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Abstract: This paper investigates basic relationships between computer automation 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 computer automation as a source of significant overall job losses. 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 requiring college-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 1.7% 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 relationship between computer use and employment is positive but small (0.45% per year). However, computer use is associated with growth in well-paid jobs and decreases in low-paid jobs, hence 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 appears to contribute to wage inequality, accounting for 45% of the growth in the wage gap between the 90^{th} and 50^{th} percentiles of the entire workforce since 1990; it can account for 38% 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.

Are new computer technologies eliminating jobs at an increasing rate, generating technological unemployment and growing economic inequality (Brynjolfsson and McAfee 2014)? 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). While others see a more modest impact across occupations (Arntz et al. 2016, Autor 2015), the view that computer automation has been causing and will increasingly generate major job losses in many occupations has prompted calls for new policies such as a minimum basic income.

Yet automation does not necessarily cause job losses even in the affected occupations, let alone in the economy as a whole. Automation of an occupation happens when machines take over one or more tasks, either completely performing those tasks or reducing the human labor time needed to perform them. That is, automation augments labor. Labor augmenting change does not necessarily lead to job losses in automated occupations for two reasons. First, greater productivity might reduce prices and thus increase product demand, offsetting the labor-saving effect. Second, increasing the productivity of one occupation might induce a substitution with other occupations; work may be transferred to the newly more productive occupation. Both of these effects can result in an increase in employment in automated occupations rather than a decrease. Of course, economy-wide adjustments can also offset job losses in one occupation with growth elsewhere.

This paper seeks to understand what the actual relationship has been between computer automation and relative occupational employment since 1980. It estimates basic demand relationships between computer technology and occupations using detailed US occupational data and a partial equilibrium model that encompasses different ways automation 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 job losses. 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. It is helpful to draw some distinctions.

Background

Automating tasks and occupations

Occupations are an important unit of analysis because technologies tend to automate tasks in 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.

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 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. Nevertheless, the model Autor, Levy, and Murnane develop is based on *tasks* only, rather than on occupations.[1] This paper presents a model that integrates automation of tasks with a generalized treatment of occupations. The distinction between tasks and occupations is important because conclusions about tasks do not translate unambiguously into conclusions about occupations.

Partial automation vs. complete automation

Critically, automating a task is not the same as completely automating an occupation. This distinction appears to be a source of some confusion. Automation is sometimes framed as a problem of machines completely replacing a human job. For example, Frey and

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[1] See also Autor and Acemoglu (2011) and Goos, Manning, and Solomons (2014). The latter paper models both tasks and occupations, but assumes that each occupation only performs one task. This focus on tasks makes sense from the perspective of the routine-biased technical change hypothesis, see below.

Osborne (2013) begin by subjectively evaluating 70 occupations to determine which are "fully automatable" "by state of the art computer controlled-equipment" given big data. They and a group of machine learning researchers decided in 2013 that using then current technology, 37 occupations were fully automatable, including accountants and auditors, bank loan officers, and messengers and couriers. Based on this analysis they project that nearly half of all jobs are susceptible to complete automation in the near future. Significantly, however, *none* of these 37 occupations has been completely automated so far.[2]

More generally, technology rarely automates major occupations completely. Consider what happened to the 271 detailed occupations used in the 1950 Census by 2010.[3] Many occupations were eliminated for a variety of reasons. In many cases, demand for the occupational services declined (e.g., boardinghouse keepers); in some cases, demand declined because of technological obsolescence (e.g., telegraph operators). This, however, is not the same as automation. In only one case—elevator operators—can the decline and disappearance of an occupation be largely attributed to automation. Nevertheless, this 60-year period witnessed extensive automation, but it was almost entirely partial automation.

The aim of this paper is to understand how computer automation has affected jobs in the recent past. Consequently I focus on partial automation. In the future, of course, new artificial intelligence technologies might be capable of fully automating jobs. However, that is not what has been happening so far nor would it seem likely to happen in more than a few occupations in the near future (Arntz, Gregory, and Zierahn 2016).

This distinction between partial and complete automation might seem irrelevant when many or most of the tasks of an occupation have been automated. However, the economic difference between being *mostly* automated and being *completely* automated can be critical. Complete automation implies a net loss of jobs; partial automation does not. During the 19th century, 98% of the labor required to weave a yard of cloth was automated, however, the number of weaving jobs actually increased (Bessen 2015). Automation drove the price of cloth down, increasing the highly elastic demand, resulting in net job growth despite the labor saving technology. Similar demand responses are seen with computer

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[2] This suggests that either they are wrong about which occupations are fully automatable or there are substantial economic or technical obstacles to actually automating occupations, making their predictions inaccurate.

[3] IPUMS has mapped these occupations to the 1990 and 2010 Census classifications (Ruggles et al. 2015). When occupations become too small, they are combined with other occupations, so I looked at all instances where the 1950 occupation was either renamed or combined into a broader category.

automation. Consider, for example, the effect of the automated teller machine (ATM) on bank tellers. The ATM is sometimes taken as a paradigmatic case of technology substituting for workers; the ATM took over cash handling tasks. Yet the number of fulltime equivalent bank tellers has grown since ATMs were widely deployed during the late 1990s and early 2000s (see Figure 1). Indeed, since 2000, the number of fulltime equivalent bank tellers has increased 2.0% per annum, substantially faster than the entire labor force.[4] 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 (their demand was elastic), offsetting the erstwhile loss in teller jobs (Bessen 2015). Nor are the examples of weavers and bank tellers exceptional.[5] As we shall see, employment growth has been associated with computer use overall. The ATM may be more a representative example than an exception.

