Forever Young: Where Older Workers Keep on Working

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ABSTRACT

This paper examines inter-industry patterns of the employment of older workers over the last 20 years to gain insight into characteristics of firms that are most likely to employ such workers, as well as how labor market shocks impact workers of different age groups within an industry. The underlying premise is that firms strategically align the age mix of their workforce depending on production function and labor cost parameters, including human capital investments. The key findings are that the industries that had the largest increases in the percentage of older workers were the industries that had the broadest pension coverage and the industries that made the greatest use of high-tech capital. There also is evidence in 2001-07 that the percentage of older workers increased more in the industries most exposed to increased Chinese imports (albeit this really means that younger workers suffered larger job losses in those industries than older workers). We do not find evidence of (1) any shift in demand toward older workers in certain industries (as indicated by relative wages and employment moving in the same direction) or (2) any decline in employment shares of younger workers in the industries that showed the largest increases in the shares of older workers.

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Older workers have become increasingly likely to delay retirement and remain employed. The employment-population ratio for men 55 and over increased from 35.9 percent in 1993 to 45.1 percent in 2019. Over the same period, the ratio for women rose from 22.0 percent to 34.0 percent.[1] These upward trends stand in contrast to the downward trajectory of employment odds for younger and middle-aged persons.[2] Longer careers, combined with the large birth cohorts after World War II, have resulted in an aging labor force.

Workforce aging has several important implications. On the surface, longer careers would mean more output and more labor income, thereby leading to higher GDP. Yet questions have been raised about the productivity of older workers and whether it impacts aggregate productivity, especially as technology mastery becomes a more critical skill.[3]

Delayed retirements alter human resource decisions by organizations. Now that they have more older workers, should companies invest more in their training? Are older workers blocking promotion opportunities for others? How committed are older workers to their jobs in the years ahead? The uncertainty associated with their future retirement date complicates planning for the future. What happens if they stay "forever" and what happens if they leave all at once? A better understanding of these decisions will better inform decisions about the best employment opportunities for older workers as well as government decisions about education and training.

Government budgets are being impacted as well. Longer careers translate into more earnings leading to greater tax revenue (although this would be partially offset by delays in

[1] Economic Report of the President 2020
[2] Abraham and Kearney (2020)
[3] See, for instance, studies by Maestas et al (2016) of the US and Aiyar et al (2016) of the EU.

tapping 401k accounts). Depending on how many older workers maintain primary medical insurance with a private sector employer, there also could be reduced spending on Medicare.

There have been numerous studies examining why more older individuals are delaying retirement and working longer. Social Security, private pensions, and retiree health insurance create incentives for individuals to retire at specific ages. Personal health and accumulated savings also are critical factors, along with the availability of satisfying and rewarding work. The consensus to date is that people are working longer because of the shift from defined benefit to defined contribution pensions, cutbacks in retiree health insurance, Social Security reforms, and increased education.[4]

While we have clear indications of how labor supply factors have led to more employment of older workers, little is known about what has happened on the employer side of the equation. Within an establishment, increased willingness to work longer is unlikely to be matched equally by employer demand. In which sectors of the economy have older workers been able to successfully continue their careers or start new ones? What common characteristics do these sectors have? These are the central questions addressed in this research.

From an employer perspective an increased supply of older workers is a mixed blessing. Older workers create value when they have critical experience, knowledge and skills related to customers, internal operations, market behavior, and suppliers. There also is a tie-in between

[4] Coile (2019).

equipment and software installed 20 or more years ago and the skills that older workers provide to operate and maintain such essential capital. When few younger workers choose to invest in those skills, older workers retain more value. Longer careers mean reduced turnover, leading to savings in search and hiring costs and stronger incentives for training investments. Failure to retain critical older workers results in the loss of experience, skills, and company-specific knowledge.

At the same time firms face higher wages and benefit expenses for older workers, along with potential cognitive and physical declines in productivity associated with aging. Ameriks et al (2020) find that older workers demand more flexible work schedules. This workplace amenity can be provided at low cost in some workplaces, but not so easily in others. In some cases, there is the question of whether older workers can adapt to rapidly changing technology.

Faced with a growing supply of older workers, firms must rethink decisions regarding hiring and developing younger and middle-aged workers. One issue is whether promotion opportunities become blocked and lead to dissatisfaction among younger workers. Another is how well a firm can combine older individuals with younger age groups. Do they have complementary skills that bring out the best in each other or do they basically do the same jobs? How up to date are the skills possessed by older workers compared to those of younger workers? Do older workers have a stronger work ethic that offsets any deficiency in terms of technical knowhow? The results of this study will document which industries are retaining and hiring older workers. Explaining why certain industries have a higher or rising proportion of older workers will guide our understanding of how future job opportunities will develop for this group in the next decade.

This study starts with the basic premise of labor demand: firms select optimal combinations of different types of labor and capital based on their relative productivity and cost, while also considering which combinations work best and the adjustment costs associated with changing the mix of inputs. The focus will be on the age distribution of employees by industry. This distribution can change over time depending on the hiring, separation and retention decisions made by firms and their employees.

In the 1970s and 1980s a series of papers were written about labor demand for workers from different age groups using translog production (or cost) functions and share equations to estimate elasticities of complementarity (or substitution). In his summary of these studies Hamermesh (1993) concluded that the weight of the evidence indicated that older and younger workers are substitutes. Two more recent studies by Bovini and Paradisi (2019) and Mohnen (2021) reach a similar conclusion. Bovini and Paradisi examine the impact of a pension reform in Italy and found that new hires fell the most in firms with the most delayed retirements. Mohnen examined patterns across U.S. commuting zones and found that there was no tradeoff in employment levels in areas with the largest increases in employment of older workers. However, in those areas younger workers were less likely to be in full-time jobs and less likely to be in high-skill jobs.

This paper focuses on economy-wide data for 60 industries so that data on different types of capital can be matched with data on employment patterns and other variables. There will not be any attempt to estimate structural parameters; instead, the focus will be on developing measures of key observable variables that will provide some insights into the varying degrees of growth in the percentage of older workers across different sectors of the economy.

A key focus of this paper is how employment shares for older workers relate to the use of different types of capital. Regarding the adaptability of older workers to changes in technology, there are two recent studies of note. Hudomiet and Willis (2021) examined the labor market impact of computers on older workers from 1984 to 2017. They found that older workers initially lagged their younger counterparts in terms of computer knowledge but eventually caught up in most arenas. The gaps were largest in the 1980s and 1990s but were still present among workers 65 and over after 2000. They find lower wages and earlier retirements for older workers with sizable gaps in computer knowledge. Barth, Davis, Freeman, and McElheran (2020) focus on software capital intensity and find that middle-aged workers gain more than young and older workers from software investments in terms of wages and employment.

This paper is also related to recent studies by Acemoglu and Restrepo (2020, 2021) in that it uses industry data to examine the interaction of technology and labor market outcomes. Acemoglu and Restrepo (2020) focus on robots and find negative effects on wages and employment. They do not examine the possibility of differential impacts on workers of different age groups. In most of the literature on technological change and labor markets, the presumption is that technological change happens exogenously. Acemoglu and Restrepo (2021) argue that in some instances demographic challenges induce investments in automation. Using data on manufacturing industries for different countries, they show that workforce aging is associated with increased use of robots.

This paper begins in Section 1 with evidence on how the employment of older workers (defined here as those age 55 and over) has changed since 2000 with a particular focus on their

distribution across industries. Simple demographic arithmetic dictates that, if more people delay retirement, there will be more older workers employed across virtually every industry. The results show that there is considerable variation in the degree to which different industries have increased their utilization of older workers.

To understand what is driving these changes, Section 2 develops some simple frameworks to explain (1) the determinants of an industry's optimal age structure and (2) the factors driving changes in the age structure over time. The key underlying questions concern why some industries make more intensive use of older workers than others and, given rising labor force participation rates among the elderly, why have some industries hired or retained more older workers than others? The empirical model, a reduced-form employment share equation, is explained in Section 3, with particular attention paid to the choice of independent variables and to potential sources of misspecification. The data sources and variable definitions are summarized in Section 4. The empirical results are reported in Section 5, while Section 6 concludes.

The key findings are that the industries that had the largest increases in the percentage of older workers were the industries that had the broadest pension coverage and the industries that made the greatest use of high-tech capital. There also is evidence in 2001-07 that the percentage of older workers increased more in the industries most exposed to increased Chinese imports (albeit this really means that younger workers suffered larger job losses in those industries than older workers). We do not find evidence of (1) any shift in demand toward older workers in certain industries (as indicated by relative wages and employment

moving in the same direction) and (2) any decline in employment shares of younger workers in the industries that showed the largest increases in the shares of older workers.

1. Descriptive background

Older workers, defined as those who are age 55 or above, represent a rapidly growing segment of the workforce. In 2000 older workers accounted for 12 percent of all employees; by 2019 their share had increased to 22 percent, as shown in Figure 1. Over the same period, the share of younger workers (16 to 29) held roughly constant in the 26 to 27 percent range whereas the share of middle-aged workers (30 to 54) fell from 60 to 52 percent. The drop in the share of middle-aged workers largely reflects the aging of the baby boomer population.

Before turning to the distribution of older workers by industry, it is instructive to take a quick look at worker and job characteristics have changed over the last 20 years for this age group. Table 1 reports data on older workers from the American Community Survey public use files for 2001 and 2019. As the older cohorts exit from the labor market and are replaced by younger cohorts, older employees in 2019 have more years of schooling than their counterparts in 2001. In 2001 46.1 percent of older workers had some post-secondary education, whereas by 2019, 57.9 percent of them did. The increase was more pronounced for women (43 to 59 percent) than men (49 to 57 percent). The occupational mix adjusted as well, with more managerial and professional jobs and fewer positions in sales, support, and production occupations. Again, the shift was greater for women who by 2019 were more likely to be in professional or managerial jobs than men. The share of women in professional jobs increased from 33 to 43 percent, whereas the share for men rose from 33 to 38 percent.

The overwhelming majority of older employees work 35 or more hours per week. In 2001 75.6 percent of older workers were full-time; this increased to 77.6 percent in 2019. The upward trend was a bit stronger for women than men.

Men account for a slight majority of older workers. Percentage male dropped from 51.5 to 50.7 percent between 2001 and 2019. At first glance these numbers seem out of sync with the well-known data on employment-population ratios by gender (45 percent for men and 34 percent for women) for this age bracket. This is offset by the longer life spans of women and the exclusion of the armed forces and the self-employed in Table 1.

The shape of the age distribution of older employees changed between 2001 and 2019, with a shrinking percentage in the 55-59 bracket and a growing percentage in the 60 and over bracket. This reflects both cohort aging and longer careers.

Average annual earnings of older workers increased by 69.2 percent (from $36812 to $62316) between 2001 and 2019 and average hourly earnings rose by 66.6 percent ($20.89 to $34.80). As a benchmark the annual personal consumption expenditure deflator rose by 38.0 percent over this period. It should be kept in mind that the composition of the older workforce changed considerably over this period, with higher levels of education and a larger percentage of professional workers as noted above. Average hourly earnings for older women grew more than for older men (78.1 versus 60.0 percent). There also was an increase in wage inequality. The standard deviation of log average hourly earnings increased from 0.74 in 2001 to 0.80 in 2019, with a somewhat larger increase for women than for men.

A natural question to ask at this point is how the earnings pattern for older workers compares to that of other age groups. Over the same period, average hourly earnings

increased by 55.4 percent for 16- to 29-year-olds ($12.14 to $18.88) and by 58.7 percent for 30- to 54-year-olds ($20.00 to $31.76). On the surface this might infer that demand for older workers increased over this period in that they gained in terms of both employment share and relative earnings. It also is possible that educational attainment among older workers increased by more for older workers during this period than it did for middle-aged or younger workers.

Labor mobility, or lack thereof, is a critical driver of any changes to be observed in the age distribution of older workers across industries. Figure 2 shows two notable trends over the last 20 years. First, job tenure for older workers has increased for those 65 and over. Among women the percentage who have been with their employer 20 or more years increased from 23 to 26 percent between 2000 and 2020. The same share for 65 and older men increased from 28 to 34 percent between 2000 and 2008. It then dropped to 30 percent in 2010 as a consequence of the Great Recession and essentially stayed at that level through 2020. There are also slight increases in long-term job holding for men (30.6 to 31.4 years) and women (24.3 to 24.6) in the 55 to 64 age bracket.

