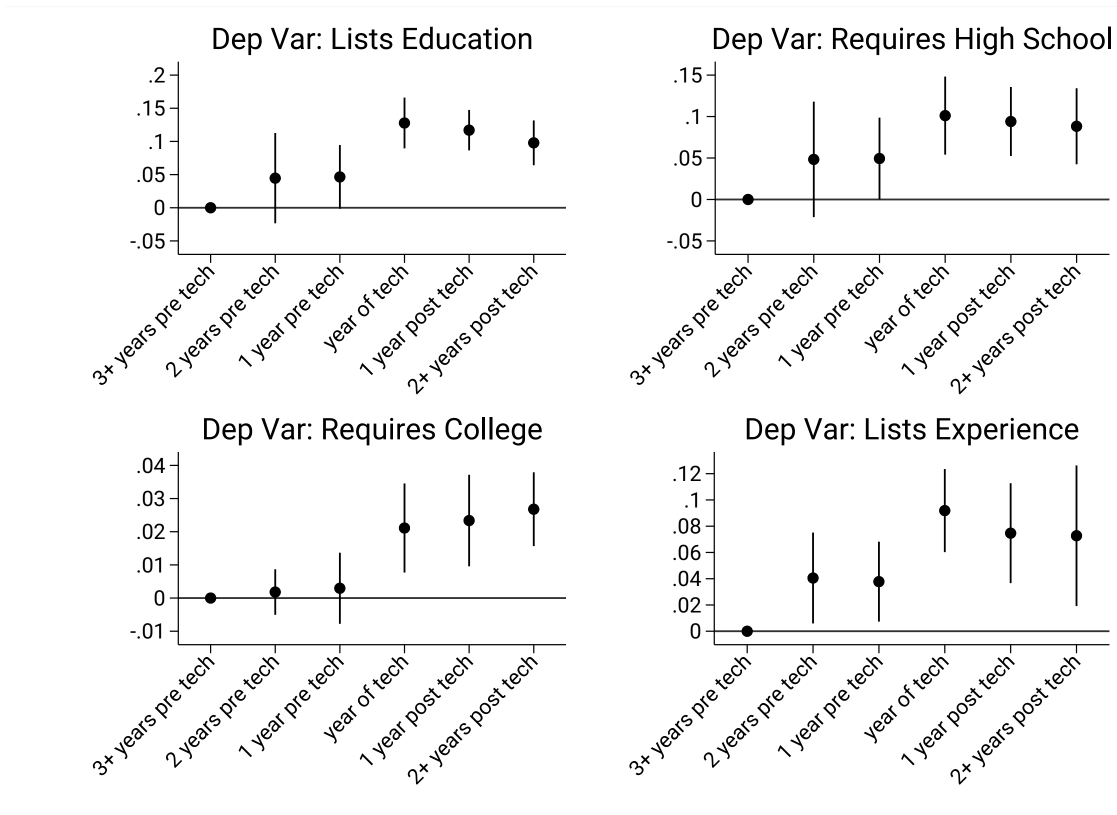
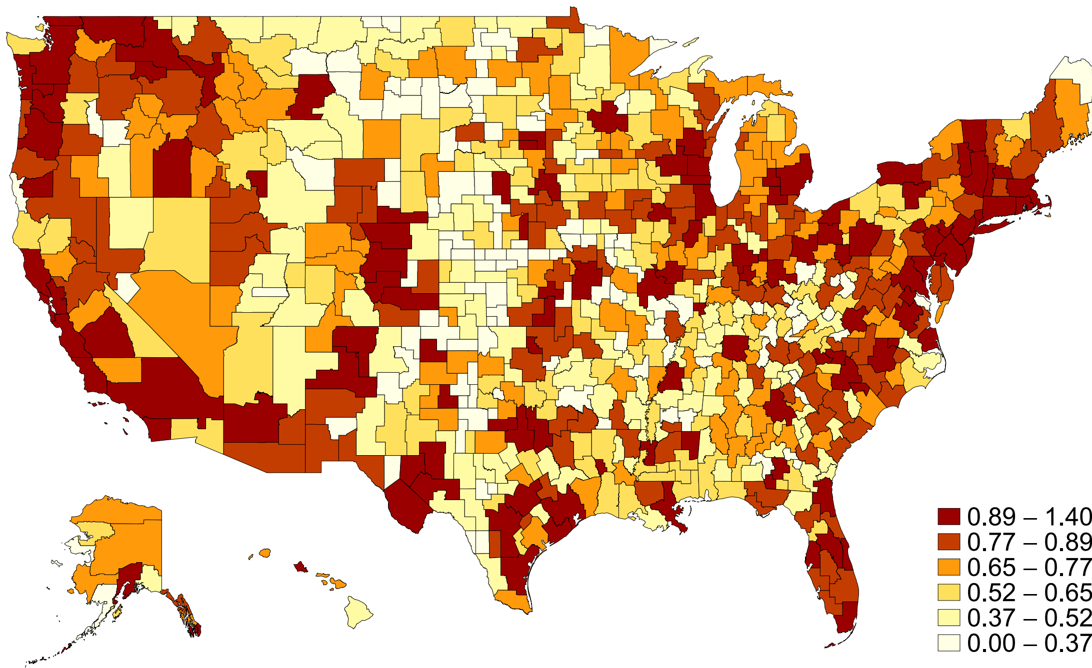


Figure 3: Fixed Effects Models–Event Study of Changes in Other Skill Requirements as Firms Begin Asking for Technology



Each graph plots coefficients on the Technology by time-indicator variables in Equation (2) along with 95 percent confidence intervals calculated using standard errors clustered at the employer level. All specifications include year-month fixed effects and employer fixed effects and contain 1,060,605 advertisements.

Figure 4: Geographic Variation in Technology Intensity Measure, 2016



Average number of OAS software listed in OAS job postings, weighted by each occupation's share of OAS employment.