Of course, partial automation can also decrease employment in an occupation. This can happen in two ways. First, if demand for the occupation is inelastic, automation reduces employment. Second, automation can lead to substitution of one occupation for another. For example, there are fewer telephone operators, but more receptionists; there are fewer typesetters, but more graphic designers and desktop publishers. During the 1980s, desktop publishing software automated some of the tasks of setting type for publication. Prior to this, designers would draw a page design and send it to typesetters and compositors to produce pasted up pages; designers would mark revisions and send them back to the typesetters to redo. With computerized publishing, revisions could be made interactively, making it advantageous for designers to use the software themselves to produce composed pages. The effect was to reduce employment of typesetters and compositors and to increase employment of graphic designers. That is, designers using computers substituted for typesetters. A full model of occupations and automation thus needs to allow for increases

[4] 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).

[5] Some other examples: Barcode scanners reduced cashiers' checkout times by 18-19% (Basker 2015), but the number of cashiers has grown since scanners were widely deployed during the 1980s; 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; the manufacturing share of the workforce grew from less than 12% in 1820 to 26% by 1920 (US Dept. of Commerce 1975) despite pervasive labor-saving automation.

and decreases in occupational employment and to also allow occupations to substitute for and complement each other.

Computer automation vs. other technological change

Automation is not the only way that technology affects occupations. Technology can make industries and products obsolete, eliminating industry-specific occupations. For example, the automobile eliminated jobs in horse-related occupations, often replacing them with new jobs (carriage makers to auto body makers). Technology can also change the organization of work, shifting work between occupations, between industries, or from producers to consumers. Digital technology may lower communication costs, facilitating decentralization, outsourcing, and offshoring; it may improve ease of use, facilitating self-service. For example, the airline ticket kiosk transferred work from airline ticket agents to air travelers. However, this is not an example of automation. Shifts such as these represent a change in who is performing the work without necessarily changing the amount of labor required per unit output. Self-service technologies might even increase the amount of labor needed. For this reason, although these changes can be disruptive and can eliminate particular jobs, there is no particular reason to expect them to create major job losses overall.

In contrast, automation might lead to job losses because it reduces the labor needed to perform tasks. Automation is labor augmenting, although automation might also shift work between occupations. Furthermore, jobs that perform computer-automated tasks are jobs that use computers; that is not necessarily true for the other impacts of computers. With computer automation, one occupation ultimately performs each automated task, initiating and controlling the automated system, and integrating the outputs of the automated process with other occupational services. That occupation necessarily uses computers. This means that the share or workers in an occupation who use computers is a rough proxy for the degree to which the labor of that occupation is augmented by computers. This theoretical proposition is borne out by empirical evidence. The Bureau of Labor Statistics had experts rate the "degree of automation" of detailed occupations; that automation measure is highly correlated with the share of workers using computers in each occupation (correlation coefficient of 0.45).[6]

[6] O*NET, weighted by hours worked;0.42 if unweighted.

The focus of this paper is strictly on automation and I employ computer use as a measure of the degree to which computers automate occupations.

Routine-biased technical change

In this regard, this paper's focus is narrower than the literature on routine-biased technical change (RBTC), the hypothesis that technical change is biased towards replacing labor performing routine tasks. Autor, Levy, and Murnane (2003) showed a long-term decline in the share of work done in routine-intensive occupations. Autor, Katz, and Kearney (2008) proposed RBTC as an explanation for "job polarization," the recent tendency for employment in mid-wage occupations to grow more slowly than both low-wage and high-wage occupations. Because routine tasks are important in many mid-wage jobs, the hypothesis holds that technical change is the reason for the slower growth in the middle. A substantial empirical literature finds that routine-intensive groups of workers have relatively slower job growth.[7]

However, computer automation might not be the only or even the main cause of the decline in the share of routine work. Routine tasks might be mechanized using non-computer technologies. Indeed, Autor, Levy, and Murnane (2003) found that the decline in the share of work done by routine-intensive occupations began well before computers were widely used. Routine jobs might also be easier to outsource and specialized service providers might be more efficient, reducing labor. Similarly, routine jobs might be easier to send offshore. Organizational decentralization might also transfer work away from routine-intensive jobs at headquarters (e.g. clerical staff) to other occupations in the field (e.g., regional sales managers).

These possibilities suggest that RBTC and computer automation are not necessarily identical although they may be related. My analysis focuses exclusively on computer automation and because occupations vary in their degree of automation, I estimate a model with a consistent set of detailed occupations from 1980 through 2013. In contrast, much of the RBTC literature aggregates occupational task characteristics over industries or local labor markets or broad occupational groups. For example, a number of studies identify the broad grouping of administrative support and sales occupations as those that are most routine and

[7] 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).

therefore most prone to computerization. While these approaches reveal aspects of broad RBTC, they potentially conflate the effect of automation with some of the other factors that might affect routine jobs.[8] My disaggregated approach allows clearer identification of the effects of automation but also allows me to look at different groups of occupations such as administrative support occupations.

I begin by developing a simple general model of the demand for 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 skills 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,

[8] Goos, Manning, and Salomons (2014) and Autor, Dorn, and Hanson (2015) attempt to disentangle trade and technology effects.

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

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 historians 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.

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. I assume that these skills represent general human capital to the occupation so that 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).[9] 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 $A_k \to \infty$ so that $t_{ik} \to 0$.

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

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

(3)

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

In this case, an increase in A_k generates a corresponding increase a_j.[10] 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) $p_j = w_j / a_j.$

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

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

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

[10] 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.[11] 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)

$$\frac{d \ln L_k}{d \ln a_j} = S_j(\epsilon - \sigma)/\epsilon, \qquad S_j \equiv \frac{w_j L_j}{\sum_i w_i L_i}; \quad j \neq k$$

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*, 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. Clearly, automation does not necessarily eliminate jobs for either the automated occupation or for other occupations in the firm.

[11] This implementation is similar to one in Goos, Manning, and Salomons (2014), however, here I derive demand equations and use computer use as a specific measure of automation.

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)

$$d\ln L_{ij} = \alpha U_{ij} + \beta X_i + \gamma Z_i + \mu_{ij}$$

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

where X_i is a wage-weighted average of industry computer use, Z_i is a vector of other factors that might influence employment growth, and μ_{ij} is an error term.

Equation (6) describes the effect of computer automation on occupational job growth. If computers are causing major job losses, then this should appear as a net negative effect of α and β.