Second, the odds that an older worker is in a new job have decreased substantially. Among men, 11.2 percent of those age 55-64 and 14.4 percent of those 65 and over were in new jobs in 2000. By 2020, these percentages dropped to 9.8 and 9.7 percent. The percentage of women with a new employer declined as well, from 11.3 to 9.5 percent for the 55-64 age group and from 11.5 to 8.2 percent for the 65 and over group. The key lesson from Figure 2 is that the main driver for any changes in the age distribution of workers in an industry will be workers staying in their jobs longer as opposed to a rising share of workers pursuing new work opportunities.

To get further insight into prolonged careers of older workers, the American Community Survey (ACS) public use files were used to approximate their annual retention rate. The true retention rate requires information on employment flows, which is not available in this annual cross section survey. The ACS is used to calculate the annual ratio from 2001 to 2019 of the number of workers aged 56 and older each year to the number of workers aged 55 and older in the previous year. This ratio overstates the true retention rate because no accounting is made for those who were employed this year but were not employed the previous year, most of whom would be new hires. Since the number of older workers who are new hires is so small, the magnitude of this overestimate should be relatively small.

The retention rate estimates displayed in Figure 3 show an upward trend along with a strong cyclical component. The retention rate grew steadily from 90 percent in 2001 to 96 percent in 2008. It dipped to 89 percent the following year as the Great Recession hit. Note, however, that this value is only slightly below the 2001 value. The rate increased to 95 percent in 2019. Overall, this is another indication of how older workers are extending their careers.

The percentage of workers aged 55 and above in an industry is an intuitive measure at a given point in time of how intensively older workers are employed in that industry. A key question in this paper is how and why this percentage varies across industries and within industries over time. Table 2 reports the 17 industries with the highest average percentage of older workers for 2001-2019 and the 14 industries with the lowest percentage. It shows that there is a very wide range in the share of older workers across industries. Over this 20-year period, urban transit had the highest percentage of older workers at 31 percent, followed by

real estate at 26 percent. Food services and motion pictures had the lowest percentage at six and nine percent. Appendix Table A1 displays the values for all industries.

The top employers of older workers include seven manufacturing industries, four service industries, four transportation industries, mining, and utilities. Older workers are least likely to be found on the payroll in five service industries, two information industries, two financial industries, and one manufacturing industry, along with construction, mining support, retail trade, and warehousing.

Table 2 shows that there is considerable dispersion in the change in the share of older workers. As a benchmark, the average industry had 13 percent older workers in 2001 and 23 percent in 2019, a 10-point increase. It increased at a slightly higher rate in the 17 industries with the highest average share of older workers (11.0 points) as opposed to the 14 with the lowest (8.2 points). Among the industries that have the highest share of older workers, the increase in their share ranges from as low as two percentage points (railroads) to as much as 15 points (paper, utilities). Looking at the industries that have the lowest share of older workers, the change ranges from a low three points in motion pictures and restaurants to a high of 13 points in rental and leasing services.

A simple shift-share analysis shows that changes in the distribution of all workers across industries has had no impact on the overall change in the percentage of workers who are 55 or older. Using 2001 employment weights, the mean percentage of older workers in ACS is 12.6 percent. Continuing to use the 2001 values of the percentage of older workers but shifting to 2019 employment weights, the mean percentage of older workers is 12.5 percent. This indicates that we need to focus on within industry changes, not shifts in the mix of industries.

There is a strong positive correlation between the percentage of older workers in an industry in 2001 and the same percentage in 2019, as shown in Figure 4. In a simple regression, nearly 40 percent of the variation in the 2019 values can be explained by the 2001 values. At the same time, this means that most of the variation in the 2019 values cannot be explained by the situation 18 years ago. In 16 industries the residual is four points or larger. Looking at some of the extreme values, the shares of older workers in printing and pipeline transportation in 2019 are 9 points higher than predicted by their 2001 values, whereas the share for railroad transportation is eight points lower. The change in the age mix of employees is far from a uniform process across industries.

With the percentage of older workers growing in every industry, the percentage of workers younger than 55 must fall correspondingly. One issue of concern is whether the rising share of older workers has made it more difficult for younger workers to get hired. Such displacement could take place in organizations if older workers delay retirement and the establishment's headcount remains constant. This is a modern twist on the lump of labor argument and does not consider (1) overall economic growth and (2) births and deaths of establishments. Alternatively, the rising share of older workers could merely reflect the aging of baby boomers.

Figures 5a and 5b display the raw data for the changes in the percentages of younger (16-29), middle-aged (30-54), and older workers by industry. There is no correlation between the growth in the percentage of older workers and the change in the percentage of younger workers. This casts initial doubt concerning the issue of potential displacement of younger cohorts by older generations. By necessity, this leaves us with an inverse relationship between

the growth in the percentage of older workers and the change in the percentage of middle-aged workers in an industry, as displayed in Figure 5b. This most likely reflects the aging patterns within each industry; most middle-aged workers in 2001 fall into the 55-plus category by 2019.

A likely determinant of the age mix in an industry is the growth rate of employment. Industry growth patterns vary considerably. Between 2001 and 2019 the textile industry employment dropped from 595,000 to 258,000 whereas employment in computer systems design increased from 41,000 to 417,000. Figures 6a through 6c show how the employment shares of younger, middle-aged, and older workers changed in response to employment growth (or lack thereof) by industry. Faster industry growth is associated with a larger percentage of younger workers, reflecting the tendency in many organizations to hire younger workers, especially for entry level positions. Correspondingly the percentage of older workers decreases in rapidly growing industries. The percentage of middle-aged workers is unrelated to overall employment growth in an industry.

2. What determines an industry's age mix?

The age-mix of any company or establishment hinges upon a wide range of considerations, including decisions about organizational boundaries, job design, hiring, training, and compensation.[5] The focus in this paper is on the age mix of an industry. The age structure of an industry reflects at an aggregated level the hierarchies and organizational structures of

[5] Clark and Ghent (2009) and Grund and Westergård-Nielsen (2008) are early studies that examined age structures of firms.

the establishments in that industry. Keep in mind that the mix of firms within each industry changes over time. Facebook and Tesla are not part of the data sets in the early 2000s whereas Enron and Lehman Brothers are not there in the 2010s.

Here we will consider younger, middle-aged, and older workers as separate inputs into a production function. This function also includes multiple types of capital, including specific types of equipment, structures, and intellectual property as inputs. The age-mix of the workforce reflects these considerations:

The productivity and cost of different types of labor: In the simplest production function framework, firms adjust the mix of age groups just as they would any set of inputs so that the ratio of marginal product to the cost of each input is equalized. Suppose initially that workers in age group are all doing the same jobs. Theory and evidence both indicate an upward sloping age-earnings profile, albeit with some flattening around age 62. Nonwage labor costs associated with defined benefit pensions, health insurance and paid time off also increase with age. If there are not corresponding increases in productivity, a firm will use relatively more younger workers. In practice young and old workers often do different tasks and these task assignments reflect the productivity advantages of each group. Younger workers will be more productive than older workers in some situations, such as jobs requiring the latest educational knowledge or those requiring physical labor. Older workers will be more productive in other situations, such as those where accumulated knowledge is necessary for decision making. The evidence on age and productivity, summarized in Allen (2019), does not indicate that there is a corresponding upward sloping age-productivity profile.

Hiring costs and human capital: There are fixed costs associated with bringing a new worker into an organization and training that person. These costs vary across and within organizations. In cases where it is easy to find new workers and there are negligible training costs, then we would expect firms to be indifferent about their age mix as long as wage rates are being held constant. Firms faced with sizable up-front investments in new hires have a retention incentive that should result in more older workers on the payroll. The mix of general and specific human capital also will be critical. Firms that make significant investments in firm-specific human capital will be more interested in hiring young workers and retaining older workers.

Complements or substitutes: In most organizations there is a hierarchy of jobs, and within that hierarchy there is a sorting by age group into the various positions. If the hierarchy has multiple levels and the knowledge and skills needed vary across these levels, then older and younger workers would serve complementary roles. For instance, younger workers might have a relative advantage in production tasks whereas older workers might have an advantage in managing customer or supplier relationships. Even within a job category, Bersin and Chamorro-Premuzic (2019) argue that a mix of older and younger workers leads to increased cognitive diversity and improved performance. However, there are situations where jobs are homogeneous, in which case younger and older workers would be substitutes.

Customer demand: Although they must be mindful of age discrimination issues, some employers consider customer preferences when making staffing decisions about customer-facing jobs, especially in youth-oriented industries such as entertainment and hospitality. There is a flip side. Customer preferences help explain why shoe repair, retail florists, religious

organizations and funeral homes are among the industries with the highest percentages of older workers.[6]

Technology: Whether based on perceptions or reality, the adaptability of workers to changes in technology influences employer decisions about age-mix. Younger persons have more recent training, as well as a longer time horizon to benefit from investments in new knowledge and skills, than older workers. In contrast, older workers have more perspective from their experience and will accurately realize in some cases that the latest new way of doing things need not be the most appropriate. Lazear (1998) argues that the two age groups will be complements in production under these circumstances.

In light of these considerations, what would we expect age distributions to actually look like? The age distribution would be flat in situations where the firm stays the same size, hires at the entry level, emphasizes training and promotion from within, and sets new hires equal to retirements. In firms that hire at multiple levels of the age distribution, there would still be a flat distribution if hires equal separations within each cohort. The age structure should tilt heavily toward young workers if human capital investments are modest or if there is an inverted-pyramid hierarchy with few opportunities to advance. Such a tilt also would be observed in growing firms if most new hires come from the lower tail of the age distribution. A tilt toward older workers would take place in situations where wage differentials by age are less than the productivity differentials, or where customer preferences dictate a tilt toward older workers.

[6] The age distribution of employees by industry for each year since 2011 is available at https://www.bls.gov/cps/demographics.htm#age

Changes in the age structure

From a strategic perspective, the discussion so far has demonstrated how employer decisions about capital, employment and compensation determine the age structure of an organization. The age structure of an enterprise changes over time as the firm executes on that strategy through hiring and separation decisions. In any given period, there will be persons in different age brackets who leave by quitting, being terminated or retiring. At the same time there will be others who arrive as either new hires or rehires. The age structure will tilt toward older workers if many young workers leave or more older workers get hired, whereas it will tilt toward younger workers if many older workers exit, or more younger workers get hired. Demographics accentuate these forces. Many organizations hired lots of baby boomers in the 1960s and 1970s, creating a bulge in the left tail of the age-distribution at that time, followed by a bulge in the middle twenty years later and a bulge on the right in the 2010s.

From a simple accounting perspective, changes in the age structure of an industry reflect hiring and separation decisions within existing establishments as well as the entry and exit of establishments. The underlying economic forces behind these adjustments can best be categorized into a set of supply and demand considerations.

It is entirely possible that changes in an industry's age structure can be accounted for by decisions by individual workers to delay retirement (along, of course, with decisions by their employers to hire or retain them). The Social Security reforms of 1983 created incentives to delay retirement across all industries. In addition, many firms switched from defined benefit to defined contribution pensions in the 1980s and 1990s and very few new firms that have opened in the last 40 years have set up defined benefit plans. Defined benefit plans typically have

strong incentives for retirement before age 65, whereas the benefit stream from a defined contribution plans is age neutral. As a result, we would expect to see more delayed retirement in industries where the shift from defined benefit to defined contribution plans has been the greatest. Employee health and longevity also could be a factor leading to changes in the age distribution at different rates across industries. Delayed retirement is more likely to happen among workers who are healthier and expect to live longer.

On the demand side, there are several forces that could have differential impacts for employment by age group. One possibility is a simple shift-share argument. We know that some industries employ older workers more intensively than others and that the older population is a growing share of the overall population. As a result, product demand shifts could end up impacting the age distribution of employees. For instance, older households spend more on health care and financial and legal services and less on apparel and furniture. Aggregate this pattern across an aging population and there will be increased demand for older workers in some sectors and reduced demand in others. The net impact is an empirical matter.

Relative wages play a central role in labor demand theory. In a textbook world, an increase (decrease) in the wages of older workers relative to that of younger or middle-aged workers leads to a decrease (increase) in demand for older workers. The wages we observe in the data reflect a complex selection process. A rising percentage of workers within a cohort leaves the labor market as that cohort ages. It is quite unlikely that labor market exits are pulled evenly throughout the wage distribution. Those with the highest earnings potential may tend to retire early to purchase more leisure. Alternatively, they may delay retirement more than others because their work is more financially rewarding. Similar arguments apply to those

with the lowest earnings potential. Wages by age group also hinge on demographic considerations, especially the impact of the aging of the baby boom generation.

