White Collar Technological Change: Evidence from Job Posting Data

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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. Further, 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 one standard deviation increase in OAS technology usage reduces employment in OAS occupations by about one percentage point and increases wages for college graduates in OAS jobs by over three 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 total employment increases with computerization, despite the direct job losses in OAS employment.

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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 comprised 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% of all jobs could be automated in coming decades, contributing to popular anxiety and calls for pre-emptive 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% of all employment in 1980, the OAS employment share has steadily fallen each year to its current level of below 13%.[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 then construct indices of technological intensity, allowing us to measure the

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

effect of technological adoption on employment and wage outcomes in the local labor market. We find that the task-content of jobs changes when firms adopt technology, leading office and administrative support jobs to become higher-skilled and encompass cognitive tasks that are less at risk of computerization. In particular, we find an increase in tasks assigned to OES jobs that are associated with finance, accounting, legal, and management jobs.

By constructing a Bartik-style instrument using national technology adoption and historic employment patterns, we find that a one standard deviation increase in technology usage in a local labor market leads to a one percentage point decrease in OAS employment and a 2.5 percentage point increase in the share of OAS employment with a college degree. Further, we find technology adoption increases wages for OAS workers with a college degree by more than three 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 overall employment per population increases in commuting zones with larger increases in technology adoption, with a one unit increase in technology leading to a one 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 one standard deviation increase in OAS technology adoption associated with a one percent decrease in wages for college graduates and a four 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 that are majority 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 this may be driven by the occupations from 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 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 OAS workers' wages rise compared with both non-college 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.

Overall, 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, while employment gains are diffuse, wage losses are concentrated in non-OAS workers, with the largest losses for those in pink-collar occupations. We see gains for OAS workers; however, these gains accrue to a shrinking base that is increasingly college-educated. Nonetheless, 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-on 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 primary 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. In more recent work, 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.

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 depress 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 (2016). Several papers use the same source of data we employ, online job postings collected by Burning Glass Technologies: Rothwell (2014), Modestino, Shoag, and Ballance (2016a), Modestino, Shoag, and Ballance (2016b), 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 clerks, schedule and dispatching workers, and other related categories. See Table A.3 for a list of occupational categories and employment shares.

spective.

As discussed in the introduction, OAS occupations experienced a rapid growth in employment in the post-war era, growing from below 12% of all employment in the United States in 1950 to a peak of nearly 17% by 1980. However, after 1980, the employment share suffered a precipitous decline. By 2016, the employment share fell 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). In Figure 2 we see that, for all office and administrative support occupations, computer usage continued to rise through the 1990s.

Over the same time period education levels rose substantially for all workers; Figure 3 shows the share of workers with college degrees among OAS and non-OAS workers. In the 1950 Census less than 1% of OAS workers had college degrees. This increased to 21% 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: falling employment levels since 1980, rising computer use through the 1980s and 1990s and continued adoption of new software through 2016, and 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 from the task-view of technology to connect changes in how tasks are performed to changes in job design as well as 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 provide productivity improvements for office support workers. For instance, mastering mail merge can allow an office worker to automate mass mailing, freeing up time for other tasks or allowing the employer to reduce OAS headcount. However, such proficiency requires training and general computer literacy. Thus it is very likely that technology adoption is complementary 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.

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 middle-skill occupations.

There are two ways in which technological change can affect the labor market: factor-augmenting and 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-skilled workers.[4]

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.[5] 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 should broaden their task space. In addition, even if employers reduce headcount, the 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

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

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

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 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 to be 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 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 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, American Community Survey, and 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 through 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.[6]

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 over-represent computer, management, and business occupations and under-represent 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 those ads, we restrict attention to the 8,589,664 advertisements that contain the firm name.

[6] 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.

5.1 Measuring Technology

Although Burning Glass Technologies processes the job ad raw text into over 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% 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 as well as the number of years of required experience. These variables are described in Table A.4.

The second focus of labor demand is measuring changes in the task content of the job. We measure this by assigning the top 1000 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 five subcategories: Basic Administrative Assistance Tasks, Tools, Physical Tasks, Mail, Routine Accounting, and Clerking Tasks. The second group of tasks are those that are associated with other office function tasks. These include the following six categories: Legal, Logistics, Human Resources, Marketing, Sales/Customer Service, and Accounting/Finance. Finally, we isolate tasks that are associated with higher-level skills. These are grouped into Writing, Research, Management, and Other Cognitive. These variables are described in Table A.5.

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: educational requirements and experience requirements. We then turn to changes in the required tasks.

6.1 Econometric Specification

Our goal in this section is to examine how firms change other characteristics of job postings in conjunction with increasing the technological component of jobs. 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 versions of the following equation:

$$y_{ifct} = \alpha + \gamma_t + \gamma_{fc} + \beta \text{Tech}_{fct} + \epsilon_{ifct} \tag{1}$$

where i indexes the ad, f indexes the firm, c indexes the commuting zone, t indexes the year and month the ad was listed, y is a measure of education or experience, γ_t is a vector of year-month indicator variables, γ_{fc} is a vector of commuting zone by firm indicator variables, and Tech is an indicator variable equal to one once a firm has ever asked for a technology skill in an OAS occupation in a specific commuting zone.