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 streamline 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.[12] Since $w_{ij} = p_j a_j s_i$, the price for an efficiency unit of occupational service *j* is

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

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.[13] However, a type *L* worker who had *already* sunk a human capital investment would not necessarily leave the occupation. As long as $p^1 a^0 s_L > z_A s_L$, 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.[14] 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,

[12] The gap might also arise from labor market frictions as in Acemoglu and Pischke (1999).
[13] It is easy to show that the worker cannot recoup her investment by using the old technology as well.
[14] Griliches (1957), Salter (1960), Mansfield (1961) and Rogers (1962).

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

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. 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.[15]

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.[16] To test this below, I identify a group of occupations consisting of top-level service providers (the superstar effect requires a personal market that

[15] 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.

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

seems unlikely for, say, a medical assistant) likely realizing lower costs from computer technology.

Technology Adoption

Finally, a key factor affecting the economic impact of computers is the nature of the occupations that adopt computers. For example, the routine-biased technical change hypothesis (Autor, Katz, and Kearney 2008) holds 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 more feasibly 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.

Nevertheless, it does not necessarily follow that jobs with many routine tasks are the ones most likely to use computers. This is because the economic calculations that firms make when choosing to adopt computer technology depend on more than just the feasibility of computerization. In particular, the payoff to firms from automating a particular task depends on the opportunity cost of the occupation that performs that task. For example, both accountants and file clerks may perform some routine arithmetic calculations. But the time the accountant spends on this task is more valuable. Hence, the payoff to automating those calculations for a highly paid accountant is much greater than it would be for automating those same calculations for a lowly paid file clerk. While the file clerk may perform more routine tasks than the accountant overall, the value to automating the accountant's routine tasks is greater.

Assuming that inventor payoffs are proportional to the payoffs technology users receive, some additional occupational characteristics might be important:[17]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. Also, 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. 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), calculating occupational growth rates for the decades of the 1980s, 1990s, and the long decade from 2000 through 2013. 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 year[18] divided by the product of usual hour worked per week times weeks worked last year.[19] I deflate the hourly wage using the Consumer Price Index.

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[17] 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.

[18] 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.

[19] 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.

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 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 supplements to the Current Population Surveys (CPS), which asked whether adult respondents directly used a computer at work.[20] As noted above, computer use is highly correlated with the rated "degree of automation" of an occupation, making it a useful proxy. This measure has some limitations. First, some workers use computers in an embedded form. For example, what is called a cash register might actually be a computer, leading some cashiers to underreport computer use. While this leads to some measurement error, the overall figures on computer use are high, suggesting that most occupations do not underreport. Moreover, many well-known examples of computer automation involve computers identified as such (bank tellers, clerks, bookkeepers). Another limitation involves the timing of computer automation. I assume that computers augment labor on an ongoing basis, that is, workers using computers benefit from a stream of new software and hardware improvements over time. Some tests reject the alternative that only new computer use matters.[21]

For each decade, I calculate computer use for each detailed occupation as the weighted average of the two observations per decade, adjusted for change in the overall size

[20] This question was asked in October of 1984, 1989, 1993, 1997, and 2003 and September of 2001.
[21] To test this assumption, I regressed the rate of occupational employment growth against the rate of growth of computer use rather than the level of computer use as in Table 2. The coefficient was not significant.

of the labor force between those years.[22] To estimate equation (6), I use the 317 occupations across the 243 detailed industry categories used in the 1990 Census. To calculate wage-weighted industry mean computer use, *X*, I obtain computer use for occupation-industry cells from the CPS, I average them across available years, I use crosswalks to convert the cells to Census categories, and then weight them using hour-weighted mean wages for each occupation-industry cell in the Census data.[23]

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.[24] Additional data fields come from the Labor Department's Occupational Information Network (O*NET).

Empirical Findings

Which Occupations Use Computers?

The effect of computers on occupations depends significantly on which occupations adopt computers. The literature on routine-biased technical change has highlighted the association between routine tasks and computer use beginning with Autor, Levy, and

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[22] For the decade from 2000 to 2013, I use only the computer use data from 2001 because 2003 used a different occupational classification. I ran regressions incorporating 2003 data using a crosswalk and obtained similar results.
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. Since this understates my results, I ignore it.

[23] 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 average of mean computer use for the occupation and mean computer use for the industry. I also tested the robustness of the data by imputing cells with small numbers of observations in the CPS. I also ran the regressions excluding imputed data. These trials produced very similar estimates.

[24] 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).

Murnane (2003). They found a correlation between computer use and the relative share of routine jobs in the industry.

However, as Table 1 shows, this correlation has weakened over time and other factors appear to be more important. This table regresses the computer use of 383 occupations against various occupational characteristics including the importance of routine tasks. The data are the same as used by Autor, Levy, and Murnane, but for the years from 1984 through 2003.[25]

The first two columns show that the importance of routine tasks is not a statistically significant predictor of occupational computer use by itself. Column 3 adds the index of the importance of abstract tasks. These are statistically important and, with their addition, the coefficients for routine-intensiveness become statistically significant at least during the early years. These trends can be seen in Figure 2. Panel 2a shows computer use for 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 2b 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 disappears in 1997.[26] 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.

Abstract tasks may be important because they reflect the opportunity cost of routine tasks and the payoff to adopting computers. Column 4 replaces the abstract task variable with more direct measures of opportunity cost and payoff, namely, the mean log wage for the occupation in 1980, log employment in the occupation, and the share of jobs in the occupation that require a college diploma (from O*NET).[27] These variables are all statistically and economically significant and the routine-intensiveness of the occupation is only significant during the 1980s. The importance of the economic payoff to automation

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[25] Autor, Levy, and Murnane used data from 1997 only. Regressions include year dummies and are weighted by CPS sample weights.

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

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

seems to be a much more important driver of endogenous adoption decisions and the payoff appears to be greater in well-paid occupations.