Wages reflect employer decisions as well. Some firms pay higher than average wages as part of a conscious strategy to attract and retain the best workers. Firms that become concerned about retaining key senior employees may choose to increase their wages, whereas those that wish to encourage exits may flatten the wage profile. We also should be aware that the observed wage rate of workers in each age category in an industry reflects their educational and occupational composition.

The question of how well older workers interact with changing technology is one of the oldest questions in the social sciences. New technologies such as robotics reduce the physical demands of work and thereby should allow older workers to have longer careers. Often new technologies, especially those related to data and information, require new human capital investments. It could be argued that firms are reluctant to invest in training older workers because they are closer to retirement. However, turnover rates among young workers are considerably higher than those of older workers, so it is unclear ex ante which group has the longer expected job duration. Bartel and Sicherman (1993) note that technological change tends to be persistent in many industries, which can result in a sorting of workers in all age categories in terms of their ability to adjust to change. If the change is rapid enough then the shorter time horizon for investment in older workers matters less.

A final potential source of disruption on the labor demand side is import competition and outsourcing. Since 2000 we have seen realignment of supply chains as well as increased imports, especially from China. In some cases, entire establishments closed and there was a

reduction in industry employment across all ranges of the age distribution. In others, there were vastly fewer production positions, but managerial and professional jobs survived to some extent, resulting in a larger percentage of older workers.

3. Empirical framework

The central question to be examined in this research is what factors have determined why the share of older workers has risen significantly in some industries between 2001 and 2019 and relatively little in others. A natural choice for a dependent variable is the change in the percentage of older workers in an industry. The appeal of this measure is that it provides information about which sectors are adding or retaining more older workers relative to younger workers. A challenge is that it is difficult to interpret directly as an index of labor demand. An industry could have a rising percentage of older workers simply by having markedly fewer younger or middle-aged workers. This can happen if there are employment reductions and seniority is the key element in retention decisions. It also can happen if an industry stops growing and stops hiring.

Another way to examine the determinants of the changing age mix of employment by industry is to examine reduced form models of changes in employment by age group. To be specific, suppose that the change in employment for each age group a (where y=young, m=middle-aged and o=old) in industry j can be expressed as

$$dL_{aj} = \theta_a X_j + \gamma_a Kj + \delta_a w_{aj} + \varepsilon_{aj},$$

where dL indicates change in log employment, X is a vector of control variables reflecting industry characteristics, K is the capital-labor ratio, and w is log wage rate. All right-hand variables are measured at the start of the sample period. Taking first differences between the

demand for older workers and the demand for young and middle-aged workers respectively, we have the estimating equations

$$dL_{oj} - dL_{yj} = (\theta_o - \theta_y)X_j + (\gamma_o - \gamma_y)K_j + (\delta_o w_{oj} - \delta_y w_{yj}) + (\varepsilon_{oj} - \varepsilon_{aj})$$

$$dL_{oj} - dL_{mj} = (\theta_o - \theta_m)X_j + (\gamma_o - \gamma_m)K_j + (\delta_o w_{oj} - \delta_m w_{mj}) + (\varepsilon_{oj} - \varepsilon_{mj})$$

An underlying assumption in this framework is that the wage coefficient varies for each age group. If instead $\delta_o = \delta_m = \delta_y$, then we have a simpler framework

$$dL_{oj} - dL_{yj} = (\theta_o - \theta_y)X_j + (\gamma_o - \gamma_y)K_j + \delta_o(w_{oj} - w_{yj}) + (\varepsilon_{oj} - \varepsilon_{aj})$$

$$dL_{oj} - dL_{mj} = (\theta_o - \theta_m)X_j + (\gamma_o - \gamma_m)K_j + \delta_o(w_{oj} - w_{mj}) + (\varepsilon_{oj} - \varepsilon_{mj})$$

A key aspect of this approach is that the change in employment is posited as a function of initial values of the right-hand variables. These models are designed to answer the question of what is likely to happen to the employment of older workers in the future based on what we know at a given point in time. These are by no means to be interpreted as structural models of labor demand. However, they should be informative about certain matters. For instance, did the employment of older workers relative to other groups increase, not change, or decrease in industries with high-capital labor ratios or those making intensive use of information technology? Similarly, how does the relative employment of different age group vary by employer characteristics such as firm size, occupational mix or pension coverage?

One challenge in this framework is the issue of whether K can truly be considered exogenous. Reverse causality is not a direct concern; relative employment growth in the 2000s and 2010s would not be impacting K in 2001. There is a question of whether the future values of K are correlated with the initial values. The use of information technology in most workplaces changed radically in the 1990s as personal computers became widely adopted.

Many of the workers aged 55 and above in 2001 were hired in the 1970s and the 1980s. Half were hired ten or more years before 2002.[7] It would be very hard to argue that, at the point in time when they were hired, their employers would have been able to anticipate the capital mix that would be in place at the turn of the century.

It is hard to imagine how one could disentangle any causal impact of relative wages on employment of older workers with an industry data set observed over two decades. Two things can be established by examining the impact of including the wage rate variable. First, the raw data show that older workers became a growing share of the labor force over the last 20 years. If the inter-industry correlations show a corresponding increase (decrease) in relative wages over that period it would provide a signal as to whether a demand (supply) increase was an important factor. Second, it would be worthwhile to determine whether the results for other variables are robust to inclusion of w.

There are a host of considerations that must be considered in the selection of independent variables, some reflecting the supply side of the market (especially delayed retirement and worker characteristics), others reflecting employer decisions, and still others reflecting labor market institutions. Industries with larger shares of college graduates should have a larger percentage of older workers as college graduates enter the labor market later than those with less schooling. There also should be a higher percentage of older workers in Industries with large shares of professional and managerial workers. Those who work in offices should be healthier and less likely to retire because of exposure to occupational hazards.

[7] https://www.bls.gov/news.release/history/tenure_09192002.txt

Women tend to retire earlier than men, so we also would expect industries with large percentages of women to have fewer older workers.

How does the age mix of workers differ between capital- and labor-intensive industries? In particular, how does the age mix vary across sectors that vary in terms of how intensively they use information technology or invest in research? To examine these issues, the empirical model will include the overall capital-labor ratio for each industry along with interaction terms that allow the capital-labor coefficient to vary for types of capital associated with information technology, instrumentation, and intellectual property.

Previous studies have shown that the shift from defined benefit to defined contribution pensions has contributed to the rising employment-population ratio for older workers. In the context of this study, this calls not just for the inclusion of a measure of pension coverage, but also for consideration of how many workers are covered by which type of plan. There should be relatively few older workers in industries where defined benefit plans dominate because of the incentives for early retirement often found in such plans. In contrast, defined contribution plans rarely have provisions that spike pension wealth at specific ages or seniority dates, so we should expect a higher percentage of older workers in industries where most workers are covered by defined contribution plans.

Firms have fewer degrees of freedom to manage the age mix of employees when they are unionized. In times of downsizing, unionized firms lay off their youngest employees because of seniority provisions in union contracts. The most unionized industries should have a higher percentage of older workers.

Output growth varies considerably across industries during the periods examined here. Between 2001 and 2019, the log change in real value added ranged between 2.047 in data processing, internet publishing, and other information services and -0.8 in apparel and leather and allied products. During growth periods firms typically add proportionally more young and middle-age employees than older employees, whereas during periods of industry decline most separations occur among younger workers. As a result, the percentage of older workers should be smaller (larger) in industries that have experienced recent growth (declines) in employment.

The variation in output growth has an independent effect on the age structure. Imagine two industries with the same average growth over a given period, one on a steady path and the other with repeated ups and downs. The latter industry will end up with a sizable contingent of older workers sheltered from the ups and downs, accompanied by fewer younger and middle-aged workers. Industries with more employment instability will have higher shares of older workers.

Two variables are included as controls to account for how industry characteristics could drive the age structure: firm size and employee tenure. Large firms are likely to provide more career opportunities and paths, so we might expect them to have a higher percentage of older workers. Some firms commit to long-lasting careers for their workers and there would be a higher percentage of older workers in such firms.

It would be hard to have a discussion about the determinants of the demand for older workers without consideration of their relative cost. In the results reported below, the log ratio of average weekly earnings of older workers compared to younger workers (age 16-29) will be used as a control. The values used in the model are those that prevail at the beginning of the

sample period, so there will not be a direct relationship between the subsequent shifts in relative labor demand and relative wages. However, the current log wage ratio is correlated with future values, raising possible endogeneity concerns. Results will be reported with and without a compensation variable.

4. Data sources

Because the concern here is labor market trends rather than year-to-year fluctuations, the focus will be on three intervals: 2001-2007, 2007-2019 and 2001-2019. The choice of intervals controls for the business cycle; the initial and final year in each period is a business cycle peak. The main data source for this study is the ACS for 2001 through 2019. ACS data are available for 2000 but the sample size is considerably smaller that year, resulting in noisy measures for smaller industries that become noisier still when first differenced over 19 years. Employees are defined as wage and salary workers; the self-employed and military are not included. The ACS was used to calculate total employment in each industry, along with its age breakdown into three groups (16-29, 30-54, and 55 and over). Average hourly earnings are estimated for each age group for 2001, 2007 and 2019 using continuous measures of wage and salary income, usual weekly hours and weeks worked. Measures of percentage college graduates, percentage female and percentage in managerial or professional occupations also were pulled from the ACS. These percentages are calculated across employees from all age groups combined.

Capital data comes from the Bureau of Economic Analysis (BEA) of the US Census, which publishes Current-Cost Net Capital Stock of Private Nonresidential Fixed Assets data for 62

industries and 96 categories of capital.[8] In the empirical analysis total capital is defined as the sum of equipment, structures, and intellectual property projects (IPP). To determine whether the employment of older workers is impacted by advanced technology, the capital coefficient is allowed to vary with different types of capital associated with information technology, instrumentation, and intellectual property. The measure used in the first set of results reported here includes 12 types of computing, instruments, and office equipment along with five types of IPP. The robustness of the results to alternate definitions is examined below.

Real value added by industry as calculated by BEA was used to construct two control variables: output growth over the 10 years preceding the sample period and the variance of output growth over the same interval.[9]

Industry measures of percentage covered by union contracts, percentage working in large firms, percentage covered by pensions, and percentage of employees with 20 or more year of service were pulled from the Current Population Survey. Lagged values from the 1980s and 1990s were used to minimize issues related to reverse causation with the dependent variable. The union variable comes from the outgoing rotation groups in the merged 1992-93 CPS public use files. The firm size measure comes from the Annual Social and Economic Supplement for the same years. The years of service data come from the 1996 and 1998 Job Tenure and Occupational Mobility Supplement. The pension coverage data comes from the 1999 CPS so that estimates of the percentage in defined benefit and defined contribution plans could be obtained from the public use files of IRS Form 5500, using data on plan participants

[8] Downloads available at https://apps.bea.gov/national/FA2004/Details/Index.htm
[9] https://apps.bea.gov/iTable/index_industry_gdpIndy.cfm

and plan characteristics. Public use files for Form 5500 are not available for download for years before 1999.

Industry definitions were established by matching NAICS codes in the ACS with those used in Bureau of Economic Analysis data sets on output and capital. Governments were not included as separate industries because the capital data is constrained to the private sector. The empirical analysis is based on 60 industry categories which are listed in the data appendix.[10] The limiting factor for industry definitions was the 62 industry categories in the BEA capital data set. Two pairs of industries had to be combined. Securities, commodity contracts and investments (NAICS code 523) and funds, trusts and other financial vehicles (NAICS code 525) have the same detailed industry code in the ACS. Hospitals (NAICS code 622) and nursing and residential care facilities (NAICS code 623) are combined in the pre-1997 SIC-based data used for lagged GDP values.

5. Empirical results

Although the focus of this research concerns changes in age distributions, it is worthwhile to begin with a quick examination of which variables are associated with the age structure of industries at a given point in time. Table 3 reports cross section regressions of the percentage of workers in each age category for 2001 and 2019. The independent variables include industry characteristics (percentage covered by pension plans, percentage covered by

[10] A concordance between the 1990 Census industry codes in the CPS and the NAICS codes in the ACS was developed to allow the CPS data to be merged with the ACS data. In two cases a 1990 Census industry was split into two NAICS industries: (1) oil and gas extraction and mining and (2) banking and credit intermediation and securities, commodities, funds, trusts, and other financial instruments. The same lagged values were used for each pair of industries.

union contracts, percentage working in firms with more than 1000 workers, and percentage of workers in the 1980s who had been with the firm 20 years or more), worker characteristics (percentage college graduates, percentage female, and percentage employed in professional and managerial occupations), the capital-labor ratio, the ratio of high tech capital to labor, the growth of GDP over the last 10 years, and the variance in GDP growth over the last 10 years.

