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TWISTING THE DEMAND CURVE:
DIGITALIZATION AND THE OLDER WORKFORCE

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ABSTRACT

This paper uses U.S. Census Bureau panel data that link firm software investment to worker earnings. We regress the log of earnings of workers by age group on the software investment by their employing firm. To unpack the potential causal factors for differential software effects by age group we extend the AKM framework by including job-spell fixed effects that allow for a correlation between the worker-firm match and age and by including time-varying firm effects that allow for a correlation between wage-enhancing productivity shocks and software investments. Within job-spell, software capital raises earnings at a rate that declines post age 50 to about zero after age 65. By contrast, the effects of non-IT equipment investment on earnings increase for workers post age 50. The difference between the software and non-IT equipment effects suggests that our results are attributable to the technology rather than to age-related bargaining power. Our data further show that software capital increases the earnings of high-wage workers relative to low-wage workers and the earnings in high-wage firms relative to low-wage firms, and may thus widen earnings inequality within and across firms.

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1. Introduction

From 1980 to 2019, spending on business software in the United States increased from 5% to 33% of spending on equipment, reflecting a far-reaching shift in investment from machines run largely by humans to digital tools. Figure 1 shows that while investments in equipment capital doubled from 1998 to 2017, investment in software capital quadrupled. The digital nature of software allows it to spread more rapidly than physical capital, while the movement of information and communication technology (ICT) to the cloud has increased the speed with which firms can access the latest software.[2] The COVID-19 crisis is likely to further accelerate these trends as firms seek more ways for humans to interact digitally rather than in close physical contact.

What workers do in this increasingly digital economy depends more and more on the software with which they work. The vast majority of white-collar workers use software regularly on their jobs and an increasing number of blue-collar workers do as well. Improvements in software, some generated by advances in AI in recent years, go beyond automating routine business activities to increasingly allow software programs to perform non-routine cognitive work.[3] U.S. Department of Labor data on software shows huge growth in the number of categories of software "necessary" for different jobs.[4]

How do workers in different age groups fare as production becomes more digital? Will digitalization of work be more complementary with older or prime workers or younger aged workers? On the one side, young workers are more likely to have programming skills but lack the "wisdom of experience". On the other side, as programs become increasingly simplified, the skills of older workers may be more valuable. To answer the question, this paper explores the relationship between business investments in software and the earnings of workers of different age groups. We utilize firm and worker data collected by the U.S. Census Bureau and made available for research in the Federal Statistical Research Data Centers. The link between firm and worker allows us to study the labor market implications of the burgeoning software investment within and across firms. Our focus is on differential effects within firms of software investments on the earnings of workers of different ages who may be more or less complementary to new technology. We also explore exit patterns within firms, comparing the impacts of firm spending on software the impacts of firm spending on traditional equipment.

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[2] See Jin and McElheran (2017) and Byrne and Corrado (2017).
[3] See e.g., Brynjolfsson and McAfee (2014), Autor (2015), Dillender and Forsythe (2019), and Webb (2020).
[4] Hu and Freeman (2020).

There are two competing views of how software might affect workers of different ages. The first is that because younger persons are more familiar with new software than older workers through programming and computer science courses in school and growing up with the latest smart phone or game playing programs, they should complement new software so that software spending will twist the demand curve for labor in favor of younger workers, raising their wages and/or employment relative to that of older workers.

The second view highlights that recent generations of software, with simplified user interfaces and smarter back-end technology, reduce the specialized knowledge required to run and interpret its output.[5] In that case, the main beneficiaries of software spending could be older workers, whose other experience-based knowledge can complement the software. For example, early users of statistical software packages benefited from knowledge of cutting-edge programming and statistics to develop the best analyses but today's programming modules, and machine learning algorithms perform those technical tasks so that the job for workers is more to assess and communicate the meaning of results for the business, which prime age or older workers presumably can do better than younger workers.

Most work on skill-biased technical change has focused on differences between workers in blue-collar versus white-collar occupations, or on workers who differ in years of schooling, finding that computer use and ICT spending benefits skilled workers more than less-skilled workers.[6] A few studies use European data to examine the impact of new technologies on workers of differing ages, with mixed results.[7] Gaining a clear view of potential age- and skill-biased outcomes at a time of rapid digitalization will illuminate the widening earnings inequality worldwide.

Our paper assesses the relative impact of software on workers by age, with a novel panel of employer-employee linked data from the U.S. for 2002 to 2014. It links data for firm software and equipment investments from the Census Annual Capital Expenditure Survey

[5]Some evidence for this is found in the higher diffusion of touchscreens compared to a wide range of advanced business technologies across the U.S. in recent years (Zolas et al. 2020).

[6]See e.g. Katz and Murphy 1992; Autor, Katz and Krueger 1998; Goldin and Katz 2009.

[7]In Norway, Schøne (2009) finds age bias related to computer use in cross-sectional comparisons, but not in changes over time. Hægeland, Rønningen and Salvanes (2007) find that only the oldest male workers (above 60) retire early in response to "extraordinary" changes in process technologies. In Germany, Battisti et al. (2020) and Beckmann (2007) find evidence of age-biased technological change that may be somewhat dampened with training. In France, ICT investment has been found to be age biased (Aubert et al. 2006), and may disproportionately affect lower-skilled older workers (Behaghel and Greenan 2010, Behaghel et al. 2014). Recent work using Dutch micro data also shows negative impacts for older workers due to automation (Bessen et al. 2019). In contrast, a U.S.-based study using CPS data on computer use in the 80s and 90s (Weinberg 2004), finds that computers complemented experienced workers who only completed high school; among college graduates, computers complemented younger workers.

(ACES) with data on individual workers in each firm from the annual Longitudinal Employment and Household Dynamics (LEHD) database. We use this detailed panel to analyze the impact of firm investments in software on the earnings of workers by age and on the exit/retirement behavior of older workers. By analyzing firm spending on software rather than on the computer usage prevalent in previous studies, we highlight the importance of modern applications that build on the waves of computer hardware and infrastructure diffusion in prior studies.[8]

Our analysis extends the Abowd, Kramarz, and Margolis (1999) AKM model that uses detailed fixed effects to sweep out the impact of invariant characteristics of firms and individuals to allow us to better identify the relationship between software and worker earnings. We first augment the AKM model by including job-spell fixed effects, as in Barth, Davis and Freeman (2018), to control for the particular match between a worker and a firm. This may be especially important for identifying mechanisms related to worker age, as match quality may change over the career of a worker. Next, we add time-varying firm effects, per Lachowska, Mas, Raffaele and Woodbury (2020) and Engbom and Moser (2020), to address the possibility that time-varying productivity shocks may be correlated with software investments,[9] which would bias estimates that assumed firm fixed effects. This allows us to identify differences in the impacts of time-varying firm-specific variables, such as software investments, on different types of workers, such as age groups, within firms.

The AKM framework is also central in our analyzing the extent to which software investments tend to widen wage dispersion within firms. We leverage it to estimate individual fixed effects for the entire labor market, which we then interact with observed software investments. In this way, we unpack whether software represents a typical skill-biased technical change or adds to a “polarization” of jobs within firms, whereby workers in the top and the bottom of the occupational earnings distribution gain at the expense of the middle.[10]

[8]Studies on PC use and labor market outcomes include Krueger (1993), Autor, Levy and Murnane (2003), Schøne (2009), Autor and Dorn (2013), and Hershbein and Kahn (2018), among others. Forman, Goldfarb and Greenstein (2012) document wage inequality related to internet use. Studies of the labor market impacts of broadband is the focus of Akermann, Gaarder and Mogstad (2015) and Poliquin (2020). Complex software is implicated in increased demand for non-routine cognitive workers in U.K. small businesses (Gaggl and Wright 2017) and *reduced* wage polarization within Chilean firms (Almeida, Fernandes and Viollaz 2020). A few recent studies of how ICT affects the skill content of jobs include measures of modern software (Dillender and Forsythe 2019; Atalay et al. 2018; Webb 2020).

[9]For instance, complementarities between ICT investments and unobserved changes in organizational design and management practices, observed in several studies (see e.g. Bartel, Ichniowski and Shaw 2007, Bresnahan, Brynjolfsson, and Hitt 2002, Brynjolfsson and McElheran 2019, Battisti et al. 2020), may have direct effects on productivity and correlate with software investments.

[10]See e.g. Autor, et al (2003), Autor and Dorn (2013), Michaels, Natraj, and Van Reenan 2014, and Harrigan, Reshef and Toubal (2016).

Similarly, we use the AKM decomposition to estimate worker and firm fixed effects that allow us to estimate the extent to which software investments increase earnings more in high-wage firms, than in low-wage firms and for high wage compared to low wage workers.[11]

2. Data

The primary independent variable in our analysis is software capital calculated using standard perpetual inventory methods taken relative to workers in the firm. Beginning in 2002, the Census Bureau's Annual Capital Expenditure Survey (ACES) – a nationally representative annual survey of 50,000 firms[12] that collects firm expenditures on new and used structures and equipment chargeable to asset accounts for which depreciation or amortization accounts are ordinarily maintained – has asked respondents to report capital expenditures for computer software developed or acquired as either prepackaged or vendor-customized for internal use. Capitalized computer software expenditures consist of the cost of materials and services directly related to the development or acquisition of software; payroll and payroll- related costs for employees directly associated with software development; and interest costs incurred while developing the software.[13] The survey covers all firms with at least 500 paid employees with certainty and randomly selected smaller firms. The sample of firms that we use comes primarily from the certainty sample because our measures of software capital stock are derived from expenditures using standard perpetual inventory methods, [14] which rules out most randomly selected smaller firms since they appear in the data set irregularly.