This finding does not contradict the routine-biased change hypothesis; it does suggest, however, that the declining share of routine-intensive jobs is not specifically driven by computer automation. Other automation or other types of technological change may be involved in RBTC.

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 and demand elasticity, effectively assuming that $\sigma = \epsilon = 0$. Imposing this constraint, (6) becomes

(7) $$d \ln L_j = \gamma U_j + \delta + \varepsilon_{j.}$$

Table 2 estimates variations on this equation using the growth rate of detailed occupations over three decades 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 1.06% 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.[28] 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

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[28] 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.

a correlation between automation and offshorability. With this additional control, computer use at the mean contributes 1.7% to employment growth per year.

Columns 3 repeats the OLS regression but breaks out computer use by each decade. The coefficient of computer use is larger during the 1980s but remains economically and statistically significant subsequently.

One concern is that faster-growing occupations might be more likely to adopt computers for some reason, exaggerating the correlation. Columns 4 and 5 conduct a Granger causality test over decades using the specification in Column 2 and lagged (to the previous decade) values of the growth rate of hours worked and computer use. The findings show that computer use Granger-causes employment growth but employment growth does not Granger-cause computer use. Column 5 in particular shows that occupations that grow faster in one decade are no more likely than others to use computers in the next.

Overall, computer use is associated with employment growth that is over 1 percent per annum faster at the sample mean. Clearly, this is at odds with the hypothesis that computers are replacing workers in computerized occupations. 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. In order to reduce sampling variance—many occupation-industry cells are quite small and many have no observations—I average the computer use variables over the three decades and I estimate the regressions using sampling weights. I cluster standard errors by major industry group (the 14 categories used in the CPS).

The first column shows the basic regression. The coefficient on computer use is smaller than the corresponding estimate 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.

Evaluated at the sample mean, the joint contribution of both computer use terms is positive, but it is neither economically nor statistically significant.

The second column adds the offshorability index. The coefficient magnitudes are larger and now the contribution of computer use to employment growth is positive, statistically significant, and economically meaningful, although not large. Column 3 introduces dummy variables for major industry groups, possibly capturing industry-related omitted variables. Now the key estimates are rather similar to those in Column 1.

This estimation raises a number of econometric concerns. First, the sample is limited to occupation-industry cells where the Census reports hours worked in both 1980 and 2013. Sample selection issues might bias the estimates. I performed a Heckman sample selection analysis using computer use as the independent variable in the sample selection equation and repeating the regression in Column 2. Again, the estimates were similar and a Wald test could not reject the null hypothesis that the equations are independent.[29]

Multicollinearity is another concern. The two key variable, U and X, are correlated (coefficient .67), 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.[30] I also tested for the influence of outliers by eliminating the one percent tails, but, again, the estimates were quite close to those in Table 3.[31]

The basic finding that computer use within an industry does not appear to have a net negative impact on jobs thus seems robust. There is no empirical support for the general hypothesis that computer automation is causing technological unemployment.

Differences across occupational groups

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 as shown in Table 1. 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

[29] The estimates were, respectively, 2.38(.23) and -.91(.47); the probability value of the Wald test was .558.
[30] The variance inflation factors for α and β are, respectively, 2.39 and 1.82.
[31] The estimates excluding the 1% tails are 2.37 and -.91.

would be if word processing software reduced the number of typists, but increased the amount of labor middle managers devote to typing themselves. Also, this analysis assumes that the key parameters, σ and ϵ, are constant across different groups of occupations.

Table 4 explores possible variation in computer use and model parameters by estimating (6) and (7) over specific groups of occupations. Panel A corresponds to Column 2 of Table 2; Panel B corresponds to Column 2 of Table 3. The first column covers occupations that ranked above the median value in 1960 on the importance of routine tasks. Routine occupations use computers at about an average level and computer use is not associated with job losses for this group.

The next three columns show occupations grouped by mean wage quartile (first, middle two, and fourth) for 1980 wages. Computer use rises sharply with wage (from 17% to 70%) and so does the impact on occupational employment growth. In the full model (Panel B), computer use is associated with job losses for the low wage group (-.43%), but with positive employment growth in mid- and high-wage occupations.

This pattern suggests that computer automation is not entirely responsible for job polarization; although high-wage occupations grow faster with computer use, few low-wage workers use computers and industry computer use is associated with a net decrease in employment for these occupations. This is illustrated, in a simplified form, in Figure 3. The top panel shows the pattern of job polarization in employment growth rates for detailed occupations from 2000 through 2013.[32] This panel displays smoothed average employment growth of occupations by the mean log hourly wage of the occupation in 2000.[33] The horizontal dotted 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). The lower 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 show a monotonic increase in job growth rather than a pattern of job polarization. Although the figure does not account for inter-occupation substitution, the estimates in Table 4 do and they show a similar pattern.

[32] 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.
[33] I use Stata's smoothing routine with an Epanechnikov kernel with a 0.27 bandwidth.

Acemoglu and Autor (2011) identify the group of administrative support and sales occupations as occupations with routine cognitive tasks. These occupations are assumed to be prone to computer automation and job losses (e.g., Jaimovich and Siu 2012). Column 7 paints a somewhat different story. These occupations tend to grow more slowly with computer use but they also appear to by more affected by offshoring. Again, computer automation does not seem to be associated with job polarization; it is possible that technology contributes to employment losses in this group of occupations not by automation, but in other ways. For instance, information technology might facilitate firm decentralization involving transfers of work away from administrative support occupations. The last column shows production occupations, which seem to reflect the overall pattern of employment growth. Interestingly, for high-wage workers, workers in occupations that require college degrees, and managerial/professional occupations, the β estimate is positive and significant, suggesting that industry computer use tends to complement these occupations.

In summary, 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 do. 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 5 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.[34]

The first column shows that both wage gaps have tended to increase with computer use. The second column repeats the exercise, using interactions to separate the effect over decades. Autor, Katz, and Kearney (2008) find that the upper wage gap (90/50) increased relatively more since 1990 while the lower wage gap (50/10) increased relatively more during the 1980s. Interestingly, the coefficients on computer use show a parallel shift, suggesting that computers might be at least partially responsible for the change. The association of computer use with growth in the upper wage gap is initially negative during the 1980s and becomes positive; the association with the lower wage gap is strong during the 1980s and then diminishes.