Pension coverage is the variable that best accounts for the sorting of workers in different age groups by industry. Compare two industries, one with 35 percent pension coverage and one with 65 percent coverage. The industry with higher coverage would have 16 to 20 percent fewer young workers. In 2001 this was equally offset with a larger number of middle-aged workers, whereas in 2019 it was offset by both more older and middle-aged workers. This is consistent with a job matching process where young workers place a lower premium on having a job with retirement benefits.

Not surprisingly, the correlates of age structure vary by age bracket. For instance, in 2001 percentage female and the overall capital-labor ratio are related to the percentage of older workers in an industry, but neither variable is related to the percentage of middle-aged or young workers.

There is not a stable correlation between the percentage of workers in any given age group and the likely determinants of that percentage. Industries with high percentages of women and large capital-labor ratios have higher percentages of older workers in 2001, but these relationships are no longer present in 2019. Similarly pension coverage is related to a large share of older workers in an industry in 2019 but not in 2001. The percentage of middle-aged workers in an industry is related to the percentage of workers in large firms and the

lagged percentage of workers with long tenure in one year but not both. Firm size is a strong predictor of the percentage of young workers in 2001 but not in 2019.

The next step is to examine which variables best predict the change in the percentage of older workers in an industry. As a first pass, Table 4 reports simple regressions of the first difference in the percentage of older workers for three different time periods: 2001-2007, 2007-2019 and 2001-2019. Two models are reported for each period: one excluding and one including the ratio of log wages of older workers to younger workers. The key results are as follows:

1) Pension coverage is the strongest predictor of which industries had the largest growth in the share of older workers. The growth in the percentage of older workers in an industry is largest in those industries where most workers are covered by a pension plan. Compare two industries one where no workers are covered by a pension and one where all are covered by a pension. Growth in the percentage of older workers was 6.1 percentage points higher between 2001 and 2007 and 12.8 points higher between 2007 and 2019 in the industry where all workers were covered by a pension as compared to the industry where none were covered.
2) The share of older workers grew most between 2007 and 2019 in the industries with the highest ratios of high-tech capital to labor. The capital-labor ratio itself was weakly and inversely related to the growth in the share of older workers in an industry. To examine the practical magnitude of this relationship, consider the following industry comparison. The mean high-tech capital labor ratio across all industries in 2007 was 19.5; the standard deviation was 28.5. Compare two industries one with the mean high-tech

capital labor ratio and one where the ratio was twice as high. Considering that a doubling of the high-tech capital-labor ratio also leads to an increase in the overall capital-labor ratio, the growth in the percentage of older workers is 0.85 percentage points higher in the industry with the higher high-tech capital ratio. Admittedly this is not a huge difference, especially over a 12-year period. However, the key takeaway is that the employment share of older workers was growing fastest in high-tech industries.

3) The percentage of older workers in an industry decreased in those industries with the most rapid output growth. This no doubt reflects the fact that expanding firms hired mostly young workers. The magnitude of the coefficient is small; a 10 percent increase in output growth is associated with a 0.1 percentage point decline in the percentage of older workers.

4) The growth in the share of older workers in an industry is unrelated to the relative wage differential between the old and the young. The coefficient of the wage variable is both small and measured with little precision. Further, the coefficients of the other variables are not sensitive to the addition of the wage variable. There is no evidence of increased demand for older workers within industries.

5) The growth in the share of older workers was lowest in industries with the largest share of college graduates. To the extent college graduates retire at later dates than workers with less schooling, this result is not what was anticipated. Neither is the finding that the percentage of older workers grew less in industries that had relatively large numbers of workers with 20 or more years of tenure in the 1990s. This variable was

included to serve as a proxy for sectors of the economy where job durations and careers were longer.

6) There is not a stable relationship between the change in the share of older workers and the independent variables examined here. The coefficients for 2001-2007 and 2007-2019 are often quite different, sometimes with opposite signs.

These results are based on first difference analysis of employment levels by age group in 60 industries. Employment levels vary considerably across industries. The average industry in the sample had 1.9 million workers in 2001, with a range from 33,000 (pipeline transportation) to 14 million (retail trade). If some very large industries ended up being statistical outliers, the results could change considerably if the regression were weighted by industry size. Also, hours per person vary across industries, with some making intensive use of part-time workers and others relying heavily on overtime. To address these considerations, the models in Table 4 were re-examined by (1) weighting each observation by the sum of employment at the beginning and end of the sample period and (2) recalculating the dependent variable so that it is measured in labor hours instead of employees. The results, reported in Table A2 in the appendix, show that neither weighting the regression nor changing the dependent variable made any meaningful difference in the findings.

The pension coverage variable does not distinguish between defined benefit and defined contribution plans. Estimates of the percentage covered by each type of plan were derived from Internal Revenue Service Form 5500 data for 1999 by counting the number of active participants in DB and DC plans for each of the 60 industry groups. The models in Table 4 were then re-estimated using separate variables for the percentage of workers covered by DB and DC

plans; the results are reported in Table A3 in the appendix. In 2001-2007 and 2007-2019 the coefficient for DC plans is roughly the same as the coefficients for all plans in Table 4, whereas the coefficient for DB plans is not measured precisely. For the 2001-2019 period, the coefficient for DB coverage is 50 percent larger than the coefficient for DC coverage but the hypothesis that the two coefficients are equal cannot be rejected. Although the impact of DB and DC plans on retirement and retention might be expected to be different, this does not show up in the data.

One might question the robustness of the results for high tech capital in Table 4 to potential changes in the classification of which types of capital are considered high tech. The measure used in the regression models includes 14 types of equipment and five types of intellectual property products. The BEA provides data on 20 additional categories of intellectual property products (IPP). To examine the sensitivity of the results to the inclusion of IPP, three additional high-tech capital-labor ratio variables were examined. One of the variables included high-tech equipment but no IPP. One added software related IPP, namely prepackaged software, custom software, and own account software, while omitting software publishing and computer systems design. The third added all 25 IPP categories to the high-tech equipment, including IPP in aerospace, motor vehicles and pharmaceuticals. As shown in Table A4, the coefficients of the first two alternate variables in 2007-2019 are similar to that of the one in Table 4. In contrast, the coefficient for the most inclusive measure is consistently smaller than its standard error. Overall, it is clear that as long as high-tech capital is defined as the usage of information technology then the results for this variable are quite robust. On the other hand, the presence

of other types of IPP in an industry does not seem to have any relationship to its increased usage of older workers.

These results reflect changes in the share of older workers compared to the share of younger and middle-aged workers. The next logical step is to compare the growth in employment of older workers to that of each of the other two groups. To do this, the focus now turns to an examination of how the log change in employment of older workers compares to that of younger and middle-aged workers respectively in Tables 5 and 6, using the same independent variables as before.

Overall, the main results from the analysis of inter-industry differences in the percentage of older workers hold when we separately examine young-old and middle-aged-old differences. Employment growth of older workers was more rapid than employment growth of younger workers between 2001 and 2007 in industries with higher levels of pension coverage. This was the case for the employment growth differential between older and middle-aged workers for the entire sample period. Industries with the highest ratios of high-tech capital to labor saw the largest growth in the employment of older workers relative to employment of the other age groups (although the relationship for middle-aged workers is somewhat weak in 2001-2007). Output growth narrowed the spread in employment growth between older workers and their middle-aged and younger counterparts. The anomalous results for industries with high percentages of college graduates and industries with a tradition of having long employment relationships continue to appear.

Two new patterns do appear in Tables 5 and 6. First, the growth of employment for older workers was much slower than that for younger workers in industries with high percentages of

unionized workers. These industries tend to still have defined benefit pensions in place for production workers, potentially limiting the growth of employment of older workers. Union density has a mean of 19 percent and a standard deviation of 16 percent. Compare two industries, one with 20 percent union members and one with 40 percent union members. The industry with more union members would have 20 percent higher employment growth among younger workers than older workers.

Second, the growth in employment of older workers compared to middle-aged and younger workers was lower in industries with high percentages of women. This could reflect higher percentages of women in the two younger age groups.

In summary, two major themes arise from this analysis. First, pension coverage and pension characteristics are strongly related to changes in the age structure of industries over time. One possible interpretation of the results is that as the first generation of workers covered largely by defined contribution plans hit the later stages of their working career, they decided to stay on the job longer. At the same time the union results in Table 5 suggest that defined benefit plans work in the opposite direction, generating earlier exits for older workers and more opportunities for younger workers. Second, there does not seem to be a technological backlash toward the employment of older workers. To the contrary, there was actually more growth in the percentage of older workers in those industries that use the most high-tech capital.

Are younger workers being squeezed out?

As more older workers delay retirement, some have speculated that this had resulted in fewer opportunities for younger workers. The simple scatterplot in Figure 5 indicated that there did not seem to be a relationship between the change in the share of older workers in an industry and the share of younger workers. Now that we know variables such as pension coverage and the capital-labor ratio have an impact on changes in the deployment of older workers in an industry, it would be logical to revisit that issue in a regression framework.

The challenge is that the shares of older, middle-aged, and younger workers in an industry are not independent variables. Further, there is no genuine source of exogenous variation in the ability of firms to hire or retain workers in different age brackets across different industries. What can be done here is to see what the data tell us about any possible tradeoff between jobs for older and younger workers within a given industry. This is done in three ways in Table 7. First, to capture the raw data pattern we report a simple regression of the change in the share of younger workers on the change in the share of older workers. Second, the percentage of older workers will be used as an independent variable in an OLS model of changes in the percentage of younger workers over time. This will tell us whether covariates have any impact on the relationship. Third, even though there are no a priori reasons to exclude some of the independent variables in the model for older workers from the model for younger workers, there are correlation patterns suggesting that they could be excluded because of their explanatory power for one age group and lack of explanatory power for the other. The control variables are the same as those used in the previous models; results with and without the relative wage of older to younger workers are reported.

The key finding across all the results reported in Table 7 is that there is no evidence of any declines in the share of younger workers being related to increases in the share of older workers. The coefficients for 2007-2019 are quite small, ranging between 0.1 and -0.1. The coefficients for 2001-2007 and 2007-2019 are larger, running from 0 to -0.5. The null hypothesis cannot be rejected in any of the models. The conclusion that can best be drawn from this exercise is that, despite the best efforts being made to find a relationship between the shares of older and younger workers across industries, there is no such relationship to be found in this data set.

Imports and older workers

China joined the World Trade Association in 2001 and the resulting reduction in trade barriers led to a surge of imports into the US. In 2001, the US imported $8.5 billion worth of goods from China, increasing to $26.8 billion by 2007. Chinese imports peaked at $44.9 billion in 2018 and subsequently dropped to $37.6 billion in 2019 after both China and the US took retaliatory trade measures.

Studies such as Autor et al (2013) have established that the surge of imports from China resulted in a decline in manufacturing jobs in the US. The question examined here is how older workers were impacted relative to younger workers. The 2001-2007 sample period used in our data set coincides with the period of the most rapid increase in Chinese imports, so this is likely to be the period where the impact of expanded trade with China has the largest impact. The 2007-2019 sample contains both the Great Recession and the ramping up of tariffs and other

trade barriers after the 2016 US Presidential Election, so the results for that period may be less clear-cut.

One challenge that arises when examining this question concerns how to handle the 37 industries in the data set outside of primary goods and manufacturing. Here two approaches are considered. The first is to restrict the sample to the 23 industries for which trade data are tabulated. This requires a reduction in the number of independent variables to allow enough degrees of freedom to obtain precise estimates of the import penetration variables.
The second is to assign values of zero to the import penetration variables for nontraded goods as well as services. This is a reasonable approach for personal services such as haircuts and spa treatments. On the surface this approach would seem less reasonable for services such as travel; American tourists in Shanghai are in effect importing Chinese services. However, there is no evidence of any surge in Chinese service "imports" that is in any way comparable to what has happened in manufacturing. Further, the service industries with zero imports are not outliers in the distribution. Manufacturing industries with little to no change in Chinese import penetration during this period include food products, petroleum and coal products, chemicals, and primary metals.

Separate variables for Chinese and all other imports were created from USA Trade Online to estimate the impact of increased import competition on the age structure of employees by industry. One variable is the change in Chinese imports in a given industry over the sample period divided by gross output in that industry in the initial year of the sample period. The second variable is the change in imports from all other countries divided by initial

gross output. Both variables are included to allow the impact of Chinese imports on employment to vary from that of the impact of the imports from other countries.