Figure 5: Relationship between OAS Employment Share and Technology Intensity

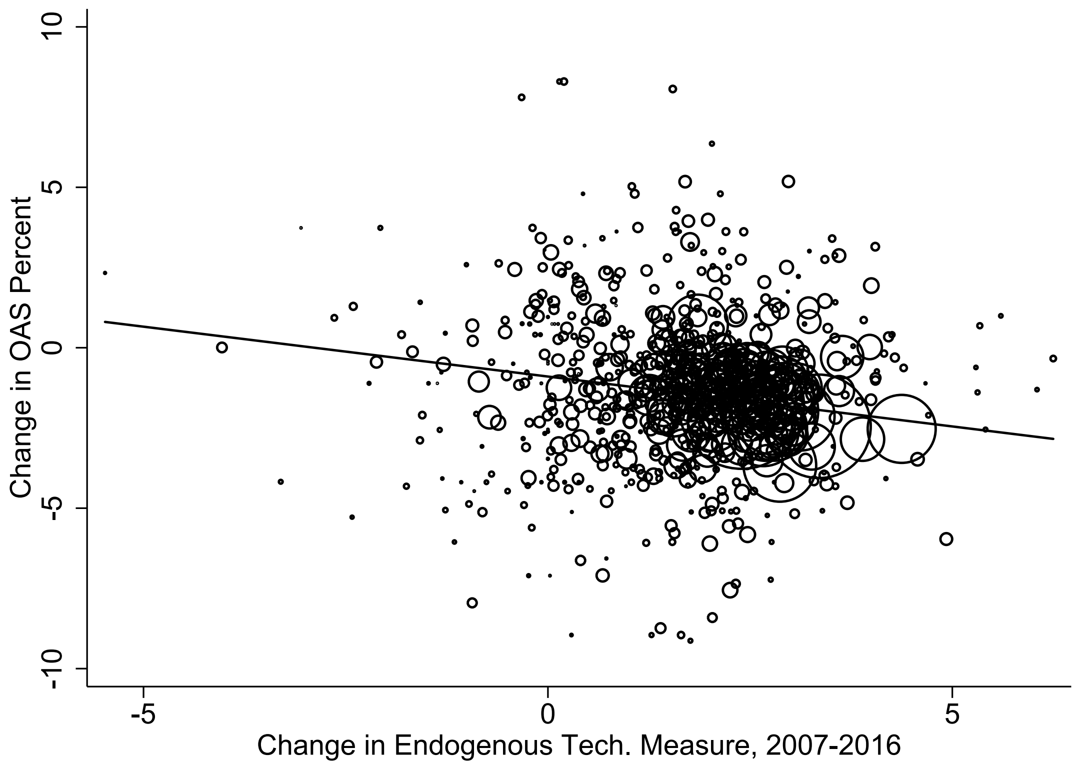


Figure 6: Relationship between Instrument and Endogenous Tech Measure

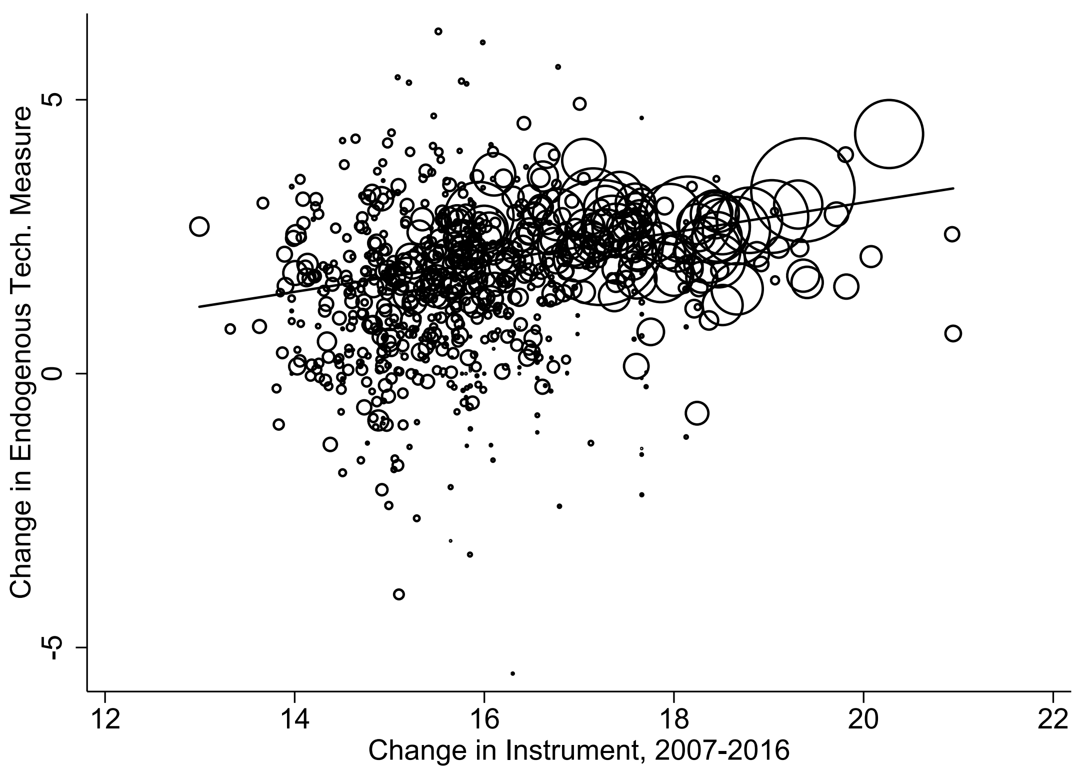


Figure 7: Defining Occupation Groups

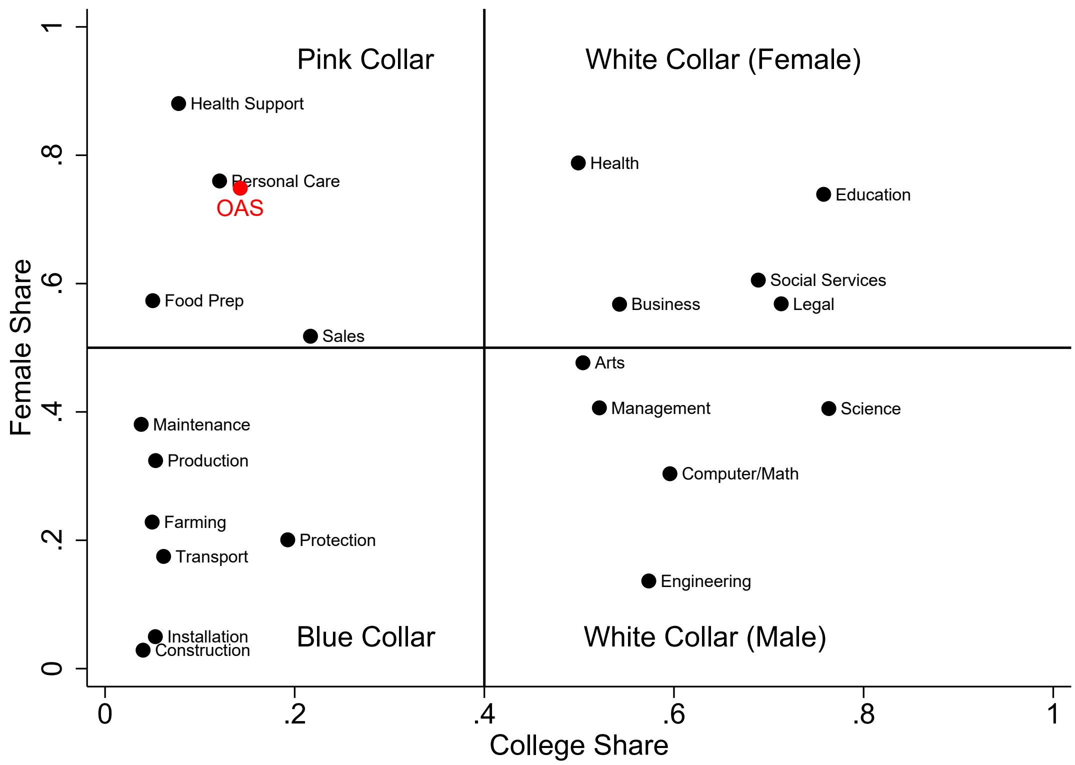


Table 1: Skill Requirements and Technology in OAS Job Ads

	(1)	(2)	(3)	(4)
Panel A: Lists Education Requirement				
Tech. Intensity	0.05753***	0.05816***	0.04028***	0.06838***
	(0.00087)	(0.00131)	(0.00065)	(0.00081)
Observations	15,452,623	5,261,935	5,261,935	5,261,935
Mean of DV	0.517	0.612	0.612	0.612
% of Mean	11.13	9.5	6.58	11.17
Panel B: Requires High School Diploma, conditional on listing education				
Tech. Intensity	-0.05285***	-0.05660***	-0.01604***	-0.00254***
	(0.00109)	(0.00158)	(0.00093)	(0.00048)
Observations	7,038,305	2,948,691	2,925,152	2,836,917
Mean of DV	0.674	0.761	0.761	0.761
% of Mean:	-7.83	-7.44	-2.1	-0.33
Panel C: Requires College Diploma, conditional on listing education				
Tech. Intensity	0.03802***	0.04138***	0.01042***	0.00296***
	(0.00134)	(0.00167)	(0.00081)	(0.00044)
Observations	7,038,305	2,948,691	2,925,152	2,836,917
Mean of DV	0.235	0.173	0.173	0.173
% of Mean	16.18	23.92	6.02	1.71
Panel D: D Lists Experience Requirement (indicator)				
Tech. Intensity	0.07274***	0.07241***	0.05329***	0.06834***
	(0.00085)	(0.00131)	(0.00080)	(0.00087)
Observations	15,452,623	5,261,935	5,261,935	5,261,935
Mean of DV	0.426	0.457	0.457	0.457
% of Mean	17.08	15.84	11.66	14.95
Panel E: Required Experience (continuous)				
Tech. Intensity	0.31609***	0.32623***	0.21869***	0.20751***
	(0.00331)	(0.00421)	(0.00298)	(0.00296)
Observations	15,452,623	5,261,935	5,261,935	5,261,935
Mean of DV	1.004	0.954	0.954	0.954
% of Mean	31.48	34.2	22.92	21.75
Sample	All	Panel	Panel	Panel
Czone FE	×	×		
CZ × Firm FE			×	
CZ× Firm × Job Title FE				×

Standard errors in parentheses, clustered at the firm name by commuting-zone level, $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include month-by-year fixed effects.