The ACES data asks firms about spending on software that firms capitalize as investment, which makes it comparable to other capital expenditures. This excludes software spending that is deductible as an expense of production or intermediate purchase and thus falls short of the National Income and Product Accounts (NIPA) estimate for private fixed investment based on sales of software reported by producing firms.[15]

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[11]See e.g. Card, Heining and Kline 2013; Barth et al. 2016; Card et al. 2018; Song et al. 2019, and Cornwell, Shmutte, and Scur (2019) for recent evidence on rising earnings inequality within and between firms as well as potential causes.

[12]ACES was expanded from 45 to 50 thousand employer firms in 2016. The survey also includes data for 15 to 30 thousand non-employer firms per year that are not used in this study.

[13]Capitalized computer software is defined by the criteria in Statement of Position 98-1, Accounting for the Costs of Computer Software Developed or Obtained for Internal Use, issued by American Institute of Certified Public Accountants.

[14]As initial conditions for the entry year, the industry average shares of software investments of total investments were combined with data on the initial gross value of assets. To accommodate for the shorter history and higher growth of software investments, the initial levels of software capital shares were set to .5 of the share of investments associated with software in each industry in the initial year.

[15]St. Louis Federal Reserve Bank FRED series B985RC1A027NBEA. As most software spending is expensed, the capital data covers only about one-third of national investment in software. Appendix A describes a Bureau

This distinction matters because expensed software typically represents routine production costs similar to materials purchases (e.g., word processing and automated payroll applications). In contrast, large custom software investments and capitalized purchased software are likely to represent firm investments in innovation (e.g. Bessen and Righi 2020). A useful example is the custom logistics software system built and maintained by Walmart. These lumpy ICT investments – and the significant "co-invention" of the organizational design and production processes that typically accompanies them (Bresnahan and Greenstein 1996, McElheran 2015) – are linked to significant productivity gains and shifts in skilled labor and wages at the firm level.[16]

Our data links information on capitalized software investment, capital equipment investment, firm employment, and sales to workers in the annual Longitudinal Employer-Household Dynamics (LEHD) Employment History Files (EHF) data from 2002 to 2014 that follow individual workers in each firm (Abowd, Haltiwanger and Lane 2004; Abowd et al. 2009; Vilhuber 2018). The EHF is derived from firm reports to state unemployment insurance agencies for all employed workers. The LEHD EHF data contain the earnings of workers. We use annualized earnings for a worker's main job, defined as the longest job across quarters with the highest earnings.[17] Worker age comes from the LEHD Individual Characteristics File (ICF), which obtains this from Social Security Number (SSN) applications to the Social Security Administration (SSA). The ICF imputes the education of workers using reported education from the 2000 decennial census. We construct shares of workers with different levels of education at the firm level from the imputed ICF values.[18] In 2012, 14% of workers in our sample have less than high school education, 26% have high school degrees, 31% have some college or trade school, and 29% have a college degree. Our LEHD data cover 22 states

of Economic Analysis investigation of the issue. We have chosen to include only capitalized software investments in our analysis, and leave the treatment of expensed items, available in the Information & Communication Technology Survey (ICTS) for the years when it was conducted, to future exploration. Note that the capital data capture a key shift in the nature of ICT investment in recent decades from computer hardware or pre-packaged software towards firm-specific software.

[16]Recent work on automation and labor market outcomes emphasizes the importance of refined ICT measures to avoid confounding technologies that automate different types of tasks (e.g., Acemoglu and Restrepo 2019, Dillender and Forsythe 2019, Almeida et al. 2020). From 2002 on, ACES data has divided capitalized computer software into prepackaged, vendor-customized and internally-developed (including payroll) sub-categories. Estimating all of the equations in this paper using a software measure constructed as the sum of the first two sub-categories of prepackaged and vendor-customized, gave results consistent with those based on the ACES measure of total capitalized computer software. Given that firms are unlikely to change their internal accounting practices from year to year, the ACES measure of capitalized software should capture changes in software investment over time, particularly large-scale software investments that may impact outcomes for workers.

[17]Jobs with earnings less than half the federal minimum wage in 2002 are excluded.

[18]This version of imputed education is reasonable for estimating the education distribution of workers at the firm but raises measurement error problems when if used for individual- level earnings specifications.

and the District of Columbia, representing half of the U.S. workforce in 2012, and appears representative of the country as a whole.[19]

We group the 11.6 million workers in our samples by five-year age groups (20-24, 25-29, 30-34, etc.). Each age group represents around 12% of the distribution of workers, except for the three older groups, whose shares decline as workers exit the labor force. Workers aged 55-59 represent 9%, 60-64 year-old workers are 6%, and aged 65+ workers are 3% of the sample, respectively.

We work with two samples: (1) the *full* LEHD data for 23 states, which we use to run an AKM decomposition to obtain quintiles of the individual and firm fixed effects for all workers and firms in those states; and (2) an *analysis* sample, which contains all workers in the 23 states working in firms in the ACES sample. Appendix B compares the two samples.

If firms with differing software-capital-to-worker ratios hire workers in the same labor market, then the distribution of worker attributes among the firms should be informative about complementarities between software and worker attributes.[20] Accordingly, we examined the composition of the work forces of firms with differing amounts of software capital per worker and found three striking patterns.

1) Large differences in the age composition of workers across firms with differing software per worker. This is shown in Figure 2 in terms of the age group for firms in the bottom quintile (Q1), median quintile (Q3), and top quintile (Q5) of software capital per worker.[21] Workers aged 20-29 are over-represented in the bottom quintile of software intensity, suggesting that their labor skills make them more suitable employees for firms that use less software. Workers in the 35-49 age group are over-represented in the top quintile of software intensity firms, suggesting the opposite – that they have skills that complement software. The share of workers in the aged 50-64 age group declines steeply from the top quintile to the bottom quintile, and the oldest group, 65+, has the lowest representation in the most software-intensive firms.

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[19]The 23 approved states are AR, AZ, CA, CO, DC, DE, IA, IL, IN, KS, MD, ME, MT, ND, NE, NM, NV, OK, PA, TN, TX, VA and WA. Average earnings for the workers in covered states is 2.7% higher than for the 28 uncovered states. Employment of workers 45 and older in the covered states is also half the total. We calculated the 0.506 employment share of these states nationally, 0.501 older worker share, and worker average earnings from the public use LEHD Quarterly Workforce Indicators (QWI) V4.6.0 downloaded 5/24/2020.

[20] In fact, Brynjolfsson and Milgrom (2013) test for complementarities based on whether production inputs are adopted together across firms with similar production functions (e.g.,).

[21] Note that there may be a lot of individual and firm demographics behind the age composition as well, see e.g. Autor and Dorn (2009) who argue that "occupations will 'get old' as their employment declines — that is, the mean age of an occupation's workforce will rise, "because older workers are less likely to leave declining occupations, and younger workers will be hired into growing occupations." The same argument may apply to firms, distorting effects related to skill complementarity in production unless estimated carefully.

The finding that workers in the 35-49 age group appear more complementary with software than younger and older workers is consistent with related work in France (Aubert, Caroli and Roger 2006), Germany (Beckmann 2007) and Norway (Schøne 2009).

2) *Software-intensive firms have more employees and proportionately more educated workers and higher labor productivity than others*

Table 1 shows average firm characteristics in 2012 by quintile of software intensity across firms. The first line displays a large dispersion across firms in the logged software capital per worker. Looking at the distribution of employment, we see that the more software-intensive firms are larger.[22] Software-intensive firms also have more equipment per worker, are older, and are more likely to have multiple establishments. The employment shares by education groups show that firms with the greatest software intensity employ proportionately more college-educated workers and fewer workers who have not completed high school.[23]

The last line in Table 1 shows that average revenue per worker in the top quintile of software intensity is more than 30 times that in the bottom quintile of software intensity.

3) Software-intensive firms employ workers with high individual fixed effects in earnings and are themselves high-wage in terms of their firm fixed effects on earnings

This result comes from the panel aspects of our data, which allows us to estimate the AKM decomposition of labor earnings into worker-fixed effects and firm-fixed effects, controlling for age and year effects, as detailed in the methodology section. Panel A of Figure 3 displays the results in terms of the average worker fixed effect.

There is a strong positive correlation between the individual fixed effects from the earnings regression and firm software intensity, indicating that software-intensive firms disproportionately employ workers with attributes associated with higher earnings. The figure also displays the average predicted value of the individual fixed effect, generated using gender, education, and age-cohort as time invariant covariates and the residual unobserved individual fixed effect. The positive slope between the individual fixed effects and software intensity is due mainly to the unobserved part of workers' time-invariant characteristics.

