



HOW COMPUTER AUTOMATION AFFECTS OCCUPATIONS: TECHNOLOGY, JOBS, AND SKILLS

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How Computer Automation Affects Occupations: Technology, jobs, and skills

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1/16

Abstract: This paper investigates basic relationships between technology and occupations. Building a general model of occupations and tasks, I look at detailed occupations since 1980 to explore whether computers are related to job losses or other sources of wage inequality. Occupations that use computers grow faster, not slower. This is true even for highly routine and mid-wage occupations. Estimates reject computers as a source of significant net technological unemployment or job polarization. But computerized occupations substitute for other occupations, shifting employment and requiring new skills. Because new skills are costly to learn, computer use is associated with substantially greater within-occupation wage inequality.

JEL codes: O33, J24, J31

Keywords: technology, automation, human capital, job polarization, occupations, wage inequality

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Summary of Empirical Findings

- Computer use is higher in highly paid occupations, in larger occupations, in occupations employing more educated workers, and, to a lesser degree, occupations performing routine tasks.
- Employment grows significantly faster in occupations that use computers more. At the sample mean, computer use is associated with about a 1.2% increase in employment per year. This association is true in general and also for occupations that perform more routine tasks and for mid-wage occupations.
- Occupations that use computers substitute for other occupations. Specifically, occupations grow more slowly the more that *other* workers in the same industry use computers. Overall, inter-occupation substitution offsets the growth effect so that the net effect of computer use on total employment is negligible (0.1% per year). However, because higher wage occupations use computers more, computer use tends to increase well-paid jobs and to decrease low-paid jobs. Generally, computer use is associated with a substantial reallocation of jobs, requiring workers to learn new skills to shift occupations.
- Computer use is also associated with greater inequality of wages within occupations. Greater wage dispersion can arise if new skills are costly or difficult to acquire, so that only some workers acquire the skills. This association contributes to wage inequality, accounting for 45% of the growth in the wage gap between the 90th and 50th percentiles of the entire workforce since 1990; it can account for 30% of the increase in the 50/10 wage gap.
- Computer use is associated with an increase in the share of an occupation's workforce with four or more years of college, even for occupations that do not require a college degree. Moreover, such increases are associated with wage increases, suggesting that they do not result from an oversupply of college graduates.

Introduction

Are new computer technologies eliminating jobs at an increasing rate, generating technological unemployment and growing economic inequality?¹ One recent paper studied occupational characteristics to conclude that computer automation will put “a substantial share of employment, across a wide range of occupations, at risk in the near future” (Frey and Osborne 2013). Or is technology specifically eliminating jobs in mid-wage occupations, leading to “job polarization”?² Or is it the case, instead, that new technology plays no major role in growing wage inequality?³

New technologies automate work in specific occupations, but it is hard to evaluate competing claims about their overall impact because technology can affect occupations in different ways. Technology can reduce demand for an occupation, or increase it, or change the skills needed to practice an occupation. This paper attempts to estimate basic relationships between computer technology and occupations using detailed US occupational data and a theoretical framework that encompasses different ways technology can affect occupations. I use the theoretical framework to test whether the dominant pattern is consistent with claims made about the effect of computers on technological unemployment, job polarization, and wage inequality. I focus the empirical analysis on computer use because computer technology is held to be central to changes in employment and inequality over the last several decades and because data on computer use are available for detailed occupations. The analysis concerns computer automation of occupations within industries. Although computer automation is the focus of much attention, digital technology affects labor in other ways, including organizational changes, as I discuss below.

Does automating an occupation reduce employment?

A key insight of the recent literature is that computers automate particular tasks in specific occupations, making occupations central to analyzing the impact of computers. Bresnahan (1999) and Autor, Levy, and Murnane (2003) provide important evidence that computers are often used to automate routine tasks that are repetitive and follow explicit

¹ Brynjolfsson and McAfee (2014).

² Autor, Katz, and Kearney (2008), Acemoglu and Autor (2011), Goos and Manning (2007), Goos, Manning, and Salomons (2014), and Michaels, Natraj, and van Reenen (2014).

³ Card and Dinardo (2002), Mishel, Schmitt, and Shierholz (2013).

rules. Such tasks make it feasible to program a machine to perform “methodical repetition of an unwavering procedure.” Autor, Levy, and Murnane (2003) show a correlation between the use of computers in an industry and an aggregate measure of the extent to which the industry’s occupations perform routine tasks compared to non-routine tasks. They argue that computers thus tend to substitute for routine tasks performed by mid-skill workers such as bookkeepers, clerks, and bank tellers.

Autor, Katz, and Kearney (2008) go further and propose that because mid-skill occupations perform many routine tasks, computers substitute for workers disproportionately in these occupations, leading to a relative loss of mid-wage jobs. This tendency, they argue, gives rise to an observed pattern of “job polarization” also identified by Goos and Manning in European data (2007).

But does computer automation necessarily lead to a loss of jobs in the affected occupations? A quick look at the data suggests things might not be so simple. The top panel of Figure 1 shows the pattern of job polarization in employment growth rates for detailed occupations from 2000 through 2013.⁴ This panel displays smoothed average employment growth of occupations by the mean log hourly wage of the occupation.⁵ The horizontal dashed line shows the growth rate of the entire workforce. Mid-wage occupations clearly grow more slowly than occupations in both the first quartile (to the left of the first dashed vertical line) and the fourth quartile (to the right of the second vertical dashed line).

Yet the bottom panel provides some reason to question the assumption that computer use *causes* mid-wage occupations to grow slowly. This panel divides the sample into the group of occupations with above-median computer use (solid line) and those with below-median computer use (dashed line). Occupations that use computers more heavily—including routine occupations such as bookkeepers, clerks, and bank tellers—show no net pattern of job polarization although higher wage occupations grow faster in this group.⁶ The occupations that do not use computers appear to drive job polarization, perhaps because of

⁴ The sample, categories, and variables are described in detail below. Some studies use mean occupational education levels on the x-axis. The data from 2000 to 2013 do not show a clear pattern of polarization when plotted against mean education levels.

⁵ I use Stata’s smoothing routine with an Epanechnikov kernel with a 0.27 bandwidth.

⁶ The relative loss of jobs in the lowest quartile is slight because relatively few low-wage occupations use computers. Only 12 occupations in the lowest wage quartile used computers above the median level, many of these occupations grew, and the aggregate change in employment for this group was a net decrease of just 135,000 fulltime equivalent jobs.

globalization or other changes. This analysis is not complete because computer use in one occupation might cause job losses in another. Below I estimate inter-occupational substitution of this sort, finding a significant effect.

Nevertheless, the figure provides reason to question the assumption that automating a task eliminates jobs in the occupation. In fact, automation can increase demand for the affected occupation as well as decrease demand. Consider, for example, the effect of the automated teller machine (ATM) on bank tellers, a routine-intensive occupation. The ATM is sometimes taken as a paradigmatic case of technology substituting for workers; the ATM took over cash handling tasks.⁷ Yet the number of fulltime equivalent bank tellers has grown since ATMs were widely deployed during the late 1990s and early 2000s (see Figure 2). Indeed, since 2000, the number of fulltime equivalent bank tellers has increased 2.0% per annum, substantially faster than the entire labor force.⁸ Why didn't employment fall? Because the ATM allowed banks to operate branch offices at lower cost; this prompted them to open many more branches, offsetting the erstwhile loss in teller jobs (Bessen 2015). At the same time, teller skills changed. Non-routine marketing and interpersonal skills became more valuable, while routine cash handling became less important. That is, although bank tellers performed relatively fewer routine tasks, their employment increased.

Even though the ATM automated routine cash handling tasks, the technology alone did not determine whether employment of tellers grew or fell; economics mattered. New technology can increase demand for an occupation, offsetting putative job losses. Nor is this example exceptional:

- Barcode scanners reduced cashiers' checkout times by 18-19%, but the number of cashiers has grown since scanners were widely deployed during the 1980s.⁹
- Since the late 1990s, electronic document discovery software for legal proceedings has grown into a billion dollar business doing work done by paralegals, but the number of paralegals has grown robustly.¹⁰

⁷ See, for instance, Autor et al. (2003), Table 1.

⁸ Data from the 1% samples of the Census and ACS survey calculating; I calculate fulltime equivalent workers by dividing total hours worked by 2080. Total bank employment surged from the 1970s to the early 1980s, partly due to deregulation, but fell during the savings and loan crisis through the 1990s and has since resumed growth despite the ATM. The case study is drawn from Bessen (2015, pp. 107-9).

⁹ Basker (2015). From 1980 through 2013, fulltime equivalent jobs for cashiers have grown at an annual rate of 2.1%.

- E-commerce has also grown rapidly since the late 1990s, now accounting for over 7% of retail sales, but the total number of people working in sales occupations has grown since 2000.¹¹
- More generally, the manufacturing share of the workforce grew from less than 12% in 1820 to 26% by 1920 despite pervasive labor-saving automation.¹² For example, during the 19th century, technology automated 98% of the labor involved in weaving cloth, but the number of weavers grew nevertheless (Bessen 2015).

As we shall see, employment growth has been associated with computer use overall. The ATM may be more a representative example than an exception.

Occupations and the impact of technology

In evaluating the impact of technology on occupations, it would help to have a theory that can accommodate both growth and decline in occupational employment in response to the automation of some tasks. That is, we need a model of occupations *and* tasks. Occupations are an important unit of analysis because technologies tend to automate specific occupations and also because a considerable portion of human capital appears to be occupation specific (Shaw 1984, 1987, Kambourov and Manovskii 2009). Occupations have become increasingly important in research on wage inequality. Researchers have proposed that occupational differences help explain “job polarization” (Autor, Katz, and Kearney 2008, Goos and Manning 2007) and offshoring (Blinder 2007, Jensen and Kletzer 2010). Acemoglu and Autor (2011) argue that occupations have increasing explanatory power for predicting wages.

However, most of the theoretical literature on wage inequality abstracts away from formal consideration of occupations *per se*, speaking, instead, of skilled or unskilled workers individually. Even the model of Autor, Levy, and Murnane is based on *tasks* only, rather than on occupations.¹³ This paper presents a model that integrates automation of tasks with a

¹⁰ From 2000 through 2013, fulltime equivalent jobs for legal assistants, paralegals, and legal support occupations grew 1.1% per year, faster than the workforce. This growth occurred despite substantial offshoring as well.

¹¹ From 2000 through 2013, fulltime equivalent jobs in sales occupations grew 0.4% per year, slightly slower than the overall growth in the workforce (0.6% per year).

¹² US Dept. of Commerce (1975). The 1820 figure includes construction workers.

¹³ See also Autor and Acemoglu (2011) and Goos, Manning, and Solomons (2014). The latter models both tasks and occupations but assumes that each occupation only performs one task.

generalized treatment of occupations. The distinction between tasks and occupations is important because conclusions about tasks do not translate unambiguously into conclusions about occupations, as the example of the bank tellers shows.

Demand for tellers increased when cash handling tasks were automated. There are at least two reasons why automation might increase demand for an occupation in general. First, by reducing product cost (and hence price in a competitive market), automation can increase product demand, thus increasing demand for labor. Second, because automation increases the efficiency of labor in an occupation, firms may demand relatively more labor from that occupation compared to others. That is, firms might substitute labor in the automated occupation for labor in other occupations.