The empirical models have so far included as many as 12 independent variables, a strategy that is not likely to be successful when adding two more variables to a data set with 23 observations. The set of independent variables in Table 8 for the 23-industry sample is restricted to those that have proven to be of critical importance to the model: GDP growth, overall capital-labor ratio, high-tech capital-labor ratio, pension coverage, and the relative wage of older to younger workers. The full set of independent variables is used for the 60-industry sample.

The results for both samples show that the percentage of older workers increased more in those industries with the largest surges in Chinese imports in 2001-2007. Compare two industries one with a 20 percent change in import penetration and one with no change in import penetration. The growth in the percentage of older workers is 0.8 to 1.0 percentage points higher between 2001 and 2007 in the industry with the higher degree of new import competition. In the 23-industry sample there is no correlation between Chinese import penetration and the share of older workers between 2007 and 2019. The coefficient for Chinese import penetration for the 60-industry sample is actually more than twice as large in 2007-2019 but the standard error increases to an even greater degree, making it unwise to draw any conclusions for that sample in that time period.

Focusing further on the 2001-2007 period, equations estimating the change in the percentage of younger workers was estimated with the same independent variables for the two samples. In the 23-industry sample, the China imports coefficient (S.E.) was -0.038 (0.053), but

it was -0.085 (0.031) in the 60-industry sample. This indicates the surge in Chinese imports led to employment reductions among younger workers, thereby decreasing their share and increasing that of older workers.

As for import penetration from countries other than China, the results are mixed. In the 23-industry sample, the percentage of older workers grew more slowly in 2007-2019 in industries with the fastest growth in imports from other countries. However, there was no relationship in any period between import growth from these countries and the change in the share of older workers in the 60-industry sample.

The takeaway from this analysis is that Chinese import growth had a sizable impact on the age structure of industries between 2001 and 2007, mainly by reducing the employment of younger workers relative to older workers. This impact appears to have dissipated in 2007-2019, perhaps because the rate of import growth slowed down.

6. Conclusion

More older people are working than ever before. This study has demonstrated that there is considerable inter-industry variation in the percentage of older workers at a given point in time, as well as in the rate at which those percentages change over time. The empirical analysis has attempted to determine the characteristics of those industries where they have found the greatest opportunities.

Pension coverage is the single strongest predictor of whether an industry will have a growing percentage of older workers during the first two decades of this century. Now that defined contribution plans dominate in the private sector, workers in industries with high

pension coverage can make their organizational exit and retirement decisions without having to consider spikes in pension wealth at certain ages that take place under defined benefit plans. Better health and higher longevity appear to be translating into longer careers for these workers.

Older workers now comprise a larger share of the employees in industries that make the most intensive use of high-tech capital. Even if they may not be proficient in Python or R, they are making contributions in managerial and professional roles. There also is evidence that older workers became a smaller percentage of the workforce in industries where that make intensive use of traditional types of capital, namely equipment and structures.

Employment patterns by age react to changes in output and trade patterns. Older workers became a smaller percentage of the workforce in industries with the fastest growth of output, reflecting firm's decisions to hire younger or middle-aged workers with a longer potential training horizon. In the industries that were most impacted by Chinese imports in the 2001-2007 period, the employment of all age groups declined but older workers had smaller proportional job losses than the other two age groups.

In closing, we also should note some things we did not find. There is no evidence the percentage of older workers is rising more in industries where the wage gap between older and younger workers was greatest. In other words, there does not seem to be a demand shift toward older workers. Also, there is no evidence that an increase in the percentage of older workers in an industry leads to a decrease in the percentage of younger workers. Further work needs to be done to examine more detailed data on hiring patterns by age and how it relates to the growth of the employment of older workers by industry.

The focus here has been to reveal basic patterns in the data. To establish causality more rigorously, Acemoglu and Restrepo (2020) and Autor, Dorn and Hanson (2013) used values from other countries as instruments for technology and trade variables. Matching industry codes over multiple data sets over this period (pre and post NAICS industry codes) for the US was no small challenge for this study. One option would be to examine the EU KLEMS data set. It provides capital variables for dozens of other countries but with a more highly aggregated set of industry definitions.

This study intentionally ended with annual data for 2019. A logical next step will be to examine what happened to the employment of older workers by industry month-by-month in the subsequent years. The aggregate data show that there was a sharp downward spike in labor force participation starting in April 2020. It remains to be seen whether many of those who left the labor force during the pandemic will return. Some important clues may very well be found in their inter-industry employment patterns.

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Table 1. Demographic and job characteristics of older wage and salary workers, 2001 and 2019 American Community Survey

	Men and women 2001	Men and women 2019	Men 2001	Men 2019	Women 2001	Women 2019
Occupation						
Managerial, Professional	32.9	40.6	33.0	38.0	32.8	43.3
Service	14.9	14.7	12.5	12.0	17.4	17.5
Sales	11.1	9.0	11.0	8.8	11.3	9.1
Support	18.3	14.2	7.9	6.3	29.2	22.4
Production	22.8	21.5	35.5	34.9	9.3	7.7
Years of schooling						
Below 12	12.5	6.7	13.5	7.7	11.4	5.6
12	41.3	35.4	37.2	35.5	45.7	35.3
13 to 15	19.1	23.4	18.6	21.6	19.8	25.3
16 or above	27.0	34.5	30.7	35.2	23.2	33.8
Percentage full-time	75.6	77.6	82.6	83.9	68.2	71.0
Percentage male	51.5	50.7				
Age distribution						
55-59	51.7	42.4	51.3	42.1	52.2	42.8
60-64	27.6	32.7	27.9	32.4	27.2	33.0
65-69	11.5	14.9	11.5	15.1	11.5	14.7
70+	9.2	10.0	9.3	10.4	9.1	9.5
Income						
Weekly earnings	36812	62316	46703	76044	26305	48221
Hourly earnings	20.89	34.80	24.99	39.99	16.54	29.46
Standard deviation of log hourly earnings	0.740	0.797	0.768	0.818	0.668	0.752

Table 2. Industries with lowest and highest percentage of older workers, American Community Survey, 2001-2019

	2001-2019 average	2001	2019	Change 2000-2019
Industries with highest percentage of older workers				
Urban transit	31	21	35	14
Real estate	26	22	31	9
Transportation equipment manufacturing other than motor vehicles	23	17	28	11
Educational services	23	17	24	7
Water transportation	22	18	27	9
Textile product manufacturing	22	15	27	12
Other services, except public administration	22	17	26	9
Paper product manufacturing	22	14	29	15
Utilities	22	12	27	15
Information and data processing services	22	12	21	9
Railroad transportation	21	17	19	2
Primary metal manufacturing	21	14	26	12
Truck transportation	21	15	28	13
Electrical equipment, appliances, and component manufacturing	21	14	28	14
Machinery manufacturing	21	14	26	12
Fabricated metal products	21	14	28	14
Mining	21	13	24	11
Industries with lowest percentage of older workers				
Rental and leasing services	16	10	23	13
Retail trade	16	13	20	7
Amusements, gambling, and recreation	16	13	19	6
Food product manufacturing	16	11	21	10
Securities, commodities, funds, trusts, and other financial investments	16	10	21	11
Administrative and support services	16	12	20	8
Banking and credit intermediation	15	10	19	9
Support activities for mining	14	8	19	11
Broadcasting and telecommunications	13	7	19	12
Warehousing and storage	13	11	15	4
Construction	13	8	18	10
Computer systems design and related services	11	6	14	8
Motion picture and sound recording	9	7	10	3
Food services and drinking places	6	5	8	3
Unweighted mean for all industries	19	13	23	10

Table 3. Cross section regressions

Dependent variable	Ratio of employment in given age group to total employment					
Age group	55 and above	55 and above	30 to 54	30 to 54	16 to 29	16 to 29
Year	2001	2019	2001	2019	2001	2019
Percent college	-0.0112	-0.0962	-0.0572	0.00396	0.0684	0.0923
graduates	(0.0352)	(0.0660)	(0.0635)	(0.0656)	(0.0727)	(0.0842)
Percent female	0.0555*	0.0507	0.0113	-0.0499	-0.0669	-0.000825
	(0.0255)	(0.0473)	(0.0447)	(0.0502)	(0.0517)	(0.0535)
Percent	-0.112	-0.132	-0.0167	0.181	0.129	-0.0491
professional	(0.167)	(0.175)	(0.203)	(0.101)	(0.317)	(0.214)
Ln(K/L)	0.0129*	0.00735	-0.00398	-0.0170	-0.00892	0.00969
	(0.00588)	(0.00898)	(0.00969)	(0.0125)	(0.0124)	(0.0146)
Ln(HiTecK/L)	-0.00289	0.00136	0.00693	0.0160	-0.00405	-0.0173
	(0.00588)	(0.00750)	(0.0100)	(0.0100)	(0.0132)	(0.0119)
GDP growth	0.00246	-0.00803	0.000332	-0.00795	-0.00279	0.0160
	(0.00314)	(0.0107)	(0.00319)	(0.0108)	(0.00492)	(0.0142)
GDP	-0.668	-0.142	0.940	0.110	-0.273	0.0321
variance	(0.523)	(0.123)	(1.048)	(0.138)	(1.236)	(0.114)
Pension	0.0244	0.255**	0.445***	0.163*	-0.469***	-0.418***
coverage	(0.0525)	(0.0811)	(0.0785)	(0.0690)	(0.116)	(0.116)
Union	0.0821	0.0453	0.0195	-0.0615	-0.102	0.0162
coverage	(0.0545)	(0.0807)	(0.0773)	(0.0563)	(0.114)	(0.109)
Percent in	-0.0843	-0.115	-0.145*	-0.0496	0.229*	0.165
large firms	(0.0551)	(0.0649)	(0.0678)	(0.0601)	(0.103)	(0.0994)
Percent long	0.000510	-0.236	0.0973	0.352*	-0.0978	-0.115
term workers	(0.115)	(0.185)	(0.163)	(0.136)	(0.238)	(0.219)
Constant	0.0663*	0.150**	0.457***	0.496***	0.477***	0.355***
	(0.0310)	(0.0464)	(0.0470)	(0.0490)	(0.0643)	(0.0648)
N	60	60	60	60	60	60
R^2	0.290	0.283	0.726	0.577	0.620	0.528

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Regression results: first difference in percent older workers

Dependent variable	Change in percentage of workers 55 and above					
Years	2001-2007	2001-2007	2007-2019	2007-2019	2001-2019	2001-2019
Percent college	0.019	0.0203	-0.108***	-0.122***	-0.108***	-0.110***
graduates	(0.019)	(0.0187)	(0.0390)	(0.0409)	(0.0379)	(0.0376)
Percent female	0.021*	0.0187	-0.0367	-0.0309	-0.00854	-0.00521
	(0.012)	(0.0124)	(0.0231)	(0.0236)	(0.0281)	(0.0285)
Percent	-0.079	-0.0688	-0.0791	-0.0812	-0.135	-0.149
professional	(0.053)	(0.0547)	(0.102)	(0.106)	(0.120)	(0.124)
GDP growth	-0.014*	-0.0181*	-0.0161**	-0.0143**	-0.0126	-0.00760
	(0.008)	(0.00939)	(0.00640)	(0.00682)	(0.0225)	(0.0233)
GDP	0.120	0.143	0.0386	0.0149	0.00495	-0.0267
variance	(0.109)	(0.111)	(0.108)	(0.110)	(0.318)	(0.278)
Ln(K/L)	-0.0012	-0.000807	-0.00534	-0.00576	-0.00547	-0.00603
	(0.0018)	(0.00172)	(0.00470)	(0.00485)	(0.00494)	(0.00492)
Ln(HiTecK/L)	0.0027	0.00340	0.0126***	0.0117**	0.0120**	0.0110*
	(0.0021)	(0.00223)	(0.00421)	(0.00450)	(0.00561)	(0.00603)
Pension	0.058***	0.0591***	0.128***	0.125***	0.200***	0.199***
coverage	(0.017)	(0.0171)	(0.0413)	(0.0412)	(0.0497)	(0.0505)
Percent in	-0.015	-0.0156	-0.0139	-0.0124	-0.0350	-0.0337
Large firms	(0.014)	(0.0134)	(0.0374)	(0.0380)	(0.0427)	(0.0445)
Percent long	0.005	-0.0116	-0.247**	-0.240**	-0.243**	-0.220**
term workers	(0.040)	(0.0401)	(0.101)	(0.0936)	(0.102)	(0.100)
Union	0.011	0.0132	-0.0378	-0.0372	-0.0344	-0.0378
coverage	(0.018)	(0.0166)	(0.0336)	(0.0360)	(0.0407)	(0.0425)
Ln wage ratio		-0.0138		0.0307		0.0189
55+ to 16-29		(0.00941)		(0.0493)		(0.0333)
Constant	0.010	0.0144	0.0931***	0.0819***	0.0968***	0.0905***
	(0.012)	(0.0124)	(0.0222)	(0.0301)	(0.0274)	(0.0312)
N	60	60	60	60	60	60
R^2	0.563	0.583	0.435	0.443	0.434	0.441