Panel B displays the result of the analogous calculation for firms. The slope linking software intensity to the average firm fixed effect is steeper than the slope in Panel A, with a gap between the bottom and the top quintile of more than 0.5 log points. Both the observed

[22]See Tambe and Hitt (2012), McElheran (2015) for evidence showing similar patterns.

[23]This is consistent with the relationship between ICT adoption and skilled labor found in prior work where skill is measured in terms of formal education (e.g. Bresnahan et al. 2002).

part of the firm fixed effects (predicted using average firm and establishment employment, firm age, and industry) and the unobserved part are positively related to software intensity.

Several mechanisms might explain these observations: the effects of productivity-enhancing software capital on demand for labor at different ages, selectivity of high software investments from high wage firms, and selectivity of high wage workers into firms, all of which may vary by the age of workers. To assess the impact of each mechanism we augment the AKM model using the framework given next.

3. Framework

Software capital can affect younger and older persons differently in three ways.

First is through differences in the knowledge and skills of particular cohorts of workers. C*ohort effects* evoke Johansen's (1959) "putty-clay" framework for physical capital. When persons invest in human capital, they embody the technology/knowledge at that time but tend to fall behind advances, which younger generations learn directly. To the extent that software technologies change more rapidly than physical equipment, a rising share of software in capital will twist demand for labor toward younger persons due to cohort effects.[24]

Second through *aging*. Aging changes the comparative advantage of workers to undertake different tasks. Biological processes give the young an advantage in physical strength, dexterity, and a short reaction time, while older persons may gain an advantage in careful deliberations, collaboration, and the ability to combine information with experience.[25] The tasks workers do most productively are thus likely to change, as is the fit of their skills with different types of firm investment. Firm investments in labor-saving physical equipment such as robots are likely to twist demand against the young.[26] But, as noted in the introduction, there are competing views of how software investments affect the productivity of labor of differing age.

Third is through the incentive to invest in knowledge that keeps pace. Older workers may have more to gain from training to keep pace with new software packages because their knowledge is of older vintage, but their greater distance from the technological frontier may require higher investments in training. Most important, the shorter time remaining until

[24]Work on skill obsolescence dates back to Rosen (1975). Chari and Hopenhayn (1991) argue that new technologies require vintage-specific skills, so any increase in the rate of technological change increases returns for more-recent vintages and flattens the age-earnings profile.

[25]For instance, Paccagnella (2016) provides evidence that individuals replace declining standardized proficiencies with other, more difficult-to measure, skills based on experience as they age.

[26]Recent work indicates that this is more difficult in contexts of rapid technological change and has been shifting returns to experience in the U.S. in recent years (e.g., Deming and Noray, forthcoming).

retirement skews the investment decision to favor training the young (e.g., Friedberg 2003, Behaghel and Greenan 2010).

We analyze these issues in the framework of firms optimizing their use of labor in a standard production function model. Consider the simple production function (ignoring subscripts for firm j and time t):

$$Y = \Omega \mathrm{K}^{\alpha_K} \mathrm{S}^{\alpha_S} \tilde{L}^{\alpha_L}$$

where Y is revenue, Ω is total factor productivity, K is capital (without software, but including computer hardware capital), S is a measure of software capital, and $\tilde{L}$ is efficiency units of labor. Assuming that workers of different age groups are perfect substitutes, but with potentially different productivities, efficiency units of labor is given by $\tilde{L} = \sum_g (e^{\omega_g} L_g)$, where ω_g is the productivity of each age group, g.

To investigate the extent to which software capital affects the relative productivity of each type of labor, g, we assume that: $\omega_g = \pi_g + \delta_g^s lns + \delta_g^k lnk$, where π_g is an age-specific productivity term, s=S/L and k=K/L are capital intensities, and δ_g^κ, κ=s,k, represents the relative impact of software and equipment capital intensities on age group g. The marginal productivity of labor of age g is given by:

$$\frac{\delta Y}{\delta L_g} = \alpha_L \frac{Y}{\tilde{L}} \frac{\delta \tilde{L}}{\delta L_g} = \alpha_L \Omega \mathrm{k}^{\alpha_K} \mathrm{s}^{\alpha_S} L^{(\alpha_K + \alpha_S + \alpha_L - 1)} \left(\frac{L}{\tilde{L}}\right)^{1-\alpha_L} e^{\pi_g + \delta_g^s lns + \delta_g^k lnk}$$

Software capital per worker affects the productivity of labor of type g in two ways. First it affects the average productivity of efficiency units of labor. In addition, it affects the relative productivity of each age group of workers. α_S>0 suggests complementarity between the two types of capital, while the effect of software on the efficiency units of labor differs between groups, and is given by $\alpha_S + \delta_g^s$ which may take any sign. A similar argument applies to equipment capital. We discuss issues of normalization in the empirical implementation below.

Wage Determination

We allow for firm-specific wage determination, and consider a simple monopsony model (see Manning, 2002; Card, Cardoso, Heining and Kline 2018). Let w_g be the wage of age group g in the firm. The labor supply facing each firm is given by $L_g(w_g)$, where $\frac{\delta L_g}{\delta w_g} > 0$. Let ε > 0 be the elasticity of labor supply facing the firm. Profits are given by:

$$\Pi(\boldsymbol{w}) = Y\big(K, S, \tilde{L}(\boldsymbol{w})\big) - \sum w_g L_g(w_g)$$

where **w** is the vector of wages. Profit maximization w.r.t w_g gives:

(1) $$w_g = \frac{\varepsilon}{1+\varepsilon}\frac{\delta Y}{\delta L_g} = m_g \alpha_L \frac{Y}{L}\frac{L}{\tilde{L}} e^{\pi_g + \delta_g^s lnS + \delta_g^k lnK}$$

Where m= is the "monopsony discount" of wages on marginal productivity. The assumption that age groups are perfect substitutes implies that the marginal productivity of each group is independent of its relative size, and we note that the term $\alpha_L \frac{Y}{L}\frac{L}{\tilde{L}}$ is firm specific and common for all age groups within the firm.

4. Empirical Implementation

The age-specific wage in firm j at t, w_{gjt}, is given by equation (1). Let the wage of individual i (of age group g), in firm j at time t, be given by $w_{ijt} = e^{c_i + X_{it}b + \xi_{ij}} w_{gjt}$. $c_i = Z_i b^z + \tilde{c}_i$ is an individual fixed component, including observables, Z_i, such as gender and education, and an unobserved fixed effect, $\tilde{c}_i$. X is a vector of time-varying individual characteristics, ξ_{ij} a match specific component between the individual and firm.

We represent the monopsony discount of group g in firm j at t by the decomposition $m = e^{\mu_g + b_{jt}}$, where μ_g is age specific (determined by factors such as the relative size of each age group in the labor market) and b_{jt} is firm specific (determined by factors such as the firm's position in the wage distribution across firms in the labor market). Adding an error term, u, we obtain:

(2) $$w_{ijt} = \alpha_L \frac{Y_{jt}}{L_{jt}}\frac{L_{jt}}{\tilde{L}_{jt}} e^{c_i + X_{it}b + \xi_{ij} + \mu_g + b_{jt} + \pi_g + \delta_g^s lns_{jt} + \delta_g^k lnk_{jt} + u_{ijt}}.$$

Identification Within Job-Spell

We first estimate a log wage regression on the observed time-varying covariates, including dummies for age groups, the interaction terms between age groups and the two measures of capital (S and K), log of employment, year dummies, and a job-spell fixed effect:

(3) $$lnw_{ijt} = X_{it}b + \mu_g + \pi_g + \left(\alpha^s + \delta_g^s\right)lns_{jt} + (\alpha^k + \delta_g^k)lnk_{jt} +$$
$$(\alpha_S + \alpha_K + \alpha_L - 1)lnL_{jt} + ln\alpha_L + \psi_{ij} + \gamma_t + e_{ijt}$$

The job-spell fixed effect, $\psi_{ij} = c_i + \varphi_j + \xi_{ij}$, incorporates the AKM specification, with a worker fixed effect, c_i, a firm fixed effect, φ_j, and a match fixed effect, ξ_{ij}, related to the specific match between firm and worker.[27] We discuss the parameters absorbed by the job fixed effects below.

For each age group, g, we obtain the estimate for $\tilde{\delta}_g^\kappa = (\alpha^\kappa + \delta_g^\kappa)$, which incorporates the effect of capital on the labor productivity of the firm, as well as the group-specific parameter. Even if we cannot identify the capital-specific parameters separately from the group-specific parameters, we can identify the difference between the group-specific parameters by taking the difference between the estimates for different age groups. Since the firm specific term is constant across age groups, it drops out of the difference: $\tilde{\delta}_g^\kappa - \tilde{\delta}_h^\kappa = \delta_g^\kappa - \delta_h^\kappa$.