Table 2: Change in Task Demand Technology Adoption

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Routine OAS Tasks						
	Basic Admin.	Clerk	Mail	Routine Accounting	Physical Tasks	
Tech. Intensity	0.29494***	0.03310***	0.02083***	0.09362***	-0.00234***	
	(0.00331)	(0.00053)	(0.00050)	(0.00195)	(0.00024)	
Mean of DV	0.948	0.0845	0.101	0.386	0.0245	
% of Mean	31.11	39.17	20.62	24.25	-9.55	
Panel B: Functional Tasks						
	Legal	Accounting/Finance	Sales	Marketing	Logistics	HR
Tech. Intensity	0.00739***	0.12274***	-0.03106***	-0.00413***	0.02993***	0.01139***
	(0.00023)	(0.00195)	(0.00114)	(0.00022)	(0.00104)	(0.00032)
Mean of DV	0.0260	0.249	0.429	0.0277	0.103	0.0360
% of Mean	28.42	49.29	-7.24	-14.91	29.06	31.64
Panel C: High-Skill/Cognitive Tasks						
	Research	Management	Cognitive	Writing-Related		
Tech. Intensity	0.03264***	0.06181***	0.02482***	0.11575***		
	(0.00051)	(0.00098)	(0.00047)	(0.00182)		
Mean of DV	0.0897	0.183	0.0502	0.247		
% of Mean	36.39	33.78	49.44	46.86		
Observations	15,452,623	15,452,623	15,452,623	15,452,623	15,452,623	15,452,623

Standard errors in parentheses, clustered at the firm name by commuting-zone level, $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include month-by-year fixed effects.

Table 3: Tasks from Other Occupational Groups

	(1)	(2)	(3)	(4)
Panel A: Dependent Variable: Blue Collar Tasks				
Tech. Intensity	-0.00629***	-0.01335***	-0.00745***	0.00818***
	(0.00040)	(0.00050)	(0.00046)	(0.00051)
Mean of DV	0.0725	0.106	0.106	0.106
% of Mean	-8.55	-12.55	-6.98	7.72
Panel B: Dependent Variable: Pink Collar Tasks				
Tech. Intensity	-0.01075***	-0.02546***	0.01815***	0.04882***
	(0.00161)	(0.00282)	(0.00188)	(0.00129)
Mean of DV	0.319	0.473	0.473	0.473
% of Mean	-3.35	-5.37	3.84	10.32
Panel C: Dependent Variable: Male White Collar Tasks				
Tech. Intensity	0.05860***	0.06670***	0.05470***	0.05601***
	(0.00158)	(0.00195)	(0.00116)	(0.00159)
Mean of DV	0.0869	0.0880	0.0880	0.0880
% of Mean	57.79	65.36	50.61	52.76
Panel D: Dependent Variable: Female White Collar Tasks				
Tech. Intensity	0.04037***	0.04153***	0.02589***	0.03202***
	(0.00070)	(0.00098)	(0.00087)	(0.00112)
Mean of DV	0.133	0.132	0.132	0.132
% of Mean	30.35	31.46	19.61	24.26
Sample	All	Panel	Panel	Panel
Czone FE	×	×		
Czone × Firm FE			×	
Czone × Firm × Job Title FE				×
Observations	15,452,623	5,261,935	5,261,935	5,261,935

Standard errors in parentheses, clustered at the firm name by commuting-zone level, $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include month-by-year fixed effects.

Table 4: Example Industry OAS Share of Employment, 2000

High-Share OAS:	
U.S. Postal Service	79.5%
Banking	51.4%
Legal services	39.2%
Offices and clinics of physicians	37.4%
Insurance	35.6%
Low-Share OAS:	
Nursing and personal care facilities	5.09%
Agricultural production, crops	4.84%
Landscape and horticultural services	4.63%
Child day care services	2.73%
Eating and drinking places	2.35%

Source: U.S. Census.

Table 5: First Stage

	(1)	(2)
Tech Instrument 2000	0.24692***	
	(0.04718)	
Tech Instrument 1970		0.22472***
		(0.04055)
Observations	5,928	5,928
R-squared	0.86842	0.86929
F-test	278.35***	314.89***

Standard errors in parentheses, clustered at the state level: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include commuting zone and year fixed effects.

Table 6: Average Mentioned Software Names per Job Ad, Ten Largest OAS Occupations

SOC Code	Occupation Title	Employment	Mean Tech 2007	Mean Tech 2016	. Change in Tech.
43-6010	Secretaries and Administrative Assistants	3,675,140	0.885	1.676	0.790
43-9061	Office Clerks, General	2,955,550	0.527	1.277	0.750
43-4051	Customer Service Representatives	2,707,040	0.335	0.609	0.274
43-5081	Stock Clerks and Order Fillers	2,016,340	0.206	0.229	0.022
43-3031	Bookkeeping, Accounting, and Auditing Clerks	1,566,960	0.687	1.645	0.959
43-1011	First-Line Supervisors	1,443,150	0.593	1.237	0.644
43-4171	Receptionists and Information Clerks	997,770	0.447	0.702	0.255
43-5071	Shipping, Receiving, and Traffic Clerks	676,990	0.246	0.459	0.214
43-3071	Tellers	496,760	0.031	0.279	0.248
43-3021	Billing and Posting Clerks	485,220	0.574	1.401	0.827

The ten largest OAS occupations from May 2016 OAS estimates of national employment collectively represent 77 percent of OAS employment. "Average tech" measures the average number of OAS-affiliated technologies in job ads for the occupation, calculated from Burning Glass Data.

Table 7: Employment Outcomes for OAS Workers

	(1) OAS % Emp.	(2) OAS % Pop.	(3) % of OAS College
Panel A: OLS			
Tech. Exposure	-0.07371*	-0.02414	0.27676*
	(0.03046)	(0.02030)	(0.11280)
R-squared	0.67546	0.78152	0.86555
Panel B: Reduced Form, 2000 Instrument			
Tech. Exposure	-0.26269***	-0.14354***	0.69539***
	(0.04733)	(0.02879)	(0.13463)
R-squared	0.68151	0.78498	0.86756
Panel C: 2SLS, 2000 Instrument			
Tech. Exposure	-1.06386***	-0.58130***	2.81619***
	(0.25096)	(0.15483)	(0.66677)
R-squared	0.56204	0.71704	0.82600
Panel D: Reduced Form, 1970 Instrument			
Tech. Exposure	-0.20399***	-0.10269***	0.57186***
	(0.03271)	(0.01905)	(0.10466)
R-squared	0.68029	0.78388	0.86736
Panel C: 2SLS, 1970 Instrument			
Tech. Exposure	-0.90772***	-0.45694***	2.54471***
	(0.20755)	(0.11081)	(0.64448)
R-squared	0.59499	0.74261	0.83400
Observations	5,928	5,928	5,928

Standard errors in parentheses, clustered at the state level: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include commuting-zone and year fixed effects and are weighted using commuting-zone population.

Table 8: Real Annual Log Wages for OAS Workers

	(1) Real Annual Wage	(2) Real Annual Wage, College	(3) Real Annual Wage, No College	(4) Real Annual Wage, Demo-Adjusted
		Panel A: OLS		
Tech. Exposure	0.00266	0.00490	0.00001	0.00244
	(0.00240)	(0.00490)	(0.00226)	(0.00236)
R-squared	0.89136	0.64547	0.83517	0.88677
		Panel B: Reduced Form, 2000 Instrument		
Tech. Exposure	0.00306	0.00855	-0.00453	0.00265
	(0.00328)	(0.00566)	(0.00325)	(0.00326)
R-squared	0.89137	0.64567	0.83543	0.88677
		Panel C: 2SLS, 2000 Instrument		
Tech. Exposure	0.01240	0.03464+	-0.01835	0.01074
	(0.01169)	(0.02021)	(0.01321)	(0.01171)
R-squared	0.89033	0.64060	0.83012	0.88596
		Panel D: Reduced Form, 1970 Instrument		
Tech. Exposure	0.00298	0.00856+	-0.00404	0.00274
	(0.00330)	(0.00493)	(0.00362)	(0.00325)
R-squared	0.89140	0.64579	0.83545	0.88680
		Panel E: 2SLS, 1970 Instrument		
Tech. Exposure	0.01327	0.03807*	-0.01799	0.01219
	(0.01271)	(0.01926)	(0.01633)	(0.01258)
R-squared	0.89014	0.63941	0.83031	0.88566
Observations	5,928	5,928	5,928	5,928

Standard errors in parentheses, clustered at the state level: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include commuting-zone and year fixed effects and are weighted using commuting-zone population.