This latter case is an instance of biased technical change, but one quite distinct from the standard account of skill-biased technical change discussed in the literature.¹⁴ In the “canonical” version, unskilled labor and skilled labor—usually meaning college-educated labor—are substitutes in production. Computers enhance the efficiency of college-educated labor, leading to greater relative demand for college-educated workers. While this canonical model provides a simple explanation for the rising relative demand for college-educated workers during the 1980s, it has been seen as unable to explain stagnant real wages for college educated workers during recent years and disparate patterns of job growth across different wage levels (Mishel, Schmitt, and Shierholz 2013; Acemoglu and Autor 2011).

This paper presents a simple model of occupations where automation of tasks can induce substitution of one occupation for another. The model includes cases where occupations of college-educated workers substitute for occupations of less educated workers, but it also includes a wide variety of other interactions. The model contemplates a different sort of skill-biased technical change, one where the relevant skills are occupation-specific rather than corresponding to schooling per se.¹⁵ Moreover, to the extent that new occupation-specific skills are costly to acquire, the model implies that wage inequality may increase within occupations. This happens because the payoffs to learning may be greater for more capable workers. Occupational sorting may also contribute to shifts in skill characteristics of occupations.¹⁶

¹⁴ See Acemoglu (2002) for a review of this literature.

¹⁵ Schooling, of course, is often correlated with occupational skills.

¹⁶ Roy (1951), Autor, Levy, and Murnane (2003), and Acemoglu and Autor (2011).

The notion that automation causes technological unemployment ignores inter-occupation substitution, effectively assuming that the elasticity of substitution is zero. I build a general model that includes both task automation and inter-occupation substitution so that I can test whether the latter is a significant effect and hence test the technological unemployment hypothesis. I can also test similar hypotheses about computers substituting for workers in routine or mid-wage jobs.

I estimate the model for a consistent set of detailed occupations from 1980 through 2013. In contrast, most of the empirical research that considers occupation does not use detailed occupations as the unit of analysis, but instead aggregates occupational task characteristics over industries or local labor markets or broad occupational groups.¹⁷

Aggregation of this sort risks conflating the effect of automation with other factors such as offshoring, technology-driven changes in industry demand, organizational changes, and the effects of older technologies.¹⁸ Establishing more direct relationships between computer technology and disaggregated occupations might be critical for identifying the impact of automation. The use of disaggregated data also allows differences in the impact of computers to be distinguished from differences in computer adoption. I look at differences in adoption and impact across different groups including occupations that perform routine tasks (Autor, Levy, Murnane 2003), low-, mid-, and high-wage occupations, occupations where capital-skill complementarity might be important (Griliches 1969, Goldin and Katz 1998), and winner-take-all occupations (Rosen 1981, Frank and Cook 1995).

In another respect, this analysis is limited: it only concerns computer automation, not the entire range of computer-related technological change. The model considers only the direct effects of using computers in occupations and on other occupations in the same industry. Yet digital technology may also play an important role in extra-industry organizational changes that affect employment. For example, lower communication costs and miniaturization might encourage the transfer of work offshore or decentralization; computer systems can facilitate self-service business models, transferring work to households. Although these changes do not necessarily reduce the total amount of labor performed, they do impact domestic employment. Most of the concern about computers

¹⁷ Autor, Levy, and Murnane (2003), Autor and Dorn (2013), Autor, Dorn, and Hanson (2015), Goos and Manning (2007), Goos, Manning, and Salomons (2014), and Michaels, Natraj, and van Reenen (2014).

¹⁸ Autor, Dorn, and Hanson (2015) attempt to disentangle trade and technology effects using local labor markets as the unit of analysis.

focuses on automation, however. To the extent that extra-industry organizational changes are orthogonal to within-industry automation, automation can be analyzed separately; to the extent that offshoring and other changes are correlated with automation, the econometric analysis needs to control for these trends.

I begin by developing a simple general model of occupations and task automation.

Models of Technology and Occupations

Production and Occupations

Suppose firms use labor delivered in the form of occupational services such as the services of accountants, computer programmers, etc. Two features characterize occupations. First, the services provided by any worker within the occupation are highly substitutable with the services provided by another in the same occupation. While workers within an occupation may differ in the quantity and quality of the services they provide, their inputs are much more substitutable with each other than they are with services provided by workers in other occupations. Firms seek carpenters to do a particular job, but not bakers. This limited substitutability between occupations implicitly arises because of different occupation-specific skills.

Second, workers in each occupation perform a bundle of multiple tasks. Following Rosen (1983), indivisibilities in learning occupation-specific limit the division of labor given the size of the market for an occupation. Because of these indivisibilities, firms hire workers to perform a bundle of interrelated tasks rather than having them specialize in a single task. For this reason, a model of occupations differs fundamentally from models of tasks in Autor, Levy, and Murnane (2003) or Acemoglu and Autor (2011).

These characteristics of occupations are, of course, stylized abstractions. Workers within an occupation might have sub-specialties that make some more substitutable with each other than with others. Also, the division of labor sometimes changes, transferring tasks from one occupation to another; that is, occupations can be redefined. Nevertheless, the notion of highly substitutable labor performing a discrete bundle of tasks is essential to what we mean by occupation.

To take the stylization one step further, I assume that the services of one worker within an occupation are perfectly substitutable for the services of another, so that the level

of services can be measured in quality-adjusted efficiency units. That is, the total services of occupation j used by a firm, Y_j , can be written as the sum of the occupational services of individual workers, y_{ij} ,

$$Y_j = \sum_i y_{ij},$$

and the firm production function can be written

$$(1) \quad Q = Q(Y_1, Y_2, \dots, K),$$

where K is capital and Q is a constant returns concave function, continuous and twice-differentiable. Goos, Manning, and Salomons (2014) model a similar production function, however, they assign a single task to each occupation. To gain a richer picture of the interaction between task automation and occupational employment, I next develop a model where occupations perform multiple tasks.

Occupations, Tasks, and Skills

Occupational services are delivered through the performance of discrete tasks; automation reduces or eliminates the time needed to perform a task.

Economic histories typically find that technological innovations sequentially improve discrete steps in production processes over a long period of time (Rosenberg 1979, Hollander 1965, Nuvolari 2004). Labor is affected when technology automates discrete tasks. Bessen (2012) studied the major inventions affecting US cotton weaving over the 19th century. Some inventions, such as improvements in steam engines, affected capital efficiency, but labor efficiency was improved by inventions that automated discrete tasks such as replacing empty bobbins or fixing thread breaks. These inventions reduced the time it took a weaver to perform a task or reduced the frequency with which a task had to be performed, in some cases completely automating the task. That is, automation was labor augmenting.

Computer automation appears to play a similar role. For example, in their study of computer technology for valve manufacture, Bartel, Ichniowski, and Shaw (2007) found that different IT technologies automated tasks involved in setting up production runs, reduced the time involved in transferring work from one machine to another, and automated some inspection tasks. Similarly, common computer applications allow workers to perform specific tasks faster or better: word processing reduces the time needed to edit documents,

spreadsheets reduce the time needed to perform routine calculations, and search functions speed the recovery of documents.

Following Acemoglu and Autor (2011), for each task, k , each worker i produces $A_k s_i^k$ of task output per unit of labor time, where A_k represents the state of factor-augmenting technology and s_i^k measures the skill of the worker at task k . The skill level reflects differences in workers' inherent talents, education, and experience, including occupation-specific training. It may also reflect the ability of a worker to learn occupation-specific skills on the job. I assume that these skills represent general human capital to the occupation, that is, individual i would deliver the same level of services in occupation j to any firm within the industry.

The time it takes worker i to produce a unit of task k services is

$$t_{ik} = \frac{1}{A_k s_i^k}$$

Assuming that a unit of occupational service j requires a unit of each task output for tasks 1, 2, ..., n , the labor time worker i needs to produce a unit of occupational service j is $t_{i1} + t_{i2} + \dots + t_{in}$. Equivalently, worker i 's output of occupational service j per unit of labor time is (2)

$$y_{ij} = \frac{1}{t_{i1} + t_{i2} + \dots + t_{in}} = \frac{1}{1/A_1 s_i^1 + 1/A_2 s_i^2 + \dots + 1/A_n s_i^n}.$$

This production function has been studied before by Arrow, Levhari and Sheshinski (1972) and Levhari and Sheshinski (1970).¹⁹ Bessen (2012) found that this task-level production function provides a good first order approximation to actual output in textile production over a range of automating inventions. Changes in technology that automate task k can be represented as increases in A_k . The case where technology completely automates task k is represented by $A_k \rightarrow \infty$ so that $t_{ik} \rightarrow 0$.

For the most basic model, I assume that worker skills are the same across tasks, $s_i = s_i^1 = s_i^2 = \dots = s_i^n$. Then

¹⁹ In operations research it is known as the solution to a queuing problem with a finite calling population.

(3)

$$y_{ij} = a_j s_i, \quad a_j \equiv \frac{1}{1/A_1 + 1/A_2 \dots + 1/A_n}.$$

In this case, an increase in A_k generates a corresponding increase a_j .²⁰ In the Appendix I consider the case where skills might take more than one dimension, e.g., non-routine skills and routine skills. Assume that the values of s_i are normalized so that the mean value for workers in occupation j is 1.

Wages and Employment

Since each worker's output of occupational services is equivalent, the firm will pay workers based on the services they provide. Let p_j be the price paid for an efficiency unit of service j so that each worker i earns $p_j a_j s_i$. Then, given the normalization of s , we can define the mean occupational wage $w_j \equiv p_j a_j$ or,

$$(4) \quad p_j = w_j/a_j.$$

I assume that the occupational wage is determined at a labor market equilibrium. Given the prices for occupational services, the firm's profit is

$$\pi = P \cdot Q(Y_1, Y_2, \dots, K) - \sum_j p_j Y_j - rK,$$

where P is product price and r is the capital rental price. The profit maximizing condition for the j th service is then

$$P \frac{\partial Q}{\partial Y_j} = p_j = w_j/a_j.$$

Finally, the number of workers in occupation j , is

$$L_j = Y_j/a_j.$$

First-order Effect of Automation

We can explore the first-order effect of a change in a_j in a partial equilibrium setting where wages are held constant. To the extent that this change only affects one occupation, it will have little impact by itself on aggregate demand for labor and hence little immediate effect on wages. In a general equilibrium model with automation of tasks across many

²⁰ And I assume that in general, a will remain finite. If *all* of the tasks involved in an occupation were completely automated this would not be the case. However, while computers may one day reach that level of automation, one is hard pressed to find an example of that case today.

occupations, labor demand and wages will change, but these changes will affect all occupations. The partial equilibrium analysis nevertheless helps analyze why employment increases in some occupations and decreases in others in response to automation.

Looking at (4), the effect of an increase in a_j is to reduce the price of the j th occupational service in efficiency units, p_j . This change, in turn, affects employment levels. Whether that price change increases or decreases employment in the j th occupation depends on how easily the services of this occupation substitute for the services of other occupations.