Adding Time-Varying Firm Effects

We may write log wages given by (2) as:

(4) $lnw_{ijt} = X_{it}b + \pi_g + \mu_g + \varphi_{jt} + \psi_{ij} + \gamma_t + \delta_g^s lns_{jt} + \delta_g^k lnk_{jt} + u_{ijt}$ where we add a year specific time-varying firm effect that absorbs time-varying firm-specific factors:

(5) $\varphi_{jt} = b_{jt} + \omega_{jt} + \alpha^s lns_{jt} + \alpha^k lnk_{jt} + (\alpha_S + \alpha_K + \alpha_L - 1)lnL_{jt} + (1-\alpha_L)\left(lnL_{jt} - ln\tilde{L}_{jt}\right)$

which includes both the unobserved productivity and monopsony discount, and the observable time-varying firm-level covariates.

In the job-spell fixed effect equation (3), firm-specific shocks to b_{jt} and ω_{jt} (deviations from their job-spell-specific means that are not captured by the common year effect γ_t) are included in the error term, e. To the extent that such shocks are correlated with investments in software or equipment, they will bias the within job-spell estimates. A similar concern arises with regard to the unobserved time-varying efficiency units of labor, $\tilde{L}_{jt}$. Adding time-varying firm effects removes such biases.

In equation (4), both $X_{it}b$ and $\pi_g + \mu_g$ are observable time-varying individual variables (as also g may vary over time within individual in the panel). The component $\delta_g^s lns_{jt} + \delta_g^k lnk_{jt}$ varies between groups within the firm over time, and may be estimated using interaction terms between age group and capital intensities. Estimating equation (4) with time-varying firm effects effectively controls for both observable and unobservable wage shocks that affect wages of every worker in the firm in any year. In particular, the time-

[27] ψ_{ij} may easily be decomposed into its three parts by defining the match effect as orthogonal to the individual and firm effects (but not necessarily to the other covariates of the model) and appropriate normalizations.

varying firm effect includes two unobserved time-varying firm-specific terms: b_{jt} and ω_{jt} that represent temporal variation in the monopsony discount of the firm (i.e. market power or bargaining power in the labor market) and potential temporal variation in the unobserved productivity of the firm, respectively.

The interpretation and identification of the time-varying firm effects and the job-spell fixed effects require normalization. Excluding a reference year (t=0), i.e. the first year a firm appears in the panel, from the φ_{jt} vector in the estimation, the job-spell fixed effects will absorb the worker fixed effect, the firm fixed effect *for the reference year*, and the job-spell fixed effect: $\psi_{ij} = c_i + \varphi_{j0} + \xi_{ij}$. The estimated time-varying firm effects will then be defined in terms of the difference from the reference year: $\tilde{\varphi}_{jt} = \varphi_{jt} - \varphi_{j0}$.

The last terms, $\delta_g^{\kappa} ln\kappa$ for κ=S,K, represent the impact of software and equipment capital of age group g, in addition to the overall effect absorbed by φ_{jt}. Again, we are not able to separately identify the overall impact and the group-specific impact of capital without some normalization. We thus normalize the overall efficiency of the firm to that of a base age group, $L_{g=0}$, and exclude the interaction with the base group in the estimation of equation (4). The parameters $\delta_{g\neq 0}^{\kappa}$ of equation (4) should then be interpreted as a relative effect for age group g compared to the base age group.[28]

5. Results

Software Earnings Premiums by Age

Figure 4 shows the estimated elasticity of individual earnings with respect to software capital per worker, estimated for each age group in models that also control flexibly for equipment capital by age group.[29] The figure clearly shows a hump-shaped relationship by age. High-wage industries are more software intensive, and within industries, high-wage firms are more software intensive. This is visible in the figure by the downward shifts as additional fixed effects are added to the model.

The idea behind the AKM model is to control for systematic selection of *both* firms and workers. For instance, high-wage workers may be more likely to work in high-wage firms, and high-wage workers may be more likely to work in software-intensive firms, conditional on the firm wage premium. Notably, this selection may also be systematically

[28] The parameters δ_0^{κ} (κ=k,s) are incorporated into α^{κ} of the time-varying firm effect, and $\pi_0 + \mu_0$ is added into the constant term of the equation.

[29] The models also include indicators for age groups interacted with gender, and controls for year, education, firm and establishment size (employment), and firm age and firm age squared.

different by age group, as workers sort into different firms over their careers. Adding dummies for both individuals and firms effectively controls for such selection.

Our next step is to see how the estimated elasticities respond to the inclusion of such controls. We go one step further and add job-spell fixed effects: indicators for the specific job-spell of one particular worker in a particular firm, which comprise the individual fixed effect, the firm fixed effect, and any match-specific fixed effect.

The hump shape is retained when we estimate the elasticity of earnings with respect to software capital per worker within job-spell. The first column of Table 2 reports the estimated elasticity by age group. The model includes the same covariates as in Figure 4 (adjusted to accommodate for collinearity with the fixed effects, e.g. by dropping indicators for education and the linear term for firm age). Only the oldest workers (65+) have lower earnings in years with higher software intensity. The largest earnings premiums associated with software capital per worker accrue to workers in the 30-49 age range, with the highest elasticity for workers between 35 and 39 years of age. Controlling for individual and match specific fixed effects in addition to the firm fixed effect in Table 2 has a positive impact on the estimated coefficients among the young (particularly below 30 years of age), and a negative impact on the coefficients for older workers (from 40 years onwards), compared to the previous results from Figure 4.

Bargaining Power or Differential Productivity Impact?

The different effects estimated by age group suggests that software is complementary to workers in the 30-49 age group, enhancing their productivity; but older workers appear to gain less and even lose out when the use of software goes up. Is there another plausible hypothesis for this? One alternative explanation could be that the productivity gains accrue to all, but only workers in the middle of the age distribution are able to turn these productivity gains into higher wages because they have greater bargaining power. The young may be easily replaceable by other youth of similar qualifications, and the old may lack credible alternatives outside of the firm.

Comparing the age profiles of equipment capital to that of software capital provides a way to explore this explanation for the hump shaped relation between software and earnings by age.[30] Equipment capital, like software capital, should improve revenue per worker, so that if differential bargaining power was the cause for the hump shape, we should find a similar

[30]We have experimented with measures of equipment capital excluding computer investments, and our main results appear not to be sensitive to this change.

shape for the relation between earnings by age and equipment capital. Column 2 in Table 2 reports the profile for equipment capital per worker. Instead of the hump shape these data show an almost linearly increasing elasticity of earnings with respect to equipment capital by age group. It starts out with a negative elasticity for the young, and only workers above 45 years of age seem to gain from higher equipment capital, ending at almost 2 percent for the oldest. These different patterns suggest that the strong decline in software elasticities by age after 45, is not due to any general age-related bargaining power.

Adding log sales per worker into the equation interacted with age groups provides another test of a differential bargaining power by age group explanation for the software result. Table 3 reports the results from such a regression model with job-spell fixed effects, but with an added interaction term for log sales per worker. Conditional on the two capital measures and log employment (both at the firm and establishment level), the coefficients for log sales per worker shows lower coefficients for the young and the old but with negligible elasticities. The coefficients and patterns of earnings premiums by age for the two capital measures hardly change from those in Table 2. It appears that differential bargaining power by age group does not contribute much to our estimated pattern.

High-Wage Workers and High-Wage Firms: Polarization or Skill Biased Tech Change

To explore the extent to which investments in software capital benefit workers higher or lower in the earnings distribution, we first use an AKM decomposition on the entire LEHD sample,[31] and place each worker in quintiles of the distribution across individuals overall and in quintiles of the distribution across firms[32] in our ACES sample. Following the AKM terminology we refer to workers in the top (bottom) quintile among individual fixed effects as high-wage (low-wage) workers, and to workers in firms in the top (bottom) quintile of the firm fixed effects as workers in high-wage (low-wage) firms.

Moving to our ACES sample, we estimate the log earnings equation including software and equipment capital per worker, interacted with age groups as before, and add interactions between the capital measures and quintiles of worker and firm fixed effects. The results, displayed in Figure 5,[33] show that the elasticity of earnings with respect to software is

[31]This means all jobs in our sample of LEHD states are included, and not only those that are participants in the ACES sample. The AKM decomposition is done after estimating a step one regression with job-spell fixed effects, conditional on year fixed effects and age squared, and then a step two, regressing the job-spell fixed effects on a dummy for each age measured at year 2000.

[32]The quintiles of both workers and firms fixed effects are calculated over all observations of workers in the ACES sample of our LEHD states (approximately 161 million observations)

[33]Regression results available on request.

strongly increasing in the workers' rank in the distributions of both the individual and firm fixed effects. The left panel shows the pattern across quintiles of individual fixed effects. The lines are drawn for workers in the middle of the firm distribution: high-wage workers in median firms display an elasticity of 3 percent, whereas low-wage workers in median firms display an elasticity of 0.7 percent. The right panel shows the pattern across quintiles of firm fixed effects. The pattern is similar: workers in high-wage firms display a much larger elasticity than do workers in low-wage firms, suggesting that software investments are more productive in high-productivity firms.

Since the lines in each panel are drawn for median values (3rd quintile) in the other panel, and the model is additive linear, the effects may be added together using the difference from the median value from the other panel. For instance, high-wage workers in high-wage firms display an elasticity of approximately 5 percent (0.03 + (0.032−0.012) = 0.05), while low-wage workers in low-wage firms have an elasticity of approximately zero (0.007 + (0.005−0.012) = 0).