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% 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 0.18% faster than the 10th percentile wage.[35] This means that computer use can account for about 45% of the rise

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[34] 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.

[35] 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.

in the 90/50 wage gap ($1-.33/.59$) and about 38% of the rise in the 50/10 wage gap ($1-.18/.28$) 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 3 and 4 add two different dummy variables if the occupation is more likely to experience superstar effects.[36] 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 3 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, contrary to the superstar hypothesis. Column 4 uses a narrower definition of superstar occupations, accounting for only 8% of the workforce.[37] 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.

The model of costly learning also suggests that occupations adopting new technology might employ relatively more workers with better pre-existing skills. Table 6 explores changes in the share of workers within an occupation who 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. Column 2 interacts computer use with decade dummies, showing that the relationship is persistent over the entire sample period.

Moreover, this association holds not just for occupations that involve a high level of cognitive tasks or for occupations that require college degrees. Column 3 shows the

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[36] These tests are similar to those performed by Meyer (2008).

[37] 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.

regression for occupations where the abstract task rating is less than 5 (the 1960 median). Column 4 shows the regression for occupations where fewer than 10% of the jobs require college degrees or higher.[38] 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.[39] On the other hand, the real wage of workers with only a high school diploma declined even more,[40] 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 5 repeats the regression of column 4 but adds two independent variables, the rate of growth of the mean wage for the occupation and the interaction term, *computer use x 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.

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 widespread computer automation must be

[38] This variable are from the Occupational Information Network (O*NET) database and are based on assessments of individual occupations by panels of experts.
[39] 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.
[40] The deflated mean log wage for workers with a high school diploma or GED fell 9.9%.

associated with major job losses. But this view fundamentally misunderstands what has been happening. The evidence shows that computer automation of an occupation is associated with increased demand for that occupation, partly by substituting for the inputs of other occupations. On average, the direct demand effect is largely offset by the substitution effect. The net result is that computer use is associated with a small increase in employment on average, not major job losses.

However, although computer automation is not associated with job losses overall, specific groups of occupations are negatively affected. In particular, computer automation is linked to job losses for low-wage jobs and job gains for high-wage occupations. That is, computer automation is implicated in a major reallocation of labor across occupations. Of course, if labor markets were not flexible, than the implied job transitions might indeed create unemployment. But that is not what appears to be happening in the US at least.

Nevertheless, this job transition could be difficult if it requires workers to learn new skills or if it implies considerable organizational change. A substantial literature finds evidence that computer adoption involves organizational change and investments in new skills, often learned on the job.[41] The nature of work also changes within occupations.[42] Consistent with this evidence, I find that 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. Thus although automation is not linked to major job losses, the development of new skills may present a major challenge to the workforce.

The pattern of job growth associated with computer automation is quite distinct from the pattern implied by routine-biased technical change. Computer automation is not associated with job losses in administrative support and sales jobs nor losses among routine-intensive jobs generally. This does not diminish the routine-biased technical change hypothesis. Rather it suggests that something other than computer automation is mainly

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[41] 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. Bessen (2015) reviews historical evidence.

[42] Autor, Levy, and Murnane (2003) and Spitz-Oener (2006).

responsible for any technical bias against routine jobs. Nor does job polarization seem to be exclusively a result of computer automation, especially for low-wage occupations.

While I show that computer use in an occupation Granger-causes employment growth, my analysis is not strictly causal. Two studies do evaluate causality and find patterns consistent with my results. 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. Akerman, Gaarder, and Mogstad (2015) find a similar pattern in response to the roll out of broadband Internet in Norway.

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.

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 may often require new skills that are difficult to acquire.

Appendix

Derivation of equation (5)

The production function over occupations $i = 1,\ldots,N$ 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)

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

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

(A3)

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

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:

$$\frac{d \ln \hat{L}_j}{d \ln a_j} = \frac{\rho}{1-\rho} + \left(1 - \frac{1}{\epsilon(1-\rho)}\right) \cdot S_j = (\sigma - 1) + (\epsilon - \sigma) \cdot S_j/\epsilon$$

$$\frac{d \ln \hat{L}_j}{d \ln a_{k \neq j}} = (\epsilon - \sigma) \cdot S_k/\epsilon$$

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

$$y_{ij} = \frac{1}{\frac{1}{A_1 s_i^R} + \cdots + \frac{1}{A_\mathrm{n} s_i^R} \ldots + \frac{1}{A_{\mathrm{n+m}} s_i^N}} = \frac{1}{\frac{1}{a_j^R s_i^R} + \frac{1}{a_j^N s_i^N}}$$

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

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

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.[43] 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.

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[43] 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 in Occupations

Occupation characteristics	1	2	3	4
Routine tasks	.002 (.005)			
x 1984		.013 (.009)	.026 (.007)**	.032 (.009)**
x 1989		.013 (.014)	.030 (.012)*	.033 (.014)*
x 1993		.009 (.014)	.028 (.012)*	.026 (.014)
x 1997		.000 (.014)	.020 (.012)	.017 (.013)
x 2001		-.012 (.013)	.008 (.010)	.006 (.011)
x 2003		-.010 (.013)	.007 (.012)	.007 (.012)
Abstract tasks				
x 1984			.055 (.006)**	
x 1989			.071 (.008)**	
x 1993			.082 (.007)**	
x 1997			.084 (.008)**	
x 2001			.085 (.007)**	
x 2003			.083 (.007)**	
Log wage (1980)				.218 (.028)**
Log employment				.016 (.007)*
College diploma required				.453 (.031)**
Adjusted R-squared	.11	.12	.46	.53
N	2,179	2,179	2,179	1,830

Note: By occupation-year, least squares regressions weighted by sample weights. Computer use data are from the Current Population Survey Supplements question about computer use at work. Regressions include year dummies. Robust standard errors are in parentheses. * = significant at the 5% level, **=significant at the 1% level.