The interaction can be neatly shown for the case of a constant elasticity of substitution production function for a firm with multiple occupations:

$$Q = \left(\sum_j Y_j^\rho \right)^{1/\rho} = \left(\sum_j (a_j L_j)^\rho \right)^{1/\rho}, \quad \rho \equiv \frac{\sigma - 1}{\sigma}$$

where σ is the elasticity of substitution. Assuming that the firm maximizes profits and that the product market is competitive with constant elasticity of demand ϵ , then (see Appendix) equilibrium employment in occupations j and k change as

(5a)

$$\frac{d \ln L_j}{d \ln a_j} = \sigma - 1 + S_j(\epsilon - \sigma)/\epsilon,$$

(5b)

$$\frac{d \ln L_k}{d \ln a_j} = S_j(\epsilon - \sigma)/\epsilon, \quad S_j \equiv \frac{p_j Y_j}{p_j Y_j + p_k Y_k}; \quad j \neq k$$

Factor augmentation of occupation j will increase or decrease employment in occupations j and k depending on the elasticity of substitution, the elasticity of demand, and on S_j , the share of the wage bill going to j . These equations capture both substitution effects and demand growth effects on occupational employment. The term, $S(\epsilon - \sigma)/\epsilon$, captures the tradeoff between employment gains from demand growth and losses from substitution; the term, $\sigma - 1$, captures the relative gain in employment that the augmenting occupation gets from substitution. Setting (5a) and (5b) to zero lets us solve for parameter values that form solution regions displayed in Figure 3. Each region exhibits a different pattern of employment changes in response to the automation of one occupation as shown in the table below the figure. Clearly, automation does not necessarily eliminate jobs for either the automated occupation or other occupations in the firm.

Equations (5a) and (5b) can be combined to derive an equation that can be estimated. The growth rate of employment in occupation j can be written

$$d \ln L_j = \sum_k \frac{\partial \ln L_j}{\partial \ln a_k} d \ln a_k = (\sigma - 1) d \ln a_j + \frac{\epsilon - \sigma}{\epsilon} \sum_k S_k \cdot d \ln a_k$$

where k counts all occupations. Let $d \ln a_j = bU_j$ where U_j is the level of computer use in occupation j . Assuming that all firms in an industry have the same production function, employment growth for occupation j in industry i can be estimated as

(6)

$$d \ln L_{ij} = \alpha U_{ij} + \beta X_i + D_i I(i) + \mu_{ij}$$

$$\alpha \equiv b(\sigma - 1), \quad \beta \equiv b(\epsilon - \sigma)/\epsilon, \quad X_i \equiv \sum_k S_{ik} \cdot U_{ik}.$$

where X_i is a wage-weighted average of industry computer use, D_i is an industry dummy coefficient, I is an indicator function, and μ_{ij} is an error term.

Occupation-specific skills and inequality

The employment changes in equation (6) can influence wage differences between occupations. Computers might also affect wage inequality *within* occupations. This can happen if workers' decisions to invest in learning new technology vary with worker skills. If more highly skilled workers get a greater payoff from acquiring new knowledge, they may choose to invest while less skilled workers do not; they will then command relatively higher wages and wage disparity will be greater. A simple model extension demonstrates this intuition.

To simplify the exposition, I assume that workers pay for human capital; an equivalent result can be obtained if firms pay. Suppose that the equilibrium wage for worker i in occupation j is $w_{ij} = z_j s_i$ where s_i is the worker's skill level. In general, the occupational wage will be greater than the alternative wage the worker could earn by switching to another occupation, $w_A = z_A s_i$, $z_j > z_A$. This difference arises because entry into the occupation requires human capital investments and $z_j - z_A$ represents the return on this sunk investment.²¹ Since $w_{ij} = p_j a_j s_i$, the price for an efficiency unit of occupational service j is

²¹ The gap might also arise from labor market frictions as in Acemoglu and Pischke (1999).

$$p_j = \frac{z_j}{a_j}$$

Suppose there are only two skill levels, s_L and s_H with $s_L < s_H$. Suppose also that new technology increases the efficiency of occupational service j from a^0 to a^1 , but only if a worker invests learning cost c . Designate the initial efficiency price as (suppressing the j subscript) $p^0 = z/a^0$. Assuming that workers can command some portion of rents, type H workers will initially invest in the new technology as long as $p^0 a^1 s_H - c > p^0 a^0 s_H$. Assume this condition is met and that there is a sufficient supply of type H workers; they will continue to invest until the price falls to $p^1 = z/a^1 + c/a^1 s_H$ so that $p^1 a^1 s_H - c = z s_H$.

But at this price, a type L worker will no longer choose to enter the occupation. Entering and investing would earn a wage of $p^1 a^1 s_L - c = z s_L - c(1 - s_L/s_H) < z s_L$. At this wage, the worker would not recoup the human capital investment needed to enter the occupation and the worker would be better off in alternative employment.²² However, a type L worker who had *already* sunk a human capital investment would not necessarily leave the occupation. As long as $p^1 a^0 s_L > z s_L$, the worker would be better off continuing to practice the occupation using the old technology.

In this case, the new technology is non-drastic, that is, both old and new are practiced at the same time. A well-established literature finds that old and new vintages of technology often coexist for long periods of time, sometimes stretching to several decades.²³ Non-drastic innovation appears to be the case with the use of computers within occupations: in 1997, 77% of workers were in occupations that were only partially computerized, with between 10% and 90% of workers using computers. My simple model is a version of Salter's model of technology vintages with sunk costs (1960).

Because workers of different skill levels invest differently, their efficiencies differ as well as their wages. Initially, the high and low skill workers earn wages in proportion to their skills,

$$\frac{w_H}{w_L} = \frac{p^0 a^0 s_H}{p^0 a^0 s_L} = \frac{s_H}{s_L}.$$

²² It is easy to show that the worker cannot recoup her investment by using the old technology as well.

²³ Griliches (1957), Salter (1960), Mansfield (1961) and Rogers (1962).

But after the new technology is introduced,

$$\frac{w_H}{w_L} = \frac{p^1 a^1 s_H}{p^1 a^0 s_L} = \frac{a^1 s_H}{a^0 s_L} > \frac{s_H}{s_L}.$$

This model provides a possible explanation for growing disparity of wages within occupations. Also, only skilled workers will now enter the occupation, either as employment expands or to replace workers exiting as part of normal turnover. Hence the occupation will employ relatively more skilled workers. Thus the model suggests that computer use might be associated with greater wage disparity and skill upgrading within occupations, hypotheses I test below.

In the literature, two other factors might also influence jobs and wages within occupations. Roy (1951) argues that when workers' skills vary along different dimensions, workers will choose to work in those occupations where they have comparative advantage. Autor, Levy, and Murnane (2003) and Acemoglu and Autor (2011) apply this in models where workers sort themselves into performing routine and non-routine tasks. A key finding is that automation of routine tasks tends to reallocate workers to non-routine tasks. In the Appendix, I show how occupational sorting can be integrated into my model. A key result is that although occupational sorting predicts changes in the relative demand for different skills, it does not have clear predictions about relative wages within occupations in a partial equilibrium setting.²⁴

Second, Frank and Cook (1995) suggest that technology may increase the pay of "superstars" in certain occupation. Following Rosen (1981), the very best participants in certain occupations may benefit disproportionately when technology decreases costs. For example, lower reproduction costs for films may disproportionately benefit superstar actors. It is not clear that this phenomenon might affect anybody below the very top performers in an occupation, but it is conceivable that if markets are sufficiently segmented, superstars might exist in the 90th percentile.²⁵ To test this below, I identify a group of occupations consisting of top-level service providers (the superstar effect requires a personal market that seems unlikely for, say, a medical assistant) likely realizing lower costs from computer technology.

²⁴ That is, occupational sorting changes the overall demand for different skills, affecting relative wages overall, but relative changes do not change more or less in occupations that computerize, all else equal.

²⁵ Of course, a segmented market seems at odds with the idea that new technology can greatly expand the market.

Technology Adoption

Finally, a key factor affecting the economic impact of computers is the nature of the occupations that adopt computers. For example, Autor, Katz, and Kearney (2008) suggest that computers contribute to job polarization because computers automate routine tasks and routine tasks are more important for mid-wage occupations. There is a substantial literature on technology adoption that identifies a number of endogenous factors that might influence differences in computer adoption across occupations (see Hall and Kahn 2003, Rosenberg 1972, Caselli and Coleman 2001).

The model provides a useful framework for thinking about these. Suppose that an inventor or software developer can make an improvement that increases a_j (a similar scenario can be sketched for technology adoption decisions). This developer will choose to make that improvement as long as the return from the invention exceeds the development cost. Various occupational characteristics might influence this economic calculation and thus affect which occupations adopt computers.

Bresnahan (1999) and Autor, Levy, and Murnane (2003) argue that computer programs can automate routine tasks that have formal, repeatable rules. For this reason, development costs should be less for automating routine tasks. Occupations that perform a lot of routine tasks might have lower development costs for multiple tasks and thus higher computer adoption, all else equal.

But this is not the only factor affecting development and adoption decisions. The payoffs also matter. For example, the payoff to automating routine arithmetic calculations might be much greater for a highly paid accountant than for a low-wage clerk, even if the clerk performs more routine tasks. Assuming that inventor payoffs are proportional to the payoffs technology users receive, several occupational characteristics might be important:²⁶

- Skilled employees will (temporarily) benefit more from adopting the improvement.

Since the wage for a worker with skill s is $p_j a_j s$, the worker's benefit is $p_j \Delta a_j s$, which is larger with a greater s . Since wages are also greater with skill level, occupational wages might be correlated with computer adoption. Effectively, the payoff is greater to automating more highly paid occupations.

²⁶ With some complication we could formally model intellectual property, but since the model assumes competitive markets it is simpler to assume that the developer earns temporary profits as a first mover and those profits are proportional to the payoff that technology users receive.

- If the improvement is drastic, meaning all workers in the occupation adopt the new technology, then the (temporary) payoff to firms will be proportional to the wage bill for the occupation. All else equal, occupations with a greater wage bill might have higher computer adoption.
- If the improvement is non-drastic and only new employees adopt the new technique, then the payoff to adoption will be proportional to the growth in employment in the occupation. From equation (5a), this will be greater with greater product demand elasticity and greater elasticity of substitution.

Below I explore the importance these factors empirically.

Data and Variables

The basic data on occupations come from the 1% public use samples of the US Census for 1980, 1990, and 2000, and the American Community Survey for 2013 (Ruggles et al. 2015). These samples are sufficiently large so that statistics on detailed occupations do not suffer from excessive sampling error. In my sample I include persons aged 16 through 64 who worked as wage and salary workers in the 50 US states in civilian occupations, excluding self-employed workers, unpaid family workers and workers living in institutions.

Hourly wages are calculated using the reported wage and salary income for the previous year²⁷ divided by the product of usual hour worked per week times weeks worked last year.²⁸ I deflate the hourly wage using the Consumer Price Index.

The analysis here requires a balanced panel of consistent occupations. The Census has changed occupational definitions over time, new occupations arise, and old ones are sometimes dropped. Meyer and Osborne (2005) develop a consistent set of occupational codes that covered the Census occupations from 1960 through 2000. I use their classification but I further combine some detailed occupations. I also drop 24 detailed occupations that were not found in all years. These dropped occupations accounted for less than 3% of the weighted sample in all years. My resulting panel had 317 consistent

²⁷ I make adjustment at the extreme upper and lower tails. I recode all values of the hourly wage less than the wage of the first percentile to the wage of the first percentile. Topcoded incomes were replaced with mean incomes in excess of the topcode value by state for 2000 and 2013, the median income in excess of the topcode value in 1990, and 1.5 times the topcode value in 1980. To make sure that this procedure did not distort results, I repeated key regressions below excluding topcoded individuals; the results were not significantly different.