The estimated individual and firm effects may be decomposed into an observed and an unobserved part. We estimate the fixed effect for individuals as a function of individual fixed characteristics, such as the level of education and gender, and retain the residual. The patterns for the quintiles of residual fixed effects are similar to the ones for the total fixed effects. Thus, the pattern displayed in Figure 3 mainly arises from different elasticities for workers in different quintiles in the distribution of the *unobserved* fixed effects. We similarly estimate firm fixed effects as an observed part, due to industry, and an unobserved part. The pattern for the quintiles of the residual fixed effects are similar, but attenuated compared to the pattern displayed for the total fixed effects. The pattern in Figure 5 thus largely arises from differences between quintiles in the distribution of the unobserved firm fixed effects.

The pattern for equipment capital is quite the opposite. The first three quintiles of the distributions across both individuals and firms display positive coefficients while the others do not.

The difference suggests that increased software share of investment is likely to raise earnings inequality: high-wage workers in high-wage firms gain the most, whereas low-wage workers in low-wage firms gain the least. As this pattern is conditional on the age profile of the elasticity, we need to take the age-earnings profile into account when we consider the full effects of software on inequality, but the substantial effect on high wage workers in high wage firms tells most of the story.

Time-Varying Firm Effects

A potential worry with the AKM model with firm fixed effects is possible correlations between shocks in the error term and changes in software capital. One conceivable scenario could be that the firm chooses increased software investments when it experiences a positive shock in sales. This would be an endogenous response, possibly leading to a positive bias in the estimated impact of software investments. If such shocks are correlated with the age profile of the firm and its workers, for instance because they are more common in expanding firms with a younger workforce, then the estimated age profiles could be biased as well.

Another, related, concern is that much prior research points to the complementarities between ICT investment and changes in organizational design and management practices (e.g. Bartel et al. 2007, Bresnahan et al. 2002, Brynjolfsson and McElheran 2019, Battisti et al. 2020). Our data has no information on these shifts nor on possible changes in complementary organizational capital (e.g., Saunders and Brynjolfsson 2016). This omission could lead us to overestimate the productivity gains – and associated wage increases – associated with ICT investment. Time-varying firm controls should absorb such effects.

As outlined in the methodology section, we control for such firm-specific shocks, and all other time- and firm-specific confounding factors, by adding a time varying firm effect to the model.[34] We use the 25-49 years old as a reference group, and the coefficients obtained in step 1 measure the difference between the elasticity of the particular age group and the elasticity of the 25-49 years old. We find that the youngest workers (20-24 years old) have a return to software capital which is .0056 lower than that of the reference group. We compare this difference to the difference between the coefficients for the youngest group and the 25-49 years old in the fixed job-spell model, reported in Table 2. Using the average estimate for 25-49 years old in the job-spell fixed effect model (0.0185), the difference is almost four times larger: -0.0018 −- 0.0185 = -0.0203 compared to -0.0056 here. For older workers, on the other hand, the differences from the 25-49 group are practically the same as in the job-spell model.

The results for equipment capital are much less pronounced than in the job-spell model. The return for the young is very similar to that of the reference group, and the increase in the return for 50+ is much more modest that what we found in Table 2.

We set the level of the elasticities for the reference group as outlined in the methodology section by estimating the relationship between the firm-year effects estimated in step 1 and the log of the two capital measures, using firm-year as the unit of observation.

[34]See Engbom and Moser (2020) and Lachowska et al (2020) on the identification of time- varying firm effects.

While the relative impact of capital intensity on different age groups within the firm, estimated in step 1, uses time-varying firm effects, the second step is conducted with firm fixed effects only. This means that the effect for the reference group, which determines the level of the elasticities is identified with standard AKM fixed effects assumptions.[35] The last two columns of Table 4 show the results. The reported coefficients represent the elasticities for the reference age group (25-49 of age). The elasticities of 0.0293 and -0.0001 for software and equipment respectively compare with the averages[36] of 0.0185 and -0.0031 in the job-spell model from Table 2. The step 2 models include firm fixed effects and thus effectively include controls for both individual and match effects, from step 1, and firm fixed effects from step 2. For equipment capital, including time-varying firm effects changed the results also for older workers. The average coefficient for the reference group in the fixed job-spell model from Table 2 is -.0031. Compared to the job-spell model, the age profile of the elasticity of equipment capital flattens out as firm year effects are included.

Figure 6 compares the implied elasticities from step 1 and step 2 (Job+Firm_yr) to the estimated elasticities from the job-spell model (Job FE). The difference in overall level arises from the difference in the estimated step 2 coefficients to the average effects estimated for the groups between 25 and 49 years of age. The pattern for the young and for the old arises from adding the coefficients in step 1. For software, the pattern for the young differs between the models, with a smaller decline in the firm-year model whereas the pattern for the old is much the same, with a steady decline from 50 years of age. For equipment, when estimated with firm-year effects, the earnings elasticity is small, and the age pattern less pronounced.

The changing pattern between specifications for 20-24 year olds suggests a difference in the bias from the fixed firm effect assumption between age groups. Such differences could arise from heterogeneity in terms of the correlation between productivity shocks and software investments across firms with different age profiles. Most likely, there is an over-representation of young workers in certain segments of firms, per Figure 2, which shows them primarily in low-software intensity firms. Many are likely to be students in non-career jobs in low-skill firms, younger firms, and in low-wage firms. It may be that in these segments of the labor market, the correlation between productivity shocks and software investments is more negative, inducing a negative bias for the young in the job-spell specification.

[35]IV- or other methods in the step 2 regression, estimated at the firm-year level, could address this concern.
[36]Calculated from the averages of the coefficients for software and equipment for age groups 25-29, 30-34, 35-39, 40-44, and 45-49 in Table 2.

Checking the Age Pattern in Exit Behavior

Having established that older workers gain less in earnings than workers in the middle of the age distribution from investments in software but gain more from investments in equipment, we examine next the relation between the two forms of investment and workers leaving their firm. If the two forms of investment have different effects on demand, we would expect to see the exit behavior show the same relation. If software investment reduces relative demand for older workers while equipment investment raises relative demand for them, they should be more likely to leave firms with big software investments and stay with firms with big equipment investments.

In 2012, 21% of workers 45 and over exit their job, with one-third taking a new job at another ACES firm within the 23 covered states. We treat the other 2/3rd as leaving the labor force.[37] As exit is defined as exit from the ACES sample from the LEHD states, it is not a clean measure of retirement from the labor force. Similarly, as our measure of job-to-job moves is limited to mobility to another firm within the ACES sample, it is not a clean measure of job-to-job moves.[38] While we cannot rule out bias arising from leakages out of the sample in interpreting that exit as firm to firm or as firm to retirement/exit from labor force, we fully measured the exits from the firms in the sample, which is enough to establish a different response to software investments than to equipment investments.

In the exit analysis we estimate a linear probability mobility of exit in the subsequent period, conditional on the two forms of capital per worker interacted with age. Figure 7 shows a negative upward-sloping impact on exits for all age groups, approaching zero for the 65+ group for software. This pattern is consistent with the earnings gains that workers of different ages obtain from software investments. Software investment tends to reduce exit, but the magnitude of the effect diminishes with worker age. Job-to-job moves within the sample states are positively impacted, also with an upward slope. One interpretation is that workers become more attractive to other firms as software capital goes up,[39] and that older workers take the options more often because they are not as generously rewarded from software

[37]The LEHD ICF national indicator of individuals' employment in any state can be used to separate exits into those leaving the labor force versus those taking a new job. See Hahn, Hyatt, Janicki and Tibbets (2017) and Hyatt, McEntarfer, Ueda and Zhang (2018) for details on using the LEHD data for job-to-job transitions.

[38]In the next version of this paper, exit and job-to-job mobility will be defined relative to employment in any firm in any state. Because of the temporary closure of the RDC in connection with the Covid-19 virus, we have not been able to undertake this exercise for the current version of this paper.

[39]This would be consistent with findings in Agrawal and Tambe (2016), which leverages linked employer-employee data to provide evidence that IT investment associated with private equity acquisitions creates transferable IT-related human capital.

capital in their current firms.[40] The pattern for equipment is opposite, in line with the opposing patterns in earnings.

6. Conclusion and Discussion

Combining data on software investments by firms with unemployment insurance records on the age and earnings of workers, and using an AKM decomposition framework to deal with econometric problems due to the potential impact of unobservable productivity on firms investment in software and of unobservable individual characteristics of workers in software intensive firms, we find that investments in software capital twist the demand curve for labor toward workers 25-49 compared to older and younger workers. Specifically,

1) Firm investments in software capital raise the earnings of workers aged 25-49 by an elasticity of about 3 percent, but the earnings premium declines almost linearly from 50 years of age through age 65 to essentially nothing for those 65 and older.

2) Higher software capital is also associated with lower exits among workers, but again with less impact on older workers. The share of employment of older workers does not vary much among firms with differing investments in software while high investors in software hire relatively fewer 20-24 year old workers.

As best we can tell, the smaller gains for older workers from working with more software capital is because their skills are less complementary to software technologies than younger workers.