Table 2. Employment Growth of Occupations over Decades, 1980-2013
Dependent variable: Annual growth rate (percent) of hours worked by decade

				Granger test	
	1	2	3	4	5
Dependent variable	$\Delta \ln L$	$\Delta \ln L$	$\Delta \ln L$	$\Delta \ln L$	Computer use
Computer use (α)	2.55 (.55)**	4.27 (.67)**			
Computer use x 1980s			6.64 (.99)**		
Computer use x 1990s			3.63 (1.22)**		
Computer use x 2000s			3.49 (.68)**		
Offshorability index		-1.85 (.32)**	-1.93 (.32)**	-1.72 (.41)**	.00 (.01)
Lagged $\Delta \ln L$ (previous decade)				.00 (.04)	.00 (.00)
Lagged computer use (previous decade)				2.49 (.77)**	.98 (.02)**
Adjusted R-squared	.06	.09	.10	.07	.85
N	946	900	900	601	599
Contribution of computer use to growth rate	1.06 (.23)**	1.74 (.27)**			

Note: Dependent variable in columns 1-4 is annual percentage growth in hours worked for each decade. The offshorability index was developed by Jensen and Kletzer (2010). The Granger tests use the growth in hours and computer use for the previous decade as independent variables as well as offshorability and decade dummies. Robust standard errors are in parentheses. * = significant at the 5% level, **=significant at the 1% level. Decade dummies not shown.

Table 3. Employment Growth of Occupation-Industry Cells, Full Model Estimates, 1980-2013
Dependent variable: Annual growth rate (percent) of hours worked

	1	2	3
α (own use)	1.19 (.23)**	2.39 (.23)**	1.64 (.13)**
β (industry use)	-.80 (.60)	-.91 (.47)	-1.18 (.60)
Offshorability index		-1.33 (.27)**	-.75 (.31)*
Industry dummies			✓
R-squared	.01	.06	.16
N	17,491	16,663	16,663
Contribution of computer use to growth rate	.11 (.21)	.45 (.17)**	.13 (.20)

Note: Dependent variable is annual percentage growth in hours worked for detailed occupation-industry cell. The sample includes cells where computer use variables are imputed based on occupation and industry averages. 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.

Table 4

A. Employment Growth of Occupations over Decades, 1980-2013

	1 Routine intensive	2 Low-wage	3 Mid-wage	4 High-wage	5 College required	6 Managers & professionals	7 Administrative support & sales	8 Production
Computer use	4.77 (0.89)**	4.18 (2.07)*	3.66 (0.84)**	3.72 (3.23)	3.21 (3.01)	1.26 (2.58)	0.40 (2.02)	4.90 (2.01)*
Offshorability index	-1.75 (0.47)**	-2.43 (0.60)**	-1.59 (0.39)**	-1.59 (1.24)	-1.94 (0.95)*	-0.97 (0.82)	-2.33 (0.86)**	-2.20 (1.21)
Adjusted R-squared	0.097	0.107	0.069	0.032	0.067	0.058	0.094	0.136
N	438	207	522	171	231	243	150	144
Share using computers	40%	17%	41%	70%	66%	66%	62%	21%
Computer contribution to growth	1.91 (0.36)**	0.71 (0.35)*	1.50 (0.35)**	2.62 (2.27)	2.10 (1.97)	0.83 (1.71)	0.25 (1.25)	1.02 (0.42)*

Dependent variable is annual percentage growth in hours worked for each decade for each occupation. The offshorability index was developed by Jensen and Kletzer (2010). Robust standard errors are in parentheses. * = significant at the 5% level, **=significant at the 1% level. Decade dummies included but not shown. Groups are defined as: routine intensive occupations rank above median on importance of routine tasks; low, mid, and high wage groups correspond to first quartile, middle quartiles, and fourth quartile in 1980 wages; the fifth column includes occupations where over half of jobs require a college diploma or higher (O*NET); the last three columns capture broad occupational categories.

B. Employment Growth of Occupation-Industry Cells, Full Model Estimates, 1980-2013

	Routine intensive	Low-wage	Mid-wage	High-wage	College required	Managers & professionals	Administrative support & sales	Production
α	2.37 (0.51)**	3.26 (0.79)**	2.34 (0.33)**	0.50 (1.03)	0.96 (1.61)	-0.80 (0.99)	1.69 (0.78)*	1.56 (0.64)*
β	-1.79 (1.19)	-3.24 (0.90)**	-0.98 (0.60)	3.22 (1.23)**	3.08 (1.15)**	3.37 (1.20)**	-1.69 (0.87)	0.07 (1.25)
Offshorability index	-1.11 (0.40)**	-1.28 (0.42)**	-1.65 (0.26)**	-0.21 (0.30)	-0.70 (0.32)*	-0.35 (0.22)	-2.01 (0.63)**	-1.20 (0.29)**
R-squared	0.046	0.085	0.082	0.072	0.066	0.052	0.101	0.018
N	7748	3600	10264	2799	3761	3882	4618	2196
Computer contribution to growth	0.14 (0.41)	-0.43 (0.22)†	0.43 (0.23)†	1.65 (0.78)*	1.63 (0.86)†	0.96 (0.70)	0.12 (0.49)	0.18 (0.34)

Note: Dependent variable is annual percentage growth in hours worked for detailed occupation-industry cell over the entire period. The sample includes cells where computer use variables are imputed based on occupation and industry averages. Weighted by occupation hours worked. Standard errors are in parentheses and are clustered by industry group. † = significant at 10% level, * = significant at the 5% level, **=significant at the 1% level.