²⁸ For 2013, weeks worked is only reported in intervalled categories. I replaced these values with the mean weeks worked for each category from the 2000 Census sample.

occupations populated in each year studied. It is possible that the analysis of occupational differences might be particularly sensitive to the narrowness of occupational definitions and, correspondingly, to the number of occupational categories. To check the robustness of my results both regarding the procedures used to create a balanced panel and the number of categories used, I repeated key regressions between 2000 and 2013 using 2000 Census occupation codes (using a crosswalk to combine some categories in 2013). This analysis used 450 occupational codes, but the results were broadly similar.

Computer use data come from a supplement to the October Current Population Surveys (CPS) of 1984, 1989, 1993, and 1997, which asked whether adult respondents directly used a computer at work. For the most basic measure of computer use, I take the weighted average for each occupation over all four years and I allocate these averages to Census occupations using crosswalks. While workers generally increased their use of computers from 1984 to 1997 (see below), I utilize the average level of computer use to measure computer technology, recognizing that most computer users migrate to new applications and new systems over time.²⁹ This procedure reduces measurement error. One concern is that my sample extends to 2013 and unfortunately the CPS has not included this question since 1997. However, the Labor Department's Occupational Information Network (O*NET) rates occupations on how much they involve "interacting with computers." I find that these measures are highly correlated with the averages obtained from the CPS (0.88 correlation using the 2013 O*NET), suggesting that relative use of computers has not changed much across occupations.

I use this measure of computer use in Tables 4 and 5. However, the construction of this variable introduces a possible bias when the dependent variable is the growth in occupational employment as in Tables 2 and 3. This is because occupational employment appears in the denominator of the computer use variable, which is calculated as computer users divided by total employment in the occupation. When this variable is calculated after the beginning of the period, it will be correlated with the error term, introducing a downward bias.³⁰ To minimize this bias, I rebase the computer use variables in these tables

²⁹ For the pooled sample, the weighted mean and standard deviation of computer use are 38% and 28%.

³⁰ An exogenous increase in employment will make the computer use variable smaller when the denominator uses end-of-period employment. It is straightforward to show that this will introduce a downward bias in the estimated coefficient.

using 1984 occupational employment in the denominator.³¹ In any case, the results differ only slightly from estimates using the simple average measure of computer use.

To estimate equation (6), I use the 317 occupations across 243 detailed industries from the 1990 Census. To calculate wage-weighted industry mean computer use, X , I obtain computer use for occupation-industry cells from the CPS, use crosswalks to convert them to Census categories, and then weight them using hour-weighted mean wages for each occupation-industry cell in the Census data.³²

Autor, Levy, and Murnane (2003) developed measures of occupational task characteristics based on the Dictionary of Occupational Titles (US Dept. of Labor 1991). I use their measures of the importance of routine tasks to an occupation and the importance of abstract tasks.³³

Empirical Findings

Which Occupations Use Computers?

The effect of computers on occupations will significantly depend on which occupations adopt computers. Much of the literature focuses on the role of routine tasks. Autor, Levy, and Murnane build a model that relates computer use to the share of routine tasks in production and they find a significant correlation between the use of computers in an industry and the share of routine tasks. They create a proxy for the share of routine tasks by calculating employment-weighted averages of the measures of the importance of routine and non-routine tasks across the occupations in each industry and then taking the ratio of

³¹ Specifically, the denominator is occupational employment in 1984 and the numerator is the sum of computer users in year 1984, 1989, 1993, and 1997 times the ratio of the total workforce in 1984 divided by the workforce in each year. Of course, there might still be a slight bias due to the effect of employment growth between 1980 and 1984, but this should be small compared to the growth to 2013.

³² For a significant number of occupation-industry cells, there are no observations of computer use in the CPS data. In these cases, I impute computer use by using the mean computer use for the occupation across all industries. I also tested the robustness of the data by imputing cells with small numbers of observations in the CPS. These trials produced very similar estimates.

³³ Their measures are based on five rankings from the Dictionary of Occupational Titles which they normalize to a scale from zero to ten based on the rankings of occupations in 1960, with 5 being the 1960 median. Routine task importance is the average of the ranking for requirements for Finger Dexterity and working with Set Limits, Tolerances, and Standards; abstract task importance is the average of rankings for Direction, Control, and Planning activities and GED-Math; Eye Hand and Foot coordination is an additional non-routine task is also included in some of the analyses. See Autor, Levy, and Murnane for more details. Thanks to David Autor for making these data available (<http://economics.mit.edu/faculty/dautor/data/autlevmurn03>). Descriptions of these task rankings can be found in US Dept. of Labor (1991).

the routine task importance to the sum of the routine and non-routine task importance measures.

If their model is correct, one might expect to find a positive correlation between this ratio and the level of computer use both across industries and occupations.³⁴ Autor, Levy, and Murnane do find a positive correlation across industries, but, as column 1 of Table 1 shows, the correlation is negative across occupations. This table regresses the computer use of 478 occupations against various occupational characteristics including the routine task share ratio, using the same data on occupational characteristics as Autor, Levy, and Murnane and the same measures of computer use from the CPS.³⁵

The reason for the negative correlation in the table is evident in the regression shown in column 2, which simply uses the direct measures of importance of routine tasks and abstract tasks (non-routine cognitive and interpersonal tasks) as independent variables. While the importance of routine tasks to an occupation is associated with greater computer use, the importance of abstract tasks is much more significant. Since the latter appears in the denominator of the ratio in column 1, the ratio has a negative correlation with computer use. This finding does not necessarily contradict Autor, Levy, and Murnane's basic hypothesis that routine tasks are more prone to be automated by computers. It does suggest, instead, that the importance of routine tasks to an occupation is simply not the only determinant of computer use.

Moreover, the relative importance of routine tasks in determining computer adoption has been decreasing over time. The dependent variable in column 3 of Table 1 shows the annual change in the share of workers using computers in each occupation. I calculated these rates of change by regressing computer use in each occupation against the year, excluding occupations with fewer than three observations or with only one worker observed in any year. I use the inverse of the standard error from the rate regression as the regression weight in column 3. Occupations with more routine tasks have slower growth in computer use than others; occupations where abstract tasks are more important have faster growth in computer use.

³⁴ It is possible that computers might automate tasks previously performed by a routine occupation but be used by other occupations in the industry. I explore this possibility below.

³⁵ Regressions include year dummies and are weighted by CPS sample weights.

These trends can be seen in Figure 4. Panel 4a shows the comparable trends in occupations grouped by above- and below-median rankings for the importance of abstract tasks (using the 1960 distribution). Abstract tasks are a more important factor related to computer use and that importance has increased over time. Panel 4b shows mean computer use over time for occupations with above median importance of routine tasks and below median. The gap between the two groups is small and becomes negligible in 1997.³⁶ Perhaps the first wave of computer automation targeted “low hanging fruit” in routine-intensive occupations but subsequent innovations may have targeted more valuable opportunities in occupations that perform more abstract tasks.

As above, computer use might also be influenced by factors affecting the payoff to adoption. Occupations performing abstract tasks likely recruit more highly skilled workers who are better able to learn new technology. Hence worker skill might be positively associated with adoption decisions. Also, the size of the total wage bill for the occupation might correlate with adoption. Column 4 of Table 1 replaces the abstract task variable with variables for the share of workers with four or more years of post-secondary education and the mean log wage for the occupation (in 1980), both measures of skill, and the log of employment in the occupation.³⁷ These coefficients are all statistically significant and the log wage and college share are both economically significant. The coefficient of the routine task rating is small and insignificant.

In summary, the extent to which occupations perform routine tasks is not a very important factor in determining computer use and the significance of this factor appears to have diminished over time. The importance of the economic payoff to automation seems to be a much more important driver of endogenous adoption decisions and the payoff appears to be greater in well-paid occupations.

³⁶ Running the regression in column 2 just for 1997, the coefficient for routine tasks is small and no longer statistically significant.

³⁷ The sum of log employment and log wage gives the log of the wage bill, so that is implicitly included in this specification.

Computer Use and Employment Growth

Do computers replace workers?

Much public discussion of computer automation is based on a simple view that computer automation eliminates jobs, either generally, so as to cause technological unemployment, or for specific groups such as mid-wage workers or workers doing routine work, so as to cause job polarization. These views implicitly ignore inter-occupation substitution, effectively assuming that $\sigma = 0$. Imposing this constraint and absorbing industry differences into the error term, (6) becomes

$$d \ln L_j = \gamma U_j + \delta + \varepsilon_j.$$

Table 2 estimates variations on this equation using the growth rate of detailed occupations as the dependent variable. Column 1 shows that computer use is associated with faster growth in the labor of an occupation, not a decrease. The coefficient of computer use is positive, statistically significant, and substantial. In the total sample, 42% of the workers in an occupation use computers. At this mean, computer use is associated with an increase in employment growth of 0.7 percent per year. This is quite substantial considering that the mean rate of employment growth is 1.2% per year.

One concern is that computer automation might be correlated with other organizational changes. In particular, observers have suggested that occupations that are prone to automation are also prone to being offshored.³⁸ Column 2 adds a measure of offshorability to the right hand side, Jensen and Kletzer's (2010) index of tradability. Offshorability is strongly associated with decreases in occupational employment. Also, the coefficient on computer use is substantially higher than in column 1, suggesting that there is a correlation between automation and offshorability. With this additional control, computer use at the mean contributes to employment growth of over one percent per year.

The remaining columns explore the effect of computer use on specific groups of occupations. Column 3 includes a variable, *use x capital-skills*, to capture the effect of computer use on specific computer-related occupations.³⁹ If the capital-skill complementarity

³⁸ Autor, Levy, and Murnane (2003) argue that occupations performing routine tasks are more likely to be automated; Jensen and Kletzer (2006) suggest that occupations performing routine tasks are more likely to be offshored.

³⁹ These include engineers, mathematical and computer scientists, software developers, computer and peripheral operators, and repairers of electrical and data processing equipment.

hypothesis plays a substantial explanatory role, then computer use in these occupations should have a higher coefficient. The coefficient of this interaction variable is neither statistically significant nor large, suggesting that capital-skill complementarity does not play an important role with computers. In any case, the computer-related occupations only account for about 5% of hours worked.

Columns 4 and 5 repeat the regression in column 3, but just for routine intensive occupations and mid-wage occupations.⁴⁰ These regressions test whether computer automation contributes to job polarization by eliminating jobs in these occupations. Instead, computer use is associated with substantially faster growth of an occupation.

Overall, computer use is associated with employment growth that is around 1 percent per annum faster at the sample mean, both for routine and mid-wage occupations and for the entire sample. Clearly, this is at odds both with the hypothesis that computers are causing technological unemployment and the hypothesis that computer use directly causes job polarization. These regressions, however, only measure the direct effect of computer use, ignoring the effect that computer use in one occupation might have on employment in another. The unconstrained model allows us to evaluate substitution effects.