Table 9: Employment-to-Population Ratio

	(1) E/Pop	(2) Female E/Pop	(3) Male E/Pop
Panel A: OLS			
Tech. Exposure	0.17012*	0.17076*	0.17349*
	(0.06623)	(0.06959)	(0.07433)
R-squared	0.94645	0.92933	0.92365
Panel B: Reduced Form, 2000 Instrument			
Tech. Exposure	0.25204**	0.31873***	0.19025+
	(0.08578)	(0.07843)	(0.10594)
R-squared	0.94670	0.92986	0.92365
Panel C: 2SLS, 2000 Instrument			
Tech. Exposure	1.02074***	1.29080***	0.77047*
	(0.29554)	(0.30563)	(0.36353)
R-squared	0.93888	0.91750	0.92069
Panel D: Reduced Form, 1970 Instrument			
Tech. Exposure	0.25207***	0.26352***	0.24602**
	(0.06878)	(0.07291)	(0.07643)
R-squared	0.94690	0.92980	0.92397
Panel E: 2SLS, 1970 Instrument			
Tech. Exposure	1.12171***	1.17264***	1.09479**
	(0.31832)	(0.34510)	(0.34424)
R-squared	0.93697	0.91986	0.91661
Observations	5,928	5,928	5,928

Standard errors in parentheses, clustered at the state level: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include commuting-zone and year fixed effects and are weighted using commuting-zone population.

Table 10: Real Annual Log Wage Spillovers

	(1) Real Annual Wage	(2) Annual Earnings per Pop.	(3) Real Annual Wage, Non-OAS	(4) Real Annual Wage, Non-OAS College	(5) Real Annual Wage, Non-OAS No College	(6) Real Annual Wage Non-OAS, Demo Adj.
Panel A: OLS						
Tech. Exposure	-0.00110	0.00223	-0.00188	-0.00143	-0.00412**	-0.00197
	(0.00123)	(0.00195)	(0.00128)	(0.00241)	(0.00147)	(0.00127)
R-squared	0.97972	0.97972	0.97851	0.94380	0.90640	0.97660
Panel B: Reduced Form, 2000 Instrument						
Tech. Exposure	-0.00123	0.00301	-0.00299	-0.00569*	-0.01059***	-0.00324
	(0.00201)	(0.00214)	(0.00221)	(0.00244)	(0.00273)	(0.00222)
R-squared	0.97972	0.97973	0.97854	0.94397	0.90803	0.97663
Panel C: 2SLS, 2000 Instrument						
Tech. Exposure	-0.00499	0.01219	-0.01212+	-0.02306*	-0.04290***	-0.01312+
	(0.00713)	(0.00872)	(0.00732)	(0.00954)	(0.00922)	(0.00729)
R-squared	0.97962	0.97932	0.97788	0.94052	0.87452	0.97579
Panel D: Reduced Form, 1970 Instrument						
Tech. Exposure	-0.00035	0.00392+	-0.00173	-0.00252	-0.00903***	-0.00184
	(0.00177)	(0.00204)	(0.00190)	(0.00239)	(0.00255)	(0.00188)
R-squared	0.97971	0.97977	0.97851	0.94383	0.90800	0.97660
Panel E: 2SLS, 1970 Instrument						
Tech. Exposure	-0.00156	0.01746+	-0.00768	-0.01121	-0.04017***	-0.00819
	(0.00714)	(0.00993)	(0.00710)	(0.00955)	(0.01009)	(0.00696)
R-squared	0.97972	0.97878	0.97831	0.94313	0.87885	0.97635
Observations	5,928	5,928	5,928	5,928	5,928	5,928

Standard errors in parentheses, clustered at the state level: + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include commuting-zone and year fixed effects and are weighted using commuting-zone population.

Table 11: Spillover of OAS Tech. on College Share of Other Occupations

	(1) % of OAS College	(2) % of OAS College	(3) % of Non-OAS College	(4) % of Non-OAS College
	Panel A: OLS			
Tech. Exposure	0.27676*	0.18740+	0.02966	-0.08339+
	(0.11280)	(0.09341)	(0.04441)	(0.04284)
R-squared	0.86555	0.88469	0.98041	0.99485
	Panel B: Reduced Form, 2000 Instrument			
Tech. Exposure	0.69539***	0.23780*	0.38780***	-0.21728***
	(0.13463)	(0.10638)	(0.08573)	(0.06167)
R-squared	0.86756	0.88475	0.98077	0.99494
	Panel C: 2SLS, 2000 Instrument			
Tech. Exposure	2.81619***	0.95839*	1.57054**	-0.87571***
	(0.66677)	(0.38405)	(0.54452)	(0.15720)
R-squared	0.82600	0.88106	0.97354	0.99304
	Panel D: Reduced Form, 1970 Instrument			
Tech. Exposure	0.57186***	0.21243**	0.26594**	-0.20886***
	(0.10466)	(0.07648)	(0.09544)	(0.04465)
R-squared	0.86736	0.88478	0.98064	0.99497
	Panel E: 2SLS, 1970 Instrument			
Tech. Exposure	2.54471***	0.94296**	1.18340*	-0.92715***
	(0.64448)	(0.34495)	(0.51676)	(0.15743)
R-squared	0.83400	0.88120	0.97656	0.99280
Observations	5,928	5,928	5,928	5,928
College Pop. Control?	No	Yes	No	Yes

Standard errors in parentheses, clustered at the state level: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include commuting-zone and year fixed effects and are weighted using commuting-zone population. "College Pop. Control" is the share of the commuting-zone population with a college degree each year.

Table 12: OAS Wage Premium

	(1) OAS No Col Gap	(2) OAS Col. Gap	(3) No Col. OAS No Col. Gap	(4) Col OAS Col. Gap
		Panel A: OLS		
Tech. Exposure	0.00677*	0.00408	0.00413	0.00633
	(0.00269)	(0.00331)	(0.00261)	(0.00552)
R-squared	0.62948	0.56830	0.44437	0.21592
		Panel B: Reduced Form, 2000 Instrument		
Tech. Exposure	0.01366**	0.00876*	0.00606	0.01425*
	(0.00396)	(0.00393)	(0.00410)	(0.00661)
R-squared	0.63268	0.56953	0.44492	0.21737
		Panel C: 2SLS, 2000 Instrument		
Tech. Exposure	0.05531***	0.03546**	0.02455+	0.05770*
	(0.01140)	(0.01370)	(0.01380)	(0.02376)
R-squared	0.56111	0.54282	0.42746	0.18644
		Panel D: Reduced Form, 1970 Instrument		
Tech. Exposure	0.01201**	0.00550	0.00498	0.01108+
	(0.00358)	(0.00411)	(0.00419)	(0.00566)
R-squared	0.63290	0.56876	0.44482	0.21703
		Panel E: 2SLS, 1970 Instrument		
Tech. Exposure	0.05344***	0.02448	0.02218	0.04929*
	(0.01057)	(0.01518)	(0.01543)	(0.02154)
R-squared	0.56627	0.55754	0.43116	0.19531
Observations	5,928	5,928	5,928	5,928

Standard errors in parentheses, clustered at the state level: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include commuting zone and year fixed effects and are weighted using commuting-zone population. Wage gaps are defined as the difference in real log annual wages between OAS workers and non-OAS workers.