Table 5. Change in Within-Occupation Wage Gaps

Panel A. Change Between 90th and 50th Percentiles

	1	2	3	4
	1980-2013	1980-2013	1990-2013	1990-2013
Computer use	.29 (.08)**		.49 (.09)**	.46 (.09)**
Computer use x 1980s		-.41 (.13)**		
Computer use x 1990s		.48 (.09)**		
Computer use x 2000s		.39 (.10)**		
Education, 2nd wage quartile	-.05 (.04)	-.06 (.04)	-.09 (.05)*	-.07 (.04)
Education, 4th wage quartile	.04 (.04)	.05 (.03)	.08 (.05)	.05 (.04)
Superstar I			-.09 (.06)	
Superstar II				.18 (.09)
R-squared	.057	.100	.077	.079
N	925	925	615	615

Panel B. Change Between 50th and 10th Percentiles

	1	2
Computer use	.34 (.09)**	
Computer use x 1980s		1.12 (.16)**
Computer use x 1990s		.33 (.12)**
Computer use x 2000s		-.05 (.12)
Education, 2nd wage quartile	-.01 (.05)	.01 (.05)
Education, 4th wage quartile	-.01 (.04)	-.01 (.04)
R-squared	.193	.228
N	946	946

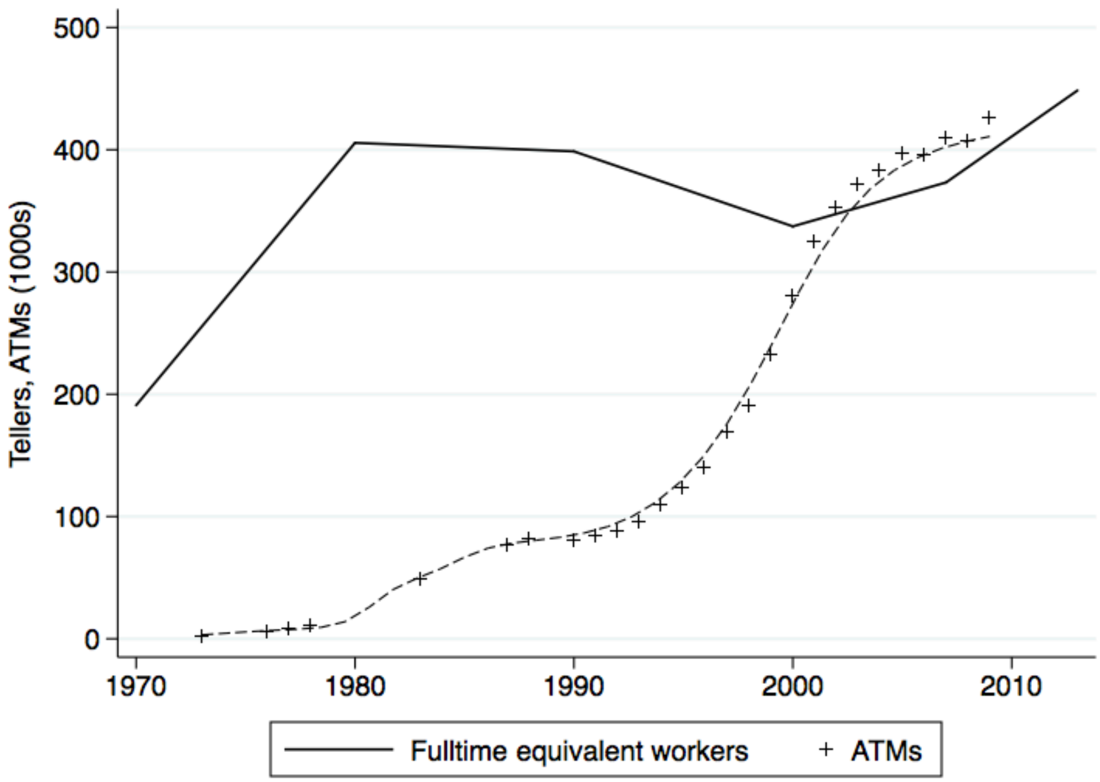
Note: Weighted least squares regressions of detailed occupation data by decade. Dependent variable is annual percentage change in the difference in log wages between the 90th (50th) and 50th (10th) percentiles in the upper (lower) panel. Top panel excludes 7 occupations where some topcoded wage observations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

Table 6. Annual Percentage Change in Share of Workforce with College Education

	1	2	3	4	5
Sample:	All	All	Few abstract tasks	College not required	College not required
Computer use	.45(.04)**		.44(.04)**	.41(.03)**	.39(.03)**
Computer use x 1980s		.49 (.09)**			
Computer use x 1990s		.36 (.06)**			
Computer use x 2000s		.52 (.06)**			
Computer use x wage growth					3.17(.45)**
Wage growth					-.05(.20)
R-squared	.163	.166	.198	.332	.458
N	946	946	725	510	510