Full Model Estimates

Table 3 provides estimates of the unconstrained model allowing substitution between occupations. The dependent variable is the annual growth rate from 1980 to 2013 of hours worked in each occupation-industry cell. All regressions include a full set of dummy variables for major occupation groups and a set for major industry groups.⁴¹ The first column shows the basic regression. The coefficient on computer use is quite similar to estimates in Table 2 and is highly significant, but now coefficient β also captures a sizeable inter-occupation substitution effect. The estimate of α implies that the elasticity of substitution between occupations is statistically greater than one.

The lower portion of the table shows the marginal effect of the two main independent variables and their mean values. The bottom row shows the combined

⁴⁰ The routine intensive occupations are those where the Dictionary of Occupational Titles rates the importance of routine tasks above the median level for 1960; mid-wage occupations are those where the mean occupational wage is between the 25th and 75th percentiles.

⁴¹ There are 9 major occupation groups and 14 major industry groups. These groups are those used in the Current Population Survey, however, I combined the service occupations (private household, protective, and other) and managerial and professional occupations.

contribution of own and other computer use to employment growth at the sample mean. The two effects roughly cancel each other out: while computer use by workers in an occupation is associated with faster job growth, workers in other occupations within the industry tend to substitute for the subject occupation when they use computers. The net combined effect of computer use, although positive, is neither economically nor statistically different from zero.

This estimation raises a number of econometric concerns. First, the sample is limited to occupation-industry cells where the CPS reports computer use and where the Census reports hours worked in both 1980 and 2013. Sample selection issues might bias the estimates. I tested the first concern by repeating the regression including cells that had no CPS data, instead imputing computer use by the overall occupation average. The coefficient estimates were highly similar.⁴² Next I performed a Heckman sample selection analysis using computer use as the independent variable in the sample selection equation. Again, the estimates were similar and a Wald test could not reject the null hypothesis that the equations are independent.⁴³

Multicollinearity is another concern. The two key variable, U and X , are correlated (coefficient .595), possibly making the parameter estimates unreliable. However, the variance inflation factors are not high, suggesting that there is sufficient independent variation to produce stable estimates.⁴⁴ I also tested for the influence of outliers using quantile regression and eliminating the one percent tails, but, again, the estimates do not suggest a problem.⁴⁵

Another concern is that computer use is endogenous. As discussed above, computer adoption is influenced by the payoff to adoption and this might be greater in faster growing occupations. Then U would be correlated with the error term. To check for this possibility, column 2 shows an instrumental variables estimate. I instrument computer use with the mean log occupational wage in 1980. From Table 1 we know that the occupational wage is related to computer adoption in an occupation, but there is little reason to expect that higher wage occupations systematically grow faster or slower. In fact, the sample correlation

⁴² The estimates of α and β were, respectively, 1.83(.32) and -1.33(.49).

⁴³ The estimates were, respectively, 1.53(.16) and -1.07(.41); the probability value of the Wald test was .328.

⁴⁴ The variance inflation factors for α and β are, respectively, 2.33 and 2.87.

⁴⁵ With quantile regression the respective estimates are 1.92 and -.85; while the second coefficient is noticeably closer to zero, this will tend to increase the estimate of employment growth. The estimates excluding the 1% tails, the estimates are 1.80(.33) and -1.37(.47).

between employment growth and 1980 log wage is .001. The IV parameter estimates have larger absolute magnitudes, but their relationship is the same, so the net contribution of computers to employment growth is roughly the same. Further, a test cannot reject the null hypothesis that computer use is exogenous (probability value .838), so endogeneity does not seem to be a major problem.

The basic finding that computer use within an industry does not appear to have a net negative impact on jobs thus seems robust. However, because this result arises from two counterpoised forces—occupations that use computers tend to have faster employment growth and also to substitute for other occupations—the net effects likely vary significantly across different occupations. This is because the adoption of computers is uneven. Inevitably some occupations use computers more and are likely to experience net growth while others use computers less and may have work transferred to other occupations. An example of this would be if word processing software reduced the number of typists, but increased the amount of labor middle managers devote to typing themselves. The last four columns of the table explore some of these differences.

Column 3 looks again at routine intensive occupations and finds, in contrast to Table 2, a modest net decline, although this estimate is not statistically significant. Apparently these jobs are relatively more likely to suffer from substitution effects. Columns 4 through 6 look at different groups according to their initial mean occupational wages. Low wage occupations suffer a statistically significant net decline associated with computer use. These occupations have low computer use (14% of workers) and a large and statistically significant substitution effect. High wage occupations experience statistically significant net growth associated with computer use. They use computers heavily (80%), the direct association between computer use and growth is strong and statistically significant, and the substitution effect is positive, although not significant. Mid-wage occupations fall in between.

These findings suggest that while computer use has little effect on the total number of jobs, the substitution effect is associated with a substantial transfer of work from low-paying occupations that do not use computers much to higher paying occupations that use computers more. That is, computers contribute to significant job displacement. Computer use does not contribute to economic inequality by causing technological unemployment. But computers might contribute to economic inequality if it is costly or difficult for workers to acquire new skills in order to transition into growing occupations.

Computer Use and the Demand for Skills Within Occupations

The model suggests that if the new skills are costly to acquire, then the dispersion of wages within occupations will increase and occupations will seek to hire more highly skilled workers. Table 4 shows regressions on the difference in log hourly pay between the 90th and 50th percentiles of an occupation (top panel) and between the 50th and 10th percentiles (bottom panel). On the right hand side, these regressions include the share of workers using computers in the occupation and two variables to capture the dispersion of education levels within the occupation, the mean years of education of the top wage quartile and of the second wage quartile. I include these latter variables because occupations with greater variation in education levels might tend to show greater growth in wage gaps just because of growing educational premiums. That is, because the wages of college educated workers have grown faster than the wages of high school educated workers, the variation in wages within an occupation will tend to rise if the composition of the workforce does not change. Of course, a rising college wage premium might cause employers to hire fewer college educated workers for that occupation. Nevertheless, I include these variables in order to make sure that there is no such mechanical effect on the dependent variables.⁴⁶

The first column shows that both wage gaps have tended to increase with computer use.⁴⁷ The second column repeats the exercise, but only from 1990 to 2013. I analyze this period separately because Autor, Katz, and Kearney (2008) find that the lower wage gap (50/10) increased relatively more during the 1980s while the upper wage gap (90/50) increased relatively more since 1990. Interestingly, the coefficients on computer use show a parallel shift, suggesting that computers might be at least partially responsible for the change.

In any case, the association between computer use and wage dispersion is substantial and statistically significant. The importance of this association between wage gaps and computer use is illustrated by the following counterfactual calculation. We can project how much of the general dispersion in wages can be explained by the regression results. From 1990 through 2013, the wages of the 90th percentile of the entire workforce grew 0.59%

⁴⁶ The results are quite similar if these variables are dropped. The top panel also excludes 7 occupations where some topcoded wage observations fall below the 90th percentile.

⁴⁷ A small number of individuals in 7 occupations have top-coded incomes yet hourly wages that fall below the estimated 90th percentile (because of very high hours worked). These occupations—chief executives and public administrators, actuaries, physicians, dentists, podiatrists, lawyers, and financial services sales occupations—account for 2.5% of the workforce. Because their presence might distort the measure of the 90/50 wage gap, I repeated the estimates in Table 4 excluding them; the results were quite similar.

faster than the wages of the 50th percentile annually; the wages of the 50th percentile grew 0.28% faster than the wages of the 10th percentile. If we subtract out the increase that can be attributed to the effect implied by the regressions in column 2, the 90th percentile wage grew only 0.33% faster than the median wage and the median wage grew 0.20% faster than the 10th percentile wage.⁴⁸ This means that computer use can account for about 45% of the rise in the 90/50 wage gap ($1 - .33/.59$) and about 30% of the rise in the 50/10 wage gap ($1 - .20/.28$) in the entire workforce from 1990 to 2013.

This growing intra-occupation dispersion could reflect greater demand for occupational specific skills that are costly to acquire. Alternatively, the rise in the 90/50 pay gap might reflect greater demand for “superstars.” To test the latter hypothesis, columns 2 and 3 add two different dummy variables if the occupation is more likely to experience superstar effects. These are occupations that tend to be at the top of job hierarchies and also conceivably benefit from lower costs of communication or information. The dummy variable used in column 2 includes managers, engineers and scientists, top level health providers, lawyers, writers, artists, entertainers, and athletes. These groups comprise 21% of the workforce. However, the coefficient on this variable is negative and statistically significant, counter to the superstar hypothesis. Column 3 uses a narrower definition of superstar occupations, accounting for only 8% of the workforce.⁴⁹ This dummy variable produces a positive coefficient, but it is small and not statistically significant. These findings suggest that at most the superstar effect only affects a relatively small number of occupations or only the very top performers within each occupation. In any case, wages are becoming more unequal over a wide range of occupations, not just those that might plausibly be winner-take-all-markets.

⁴⁸ I calculated the counterfactual wage gaps by scaling wages within occupations using the coefficients in column 2. Let the regression coefficient be β , let v be the worker's log wage, and let U_{occ} be the level of computer use in the occupation. For workers earning more than the median log wage in their occupation, v_{50}^{occ} , the counterfactual wage is calculated as $v^* = v_{50}^{occ} + (v - v_{50}^{occ}) \left(1 - \frac{\beta \cdot U_{occ}}{v_{90}^{occ} - v_{50}^{occ}}\right)$. I used corresponding calculation for workers earning less than the median occupational wage.

⁴⁹ This group includes chief executives and public administrators, financial managers, managers and specialists in marketing, advertising, and public relations, management analysts, architects, computer systems analysts and computer scientists, operations and systems researchers and analysts, actuaries, physicians, dentists, veterinarians, optometrists, podiatrists, lawyers, writers and authors, technical writers, designers, musician or composer, actors, directors, producers, art makers: painters, sculptors, craft-artists, and print-makers, photographers, dancers, art/entertainment performers and related, editors and reporters, announcers, and athletes, sports instructors, and officials.

The model of costly learning also suggests that occupations adopting new technology might employ relatively more workers with better pre-existing skills. Occupational sorting might also increase the relative employment of skilled workers. Table 5 explores changes in the share of workers within an occupation that have four years or more of post-secondary education (a college or graduate degree). Column 1 shows a significant association between computer use and growing share college educated workers.

Moreover, this association holds not just for occupations that involve a high level of cognitive tasks or for occupations that require college degrees. Column 2 shows the regression for occupations where the abstract task rating is less than 5 (the 1960 median). Column 3 shows the regression for occupations where fewer than 10% of the jobs require college degrees or higher. These estimates are from the Occupational Information Network (O*NET) database and are based on assessments of individual occupations by panels of experts. Both columns show a significant positive association between computer use and growth in the college share of workers.

In both the costly learning model and the occupational sorting model, firms hire more college educated workers not because a college education is needed to perform the tasks of the occupation, but because a college education might be correlated with higher skills or a better ability to learn new skills. But another factor could contribute to the rising college share. Beaudry, Green and Sand (2013) argue that there is a growing oversupply of college educated workers so that they are taking lower skilled jobs and displacing less educated workers. Since occupations that use computers tend to grow faster, perhaps more of these downgrading college graduates are taking jobs in these occupations. Indeed, the mean real wage of workers with four years of college declined between 2000 and 2013.⁵⁰ On the other hand, the real wage of workers with only a high school diploma declined even more,⁵¹ so relative wages of college workers have continued to grow.