Table 13: Employment and Wages by Occupational Groups

	(1) Blue Collar	(2) Pink Collar	(3) White Collar	(4) White Collar, Male	(5) White Collar, Female
			Panel A: Occs Percent of Population		
Tech. Exposure	0.25151	0.19240	0.95941**	0.35368*	0.60573**
	(0.22582)	(0.13358)	(0.31093)	(0.15327)	(0.18693)
R-squared	0.93181	0.78483	0.95900	0.96763	0.88236
			Panel B: Share of Occs with College Degree		
Tech. Exposure	0.80387***	-0.60652*	1.88287**	1.70290*	1.84751**
	(0.22243)	(0.29382)	(0.59155)	(0.66371)	(0.64328)
R-squared	0.82877	0.91284	0.91949	0.90057	0.84611
			Panel C: Real Log Annual Wages		
Tech. Exposure	-0.01944	-0.05986***	-0.01282+	-0.02115+	0.00036
	(0.01392)	(0.01291)	(0.00749)	(0.01122)	(0.00761)
R-squared	0.87944	0.90153	0.96079	0.92517	0.91144
			Panel D: Real Log Annual Wages, College Graduates		
Tech. Exposure	-0.00981	-0.02039	-0.02128*	-0.01872	-0.01049
	(0.01823)	(0.02562)	(0.01008)	(0.01328)	(0.00902)
R-squared	0.55927	0.72157	0.92908	0.84848	0.85761
			Panel E: Real Log Annual Wages, Non-College Graduates		
Tech. Exposure	-0.02493	-0.05028***	-0.03997***	-0.04620**	-0.02933**
	(0.01541)	(0.01332)	(0.00954)	(0.01431)	(0.01088)
R-squared	0.86306	0.77632	0.84803	0.76596	0.72545
			Panel F: Real Log Annual Wages, Demographic Adjusted		
Tech. Exposure	-0.02024	-0.05937***	-0.01385+	-0.02196*	-0.00103
	(0.01380)	(0.01273)	(0.00727)	(0.01102)	(0.00727)
R-squared	0.86804	0.89883	0.95879	0.92227	0.90928
Observations	5,928	5,928	5,928	5,928	5,928

Standard errors in parentheses, clustered at the state level: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include commuting zone and year fixed effects and are weighted using commuting-zone population. Each row represents the coefficient from a separate two-stage least squares regression, using the 2000 industry-weighed instrument.

Table 14: Demographic Sub-Groups

	(1) Demo E/Pop	(2) Demo Real Log Annual Wage
Sample: Female, No College		
Tech. Exposure	0.11506	-0.04764***
	(0.30589)	(0.00842)
R-squared	0.90674	0.89666
Sample: Female, College		
Tech. Exposure	2.26729***	-0.00502
	(0.66602)	(0.00958)
R-squared	0.64488	0.92588
Sample: Male, No College		
Tech. Exposure	-0.05905	-0.02959**
	(0.43037)	(0.00900)
R-squared	0.88755	0.85811
Sample: Male, College		
Tech. Exposure	-0.05578	-0.02317*
	(0.53985)	(0.01143)
R-squared	0.75275	0.88959
Observations	5,928	5,928

Standard errors in parentheses, clustered at the state level: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications are two-stage least squares, using the 2000 industry-weighted instrument, include commuting-zone and year fixed effects and are weighted using commuting-zone population.

Table 15: Alternative Specifications

	(1) Endog. Tech.	(2) OAS % Pop.	(3) Wage OAS	(4) Wage OAS, Col.	(5) Wage OAS, No Col.	(6) E/pop	(7) Female E/pop	(8) Wage All	(9) Wage Non-OAS	(10) Wage Non-OAS, Col.	(11) Wage Non-OAS, No Col.
Preferred Spec. (2000 Instrument)											
Tech.	0.24692***	-0.58130***	0.01240	0.03464+	-0.01835	1.02074***	1.29080***	-0.00499	-0.01212+	-0.02306*	-0.04290***
	(0.04718)	(0.15483)	(0.01169)	(0.02021)	(0.01321)	(0.29554)	(0.30563)	(0.00713)	(0.00732)	(0.00954)	(0.00922)
Observations	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928
*MS Office and Similar Technology Indicator, F-Stat 22.32****											
Tech.	0.07001*	-2.21268*	0.04763	0.13692	-0.07277	3.82453*	4.64785*	-0.01466	-0.04131	-0.08383+	-0.15618*
	(0.02830)	(1.03668)	(0.04804)	(0.08578)	(0.05182)	(1.70739)	(1.92374)	(0.02685)	(0.02978)	(0.04606)	(0.06110)
Observations	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928
Unweighted, F-Stat 24.55***											
Tech.	0.16583**	-1.15528**	0.01509	-0.05280	0.00709	0.69175	0.42513	-0.00461	-0.01396	-0.01763	-0.02915
	(0.05853)	(0.39756)	(0.04054)	(0.07354)	(0.04316)	(0.70454)	(0.59401)	(0.02349)	(0.02228)	(0.02629)	(0.02791)
Observations	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928	5,928
*Drop 10% Most Tech. Intensive Commuting Zones (measured in 2007), F-Stat 235.88****											
Tech.	0.25497***	-0.60256**	0.01781	0.03214	-0.00629	0.87622**	1.15200***	-0.00821	-0.01601*	-0.02276*	-0.04592***
	(0.05640)	(0.20388)	(0.01336)	(0.02145)	(0.01448)	(0.31478)	(0.32608)	(0.00773)	(0.00797)	(0.00961)	(0.01020)
Observations	5,586	5,586	5,586	5,586	5,586	5,586	5,586	5,586	5,586	5,586	5,586
*Drop 10% Least Tech. Intensive Commuting Zones (measured in 2007), F-Stat 264.17****											
Tech.	0.24851***	-0.57271***	0.01303	0.03624+	-0.01750	1.02053***	1.27415***	-0.00435	-0.01142	-0.02245*	-0.04192***
	(0.04761)	(0.15403)	(0.01162)	(0.01990)	(0.01311)	(0.29690)	(0.30371)	(0.00716)	(0.00734)	(0.00956)	(0.00905)
Observations	5,572	5,572	5,572	5,572	5,572	5,572	5,572	5,572	5,572	5,572	5,572
*Drop Smallest 10% of Commuting Zones (measured in 2007), F-Stat 260.10****											
Tech.	0.24630***	-0.58291***	0.01266	0.03513+	-0.01815	1.02379***	1.29167***	-0.00481	-0.01195	-0.02298*	-0.04279***
	(0.04740)	(0.15532)	(0.01171)	(0.02031)	(0.01322)	(0.29668)	(0.30678)	(0.00715)	(0.00734)	(0.00957)	(0.00923)
Observations	5,569	5,569	5,569	5,569	5,569	5,569	5,569	5,569	5,569	5,569	5,569
*Drop Largest 10% of Commuting Zones (measured in 2007), F-Stat 5.22**											
Tech.	0.05295	-2.79486	0.02449	0.12569	-0.09217	2.05882	3.60512	0.02296	0.00289	-0.00895	-0.09929
	(0.05161)	(2.77049)	(0.08121)	(0.20367)	(0.08673)	(2.78561)	(3.92336)	(0.06165)	(0.05495)	(0.04877)	(0.10299)
Observations	5,613	5,613	5,613	5,613	5,613	5,613	5,613	5,613	5,613	5,613	5,613
*Drop Smallest 10% of Commuting Zones (measured in 2007), unweighted, F-Stat 39.54****											
Tech.	0.20831***	-1.01684***	-0.00580	-0.04311	-0.01434	0.22399	0.25717	-0.00900	-0.01514	-0.01599	-0.03063
	(0.04428)	(0.26563)	(0.02354)	(0.04763)	(0.02614)	(0.40468)	(0.47566)	(0.01585)	(0.01598)	(0.02048)	(0.02043)
Observations	5,569	5,569	5,569	5,569	5,569	5,569	5,569	5,569	5,569	5,569	5,569
*Drop Largest 10% of Commuting Zones (measured in 2007), unweighted, F-Stat 4.26**											
Tech.	0.08178	-2.47276	0.11016	-0.09473	0.12123	0.78527	-0.98456	0.05550	0.03571	0.02993	0.03971
	(0.06813)	(1.72768)	(0.15760)	(0.20641)	(0.17106)	(1.88445)	(1.45934)	(0.08488)	(0.07199)	(0.06651)	(0.09274)
Observations	5,613	5,613	5,613	5,613	5,613	5,613	5,613	5,613	5,613	5,613	5,613
*Contemporaneous Demographic and Industry Controls, F-Stat 233.75****											
Tech.	0.23874***	-0.53515***	0.00463	0.02925	-0.01812	0.06398		-0.02837***	-0.03614***	-0.03259**	-0.04702***
	(0.04786)	(0.15208)	(0.01419)	(0.02499)	(0.01369)	(0.18025)		(0.00776)	(0.00823)	(0.00991)	(0.01048)
Observations	5,928	5,928	5,928	5,928	5,928	5,928		5,928	5,928	5,928	5,928

Standard errors in parentheses, clustered at the state level: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include commuting-zone and year fixed effects and are weighted using commuting-zone population. Each row represents the coefficient from a separate regression.