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Regression results: relative log employment growth of older and younger workers

Dependent variable	Log employment change of workers 55 and over – log employment change of workers 16-29					
Years	2001-2007	2001-2007	2007-2019	2007-2019	2001-2019	2001-2019
Percent college	-0.0495	-0.0285	-0.471	-0.623**	-0.611	-0.615
graduates	(0.289)	(0.275)	(0.296)	(0.293)	(0.375)	(0.377)
Percent female	-0.0321	-0.0643	-0.368*	-0.305*	-0.348	-0.341
	(0.203)	(0.193)	(0.189)	(0.174)	(0.271)	(0.277)
Percent	0.340	0.469	-0.284	-0.307	-0.0648	-0.0921
professional	(0.588)	(0.628)	(0.729)	(0.738)	(1.082)	(1.094)
GDP growth	0.000295	-0.0484	-0.132***	-0.113**	0.00389	0.0142
	(0.0953)	(0.115)	(0.0396)	(0.0450)	(0.120)	(0.141)
GDP	-1.422	-1.115	0.941*	0.680	-2.625	-2.690
variance	(1.348)	(1.326)	(0.519)	(0.509)	(1.613)	(1.645)
Ln(K/L)	-0.121***	-0.116***	-0.0148	-0.0195	-0.124**	-0.125**
	(0.0348)	(0.0351)	(0.0298)	(0.0304)	(0.0473)	(0.0501)
Ln(HiTecK/L)	0.0772**	0.0870**	0.0921**	0.0823**	0.150**	0.148**
	(0.0356)	(0.0372)	(0.0407)	(0.0394)	(0.0700)	(0.0720)
Pension	0.583**	0.595**	-0.0389	-0.0659	0.666	0.663
coverage	(0.285)	(0.278)	(0.314)	(0.325)	(0.525)	(0.535)
Percent in	0.0456	0.0332	0.125	0.142	0.140	0.143
Large firms	(0.270)	(0.262)	(0.252)	(0.245)	(0.441)	(0.450)
Percent long	-0.353	-0.569	-1.037	-0.955	-1.464	-1.419
term workers	(0.655)	(0.666)	(0.631)	(0.684)	(0.981)	(1.068)
Union	-0.187	-0.154	-0.616***	-0.609***	-0.875***	-0.882***
coverage	(0.255)	(0.252)	(0.221)	(0.217)	(0.297)	(0.306)
Ln wage ratio		-0.183		0.339		0.0386
55+ to 16-29		(0.148)		(0.256)		(0.220)
Constant	0.533***	0.595***	0.750***	0.626***	1.236***	1.223***
	(0.179)	(0.177)	(0.185)	(0.169)	(0.220)	(0.217)
N	60	60	60	60	60	60
R^2	0.458	0.480	0.460	0.479	0.423	0.423

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Regression results: relative log employment growth of older and middle-aged workers

Dependent variable	Log employment change of workers 55 and over – log employment change of workers 30-54					
Years	2001-2007	2001-2007	2007-2019	2007-2019	2001-2019	2001-2019
Percent college	0.268	0.267	-0.615***	-0.785***	-0.437*	-0.466**
graduates	(0.192)	(0.195)	(0.223)	(0.231)	(0.230)	(0.229)
Percent female	0.0325	0.0341	-0.296**	-0.225*	-0.244*	-0.200
	(0.116)	(0.120)	(0.114)	(0.114)	(0.144)	(0.142)
Percent	-0.546	-0.552	-0.169	-0.195	-0.470	-0.648
professional	(0.446)	(0.443)	(0.591)	(0.615)	(0.709)	(0.701)
GDP growth	-0.113*	-0.111*	-0.0797**	-0.0578	-0.0877	-0.0206
	(0.0581)	(0.0596)	(0.0387)	(0.0408)	(0.125)	(0.109)
GDP	1.225	1.210	0.779	0.486	0.869	0.447
variance	(0.893)	(0.869)	(0.730)	(0.701)	(2.271)	(1.699)
Ln(K/L)	0.00259	0.00232	-0.0600*	-0.0652**	-0.0521	-0.0597*
	(0.0170)	(0.0176)	(0.0299)	(0.0323)	(0.0315)	(0.0313)
Ln(HiTecK/L)	0.0176	0.0171	0.0628**	0.0518*	0.0562*	0.0427
	(0.0181)	(0.0189)	(0.0279)	(0.0296)	(0.0332)	(0.0336)
Pension	0.375**	0.374**	0.691**	0.661**	1.166***	1.149***
coverage	(0.164)	(0.165)	(0.268)	(0.254)	(0.295)	(0.298)
Percent in	-0.0530	-0.0524	0.0492	0.0680	-0.0172	-0.000118
Large firms	(0.131)	(0.133)	(0.222)	(0.216)	(0.249)	(0.263)
Percent long	-0.0917	-0.0810	-1.355**	-1.263**	-1.421**	-1.124*
term workers	(0.350)	(0.380)	(0.659)	(0.579)	(0.630)	(0.646)
Union	0.00741	0.00577	-0.247	-0.240	-0.294	-0.340
coverage	(0.134)	(0.136)	(0.199)	(0.214)	(0.223)	(0.244)
Ln wage ratio		0.00907		0.379		0.252
55+ to 30-54		(0.0744)		(0.283)		(0.157)
Constant	0.0952	0.0922	0.732***	0.594***	0.778***	0.694***
	(0.104)	(0.110)	(0.146)	(0.189)	(0.164)	(0.170)
N	60	60	60	60	60	60
R^2	0.548	0.548	0.443	0.477	0.478	0.516

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Regression results: relationship between shares of older and younger workers

Dependent variable	Change in percentage of workers 16-29					
Time period	2001-07	2001-07	2007-19	2007-19	2001-19	2001-19
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
	Coefficient (S.E.) of percent 55 and above					
OLS simple regression	-0.196 (0.225)		-0.022 (0.114)		-0.172 (0.150)	
Multiple regression without wage variable	-0.492 (0.387)	-0.018 (0.475)	0.091 (0.140)	-0.091 (0.310)	-0.251 (0.152)	-0.368 (0.412)
Multiple regression with wage variable	-0.233 (0.380)	-0.364 (0.406)	-0.010 (0.026)	-0.103 (0.315)	-0.240 (0.147)	-0.475 (0.393)

All equations were estimated over the 60-industry sample. Instrumental variables for 2001-07 included percentage female, GDP growth and pension coverage. Instrumental variables for 2007-19 included percentage college graduates and percentage of employees with 20 or more years of tenure in 1980s.

Table 8. Regression results: impact of Chinese and other imports

Dependent variable	Change in percentage of workers 55 and above					
Sample	23 industry sample			60 industry sample		
Years	2001-07	2007-19	2001-19	2001-07	2007-19	2001-19
Ratio of Chinese import growth to initial output	0.052** (0.016)	0.004 (0.068)	-0.001 (0.067)	0.040* (0.019)	0.168 (0.140)	0.114 (0.069)
Ratio of other import growth to initial output	0.037 (0.024)	-0.103** (0.030)	-0.075 (0.083)	-0.015 (0.016)	0.004 (0.028)	-0.062 (0.048)

Independent variables in 23 industry sample include GDP growth, log capital-labor ratio, log high tech capital labor ratio, pension coverage and log wage ratio of older to younger workers. Independent variables in 60 industry sample are same as in Tables 4, 5 and 6.

Figure 1. Percentage of employees by age group, 2000 to 2019, American Community Survey

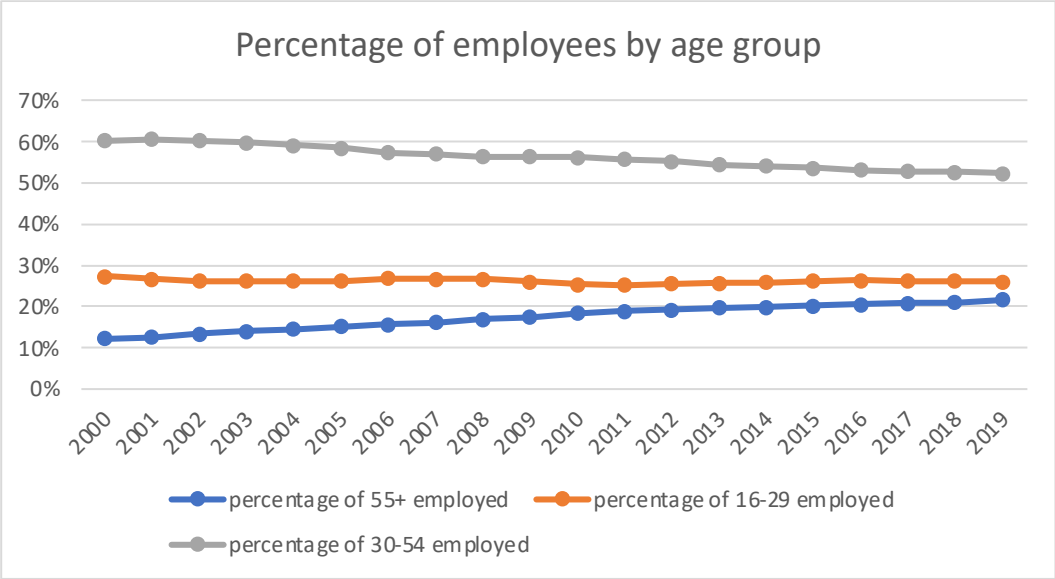
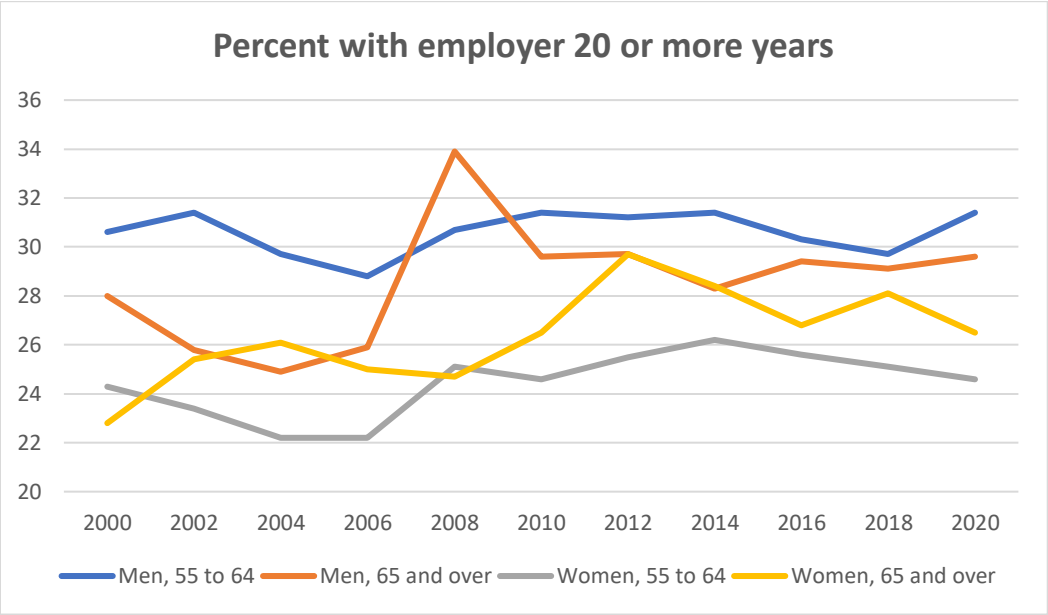
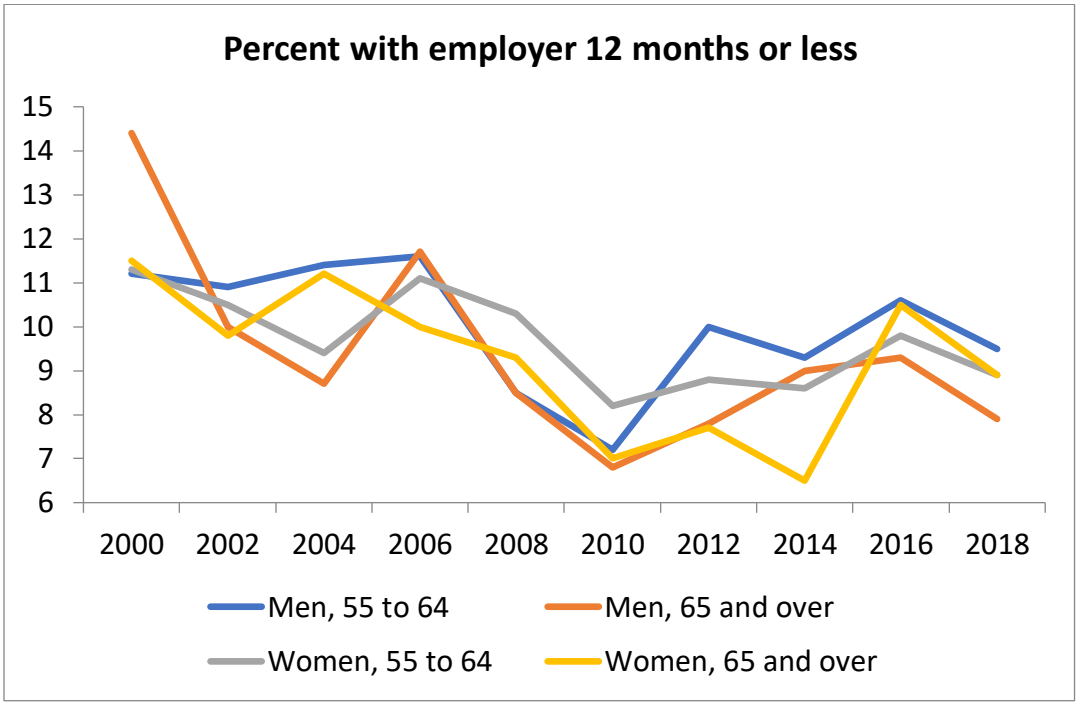