In any case, if demand for greater skills were driving the increase in the college share of workers, then we would expect occupational wages to increase; if, on the other hand, the college share consists of downgrading grads who cannot find work in higher skilled occupations, then occupational wages should not increase. Column 4 repeats the regression

⁵⁰ The mean log wage, deflated by the Consumer Price Index, declined 5.5%. Data are from the 2000 Census and 2013 ACS, weighted by hours worked.

⁵¹ The deflated mean log wage for workers with a high school diploma or GED fell 9.9%.

of column 3 but adds two independent variables, the rate of growth of the mean wage for the occupation and the interaction term, *computer use* \times *wage growth*. The growth in the college share is strongly associated with wage growth in occupations that use computers, suggesting that an oversupply of college graduates is not a major factor.

Discussion

Generally, the estimates underline the importance of the effect of automation on occupational demand. Computer automation of an occupation tends to increase demand for that occupation, partly by substituting for the inputs of other occupations. At the sample mean, computer technology falls squarely into region I of Figure 3. On average, the direct demand effect and the substitution effect roughly cancel each other out. The net result is that computer use is associated neither with a substantial decrease in total employment nor with a substantial increase.

Nor is computer automation associated with job polarization. Table 3 shows that demand and substitution effects rough offset each other for mid-wage occupations. However, low-wage occupations face a significant decline of employment from computer automation while high-wage occupations experienced significant growth. On net, computer use is associated with a shift in employment from low paid occupations to higher paid occupations rather than a “hollowing out” of the middle.

There are some limitations to my analysis. Instrumental variables estimation might not address all concerns about causality. Gaggl and Wright (2014) do a causal analysis based on a natural economic experiment in the UK for small firms. They find that ICT complements non-routine cognitive-intensive work and substitutes for routine cognitive jobs, although this latter effect is smaller. This is consistent with a pattern where ICT decreases employment in lower-wage non-manual jobs and increases employment in higher-wage non-manual jobs.⁵² Akerman, Gaarder, and Mogstad (2015) find a similar pattern in response to the roll out of broadband Internet in Norway.

Another concern is that computer automation might be poorly measured. The estimates use the share of workers using computers in an occupation as a proxy for the

⁵² The Autor, Levy, Murnane (2003) index of cognitive-intensive work (abstract tasks) increase monotonically from 1.48 to 3.34 to 5.70 for low, mid, and high wage groups respectively. The ratings for routine task-intensiveness vary less, 3.73, 3.91, and 3.45 respectively. Thus more higher wage jobs will tend to be complemented by ICT.

labor-augmenting effect of computer automation. If this relationship varies significantly, then the estimates may be biased from measurement error. Moreover, this study only measures the use of computers within an industry. Digital technology appears to play some role in extra-industry changes: digital technology might facilitate transfer of work offshore, or to consumers in the form of self-service (e.g., airline ticket kiosks), or from one industry to another. Although these shifts affect employment within particular domestic industries, they might represent a transfer in who is performing the work rather than a decrease in the total labor performed. In any case, the arguments about technological unemployment focus on the role of computers in performing tasks previously performed by humans; as such, we would expect the main impact of this replacement to occur within industries.

My findings imply that computer-driven technological unemployment does not appear to provide an explanation for rising wage inequality.⁵³ But computers might contribute to rising wage inequality in another way: computer use is associated with greater wage disparities *within* occupations. A substantial portion of the growth in the 90/50 and 50/10 wage gaps can be accounted for by computer use. This greater disparity appears to arise from a growing demand for skills, particularly occupation-specific skills that might be costly to acquire. Fujita (2015) finds additional evidence of the importance of occupation-specific skills in explaining the secular decline in employee turnover. Furthermore, computer-using occupations are significantly substituting for other occupations. This means that workers need to transition to new occupations. To the extent that occupational skills are costly to acquire, this labor displacement will also tend to increase wage inequality. Of course, other factors affect wage inequality including, possibly, slack demand, the minimum wage, and more. However, my analysis suggests that computers do have a significant impact, although not via technological unemployment.

Conclusion

It is easy to identify specific occupations where jobs have been lost to automation such as telephone operators or typesetters. Many people suppose that if technology automates tasks, as it did in these cases, then it must eliminate jobs generally, creating technological unemployment. But this view fundamentally misunderstands what has been

⁵³ A point argued in a somewhat different way by Mishel, Schmitt, and Shierholz (2013).

happening. Overall, jobs have been growing faster in occupations that use computers. The analysis shows that computers have not been replacing workers on net; instead, workers using computers are substituting for other workers. There are fewer telephone operators, but more receptionists. There are fewer typesetters, but more graphic designers and desktop publishers. Computers create about as many new jobs as are eliminated by this substitution.

This inter-occupation substitution is similar to the substitution of skilled workers for unskilled in the canonical accounts of skill-biased technical change. But the canonical account only considers pre-existing skills, mainly college education. My results suggest that computer use is associated with growing employment even in occupations where most workers do not have college degrees, suggesting a much richer pattern of change.

Indeed, large-scale substitution between occupations implies considerable organizational change. Workers need to learn new jobs and new ways of working. For example, graphic designers had to learn entirely new skills in order to use desktop publishing technology. The nature of work also changes within occupations.⁵⁴ A substantial literature finds evidence that computer adoption involves organizational change and investments in new skills, often learned on the job.⁵⁵ The evidence associating computer use with wage dispersion reinforces the idea that computers require new skills that are difficult to acquire. Thus although computers do not cause major technological unemployment, the development of new skills is nevertheless a major challenge to the workforce. Yet these skills are distinct from a college education.

Of course, automation has been affecting occupations for a long time without apparently generating sustained unemployment. Economists sometimes explain this paradox by arguing that other sectors compensate for the job losses, for example, manufacturing grew to compensate for the loss of jobs in agriculture.

⁵⁴ Autor, Levy, and Murnane (2003) find that the nature of tasks performed within occupations changes with computer use.

⁵⁵ Bresnahan and Greenstein (1996) find substantial investments in knowledge by firms adopting computers. Some of the learning involves not the technology itself, but new organizational procedures (Bresnahan 1999). Brynjolfsson, Hitt, and Yang (2002) find large investments in organizational capital with computer adoption. Juhn et al. (1993) find that much of the growth in income inequality is not explained by education or other observed worker characteristics. More generally, Abowd et al. (2002) find that education and observed characteristics account for only a small part of human capital. Growth models considering the role of technology specific human capital or learning by doing include Lucas (1988), Chari and Hopenhayn (1990), Parente (1994) and Jovanovic and Lach, 1989). Bessen (2015) reviews historical evidence.

This paper makes a different argument: automation *itself* sometimes brings growing employment to occupations and that is what is happening now. However, there is no guarantee that future computer technology will increase labor demand. If history is a guide, computers may eventually tend to reduce the number of jobs as more marginal computer applications are exploited that do not produce as much job growth. For example, automation in 19th century textile weaving was associated with growing employment of weavers through the 1920s because demand for cloth was highly elastic (Bessen 2015). Eventually, however, demand became more saturated and further technical improvements were accompanied by stable employment and then decline. Today, improvements in older manufacturing technologies contribute significantly to job losses.

Generally, this paper emphasizes the importance of occupation for understanding the impact of technology on jobs and wage inequality. Previous research has shown that a substantial part of human capital is occupation-specific (Shaw 1984, 1987, Kambourov and Manovskii 2009). The evidence here suggests that new technologies are also significantly occupation-specific and often require new skills that are difficult to acquire. Another line of literature finds that a substantial portion of the growth in wage inequality is accounted for by differences between firms or establishments.⁵⁶ This research does not contradict the importance of occupation and, in fact, a number of papers find that much of the dispersion of wages across establishments is explained by differences in technology and organization.⁵⁷ More research is needed to understand how differences in technology adoption across firms and establishments change the demand for occupations and occupation-specific skills.

⁵⁶ See, for example, Abowd, Kramarz, and Margolis (1999); Dunne et al. (2004); Song et al. (2015).

⁵⁷ See, for example, Abowd et al. (2007); Doms, Dunne, and Troske (1997); Dunne et al. (2004).

Appendix

Derivation of equation (5)

The production function over occupations $i = 1, \dots, N$ is a standard CES production function where the only inputs are labor in the N occupations, L_i ,

(A1)

$$Q = \left(\sum_i (a_i L_i)^\rho \right)^{1/\rho}$$

The elasticity of substitution is $\sigma \equiv \frac{1}{1-\rho}$. Let the demand for output be $Q = AP^{-\epsilon}$, where P is the product price. Firm profits are then

$$\pi = PQ - \sum_j w_j L_j$$

where w_j is the exogenously determined wage for occupation j . The firm hires labor in the various occupations to maximize profits. The first order maximizing condition is

$$\frac{\partial \pi}{\partial L_j} = P \frac{\partial Q}{\partial L_j} - w_j = 0$$

With some manipulation, this solves to

(A2)

$$\ln \hat{L}_j(Q, a_1, \dots) = \frac{1}{1-\rho} \left[\ln \left(\frac{\epsilon-1}{\epsilon} A^{1/\epsilon} \right) - \ln w_j \right] + \frac{\rho}{1-\rho} \ln a_j + \left(1 - \frac{1}{\epsilon(1-\rho)} \right) \ln Q$$

A useful expression for occupation j 's share of the wage bill can be obtained using this:

(A3)

$$S_j \equiv \frac{w_j L_j}{\sum_i w_i L_i} = \frac{(a_j L_j)^\rho}{\sum_i (a_i L_i)^\rho}$$

Differentiating (A2),

(A4)

$$\frac{d \ln \hat{L}_j}{d \ln a_k} = \frac{\partial \ln \hat{L}_j}{\partial \ln a_k} + \frac{\partial \ln \hat{L}_j}{\partial \ln Q} \cdot \frac{\partial \ln Q}{\partial \ln a_k} = \frac{\partial \ln \hat{L}_j}{\partial \ln a_k} + \left(1 - \frac{1}{\epsilon(1-\rho)} \right) \cdot \frac{\partial \ln Q}{\partial \ln a_k}$$

Note that using (A1) and (A3)

$$\frac{\partial \ln Q}{\partial \ln a_k} = a_k \frac{\partial \ln Q}{\partial a_k} = \frac{(a_k L_k)^\rho}{\sum_i (a_i L_i)^\rho} = S_k$$

Then, (A4) generates equation 5:

$$\begin{aligned} \frac{d \ln \hat{L}_j}{d \ln a_j} &= \frac{\rho}{1 - \rho} + \left(1 - \frac{1}{\epsilon(1 - \rho)}\right) \cdot S_j = (\sigma - 1) + (\epsilon - \sigma) \cdot S_j / \epsilon \\ \frac{d \ln \hat{L}_j}{d \ln a_{k \neq j}} &= (\epsilon - \sigma) \cdot S_k / \epsilon \end{aligned}$$

Occupational sorting

It is straightforward to extend equation (2) to the case where some tasks are routine, others are non-routine, and workers have heterogeneous skills at each. Suppose there are m routine tasks and n non-routine tasks and worker i has skills s_i^R and s_i^N at routine and non-routine tasks, respectively. Then

$$y_{ij} = \frac{1}{\frac{1}{A_1 s_i^R} + \dots + \frac{1}{A_n s_i^R} + \dots + \frac{1}{A_{n+m} s_i^N}} = \frac{1}{\frac{1}{a_j^R s_i^R} + \frac{1}{a_j^N s_i^N}}$$

with the appropriately defined a_j^R and a_j^N .