Table 16: Long Differences

	(1) OAS % Pop.	(2) OAS Col. %	(3) Wage OAS	(4) Wage OAS, Col.	(5) Wage OAS, No Col.	(6) E/pop	(7) Female E/pop	(8) Wage All	(9) Wage Non-OAS	(10) Wage Non-OAS, Col.	(11) Wage Non-OAS, No Col.
Panel A: OLS											
Change in Tech.	0.00619	-0.18544	-0.00118	0.00852	-0.00273	0.07850	0.23810+	-0.00197	-0.00204	-0.00172	-0.00065
	(0.04785)	(0.17848)	(0.00328)	(0.00774)	(0.00363)	(0.11986)	(0.12202)	(0.00224)	(0.00249)	(0.00347)	(0.00287)
R-squared	0.39144	0.36779	0.40735	0.35132	0.37789	0.71520	0.57051	0.69015	0.67165	0.51573	0.70012
Panel B: Reduced Form, 2000 Instrument											
Change in Tech.	-0.02540	-0.02407	-0.00393	0.01687	-0.00545	0.22589	0.40887*	-0.00483	-0.00528	-0.00813	-0.00692
	(0.05896)	(0.24252)	(0.00496)	(0.01074)	(0.00592)	(0.18260)	(0.19427)	(0.00359)	(0.00407)	(0.00504)	(0.00520)
R-squared	0.39171	0.36635	0.40806	0.35282	0.37874	0.71679	0.57354	0.69150	0.67315	0.51869	0.70268
Panel C: 2SLS, 2000 Instrument											
Change in Tech.	-0.09548	-0.09048	-0.01477	0.06339+	-0.02050	0.84902+	1.53673**	-0.01817+	-0.01983+	-0.03054*	-0.02602
	(0.16025)	(0.63899)	(0.01258)	(0.03360)	(0.01562)	(0.46733)	(0.49386)	(0.01016)	(0.01159)	(0.01440)	(0.01608)
R-squared	0.38309	0.36741	0.39024	0.30238	0.35067	0.67493	0.44366	0.65333	0.63192	0.44624	0.63982
Panel D: Reduced Form, 1970 Instrument											
Change in Tech.	-0.04598	0.30545	-0.00410	0.01626	-0.00700	0.24173	0.37535+	-0.00621+	-0.00692+	-0.00941+	-0.00711
	(0.06654)	(0.22907)	(0.00455)	(0.01080)	(0.00567)	(0.19796)	(0.21481)	(0.00352)	(0.00405)	(0.00480)	(0.00524)
R-squared	0.39261	0.36910	0.40832	0.35315	0.38021	0.71756	0.57368	0.69340	0.67533	0.52069	0.70340
Panel E: 2SLS, 1970 Instrument											
Change in Tech.	-0.17409	1.15646	-0.01553	0.06155*	-0.02651+	0.91520*	1.42109**	-0.02352*	-0.02619*	-0.03564*	-0.02692
	(0.19690)	(0.75950)	(0.01227)	(0.03116)	(0.01593)	(0.46390)	(0.47846)	(0.01148)	(0.01321)	(0.01592)	(0.01697)
R-squared	0.36518	0.29175	0.38826	0.30562	0.32914	0.66771	0.46525	0.62495	0.59849	0.41942	0.63549
Observations	1,482	1,482	1,482	1,482	1,482	1,482	1,482	1,482	1,482	1,482	1,482

Robust standard errors in parentheses: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Specifications are stacked, with changes between 2007–2012 and changes between 2012 and 2016. All specifications include commuting-zone and period fixed effects and are weighted using commuting-zone population in 2016.

A Appendix

A.1 Tables

Table A.1: O*NET Technology Categories and Examples

Technology Categories	Example
Access software	Tivoli
Accounting software	Intuit QuickBooks
Analytical or scientific software	SPSS
Application server software	Apache Webserver
Backup or archival software	Veritas NetBackup
Business intelligence and data analysis software	IBM Cognos Business Intelligence
Calendar and scheduling software	Calendar software
Categorization or classification software	3M Encoder
Communications server software	IBM Domino
Computer aided design CAD software	Autodesk AutoCAD
Computer based training software	Learning management system LMS software
Contact center software	Avaya software
Customer relationship management CRM software	QAD Marketing Automation
Data base management system software	Microsoft SQL Server
Data base reporting software	SAP Crystal Reports
Data base user interface and query software	Oracle
Data compression software	Corel WinZip
Data conversion software	Data conversion software
Data mining software	Informatica Data Explorer
Desktop communications software	Secure shell SSH software
Desktop publishing software	Corel Ventura
Development environment software	Microsoft Visual Studio
Document management software	SAP DMS
Electronic mail software	Microsoft Outlook
Enterprise application integration software	Enterprise application integration software
Enterprise resource planning ERP software	SAP ERP
Enterprise system management software	Microsoft Systems Management Server
Enterprise system management software	Splunk Enterprise
Expert system software	Decision support software
Facilities management software	Silverbyte Systems Optima Property Management System PMS
File versioning software	Apache Subversion
Filesystem software	Samba
Financial analysis software	Oracle E-Business Suite Financials
Graphics or photo imaging software	Adobe Systems Adobe Photoshop software
Human resources software	Oracle HRIS
Industrial control software	Computer numerical control CNC software
Information retrieval or search software	LexisNexis software
Internet protocol IP multimedia subsystem software	File transfer protocol FTP software
Inventory management software	Inventory management system software
LAN software	Local area network LAN software
Library software	WorldCat
Mailing and shipping software	Mailing and shipping software
Map creation software	ESRI ArcGIS
Materials requirements planning logistics and supply chain software	IBS Supply Chain Management
Medical software	Epic Systems software
Mobile location based services software	Transportation management system TMS software
Network monitoring software	Novell NetWare
Object or component oriented development software	C++
Object oriented data base management software	Hibernate ORM
Office suite software	Microsoft Office
Operating system software	Microsoft Windows
Optical character reader OCR or scanning software	Nuance OmniPage Professional
Point of sale POS software	CAP Automation SellWise
Presentation software	Microsoft PowerPoint
Procurement software	PurchasingNet eProcurement
Program testing software	Hewlett-Packard HP WinRunner
Project management software	Scrum software
Spreadsheet software	Microsoft Excel
Time accounting software	Kronos Workforce Timekeeper
Transaction security and virus protection software	McAfee software
Transaction server software	Customer information control system CICS
Video conferencing software	Microsoft NetMeeting
Video creation and editing software	Apple Final Cut Pro
Voice recognition software	Speech recognition software
Web page creation and editing software	Microsoft FrontPage
Web platform development software	JavaScript
Word processing software	Microsoft Word

Source: O*NET.

Table A.2: Example Tasks for Office Support Workers

			Office Support Tasks		
Basic Admin. Assist.	**Tools**	**Physical**	**Mail**	**Routing Accounting**	**Clerk**
Administrative Support	Forklift Operation	Cleaning	Mailing	Payroll Processing	File Management
Scheduling	Office Equipment	Housekeeping	Sorting	Cash Handling	Record Keeping
Data Entry	Hand Tools	Equipment Maintenance	Direct Mail	Payment Processing	Preparing Reports
Typing	Calculator	Equipment Cleaning	Receiving	Billing	Data Collection
Telephone Skills	Power Tools	Materials Moving	Mail Sorting	Estimating	Order Entry
			Office Function Tasks		
Legal	**Logistics**	**HR**	**Marketing**	**Sales/Customer Service**	**Accounting/Finance**
Contract Preparation	Purchasing	Training Programs	Marketing	Sales	Accounting
Legal Compliance	Procurement	Recruiting	Merchandising	Customer Service	Budgeting
Legal Support	Contract Management	Training Materials	Product Marketing	Outside Sales	Accounts Payable and Receivable
Contract Administration	Inventory Management	Employee Relations	Advertising	Product Sale and Delivery	Financial Analysis
E-Discovery	Logistics	Employee Training	Interactive Marketing	Inside Sales	Financial Reporting
			Higher-Skill Tasks		
Writing	**Research**	**Other Cognitive**	**Management**		
Writing	Clinical Research	Business Analysis	Project Management		
Editing	Online Research	Project Planning Skills	Planning		
Word Processing	Library Research	Data Analysis	Sales Management		
Technical Writing / Editing	Fact Checking	Process Improvement	Business Development		
Proposal Writing	Library Resources	Data Management	Business Process		

Source: Authors' categorization of Burning Glass data.