3) The biggest beneficiaries of software investments among workers inside a firm are those with high unobserved (fixed effects) earnings characteristics, whose wages are raised more by software investments than other workers' wages.

4) The biggest beneficiaries of software investments among workers across firms are those in firms with high unobserved or observed time invariant (fixed effects) earnings characteristics.

Our analysis augments the AKM framework in two directions that may be useful in other studies of worker-firm panel data. First, we added a match-specific term to the earnings equation, by estimating the effects of software on earnings within job-spell. This effectively removes a potential correlation between the match effects and age, which is important if

[40]The differential results for the oldest workers may be related to prior findings focused on training and firm-specific human capital. Bartel et al. (2007) and Battisti et al. (2020) report complementarities between ICT and on-the-job training. Workers in the top age group in our data may not have the runway to invest in sufficient training or learning-by-doing with new software prior to retirement (Friedberg 2003), and prefer to stay where firm-specific human capital is most valuable (e.g., Violante 2002).

workers' match improves over time in the labor market. Second, we added time-varying firm fixed effects to the model. This allows us to estimate the relative impact of software on older workers, relative to younger workers, with full control for time-varying productivity shocks or changes to the bargaining power of workers.

Overall, by raising earnings most for high-wage workers in the middle of the age distribution within firms, and most for workers in high-wage firms, software investments tend to increase earnings inequality. It is a form of skill-biased technical change that operates both within and across firms.

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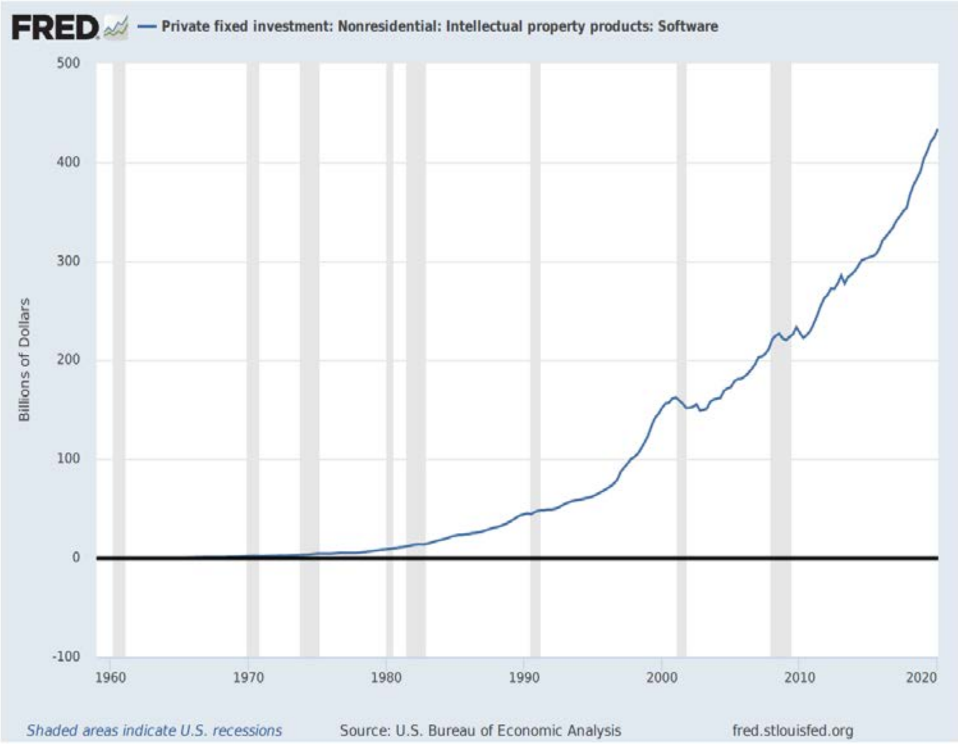
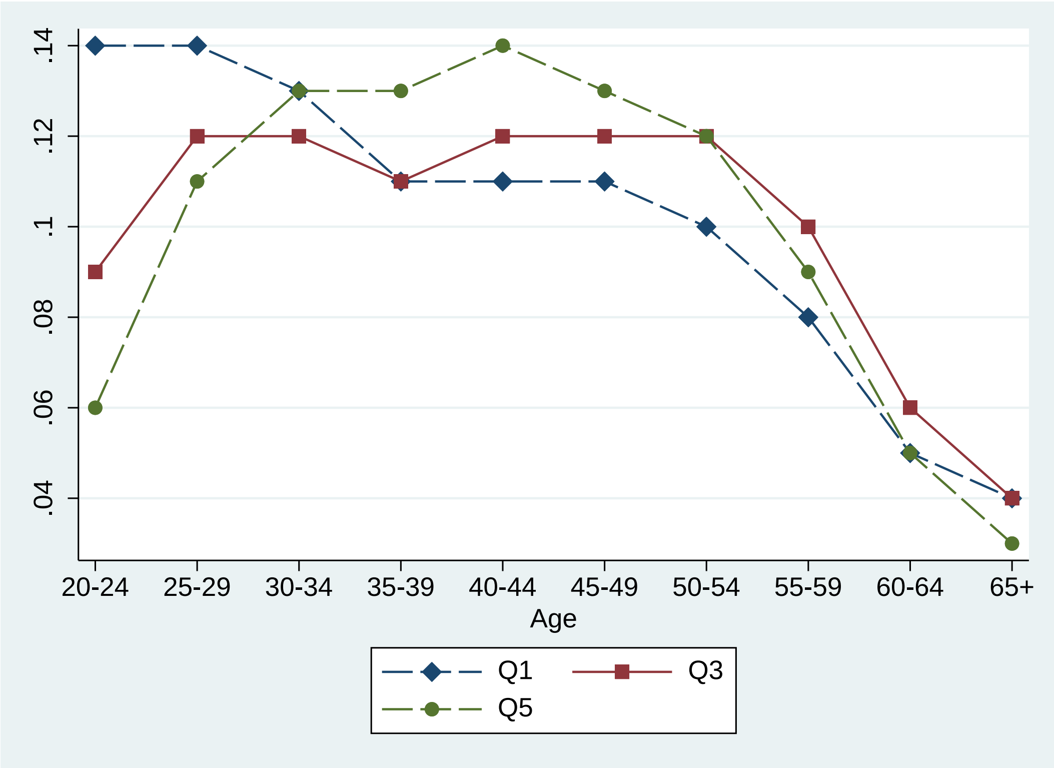
Figure 1. Investments in Software and Equipment



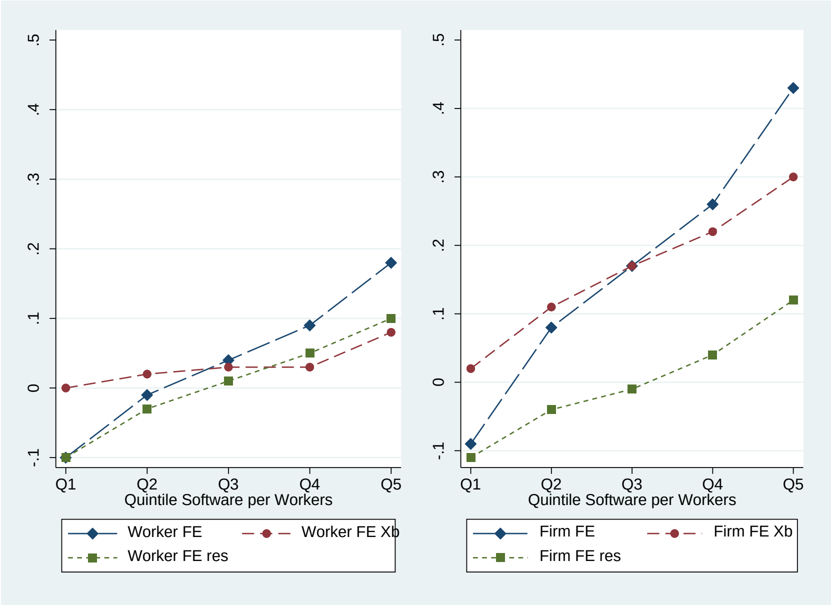
Source: St Louis Fed, Fred, software is BEA Account Code: B985RC, equipment is BEA Y033RC

Figure 2. Employment Share by Age Group. By Quintiles of Software Intensity.