To simplify the exposition, suppose that there are just two sorts of workers who differ in their skills on non-routine tasks: low skill workers who have non-routine skills s_L^N and high skill workers who have non-routine skills $s_H^N > s_L^N$; both have skills s^R on routine tasks. Suppose also that at the labor market equilibrium high skill and low skill workers earn w_H and w_L respectively, $w_H > w_L$. A necessary condition for labor market equilibrium is that $w_L/s_L^N > w_H/s_H^N$ (otherwise, skilled workers would not have an advantage in any occupation).

Given their skills, high skill and low skill workers will offer their services in occupation j at respective prices for efficiency units

$$p_{Hj} = \frac{w_H}{y_{Hj}} = \frac{w_H}{a_j^R s^R + a_j^N s_H^N} \quad \text{and} \quad p_{Lj} = \frac{w_L}{y_{Lj}} = \frac{w_L}{a_j^R s^R + a_j^N s_L^N}.$$

Low skill workers will have comparative advantage in those occupations where $p_{Lj} < p_{Hj}$ or where

$$\frac{a_j^N}{a_j^R} > \frac{s^R}{w_H - w_L} \left[\frac{w_L}{s_L^N} - \frac{w_H}{s_H^N} \right].$$

Low skill workers will have the comparative advantage in occupations where the efficiency of labor at routine tasks is relatively low compared to the efficiency at non-routine tasks. If the effect of computer automation is to increase a_j^R but not a_j^N , then automation will cause some occupations to upgrade from low skill workers to high skill workers. Thus assuming that automation only affects routine tasks, labor will be reallocated. While this model of occupational sorting implies a pattern of skill upgrading associated with computerization, it does not offer unambiguous implications about changes in the dispersion of wages within occupations in this partial equilibrium setting.⁵⁸ And to the extent that computerization decreases the price for efficiency units of occupational services, employment will change depending on model parameters as above. That is, automating a routine task can increase or decrease employment in the occupation.

⁵⁸ If technology only automates routine tasks, then the relative demand for workers with non-routine skills will increase. In a general equilibrium model, this will increase wages for workers with high non-routine skills. But this increase will occur across all occupations, not just those undergoing automation. The empirical analysis below explores the link between intra-occupational wage dispersion and computer use. The occupational sorting model does not imply any particular link.

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Tables and Figures

Table 1. Share of Workers Using Computers at Work

Dependent variable:	1 Share using computers	2 Share using computers	3 Annual change in share using computers	4 Share using computers
Routine “share” of tasks	-.230 (.030)**			
Routine tasks		.015 (.003)**	-.001 (.000)**	.000 (.003)
Abstract tasks		.064 (.002)**	.002 (.000)**	
Share with 4 or more years postsecondary education				.235 (.052)**
Mean log wage (1980)				.450 (.019)**
<u>Log employment</u>				.015 (.005)**
Adjusted R-squared	.124	.358	.294	.352
N	1912	1912	452	1467

Note: By occupation, weighted least squares regressions. Data are from 1984, 1989, 1993, and 1997 October Current Population Surveys. Regressions pool the observation years and include year dummies (except for column 3). Dependent variable in columns 1, 2 and 4 is share of workers in occupation who use a computer at work and regression weights are sum of person weights for occupation. Dependent variable in column 3 is annual change in share of workers using computers at work estimated by regressing annual observations against year for each occupation (excluding occupations with fewer than three observations or with only one observation in any year); regression weights in column 3 are the inverse of the standard error of the regression for each occupation. Wage bill is the aggregate sample weight times the exponential of the mean log hourly wage in billions of dollars. Standard errors are in parentheses. * = significant at the 5% level, **=significant at the 1% level.

Table 2. Employment Growth of Occupations, 1980-2013

Dependent variable: Annual growth rate (percent) of occupation hours worked

	1	2	3	4	5
Sample:	All	All	All	Routine intensive	Mid wage
Computer use	1.70 (.27)**	3.05 (.31)**	3.07 (.39)**	2.81 (1.06)	3.54 (.12)**
Offshorability index		-1.95 (.21)**	-1.93 (.48)*	-1.64 (.62)	-2.22 (.06)**
Use x capital skills			-.51 (.25)		
Adjusted R-squared	.11	.29	.29	.19	.37
N	317	301	299	147	138
Mean computer use	.42	.41	.41	.37	.42
Contribution of computer use to growth rate	.72 (.12)**	1.25 (.13)**	1.26 (.16)**	1.04 (.39)**	1.50 (.05)**

Note: Weighted least squares regressions of detailed occupations. Dependent variable is annual percentage growth in hours worked. Weighted by occupation hours worked. The offshorability index was developed by Jensen and Kletzer (2010). "Capital skills" refers to specific occupations that might be expected to be complementary with computers (see footnote 39). Standard errors are in parentheses. * = significant at the 5% level, **=significant at the 1% level. Errors in columns 3 through 6 are clustered by occupation group. Constant term not shown.

Table 3. Employment Growth of Occupations, Full Model Estimates, 1980-2013

Dependent variable: Annual growth rate (percent) of occupation-industry hours worked

Sample:	1	2	3	4	5	6
	All	All	Routine intensive	Low wage quartile	Mid wage quartiles	High wage quartile
	WLS	IV	WLS	WLS	WLS	WLS
α	1.84 (.33)**	2.10 (1.42)	.78 (.44)	1.21 (.87)	2.44 (.48)**	1.29 (.40)**
β	-1.37 (.47)*	-1.55 (.80)	-1.16 (.77)	-2.68 (.89)*	-2.29 (.45)**	1.16 (.85)
R-squared	.25	.11	.28	.30	.27	.38
N	10,837	10,837	4,954	2,279	6,208	2,350
Marginal effects of computer use						
Own occupation	1.66 (.33)**	1.91 (1.43)	.69 (.44)	.86 (.88)	2.16 (.49)**	1.44 (.42)**
Industry	-1.20 (.41)**	-1.36 (.70)	-1.07 (.71)	-2.33 (.77)**	-2.01 (.40)**	1.00 (.74)
Mean values of computer use						
Own occupation, U	44%	44%	39%	14%	43%	80%
Industry, X	49%	49%	49%	36%	49%	63%
Contribution of computer use to growth rate	.14 (.28)	.17 (.74)	-.26 (.41)	-.80 (.35)*	-.08 (.31)	1.76 (.63)**

Note: All regressions include a full set of dummy variables for major occupation group and for major industry group. Dependent variable is annual percentage growth in hours worked for detailed occupation-industry cell. The sample includes all cells where data are available on computer use. Weighted by occupation hours worked.

Standard errors are in parentheses and are clustered by industry group. * = significant at the 5% level,

**=significant at the 1% level. Column 2 instruments the computer use variable using the mean log wage of the occupation in 1980.

Table 4. Change in Within-Occupation Wage Gaps

Panel A. Change Between 90th and 50th Percentiles

	1 1980-2013	2 1990-2013	3 1990-2013	4 1990-2013
Share using computers	.21 (.08)**	.58 (.09)**	.62 (.09)**	.56 (.09)**
Education, 2 nd wage quartile	-.03 (.04)	-.09 (.04)*	-.11 (.04)**	-.09 (.04)*
Education, 4 th wage quartile	.02 (.04)	.06 (.04)	.10 (.04)*	.06 (.04)
Superstar I			-.13 (.05)*	
Superstar II				.15 (.08)
Adjusted R-squared	.04	.19	.20	.19
N	310	310	310	310

Panel B. Change Between 50th and 10th Percentiles

	1	2
Share using computers	.40 (.09)**	.34 (.10)**
Education, 2 nd wage quartile	.06 (.04)	-.01 (.05)
Education, 4 th wage quartile	-.05 (.04)	-.03 (.05)
Adjusted R-squared	.15	.04
N	317	317

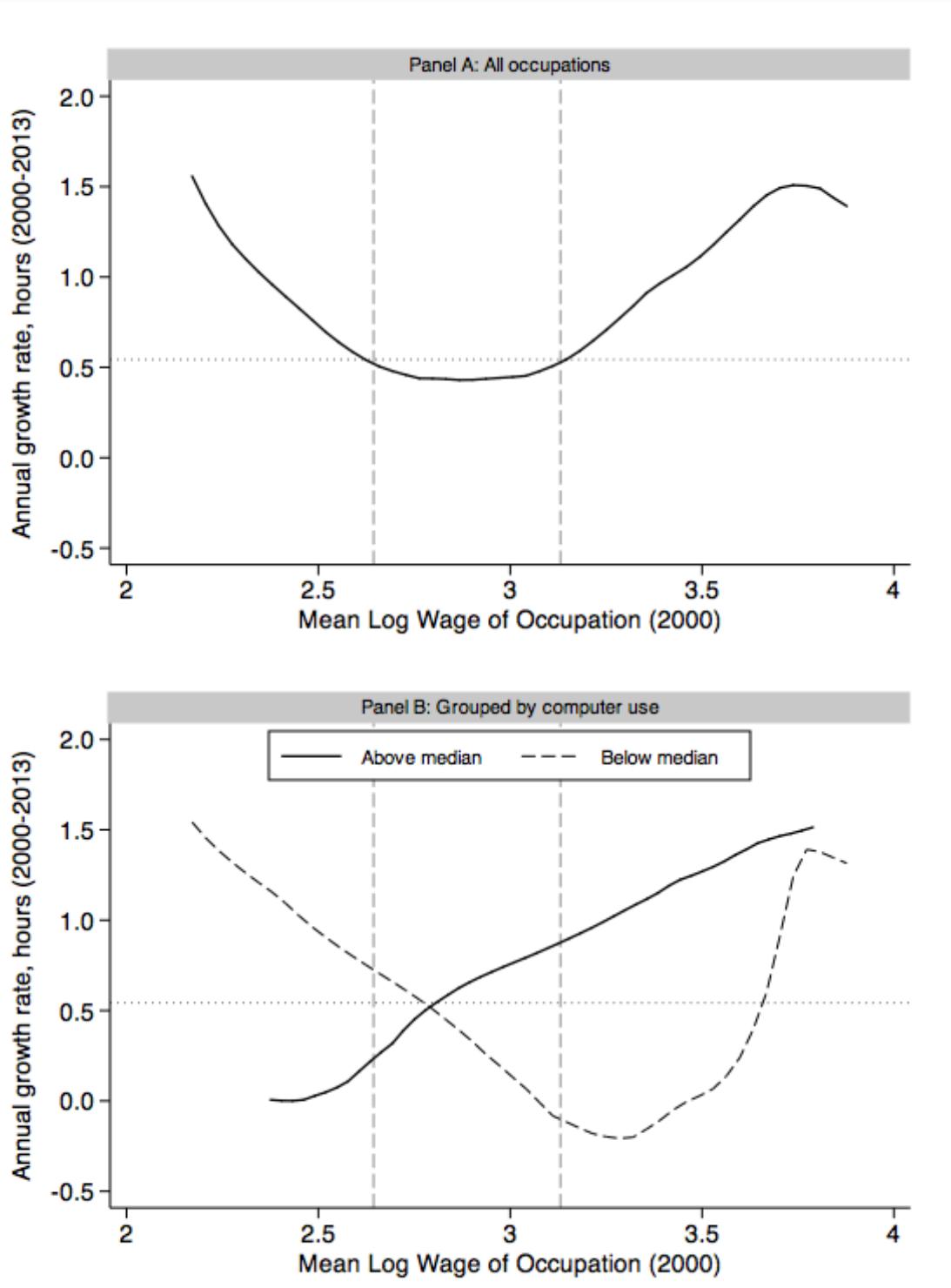
Note: Weighted least squares regressions of detailed occupation data. Dependent variable is annual percentage change in the difference in log wages between the 90th (50th) and 50th (10th) percentiles in the upper (lower) panel. Top panel excludes 7 occupations where some topcoded wage observations fall below the 90th percentile. Constant term not shown. Weighted by occupation hours worked with standard errors reported in parentheses. * = significant at the 5% level, **=significant at the 1% level.