The γ_{fc} mean we do not treat all establishments of a national chain as being the same and instead 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. The γ_t coefficients account for secular trends in skill requirements that may be associated with technology use. Identification of the coefficient on Tech is identified by how education or experience changes as a firm begins asking for technology after accounting for trends in education and experience of similar firms.

6.2 Upskilling Results

The technology coefficients from Equation (1) are shown in column 1 of Table 1. The results suggest that asking for technology is associated with increasing education requirements. Asking for technology is associated with a 9.0 percentage point increase in the likelihood the job ad includes educational requirements, which is a 23.4 percent increase relative to the base of 38 percent. About 70% of this increase comes from firms asking for a high school degree, while 23 percent comes from firms asking for a bachelor's degree. Including technology in the job ad is also associated with firms being more likely to include experience requirements. The likelihood of requiring relevant job experience rises by about 23.9 percentage points.

A potential concern with interpreting these results as an association between asking for technology and skills is that firms may have different jobs within OAS occupations, some of which require technology and some of which do not. For instance, Hertz hires receptionists and human resource coordinators, both of which have an SOC code of 43-4121. The ads indicate that human resource coordinators must have technology skills, but not receptionists. If Hertz hires receptionists in one period and human resource coordinators in the next, Equation (1) would attribute any additional education requirements of the human resource coordinator position to the technology, though they are not related. To account for this possibility, column 2 of Table 1 displays estimates that control for Commuting Zone–Firm–Job-Title fixed effects, meaning identification comes only from variation in technology requirements within a job title at a firm and commuting zone combination. A potential issue with this specification is that the firm may decide to change the name of the job when it decides to start asking for additional technology skills. By controlling for the firm's job title, we would fail to identify this as being a change in required technology skills and would instead identify it as a different job with no relation to the original job. Thus, the estimates from controlling for the job title may be biased towards zero. The point estimates fall when adding these controls, but the association is still statistically and economically significant.

These results suggest that increasing the technology requirements for a job is associated with increasing the education requirements for that job. However, another potential threat to this interpretation is that firms that begin asking for technology may have had unobservable trends in education requirements that happen to be related to technology even though the two outcomes have no relationship to each other. 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. Specifically, we 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 4 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 technology in previous years, but demand for education increases substantially in the year of technology adoption, persisting up to two years after adoption. While Figure 4 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 higher-return-to-skill aspects of the job.

6.3 Task Broadening

Next we investigate how the tasks associated with OAS jobs change when firms begin asking for technology skills. So far we have documented that technology adoption is associated with increased demand for education and experience. There are a few ways that 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 if 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 if other broad higher-skill tasks are added to job ads.

In particular, we replicate the methodology from Equation 1, however now the dependent variable is an indicator for whether or not the firm lists tasks of a specific type. In all specifications we include employer by job title by commuting zone fixed effects, in order to focus on changing task content within job titles. In Panel A of Table 2 we see that, instead of reducing demand for routine tasks, technology demand is associated with increases in the share of job ads that specify tasks in these categories. We see the biggest effect for clerking tasks, which includes tasks such as file management, record keeping, and data management. However, we also see increases for more basic administrative assistant tasks, which includes 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 physical routine tasks 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 increases for legal and accounting and finance tasks, but no statistically significant change in sales, marketing, logistics, or human resources tasks. 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 allowing 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 technology adoption is associated with robust increases in management, cognitive, writing, 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 individuals perform a broad variety of tasks, including lower-skill tasks (answering phones, typing, mailing) as well as legal research, writing, and data analysis.

Appendix Table A.6 considers changes in the likelihood that OAS advertisements ask for skills that are commonly required in other occupations. To obtain a measure for skills being commonly requested in different occupations, we identify the 100 most-frequently requested skills for management, business, legal, and sales occupations. We then create indicator variables equal to one if the OAS ad requires one of the skills. The results in Appendix Table A.6 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: adoption of technology, changing skill demands, and broadening 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. In particular, 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 these may diverge. First, since it 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 under-report 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 over-report technology usage, for instance if they strategically include a technology in their job ads as a signal to potential applicants. We believe systematic under-reporting is more likely than systematic over-reporting, leading our job-ad-based measure to be an underestimate of true technology usage.

In Figure 5 we plot the 2016 exposure measure for each commuting zone, defined as in Equation 3. Here the darkest regions show the most technology-intensive 1/6 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 6 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 one unit is one 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 one 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. Further, 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 nation-wide 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 historic industry development. In Table 3 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' office. 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 agriculture production. Thus we can take advantage of the fact that local labor markets are likely to be more exposed to OAS technological change due to the historic geographic dispersion of industries.

Third, there is heterogeneity within OAS occupations in the extent to which new software is relevant to jobs. Table 5 shows the largest ten occupations, which collectively comprise 77% 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 between 2007 and 2016.

These three features of the market for OAS software means that a portion of the local exposure to technological change will be due to the historic 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 national average number of types of software requested 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 nation-wide 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 7 illustrates the relationship between this constructed instrument and our endogenous technology measure. Here we see most commuting zones experience a substantial increase in predicted technology usage as well as the endogenous technology measure between 2007 and 2016. Further, 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 one 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 4 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 one 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 nation-wide occupational distribution by industry. However, by virtue of using a more historic industry distribution, this measure may have a weaker relationship with the contemporaneous technology measure. In the second column of Table 4 we see 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 Census/ACS, retrieved from the IPUMS data repository (Sobek et al., 2010) in the years 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).[7] 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 zero and standard deviation one 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.[8]

In addition we construct demographic 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, bachelors' degree or more), and age (under 30, 30 to 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.