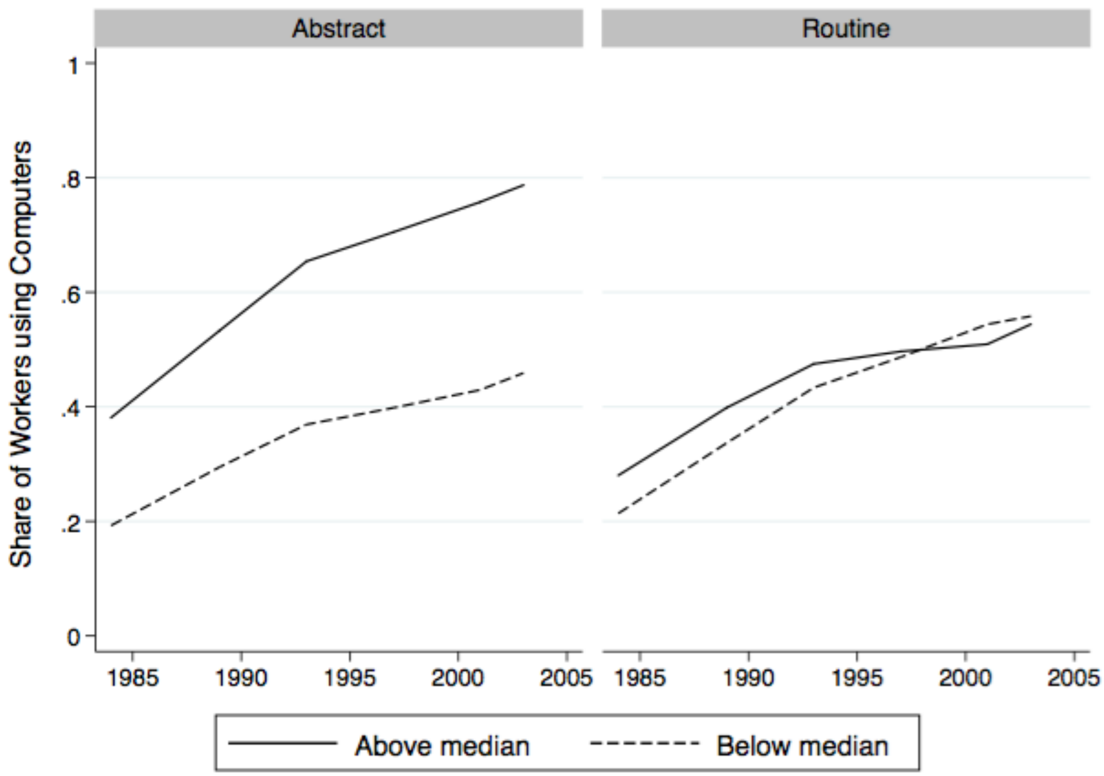
Note: Weighted least squares regressions of detailed occupation data. Dependent variable is the annual change in the share of hours worked by workers with four or more years of postsecondary education from 1980 to 2013. Observations are occupation by decade. Decade dummies not shown. Weighted by occupation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

Figure 1. Bank Tellers and Automated Teller Machines



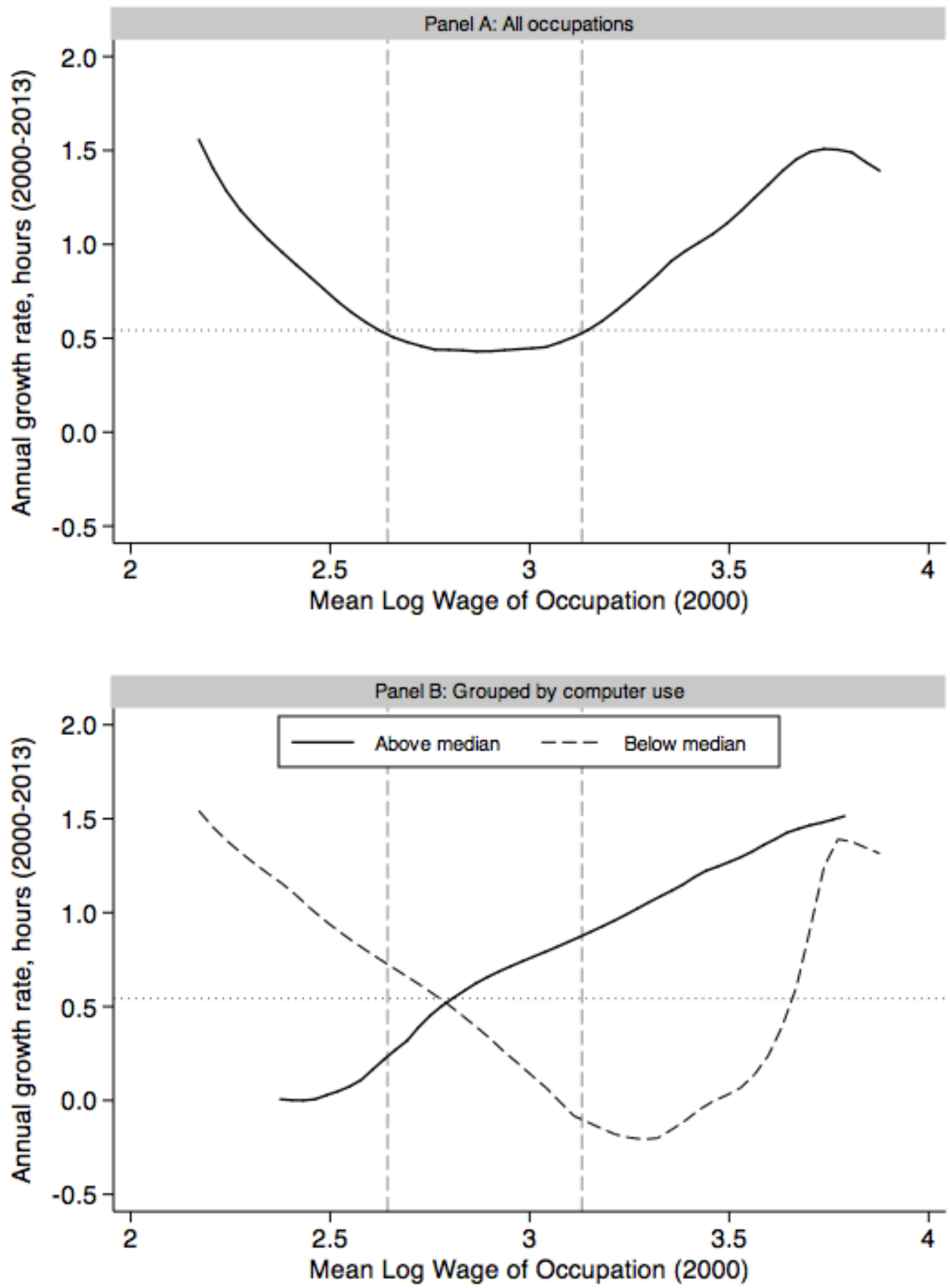
Note: Teller data from Census and ACS 1% samples. Fulltime equivalent workers calculated assuming 2080 hours per work year. Data on number of ATMs installed from the Bank for International Settlements.

Figure 2. 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.

Figure 3. 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 25^{th} and 75^{th} percentiles in the occupational wage. Horizontal dotted line is total hours growth.