Figure 2. Percentage of workers with 20 or more years of service and percentage hired in last 12 months, by age group and sex, 2000-2020





Source: US Bureau of Labor Statistics, biannual news releases on employee tenure

Figure 3. Retention rate for older workers, 2000-01 to 2018-19, American Community Survey

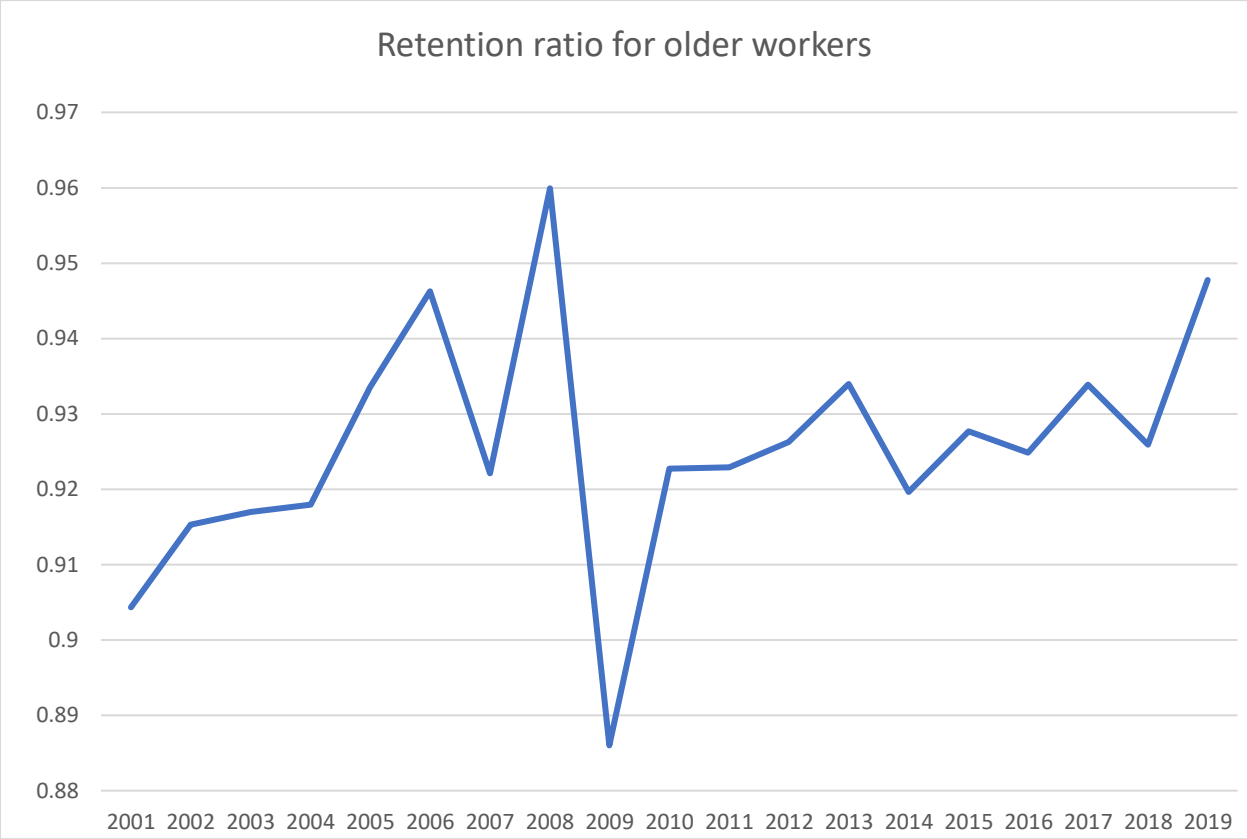


Figure 4. Percentage of older workers by industry, 2000-2001 to 2018-2019 American Community Survey

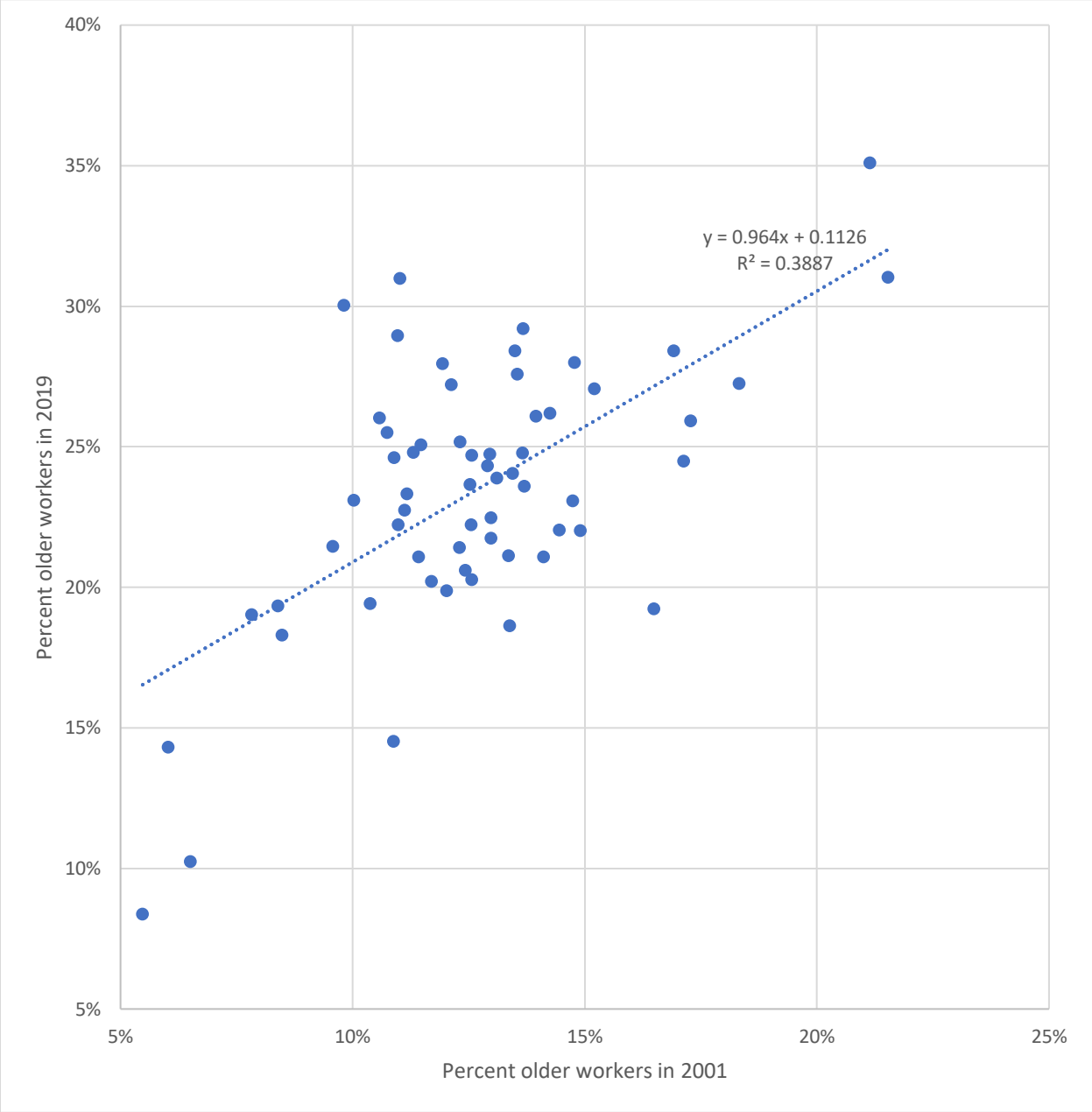


Figure 5a. Growth in percentage of older workers by industry plotted against change in percentage of younger workers, 2001-2019 American Community Survey

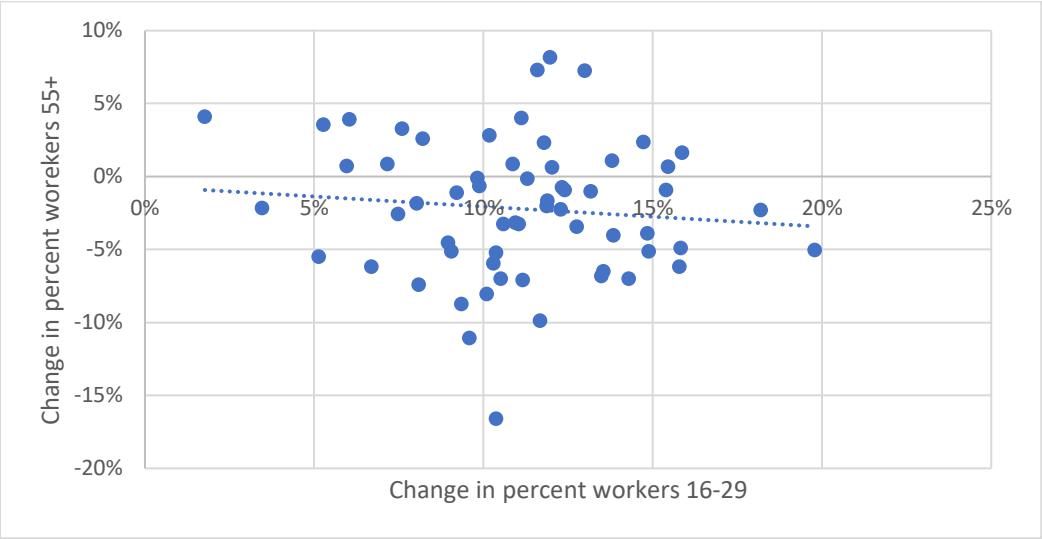


Figure 5b. Growth in percentage of older workers by industry plotted against change in percentage of middle-aged workers, 2001-2019 American Community Survey

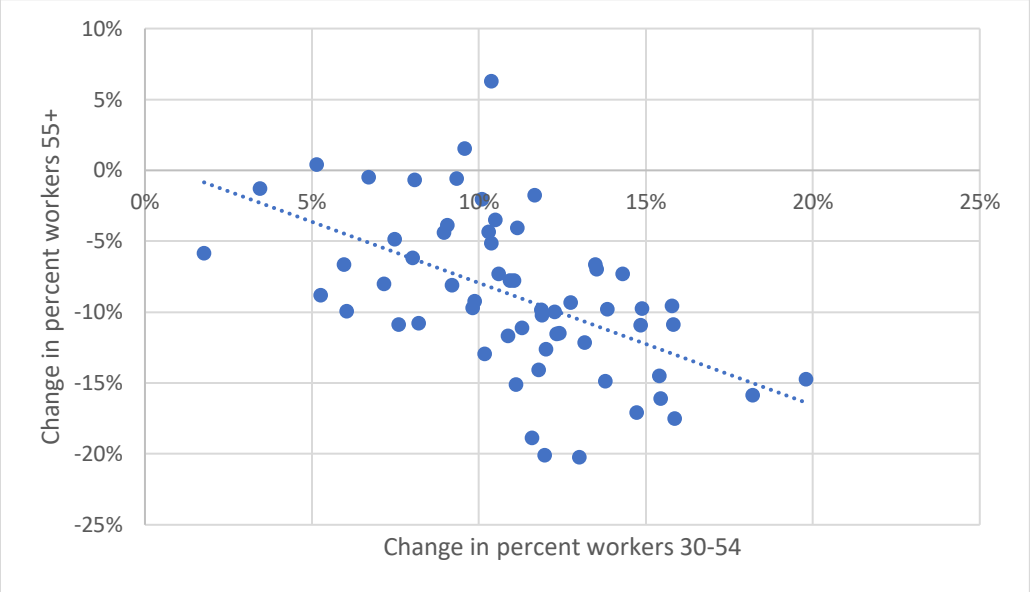


Figure 6. Change in percentage of workers in different age groups as related to log employment growth, 2001-2019 American Community Survey