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

[8] 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 6 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 6 we see 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 one-standard deviation increase in technology adoption is between 0.9 (1970 instrument) and 1 (2000 instrument) percentage points. Over our time period OAS occupations account for 13 percent of employment, thus our estimates correspond to about a seven percent decrease in OAS employment share for a one 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 6 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 these firms appear to be successful: one standard deviation increase in technology exposure leads to between 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 one 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. Due to 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 6 demand for OAS employment falls and the college share of employment increases with technological adoption, which should have offsetting effects on wages.

Here we focus on log annual wages, deflated to 2007 prices. In Column (1) of Table 7 we focus on wages for all OAS workers. Here 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 one unit increase in technology adoption is associated with about a 1/2 percentage point decrease in OAS employment share per population. Thus, if there are no spillovers, we would expect this to directly lead 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 8 we see 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 one 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 8 we show the effect of OAS technology adoption on the female and male employment-to-population ratios, respectively. Since OAS occupations are predominately female (over 70% in 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 that 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 off-setting effects. On the one hand, the increased labor demand we saw in Table 8 suggests wages should rise. On the other hand, 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 9 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 one to two 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 one 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 non-significant one 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% wage loss for these workers for each unit increase in OAS technology usage. Finally, in Column (5) we calculate the demographic 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 10 we first reproduce the results from Table 6 that show a one 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 lead 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 one percentage point. That is, the increase in 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 one 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: non-OAS workers without a college degree, OAS workers, and non-OAS workers with a college degree, which correspond to the low-, middle- and high-skill groups from the theory, respectively. In Columns (1) and (2) of Table 11 we see that an increase in technology exposure increases the OAS wage premium at a rate of about 5% compared to non-college-educated workers and a rate of about 3% 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 non-college and college, respectively. Here we see that the OAS wage premium is smaller among non-college OAS workers, but still about 2%. In contrast, the OAS wage premium is larger for college-educated OAS workers, with a premium of between 5 and 6% 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. We divide occupations into four categories based on the share female and share with a college degree in 2000, as illustrated in Figure 8. In particular, occupations with fewer than 40% 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% 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.

In Table 12 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 with 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 two percent, pink collar occupations experience the largest losses, with decreases of six percent. On the other hand, female white collar occupations show no wage losses. When we separate these wage changes into college and non-college subgroups we see losses of one to two percent across groups for college graduates and losses of between two and five percent for non-college graduates. Finally, in panel F we show that demographic-adjusted wage results are similar to the results in Panel C, indicating 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 non-college 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 these new software.

7.7 Alternative Specifications

In this section we explore how sensitive our results are to alternative specifications. In Table 13 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% 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 14 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 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 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, finding 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 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' 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