Table A.3: Example Unique Tasks from Occupational Groups

Pink Collar	**Blue Collar**
Cash Register Operation	Auto Repair
Food Preparation	Machine Operation
Retail Sales	Equipment Cleaning
Child Care	Truck Driving
Sales Planning	Facility Maintenance
Male White Collar	**Female White Collar**
Data Analysis	Critical Thinking
Editing	Case Management
Management	Financial Analysis
Strategic Planning	Marketing
Web Development	Acute Care

Source: Authors' categorization of Burning Glass data.

Table A.4: OAS Minor Occupation Categories

SOC Code	Minor Occupation Categories	Share of OAS
43-1000	Supervisors of Office and Administrative Support Workers	6.6%
43-2000	Communications Equipment Operators	0.5%
43-3000	Financial Clerks	14.2%
43-4000	Information and Record Clerks	25.6%
43-5000	Material Recording, Scheduling, Dispatching, and Distributing Workers	18.6%
43-6000	Secretaries and Administrative Assistants	16.7%
43-9000	Other Office and Administrative Support Workers	17.9%

Source: May 2016 Occupational and Employment Statistics estimates of national employment. Total employment in OAS occupations: 22,026,080 (15.7 percent of total employment).

Table A.5: Summary Statistics Skill Demand

	N	Mean	SD	Min	MAX
	Full Sample				
Lists Education	8,589,664	0.611606	0.487385	0	1
Wants High School	8,589,664	0.395756	0.489013	0	1
Wants College	8,589,664	0.117652	0.322195	0	1
Average Education (conditional)	5,253,493	11.94897	4.064818	0	21
Lists Experience	8,589,664	0.463127	0.498639	0	1
Average Experience Requirement	8,589,664	1.057868	1.819207	0	15
Hired in 2007 or 2010 and No-Technology Adoption Sample					
Lists Education	414,780	0.383345	0.486202	0	1
Wants High School	414,780	0.291526	0.454466	0	1
Wants College	414,780	0.032919	0.178424	0	1
Average Education (conditional)	159,004	11.17511	4.183943	0	21
Lists Experience	414,780	0.253402	0.43496	0	1
Average Experience Requirement	414,780	0.468684	1.328763	0	15
Hired in 2007 or 2010, Technology Adoption Sample					
Lists Education	684,001	0.595331	0.490828	0	1
Wants High School	684,001	0.426382	0.494551	0	1
Wants College	684,001	0.081604	0.27376	0	1
Average Education (conditional)	407,207	11.71344	3.906683	0	21
Lists Experience	684,001	0.421042	0.493727	0	1
Average Experience Requirement	684,001	0.846345	1.578982	0	15

Source: Burning Glass. Full sample indicates the sample of OAS job ads that include firm names. The other two samples are restricted to the set of job ads in which the firm posted at least one OAS job ad in 2007 or 2010 that did not include any technology. The no-technology-adoption sample refers to the set of job ads for which the firm never asks for any technology over the sample period (2007–2016), while the technology-adoption sample adopted technology at some point after 2010.

Table A.6: Summary Statistics for Task Measures

	Full Sample	Never Tech.	Ever Tech.
Any OAS Task	0.867	0.757	0.85
	[0.339]	[0.429]	[0.357]
Basic Admin.	0.464	0.231	0.419
	[0.499]	[0.422]	[0.493]
Clerk	0.082	0.025	0.073
	[0.274]	[0.155]	[0.261]
Mail	0.088	0.073	0.084
	[0.283]	[0.261]	[0.277]
Routine Accounting	0.276	0.179	0.256
	[0.447]	[0.384]	[0.436]
Tools	0.069	0.048	0.075
	[0.254]	[0.213]	[0.264]
Physical	0.032	0.044	0.034
	[0.176]	[0.205]	[0.182]
Legal	0.021	0.026	0.017
	[0.142]	[0.16]	[0.129]
Accounting/Finance	0.144	0.041	0.117
	[0.351]	[0.199]	[0.322]
Sales/Customer Service	0.399	0.491	0.421
	[0.49]	[0.5]	[0.494]
Marketing	0.035	0.067	0.053
	[0.184]	[0.251]	[0.224]
Logistics	0.086	0.044	0.074
	[0.281]	[0.205]	[0.261]
HR	0.037	0.022	0.033
	[0.188]	[0.146]	[0.18]
Writing	0.245	0.089	0.218
	[0.43]	[0.285]	[0.413]
Management	0.162	0.079	0.144
	[0.369]	[0.269]	[0.351]
Cognitive	0.056	0.014	0.041
	[0.23]	[0.118]	[0.199]
Research	0.098	0.039	0.078
	[0.298]	[0.194]	[0.268]

Source: Burning Glass. Means and standard deviations in brackets. Full sample indicates the sample of OAS job ads that include firm names. The other two samples are restricted to the set of job ads in which the firm posted at least one OAS job ad in 2007 or 2010 that did not include any technology. The no-technology-adoption sample refers to the set of job ads for which the firm never asked for any technology over the sample period (2007–2016), while the technology-adoption sample adopted technology at some point after 2010.

Table A.7: Descriptive Statistics of Key Variables

Variable	Obs	Mean	Std. Dev	Min.	Max
OAS % of Employment	5,928	13.84518	1.8161	6.100619	22.39415
OAS % of Population	5,928	8.117694	1.409581	3.259055	14.66242
OAS Share with College Degree	5,928	15.20739	6.022262	0.846262	49.39032
Real Log Annual Wage OAS	5,928	10.13033	0.134056	9.608685	10.74603
Real Log Annual Wage Non-OAS	5,928	10.43247	0.141984	10.02879	11.10878
Real Log Annual Wage, All	5,928	10.39627	0.136239	10.02373	11.05757
Employment-to-Population Ratio	5,928	0.585767	0.061015	0.365204	0.754362
Share of Employment in Manufacturing	5,928	0.134513	0.064135	0.012511	0.430599
Share of Employment in Services	5,928	0.420282	0.04812	0.275502	0.606449
Share of Population with College Degree	5,928	0.188818	0.059849	0.054132	0.452446
Share of Population Foreign Born	5,928	0.07635	0.067774	0.002295	0.439406
Share of Population Female	5,928	0.577742	0.064683	0.323809	0.755919
Mean Tech. Exposure, Standardized	5,928	1.05795	1.43648	-1.70723	8.247049
Instrument, Standardized	5,928	12.18887	5.254532	-2.20304	25.04665

Source: Census/ACS data, 2007 and 2010–2016 crosswalked to the commuting-zone level.