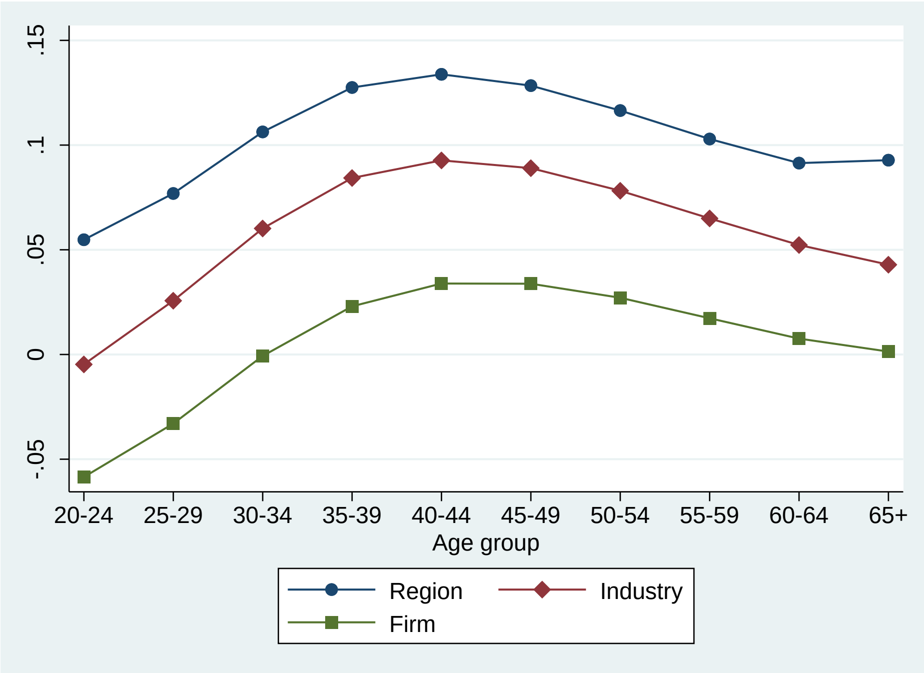
Note: Average employment share across firms by quintile of software capital per workers. Q1 is the first quintile, Q3 the median quintile, and Q5 the top quintile. Employment weighted quintiles. Cross sectional data, 23 LEHD states in 2012.

Figure 3. Average Worker and Firm Fixed Effects by Quintile of Software per Worker



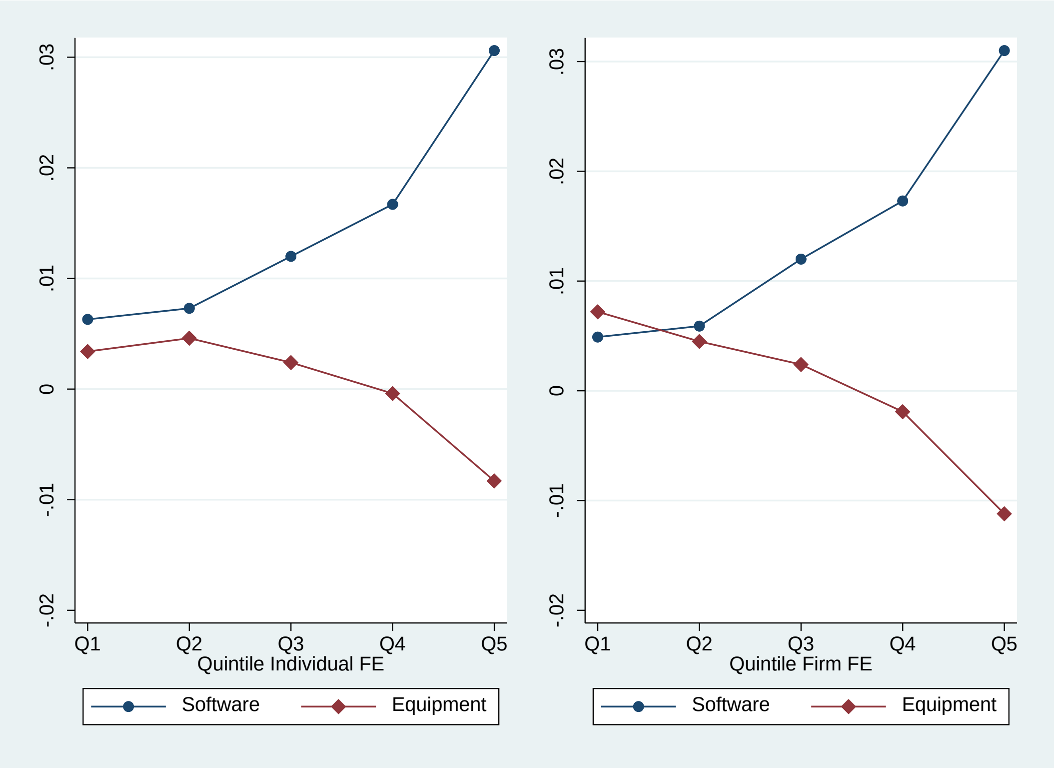
Note: Average worker and firm fixed effects across firms by quintile of software per worker. Q1 is the first quintile, Q3 the median quintile, and Q5 the top quintile. Employment weighted quintiles. Worker and firm fixed effects are first estimated from an AKM decomposition on the whole labor market of the LEHD states, controlling for worker age, age squared, and years of observation. Next, "Worker (Firm) FE res" is the residual, and "Worker (Firm) FE Xb" the predicted value, of the worker (firm) fixed effects regressed on time invariant covariates such as education, gender, and cohort (industry, average firm and establishment size, and firm age), see section 5 below.

Figure 4. Software Elasticity of Earnings by Age Group. FE: Region + Industry + Firm



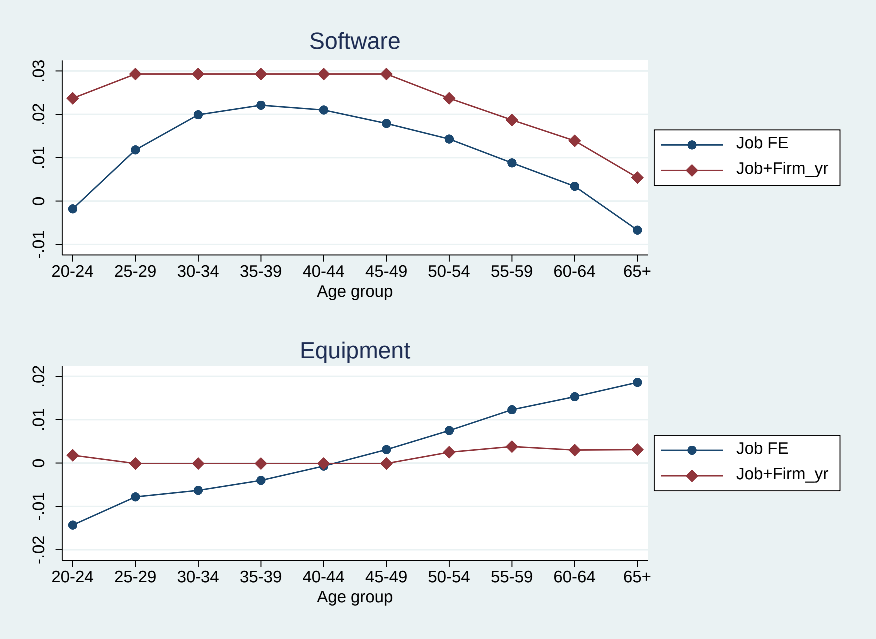
Note: Dependent variable: Log Earnings. The figure shows the coefficients for log software capital per worker interacted with ten age groups. The models control flexibly also for equipment capital by age group, and include controls for age group×gender, year dummies, three dummies for level of education, log firm employment, log establishment employment, firm age, and firm age squared. Region, industry, and firm fixed effects are added successively.

Figure 5. Earnings Elasticities by Quintiles of Individual and Firm Fixed Effects.



Note: The figure shows the elasticity of earnings with respect to the two types of capital, estimated by quintiles of individual (left panel) and firm (right panel) fixed effects. The firm and individual fixed effects displayed along the x-axis are estimated on all workers in the economy (LEHD states), but the quintiles are calculated on our ACES sample. The model also allows for separate age effects, and includes the same covariates as in Figure 4 above. Estimated with job-spell fixed effects. The effects are calculated for a worker between 35 and 39 years of age, and placed in quintile 3 (median) of the other panel (i.e. the elasticity for high-wage workers is calculated for a worker in a median firm).

Figure 6. Elasticities estimated with and without time-varying firm effects.



Note: Dependent variable: ln Earnings. The Job FE models show coefficients from Table 2, estimated with job-spell fixed effects. The Job+Firm_yr models show coefficients from step 1 and step 2 of Table 4, where time-varying firm effects are added in a step 1.

Figure 7. Exit and job-to-job mobility patterns for older workers (45+). Estimated coefficients for sofware and equipment by age.

Note: The figure shows the estimated coefficients by age for software capital per worker and equipment capital per worker in regressions of exit and job-to-job mobility. Dependent variables: *Exit* is measured as the last year an individual is observed in our ACES sample (set to missing the last year of our panel). *Job-to-Job Move* is measured as the last year an individual is observed in a firm, conditional on being employed in our ACES sample next year (set to missing the last year of our panel). The analysis includes individuals older than 44 years of age only. The linear probability models include job-spell fixed effects, age groups interacted with gender, log firm and establishment employment, firm age squared, and year dummies.

Table 1. Firm Characteristics by Quintile of Software Intensity

	All	Q1	Q2	Q3	Q4	Q5
Log Software/Worker	1.35	0.01	0.32	1.01	1.89	3.5
Log Equipment/Worker	3.38	0.54	2.66	3.87	4.47	5.36
Log Firm employment	6.40	5.90	6.44	6.33	6.55	6.77
Firm Age	27.22	20.73	26.54	28.95	30.00	29.89
Multi-unit Firm	0.70	0.50	0.68	0.69	0.77	0.84
Log Sales/Worker	4.72	2.57	4.34	5.08	5.50	6.10
Less than high school	0.14	0.20	0.16	0.15	0.12	0.09
High School	0.26	0.28	0.27	0.27	0.25	0.22
Some College	0.31	0.30	0.31	0.32	0.32	0.30
College education	0.29	0.22	0.26	0.27	0.31	0.39

Note: The quintiles of software capital per worker are calculated over observations of firms (education shares over workers). Cross sectional data, 23 LEHD states in 2012.