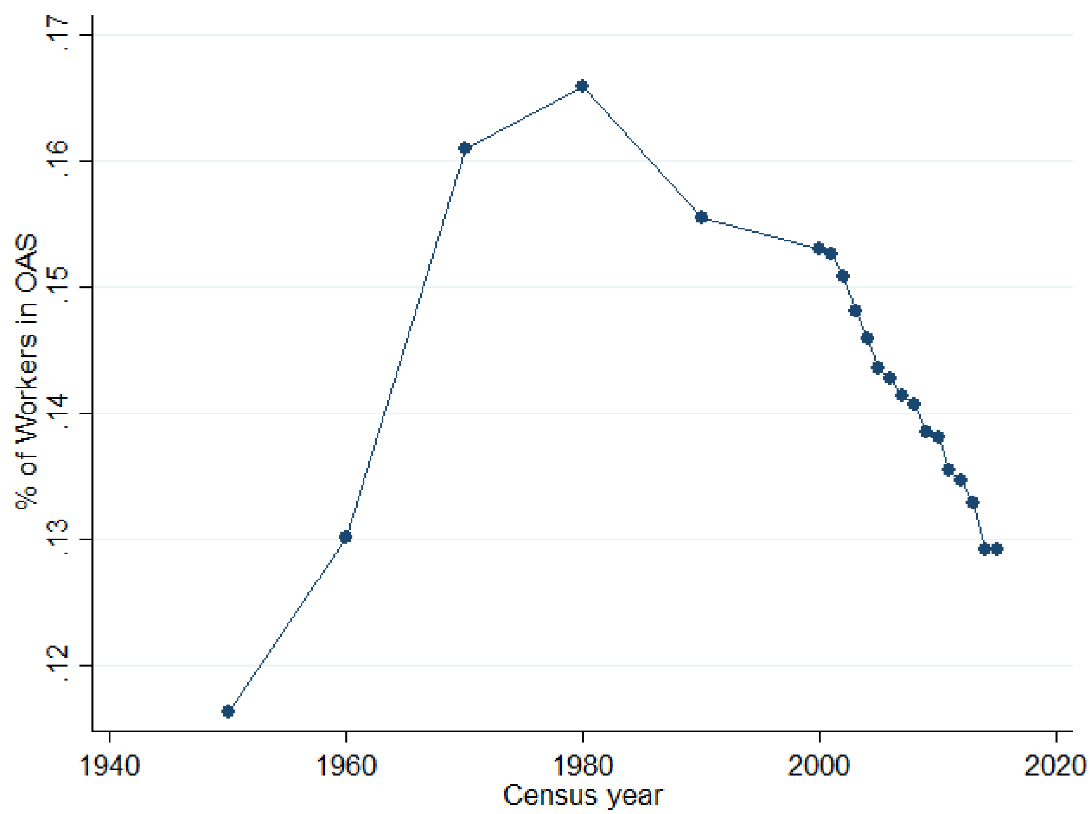


Figure 2: PC Use at Work, CPS Supplement

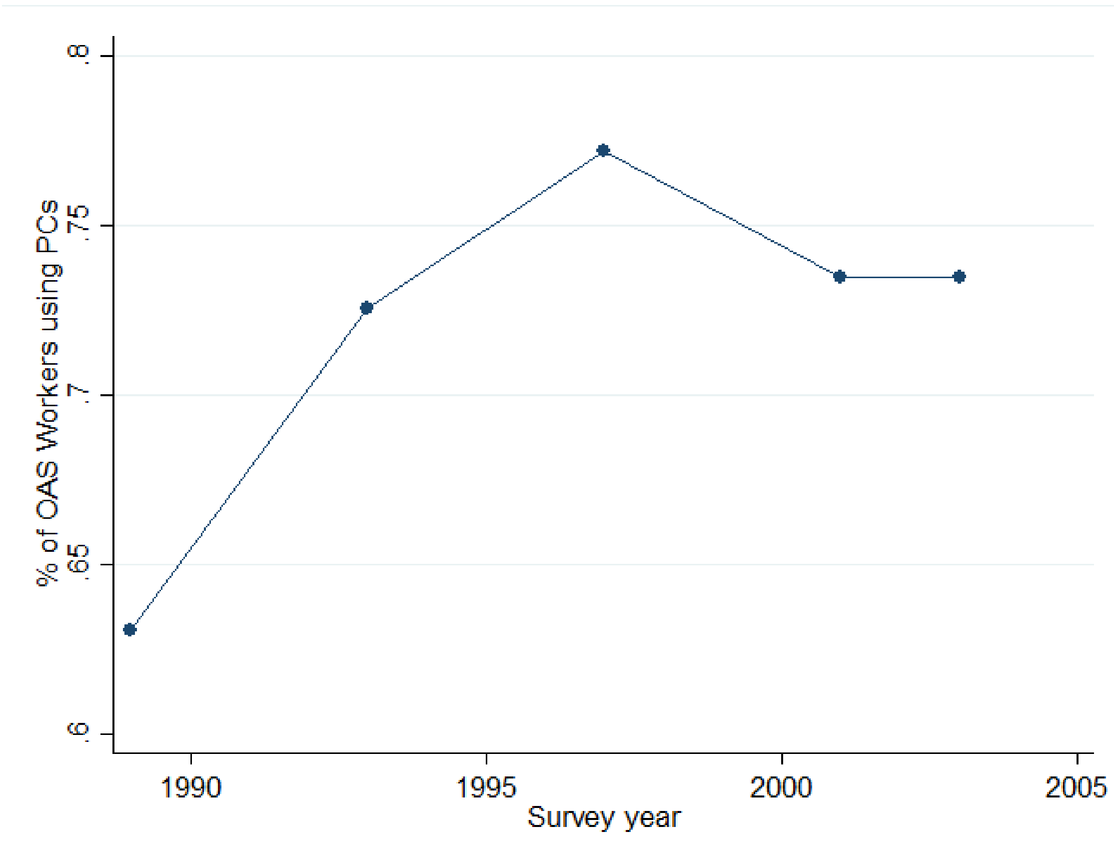


Figure 3: Share of OAS and Non-OAS