Table 5. Change in Share of Workforce with College Education

Sample:	1 All	2 Few abstract tasks	3 College not required	4 College not required
Share using computers	.11(.01)**	.11(.01)**	.12(.01)**	.12(.01)**
Computer use x wage growth				.34(.07)**
Wage growth				-.03(.03)
Adjusted R-squared	.24	.25	.48	.57
N	317	242	171	171

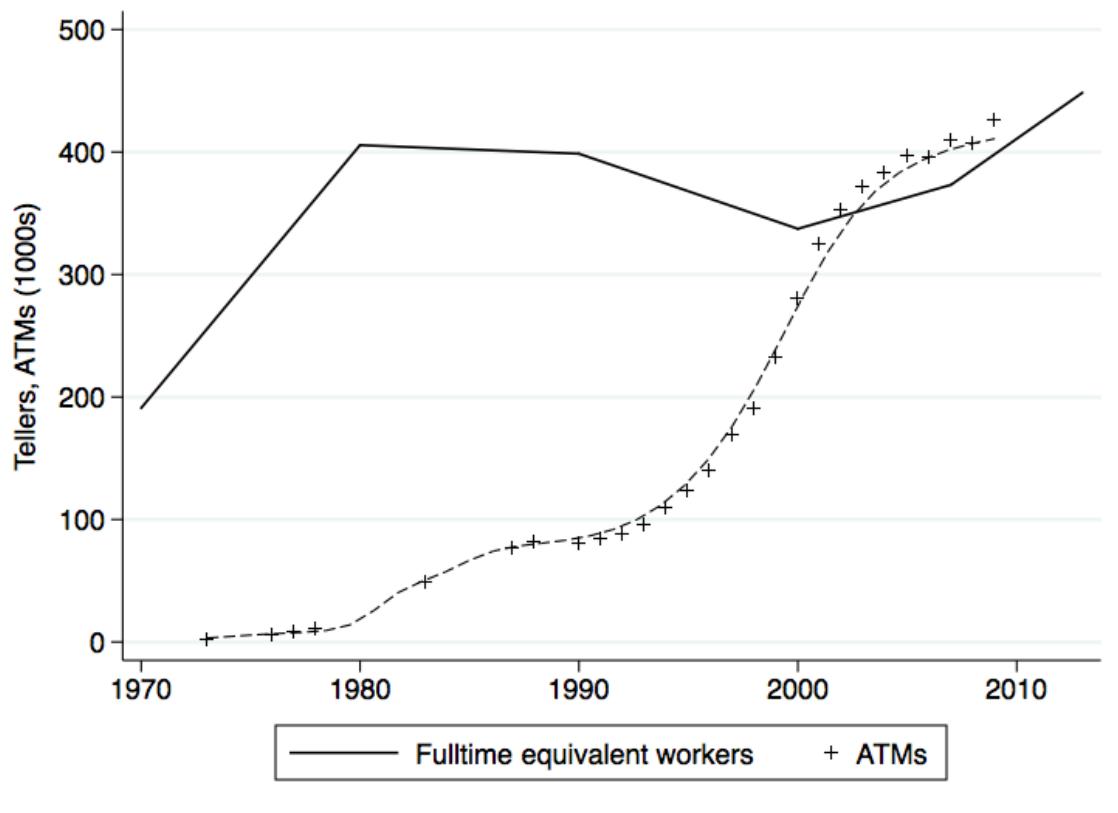
Note: Weighted least squares regressions of detailed occupation data. Dependent variable is change in the share of hours worked by workers with four or more years of postsecondary education from 1980 to 2013. Constant term not shown. Weighted by occupation hours worked with standard errors reported in parentheses. * = significant at the 5% level, **=significant at the 1% level.

Figure 1. Job Polarization: Employment Growth of Occupations by Computer Use



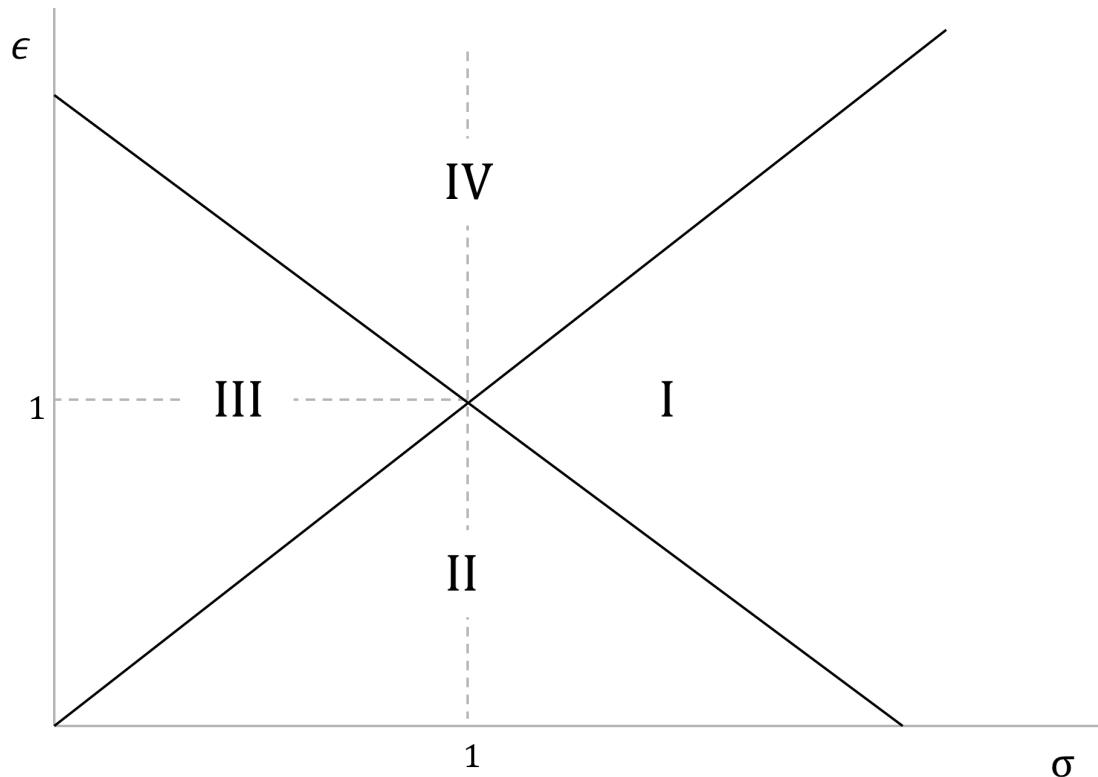
Note: Shows smoothed weighted average of percentage growth in hours worked for 317 detailed occupations. Smoothing done with an Epanechnikov kernel with .3 bandwidth. Bottom panel shows occupations with above-median and below-median computer use separately. Dashed vertical lines are at the 25th and 75th percentiles in the occupational wage. Horizontal dotted line is total hours growth.

Figure 2. Bank Tellers and Automated Teller Machines



Note: Teller data from Census and ACS 1% samples. Fulltime equivalent workers calculated assuming 2080 hours per work year. Data on number of ATMs installed from the Bank for International Settlements.

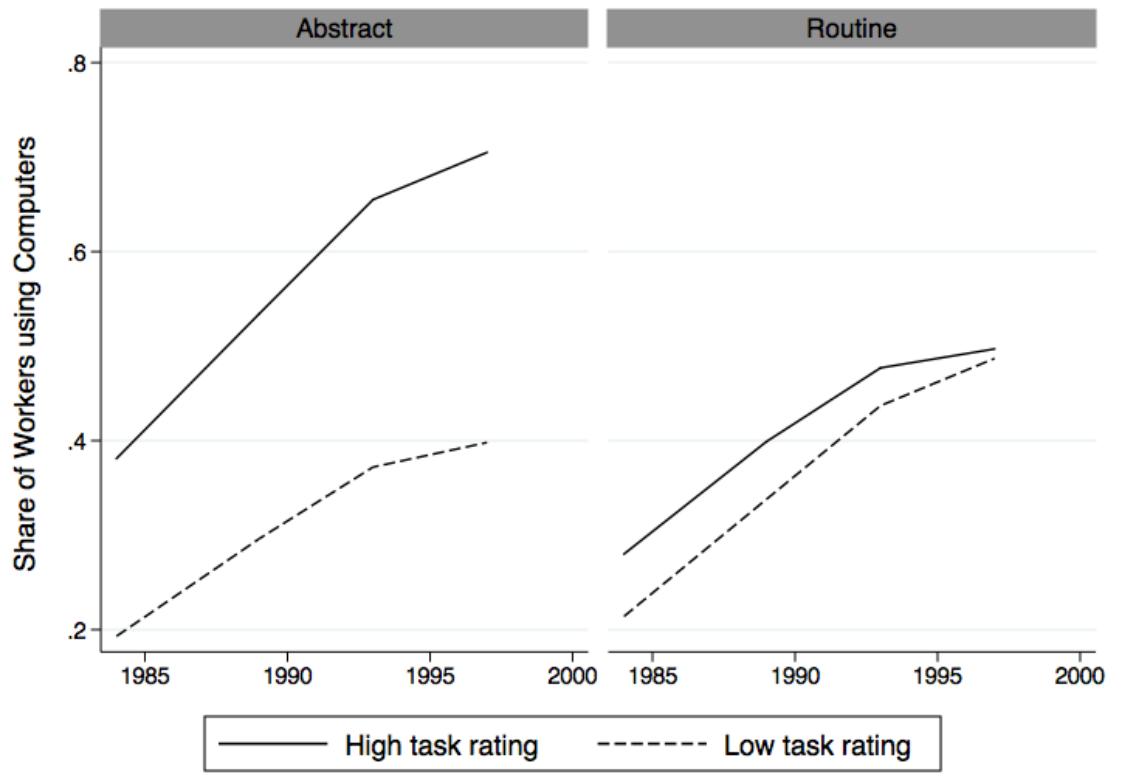
Figure 3.



Changes Between Occupations

Region	Employment Change in Automated Occupation	Employment Change in Other Occupation
I	+	-
II	-	-
III	-	+
IV	+	+

Figure 4. Share of Workers Using Computers by Characteristics of Occupational Tasks



Note: The first panel shows computer use for occupations with above-median and below-median rated importance rating of abstract tasks; the second panel shows above-median and below-median rated occupations on the importance of routine tasks.