Table 2. Earnings Elasticities by Age. Dependent variable: log Earnings, Job-spell FE

	Elasticity of Earnings with respect to	
	Software Intensity	Equipment Intensity
20-24	-0.0018	-0.0143***
	(0.0027)	(0.0017)
25-29	0.0118***	-0.0078***
	(0.0022)	(0.0015)
30-34	0.0199***	-0.0063***
	(0.0018)	(0.0014)
35-39	0.0221***	-0.0040**
	(0.0016)	(0.0014)
40-44	0.0210***	-0.0007
	(0.0015)	(0.0012)
45-49	0.0179***	0.0031*
	(0.0014)	(0.0012)
50-55	0.0143***	0.0075***
	(0.0014)	(0.0013)
55-59	0.0088***	0.0123***
	(0.0014)	(0.0015)
60-65	0.0034*	0.0153***
	(0.0016)	(0.0017)
65 +	-0.0067***	0.0186***
	(0.0019)	(0.0020)
Job-spell effects	Yes	
Adj. R squared	0.862	
N	1.61e+08	

Note: Estimated elasticities of earnings (standard errors) with respect to software and equipment capital per worker for each age group, both estimated from *the same model with job-spell fixed effects*. All capital variables are measured per worker in logs. The model also includes controls for age group×gender, year dummies, log firm employment, log establishment employment, and firm age squared. Standard errors clustered by firm-year.

Table 3. Earnings Elasticities by Age. Dependent variable: log Earnings

	Elasticity of earnings with respect to		
	Sales per worker	Software intensity	Equipment intensity
20-24	-0.0012***	-0.0009	-0.0139***
	(0.0003)	(0.0027)	(0.0017)
25-29	0.0009***	0.0121***	-0.0084***
	(0.0002)	(0.0022)	(0.0015)
30-34	0.0017***	0.0199***	-0.0072***
	(0.0002)	(0.0018)	(0.0015)
35-39	0.0018***	0.0221***	-0.0049***
	(0.0002)	(0.0016)	(0.0014)
40-44	0.0019***	0.0210***	-0.0016
	(0.0002)	(0.0015)	(0.0012)
45-49	0.0017***	0.0179***	0.0024*
	(0.0002)	(0.0014)	(0.0012)
50-55	0.0016***	0.0142***	0.0069***
	(0.0002)	(0.0014)	(0.0013)
55-59	0.0013***	0.0088***	0.0119***
	(0.0003)	(0.0014)	(0.0015)
60-65	0.0012***	0.0033*	0.0151***
	(0.0003)	(0.0016)	(0.0017)
65 +	0.0003	-0.0066***	0.0188***
	(0.0004)	(0.0019)	(0.0020)
Job-spell effects		Yes	
R squared		0.862	
N		1.61e+08	

Note: The table shows estimated earnings elasticities by age group, estimated from the *same model with job-spell fixed effects*. All variables measured per worker in logs. The model also includes controls for age group×gender, year dummies, log firm employment, log establishment employment, and firm age squared. Standard errors clustered by firm-year.

Table 4. Earnings elasticities from different job-spell FE models.

	Step 1		Step 2	
Unit of obs.	Individuals *x* year		Firm *x* year	
Dep. Var.	Ln Earnings		Firm-year fixed effects from step 1	
Fixed eff.	Job + Firm-year		Firm	
Elasticity with respect to	Software intensity	Equipment intensity	Software int.	Equipment int.
20-24	-0.0056***	0.0019***		
	(0.0002)	(0.0001)		
25-49			0.0293***	-0.0001
			(0.0009)	(0.0007)
50-55	-0.0056***	0.0026***		
	(0.0001)	(0.0001)		
55-59	-0.0106***	0.0039***		
	(0.0001)	(0.0001)		
60-65	-0.0154***	0.0031***		
	(0.0002)	(0.0002)		
65 +	-0.0239***	0.0032***		
	(0.0002)	(0.0002)		
R squared	0.857		0.560	
N	1.32e+08		2.10e+05	

Note: *Step 1 model*: Unit of observations: Individuals. Dependent variable: ln Earnings. The model also includes controls for age group X gender, job-spell fixed effects and year specific firm effects. *Step 2 model*: Unit of observation: Firms. Dependent variable: Firm *X* year fixed effects from step 1. The model also includes year dummies, log firm employment, log establishment employment, firm age squared, and firm fixed effects.

Appendix A: Relation between ACES capital investment in software and total software spending

There is a striking difference between aggregate ACES national totals for capitalized software investment and all software investment reported in the National Income and Product Accounts (NIPA) for private fixed investment.[41] The NIPA data show about three times the spending as the ACES data. Part of the aggregate difference is that NIPA includes investment by government and farms that are excluded by ACES, which surveys non-farm private firms. From the BEA 2012 benchmark input-output tables, this is approximately 6% of software expenditures. In addition, another 21% is accounted for by software exports. But most of the difference between the two series occurs because firms report most software expenditures as direct purchase of intermediate inputs rather than as capitalized investment. The ACES Information & Communication Technology Survey (ICTS), available for some years and now discontinued, asked respondents for expensed software expenditures. ICTS noncapitalized software reporting accounts for 25-35% of the NIPA figures depending on the year. Thus, in summary for 2013, ACES capitalized software expenditures represent 32% of the NIPA figures, ICTS noncapitalized software 28%, and from the BEA input-output tables, exports approximately another 21%, and agriculture and government approximately 6%. There remains a difference of 14%, potentially due to the differences in measurement approaches as discussed below. Another potential difference could be related to the treatment of software as an intermediate material input. An example of this would be when a computer laptop vendor bundles the operating system as part of the hardware product sold. The operating system is purchased from a software supplier and embedded into the hardware product for resale. These material inputs would not be reported by firms in the ACES nor ICTS survey.

Grimm, Moulton and Wasshausen (2005) and Moylan (2001) describe the way the ACES and NIPA differ in the sources of their estimate. ACES is a "demand-side" survey of firms' capital expenditures.[42] NIPA uses a commodity-flow "supply-side" approach that trace commodities from their domestic production and imports to their final purchase. A software producing firm would report all of its sales as software without distinguishing between purchases that a customer might capitalize and those that it would expense. Because IRS regulations allow firms to treat smaller expenditures that could be capitalized as expenses, many choose to expense them. According to Grimm et al (2005) "Internal Revenue Service (IRS) regulations allow for low-value items (under $17,500 for 1998) that fit the criteria for capital investment to be expensed. It is possible that much software falls into this category and that ACES respondents follow IRS guidelines when determining what is a capital investment" … (suggesting) "that capital expenditures for software are significantly understated in the ACES estimates." Moylan notes that "For software expenditures to be capitalized, firms must view these expenditures as significant and they must have a useful life of more than one year. Annual site licenses are expensed, but multi-year licenses should be capitalized. Firms decide for themselves what is maintenance and what is a major improvement that requires capitalization." In 2015 the IRS issued a Chief Counsel Advice (CCA) related to the tax treatment of software development costs (Reed, 2015). This summarized that software purchase and customization are capitalized, and internal software development costs are deductible as current expenses. In this CCA guidance however, IRS also cautioned that some taxpayers were improperly expensing all software costs.

Another difference between ACES and NIPA data is how they treat internally developed software. Since 2002, ACES breaks out a category of internally-developed capitalized computer software, but there is substantial non-response for this item. This is

[41]St. Louis Federal Reserve Bank FRED series B985RC1A027NBEA.
[42]BEA uses ACES data to allocate by industry its total investment and investment by type of asset estimates.

consistent with Moylan’s (2001) summary that “*almost no own-account software is capitalized*, while some prepackaged and custom software are capitalized. Firms not in the business of producing software for commercial sale view own-account expenditures as an expense.” and “Although in theory, prepackaged software purchases with a useful life of at least one year should be capitalized, most are treated as an expense. For example, a Fortune 500 firm said that its policy was to expense all single software purchases of $250 or less, as well as all site licenses or combined purchases that are less than $10,000.” Grimm et al (2005) and Moylan (2001) conclude that the software investments firms elect not to capitalize on their books can explain a substantial proportion of the differences between the NIPA and ACES estimates.

Appendix B:

There are some differences between the full LEHD data for 23 states used to run an AKM decomposition for all workers and firms in those states and our analysis sample that includes all workers in the 23 LEHD states with jobs in firms in the ACES sample. In the analysis sample we have 11.6 million workers in 2012 employed in approximately 16,000 ACES firms that represent a 20% share of all LEHD workers in our 23 covered states. Our sample of ACES firms are older – 27 years in business on average – and 70% are multi-location firms in 2012; average headcount is 600 employees per firm.

Linked to our samples, in 2012 the average worker’s employer had $112,000 in sales per worker, $29,400/worker in capital equipment (excluding software), and $3,800 in software capital stock per worker.