Workers with A College Degree

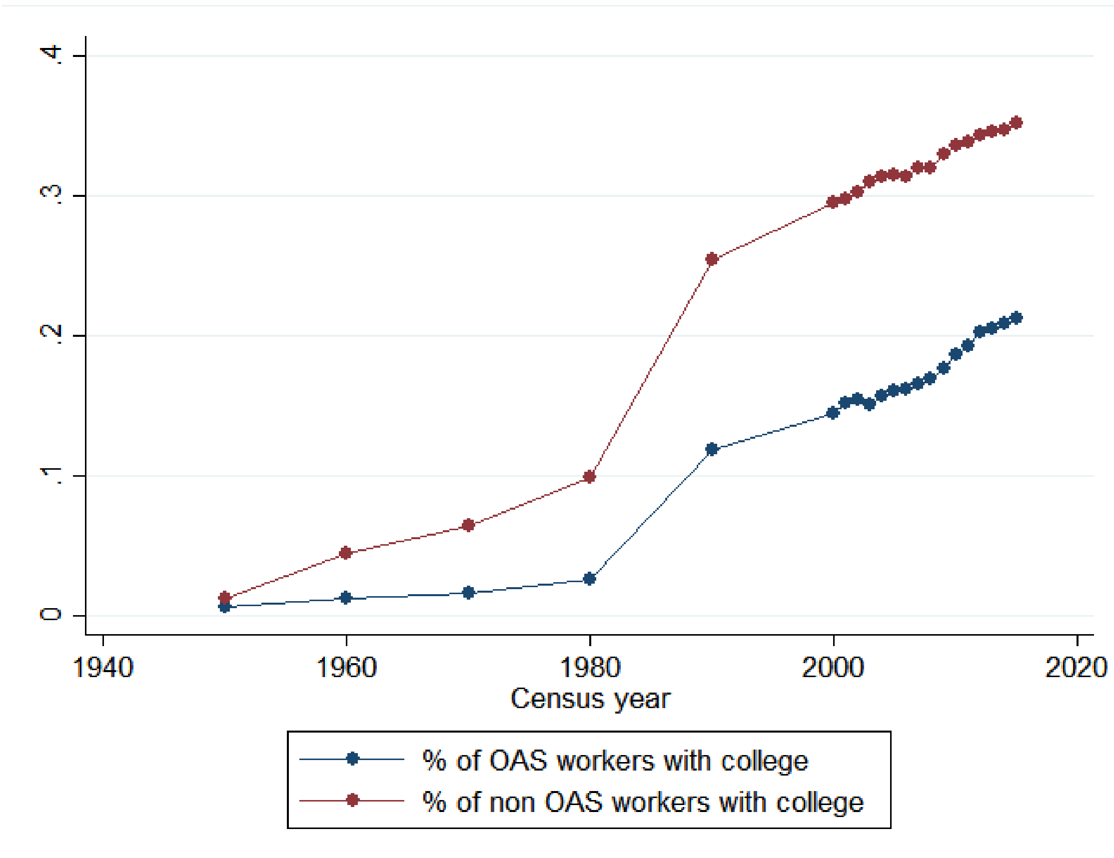
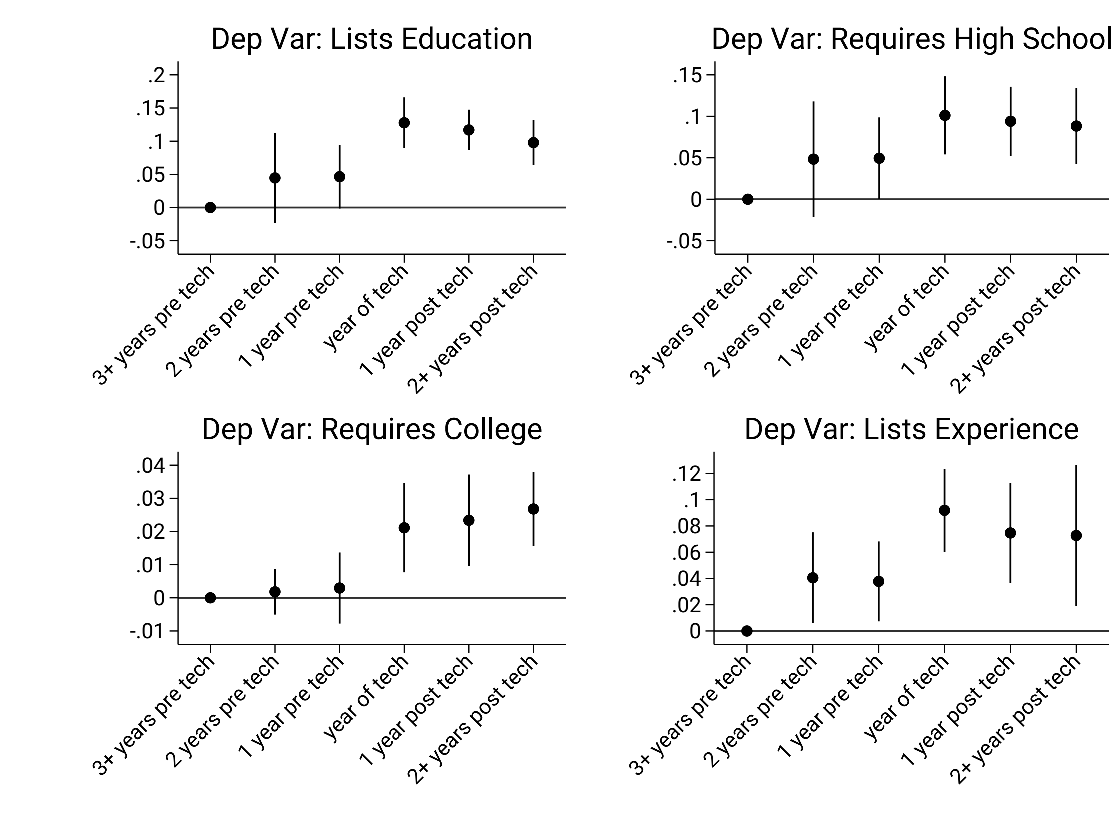
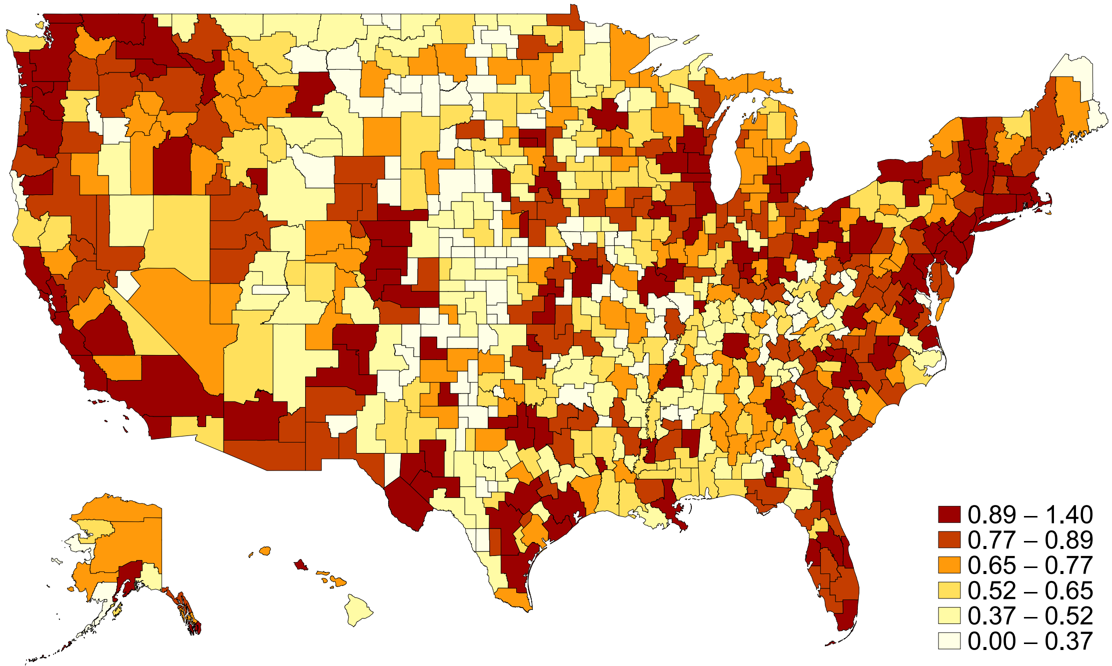