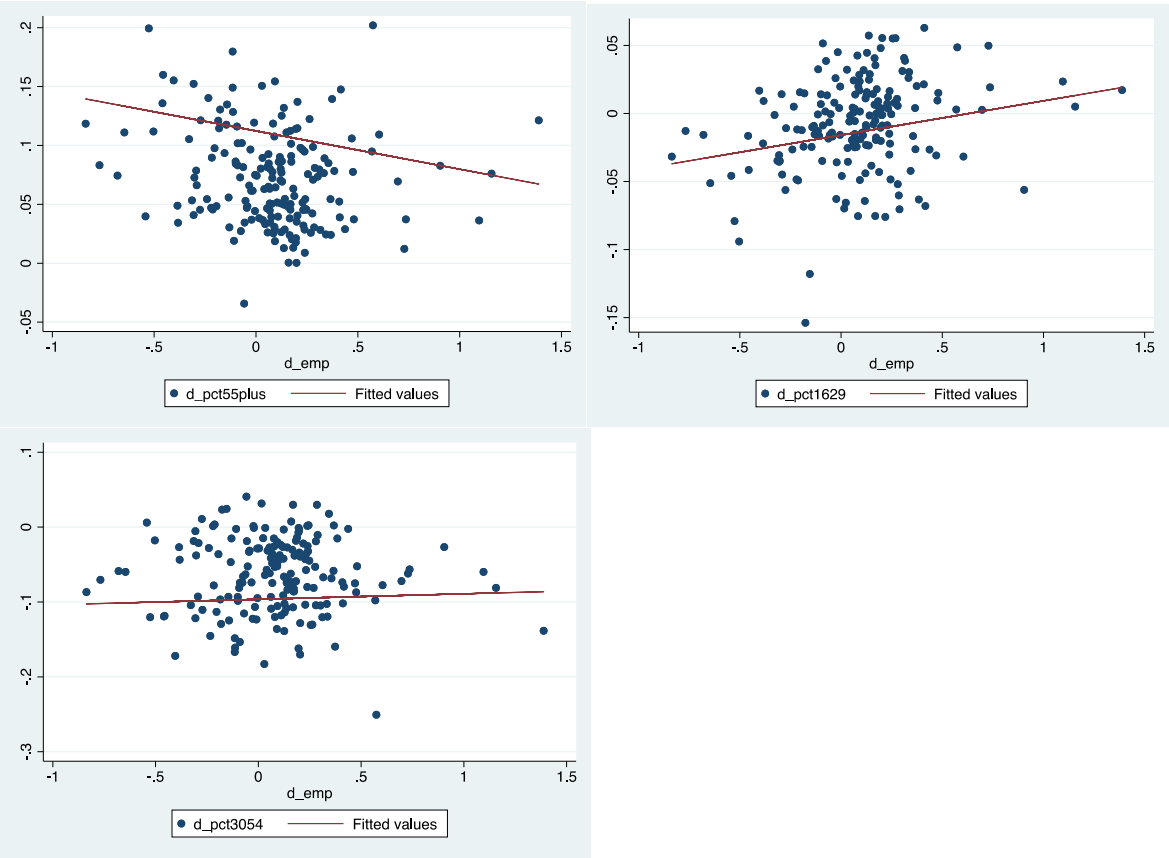


Table A1. Percentage of older workers by industry, by year

Industry	2001	2019	Change
Real estate	22%	31%	9%
Transit and ground passenger transportation	21%	35%	14%
Water transportation	18%	27%	9%
Other services, except government	17%	26%	9%
Educational Services	17%	24%	7%
Other transportation equipment	17%	28%	11%
Railroad transportation	16%	19%	3%
Textile products	15%	27%	12%
Farm	15%	22%	7%
Truck transportation	15%	28%	13%
Apparel and leather and allied products	15%	23%	8%
Petroleum and coal products	14%	22%	8%
Machinery	14%	26%	12%
Oil and gas extraction	14%	21%	7%
Primary metals	14%	26%	12%
Hospitals, Nursing and residential care facilities	14%	24%	10%
Paper products	14%	29%	16%
Publishing (including software)	14%	25%	11%
Electrical equipment, appliances, and components	14%	28%	14%
Fabricated metal products	14%	28%	15%
Social assistance	13%	24%	11%
Amusements, gambling, and recreation industries	13%	19%	5%
Performing arts, spectator sports, museums, and related activities	13%	21%	8%
Mining	13%	24%	11%
Ambulatory health care services	13%	22%	9%
Wholesale trade	13%	25%	12%
Other transportation and support activities	13%	24%	11%
Miscellaneous manufacturing	13%	25%	12%
Retail trade	13%	20%	8%
Motor vehicles, bodies and trailers, and parts	13%	22%	10%
Insurance carriers and related activities	13%	24%	11%
Information and data processing services	12%	21%	8%
Nonmetallic mineral products	12%	25%	13%
Accommodation	12%	21%	9%
Utilities	12%	27%	15%
Administrative and support services	12%	20%	8%
Computer and electronic products	12%	28%	16%
Miscellaneous professional, scientific, and technical services	12%	20%	9%
Furniture	11%	25%	14%
food products	11%	21%	10%

Plastics and rubber products	11%	25%	13%
Management of companies and enterprises	11%	23%	12%
Wood products	11%	23%	12%
Printing	11%	31%	20%
Forestry, Fishing, and Hunting	11%	22%	11%
Air transportation	11%	29%	18%
Chemical products	11%	25%	14%
Warehousing and storage	11%	15%	4%
Waste management and remediation services	11%	26%	15%
Legal services	11%	26%	15%
Banking and credit intermediations	10%	19%	9%
Rental and Leasing	10%	23%	13%
Pipeline transportation	10%	30%	20%
Securities, commodities, funds, trusts, and other financial investments	10%	21%	12%
Construction	8%	18%	10%
Support activities for mining	8%	19%	11%
Broadcasting and telecommunications	8%	19%	11%
Motion picture and sound recording	7%	10%	4%
Computer systems design and related services	6%	14%	8%
Food services and drinking places	5%	8%	3%

Table A2a. Hours-weighted regressions

Dependent variable	Change in percentage of workers 55 and above		
Years	2001-2007	2007-2019	2001-2019
Percent college	0.0250	-0.131***	-0.111***
graduates	(0.0180)	(0.0420)	(0.0371)
Percent female	0.0177	-0.0313	-0.00888
	(0.0118)	(0.0229)	(0.0278)
Percent	-0.0734	-0.0681	-0.145
professional	(0.0513)	(0.105)	(0.116)
GDP growth	-0.0224*	-0.0144**	-0.00977
	(0.0112)	(0.00625)	(0.0243)
GDP	0.0815	0.0133	-0.132
variance	(0.145)	(0.117)	(0.282)
Ln(K/L)	-0.00162	-0.00614	-0.00651
	(0.00205)	(0.00443)	(0.00490)
Ln(HiTecK/L)	0.00436*	0.0120***	0.0119*
	(0.00229)	(0.00429)	(0.00598)
Pension	0.0440**	0.120***	0.182***
coverage	(0.0180)	(0.0424)	(0.0517)
Percent in	-0.00982	-0.00169	-0.0196
Large firms	(0.0152)	(0.0383)	(0.0436)
Percent long	0.00191	-0.259***	-0.232**
term workers	(0.0450)	(0.0961)	(0.104)
Union	0.00949	-0.0300	-0.0350
coverage	(0.0185)	(0.0361)	(0.0437)
Ln wage ratio	-0.0153	0.0311	0.0142
55+ to 16-29	(0.0118)	(0.0490)	(0.0324)
Constant	0.0251*	0.0834***	0.102***
	(0.0130)	(0.0286)	(0.0317)
N	60	60	60
R^2	0.531	0.448	0.415

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2b. Employment weighted regressions

Dependent variable	Change in percentage of workers 55 and above		
Years	2001-2007	2007-2019	2001-2019
Percent college	0.0133	-0.103**	-0.106**
graduates	(0.0158)	(0.0378)	(0.0375)
Percent female	0.0189	-0.0397	-0.00978
	(0.0114)	(0.0218)	(0.0280)
Percent	-0.0637	-0.0517	-0.129
professional	(0.0541)	(0.0953)	(0.119)
GDP growth	-0.0168	-0.0154*	-0.0133
	(0.00846)	(0.00657)	(0.0231)
GDP	0.140	0.0471	0.0123
variance	(0.103)	(0.0977)	(0.329)
Ln(K/L)	0.000229	-0.00456	-0.00477
	(0.00180)	(0.00461)	(0.00487)
Ln(HiTecK/L)	0.00313	0.0110**	0.0117*
	(0.00188)	(0.00397)	(0.00560)
Pension	0.0665***	0.128**	0.203***
coverage	(0.0150)	(0.0394)	(0.0508)
Percent in	-0.0147	-0.0219	-0.0366
Large firms	(0.0121)	(0.0346)	(0.0419)
Percent long	-0.0241	-0.234*	-0.250*
term workers	(0.0371)	(0.0960)	(0.0960)
Union	0.00766	-0.0317	-0.0327
coverage	(0.0149)	(0.0317)	(0.0390)
Ln wage ratio	-0.0251**	0.00621	-0.00737
55+ to 16-29	(0.00859)	(0.0367)	(0.0302)
Constant	0.0148	0.0852**	0.0967**
	(0.0112)	(0.0270)	(0.0284)
N	60	60	60
R^2	0.651	0.457	0.438

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3. Coefficients and standard errors of pension variables.

Dependent variable	Change in percentage of workers 55 and above					
Years	2001-2007	2001-2007	2007-2019	2007-2019	2001-2019	2001-2019
Pension	0.0591***		0.125***		0.199***	
coverage	(0.0171)		(0.0412)		(0.0505)	
DB plan		0.0580		0.181		0.289**
coverage		(0.0615)		(0.114)		(0.138)
DC plan		0.0608***		0.116**		0.191***
coverage		(0.0180)		(0.0431)		(0.0529)
F-test DB=DC		0.00		0.029		0.050
Prob>F		0.966		0.592		0.483
N	60	60	60	60	60	60
R^2	0.583	0.587	0.443	0.451	0.441	0.452

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The models contain the same control variables that appear in Table 4.

Table A4. Coefficients and standard errors of selected measures of high-tech capital

Dependent variable	Change in percentage of workers 55 and above		
Years	2001-07	2007-2019	2001-2019
Measure			
1) High tech equipment	0.0026	0.0117**	0.0104+
	(0.0021)	(0.0043)	(0.0061)
2) Add software to 1	0.0035	0.0113*	0.0107+
	(0.0022)	(0.0047)	(0.0062)
3) Add systems design	0.0034	0.0117*	0.0110+
& publishers to 2	(0.0022)	(0.0450)	(0.0060)
4) Include all IPP	-0.0003	0.0015	-0.0024
	(0.0019)	(0.0048)	(0.0051)

$^{+}\ p < 0.10,\ ^{*}\ p < 0.05,\ ^{**}\ p < 0.01$

Row 1: High tech equipment consists of mainframes, PCs. DASDs, printers, terminals, tape drives, storage devices. System integrators, communications, nonelectrical medical instruments, electrical medical instruments, nonmedical instruments, photocopy and related equipment, and office and accounting equipment (codes EP1A through EP12 in BEA measures of current-cost net capital stock).

Row 2: Software consists of prepackaged software, custom software, and own account software (codes ENS1 through ENS3 in BEA measures of current-cost net capital stock)

Row 3: Software publishers (RD40) and computer systems design and related services (RD60) are added to row 2.

Row 4: Includes all high tech equipment from row 1 and all 25 categories of intellectual property products tracked by BEA.