Table A.8: Employment and Wages by Major Occupation

	Occ % of Pop	Log Real Annual Wages	Wages College	wages, No College
OAS	-0.58130***	0.01240	0.03464+	-0.01835
	(0.15483)	(0.01169)	(0.02021)	(0.01321)
Pink Collar				
Health Support	0.16214**	-0.03631*	-0.03327	-0.03675*
	(0.05487)	(0.01806)	(0.05850)	(0.01853)
Personal Care	0.08302	-0.03035	0.03376	-0.02640
	(0.05440)	(0.02804)	(0.06021)	(0.02709)
Food Prep	0.15224*	-0.08156***	-0.15608*	-0.08087***
	(0.07027)	(0.01783)	(0.07552)	(0.01873)
Sales	-0.20500	-0.02381*	-0.01013	-0.03548*
	(0.13303)	(0.01183)	(0.02820)	(0.01650)
Blue Collar				
Construction	0.02319	-0.02574*	-0.02063	-0.02407+
	(0.13057)	(0.01255)	(0.05793)	(0.01272)
Install	-0.00185	-0.02695+	-0.00123	-0.02384
	(0.04317)	(0.01445)	(0.06044)	(0.01610)
Production	0.16728+	-0.02578	0.05161	-0.04222*
	(0.09831)	(0.01818)	(0.03732)	(0.01720)
Transport	0.12620	-0.02796+	-0.00064	-0.02778+
	(0.10879)	(0.01632)	(0.04458)	(0.01671)
Protection	-0.00136	0.00307	-0.02246	0.00437
	(0.04221)	(0.01879)	(0.02970)	(0.02589)
Grounds	-0.08932	-0.01774	-0.02411	-0.02072
	(0.07984)	(0.01954)	(0.08424)	(0.02304)
Farm	0.02737	-0.19341**	-0.14700	-0.16579**
	(0.03318)	(0.07396)	(0.21706)	(0.05267)
White Collar, Female				
Social Service	0.09357**	-0.00112	0.02346+	-0.05666
	(0.03252)	(0.01423)	(0.01420)	(0.03970)
Health	0.08359	0.00347	-0.00449	-0.01005
	(0.06204)	(0.01407)	(0.01912)	(0.01366)
Ed.	0.16937*	0.02229	0.02251+	-0.04239
	(0.08593)	(0.01539)	(0.01332)	(0.02845)
Bus.	0.25920***	-0.02096	-0.04802**	-0.01320
	(0.05590)	(0.01410)	(0.01664)	(0.01625)
White Collar, Male				
Mgmt	0.05428	-0.01149	-0.01724	-0.04474**
	(0.07483)	(0.01039)	(0.01490)	(0.01549)
PC/Math	0.26154***	-0.02254	-0.04150	-0.05525
	(0.07808)	(0.02319)	(0.02972)	(0.03366)
Arc./Engineer	-0.02122	-0.00915	0.01344	-0.03142
	(0.03645)	(0.01821)	(0.02160)	(0.02120)
Science	-0.01021	-0.04910	-0.00425	-0.13681
	(0.02484)	(0.03898)	(0.03473)	(0.08994)
Legal	-0.00187	-0.05541	-0.09846*	-0.04542
	(0.03393)	(0.03754)	(0.04671)	(0.04557)
Arts	0.07115*	-0.03232	-0.01101	-0.05689
	(0.03451)	(0.03240)	(0.03624)	(0.05807)

Standard errors in parentheses, clustered at the state level: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include commuting-zone and year fixed effects and are weighted using commuting-zone population. Each row represents the coefficient from a separate regression.

A.2 Alternative Measures of Upskilling

In Table A.9, we use an alternative set of measures of upskilling. Deming and Kahn (2018) examine the incidence of upskilling using the Burning Glass data, so we reproduce their measures and reproduce our estimates from Tables 1 and 2. The results for these measures are very similar to the results for our measures. Consistent with our finding that technology usage is associated with increased demand for education and experience, we also see a positive relationship between technology and the Deming-Kahn measure of Cognitive Skills. In addition, we find a robust increase in Social and Character Skills, which is consistent with Deming and Kahn's finding of the increasing importance of social skills.

In Panel B, we see that technology adoption is associated with an increase in high-skill tasks. This is consistent with what we found in Table 2, with our measures of writing and management skills robustly increasing with the adoption of technology. Finally, in Panel C, we see a large increase in Financial Tasks, which is consistent with our measures. Furthermore, we see a negative relationship between technology and customer service tasks, which is consistent with our result for sales/customer service.

In Table A.10, we construct measures of upskilling based on the tasks within occupations. This is constructed as in Table 3; however, here we focus on four specific white-collar office occupations: 1) management, 2) business, 3) legal, and 4) sales occupations. In column (1), we see that office-support job ads that ask for more technology are more likely to request management, business, and legal tasks, but less likely to request sales tasks. However, as we introduce firm and job-title fixed effects, we see that within jobs, an increase in technology demand is associated with increases in all four measures.

In Table A.11, we reproduce Table 2, however, now with a focus on the specification that includes firm-by-job-title fixed effects. That is, we measure how the functional tasks within the job vary as firms demand more OAS technology. Here we see that the tasks that were negatively correlated in 2 are now small and positive, suggesting that within job titles, firms do not remove tasks, only broaden the tasks to encompass more high-skill activities.

Table A.9: Deming and Kahn Skill Measures

	(1)	(2)	(3)
	Panel A: Skills		
	Cognitive	Social	Character
Tech	0.06458***	0.06656***	0.15906***
	(0.00108)	(0.00085)	(0.00176)
Mean	0.256	0.306	0.513
% of Mean	25.23	21.75	31.01
	Panel B: High-Skill Tasks		
	Writing	Project Mgmt	People Mgmt
Tech	0.05096***	0.01456***	0.02202***
	(0.00053)	(0.00034)	(0.00043)
Mean	0.163	0.0262	0.109
% of Mean	31.26	55.57	20.2
	Panel C: Functional Tasks		
	Financial	Customer Service	
Tech	0.06309***	-0.00555***	
	(0.00098)	(0.00189)	
Mean	0.137	0.668	
% of Mean	46.05	-0.82	
Observations	15,452,623	15,452,623	15,452,623

Standard errors in parentheses, clustered at the firm name by commuting-zone level, $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Specifications include month-by-year fixed effects.

Table A.10: Occupation-Based Task Measures

	(1)	(2)	(3)	(4)
Panel A: Dependent Variable: Management Occupation Tasks				
Tech. Intensity	0.01974***	0.02417***	0.01430***	0.02592***
	(0.00049)	(0.00064)	(0.00066)	(0.00067)
R-squared	0.01358	0.01361	0.28034	0.82529
Mean of DV	0.101	0.117	0.117	0.117
% of Mean	19.54	20.66	12.22	22.15
Panel B: Dependent Variable: Business Occupation Tasks				
Tech. Intensity	0.05624***	0.05539***	0.04258***	0.03257***
	(0.00092)	(0.00122)	(0.00076)	(0.00089)
R-squared	0.04880	0.05098	0.30855	0.83566
Mean of DV	0.112	0.0958	0.0958	0.0958
% of Mean	50.21	57.82	44.45	34
Panel C: Dependent Variable: Legal Occupation Tasks				
Tech. Intensity	0.15989***	0.18237***	0.15861***	0.08194***
	(0.00212)	(0.00312)	(0.00196)	(0.00142)
R-squared	0.09716	0.12467	0.40455	0.89010
Mean of DV	0.389	0.343	0.343	0.343
% of Mean	41.1	53.17	46.24	23.89
Panel D: Dependent Variable: Sales Occupation Tasks				
Tech. Intensity	-0.02624***	-0.06056***	0.00812***	0.05816***
	(0.00202)	(0.00355)	(0.00162)	(0.00174)
R-squared	0.02121	0.03131	0.52975	0.85575
Mean of DV	0.450	0.671	0.671	0.671
% of Mean	-5.82	-9.02	1.21	8.67
Sample	All	Panel	Panel	Panel
Czone FE	×	×		
Czone × Firm FE			×	
Czone × Firm × Job Title FE				×
Observations	15,452,623	5,261,935	5,261,935	5,261,935

Standard errors in parentheses, clustered at the firm name by commuting-zone level, $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include month-by-year fixed effects.

Table A.11: Change in Task Demand with Technology Adoption within Job Titles

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Routine OAS Tasks						
	Basic Admin.	Clerk	Mail	Routine Accounting	Physical Tasks	
Tech. Intensity	0.21427***	0.02694***	0.02319***	0.07595***	0.00385***	
	(0.00266)	(0.00052)	(0.00065)	(0.00152)	(0.00021)	
Mean of DV	0.911	0.0861	0.107	0.411	0.0396	
% of Mean	23.52	31.29	21.67	18.48	9.72	
Panel B: Functional Tasks						
	Legal	Accounting/Finance	Sales	Marketing	Logistics	HR
Tech. Intensity	0.00467***	0.06462***	0.03356***	0.00310***	0.02383***	0.00975***
	(0.00027)	(0.00136)	(0.00088)	(0.00023)	(0.00062)	(0.00030)
Mean of DV	0.0220	0.192	0.559	0.0426	0.108	0.0355
% of Mean	21.23	33.66	6	7.28	22.06	27.46
Panel C: High-Skill/Cognitive Tasks						
	Research	Management	Cognitive	Writing-Related		
Tech. Intensity	0.02450***	0.05074***	0.02070***	0.11928***		
	(0.00049)	(0.00091)	(0.00052)	(0.00140)		
Mean of DV	0.0916	0.183	0.0517	0.272		
% of Mean	26.75	27.73	40.04	43.85		
Observations	5,261,935	5,261,935	5,261,935	5,261,935	5,261,935	5,261,935

Standard errors in parentheses, clustered at the firm name by commuting-zone level, $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Specifications include firm × commuting zone × job-title fixed effects, as well as month-by-year fixed effects.