Figure 4: Fixed Effects Models–Event Study of Changes in Other Skill Requirements as Firms Begin Asking for Technology



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 5: 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 6: Relationship between OAS Employment Share and Technology Intensity

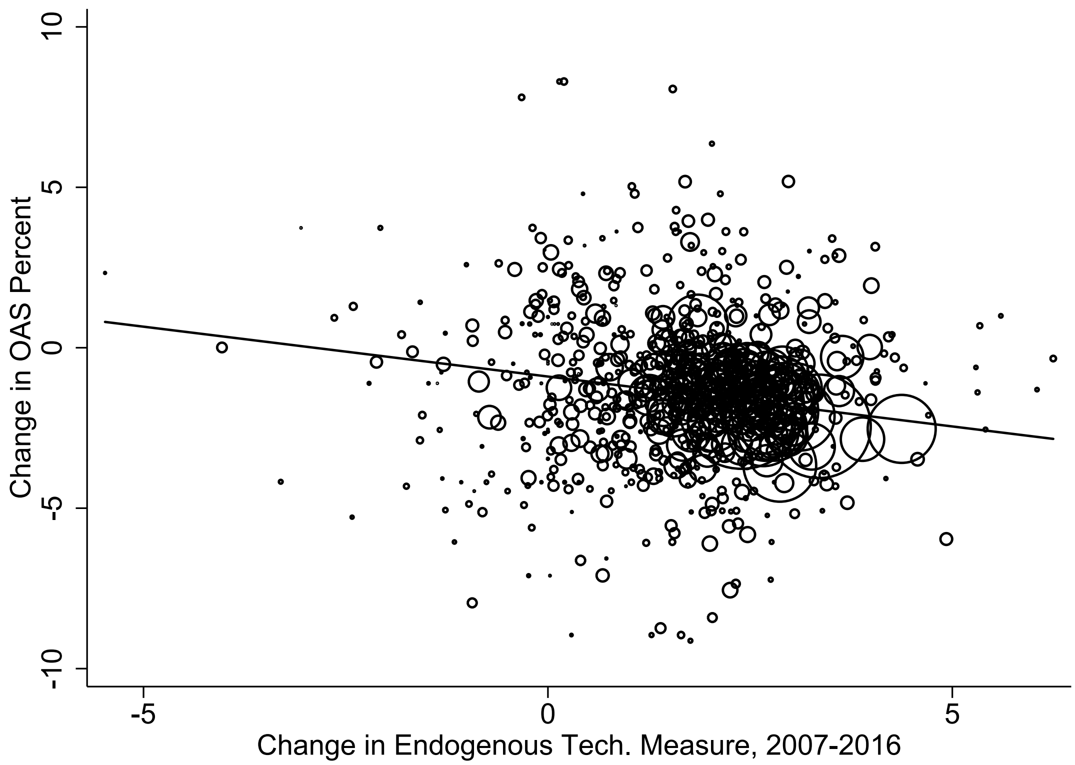


Figure 7: Relationship between Instrument and Endogenous Tech Measure

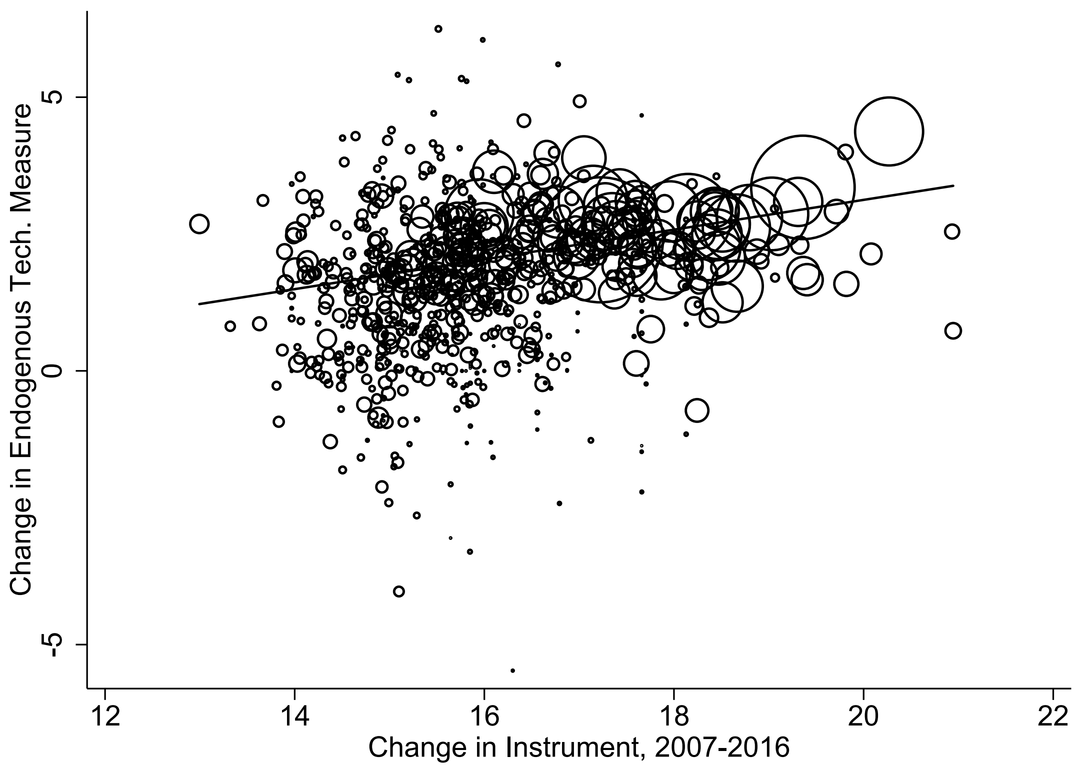


Figure 8: Defining Occupation Groups

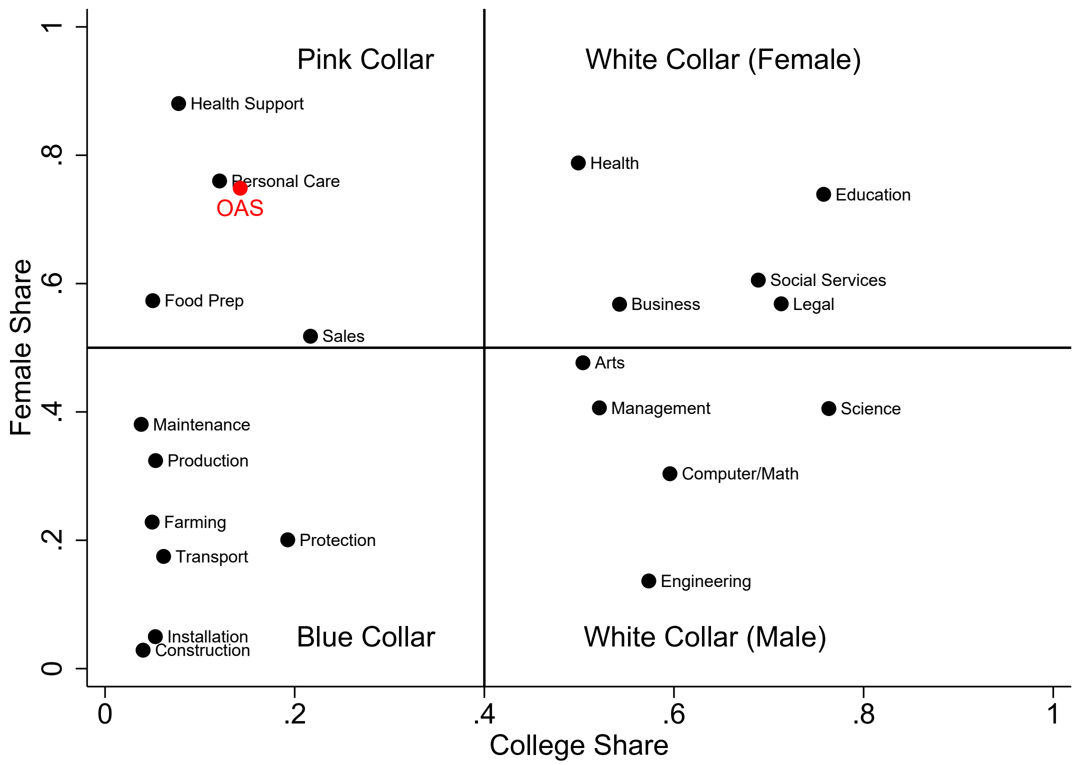


Table 1: Fixed Effects Models: Changes in Other Skill Requirements after Firms Begin Asking for Technology

	(1)	(2)
Lists Education Requirement	0.08964***	0.06283***
	(0.01182)	(0.00957)
% of Mean (0.383):	23.4%	16.4%
Requires High School	0.06294***	0.05119***
	(0.01046)	(0.00726)
% of Mean (0.292):	21.6%	17.5%
Requires College	0.02027***	0.00661***
	(0.00395)	(0.00231)
% of Mean (0.0329):	61.6%	20.1%
Lists Experience Requirement	0.05792***	0.03039**
	(0.01401)	(0.01547)
% of Mean (0.253):	22.9%	12.0%
Experience	0.11222	-0.00901
	(0.09068)	(0.08611)
% of Mean (0.469):	23.9%	-1.9%
n	1,060,605	769,884

$^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Each cell is the coefficient on the Technology indicator variable in Equation (1). Standard errors are clustered at the employer level and are shown in parentheses below the estimates. All specifications include year-month fixed effects.

Table 2: Change in Task Demand Associated with Technology Adoption

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Routine OAS Tasks			
VARIABLES	Basic Admin.	Clerk	Mail	Routine Accounting	Physical Tasks	
Tech	0.05274**	0.01688***	0.01367***	0.01430*	0.00564	
	(0.02428)	(0.00318)	(0.00344)	(0.00763)	(0.00685)	
% of Mean	23%	68%	19%	8%	13%	
R-squared	0.86004	0.84971	0.89291	0.86449	0.79840	
Mean	0.231	0.0247	0.0733	0.179	0.0440	
			Panel B: Functional Tasks			
VARIABLES	Legal	Accounting/Finance	Sales	Marketing	Logistics	HR
Tech	0.00206**	0.01483***	0.00497	-0.00626	-0.00115	-0.00444
	(0.00103)	(0.00431)	(0.01499)	(0.00560)	(0.00670)	(0.00639)
% of Mean	8%	36%	1%	-9%	-2%	-20%
R-squared	0.92427	0.84725	0.87641	0.88988	0.83532	0.81802
Mean	0.0263	0.0413	0.491	0.0673	0.0442	0.0217
			Panel C: High-Skill/Cognitive Tasks			
VARIABLES	Management	Cognitive	Writing	Research		
Tech	0.01086***	0.00517***	0.02878***	0.00705*		
	(0.00419)	(0.00180)	(0.00699)	(0.00406)		
% of Mean	13.8%	36.4%	32.2%	18.1%		
R-squared	0.83349	0.83757	0.83356	0.83529		
Mean	0.0787	0.0142	0.0892	0.0390		
Observations	769,884	769,884	769,884	769,884	769,884	769,884

$^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. Each cell is the coefficient on the Technology indicator variable in Equation (1). Standard errors are clustered at the employer level and are shown in parentheses below the estimates. All specifications include year-month fixed effects.

Table 3: 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%

Table 4: 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 5: 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

Ten largest OAS occupations from May 2016 OES estimates of national employment, collectively represent 77% 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 6: 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 7: 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 8: 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 9: 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 10: 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 11: 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 12: 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 13: 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											
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											
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)											
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)											
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)											
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)											
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											
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											
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											
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 14: 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

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		

Table A.3: 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% of total employment).

Table A.4: 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.5: 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 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: Changes in Skills Commonly Required in Other Occupations

VARIABLES	Management	Business	Legal	Sales
Tech	0.03542**	0.03746**	0.02621*	0.04448*
	(0.01774)	(0.01817)	(0.01514)	(0.02274)
% of mean	5.0%	5.2%	3.6%	5.9%
R-squared	0.77337	0.77391	0.78846	0.73458
Mean	0.715	0.716	0.728	0.749
Observations	769,884	769,884	769,884	769,884

$^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Each cell is the coefficient on the *technology* indicator variable in Equation (1). Standard errors are clustered at the employer level and are shown in parentheses below the estimates. All specifications include year-month fixed effects and employer by job-title fixed effects.

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

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. Although we found that adoption of technology was associated with increased demand for education and experience, we do not see a direct effect on the Deming-Kahn measure of Cognitive Skills. However, we do see 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 technology adoption is associated with an increase in high-skill tasks, in particular for writing and project management tasks. Although we also see an increase in people-management tasks, the relative magnitude is quite small compared to the mean. 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. However, we also see an increase in Customer Service Tasks, while our measure of Sales/Customer Service did not have a statistically significant increase.

Table A.9: Deming and Kahn Skill Measures

	(1)	(2)	(3)
	Panel A: Skills		
VARIABLES	Cognitive	Social	Character
Tech	0.00468	0.03197***	0.04075***
	(0.01538)	(0.00960)	(0.01577)
% of Mean	2%	13%	13%
Observations	769,884	769,884	769,884
R-squared	0.86267	0.81533	0.84351
Mean	0.201	0.248	0.310
	Panel B: High-Skill Tasks		
VARIABLES	Writing	Project Mgmt	People Mgmt
Tech	0.01582**	0.00283***	0.01894***
	(0.00630)	(0.00062)	(0.00430)
% of Mean	19%	56%	2%
Observations	769,884	769,884	769,884
R-squared	0.83247	0.81051	0.84240
Mean	0.0833	0.00509	0.0599
	Panel C: Functional Tasks		
VARIABLES	Financial	Customer Service	
Tech	0.01117***	0.05853**	
	(0.00336)	(0.02609)	
% of Mean	40%	8%	
Observations	769,884	769,884	
R-squared	0.84482	0.86936	
Mean	0.0281	0.774	