# Aging, Technology Adoption, and Growth [*PRELIMINARY*]

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**Abstract**

This paper explores whether workforce aging in the US has contributed to the recent slowdown in productivity growth and investment through its impact on technology adoption. I document that older workers were slow to adopt computers during the peak adoption period from 1989 to 2003. Motivated by this evidence I build an endogenous growth, overlapping generation model with costly learning that replicates the observed cohort effects. The model predicts a slowdown in investment in new equipment and R&D in response to an aging workforce as well as lower productivity growth in the long run. I confirm the first two predictions using a local labor markets approach by showing that firms in commuting zones with an aging workforce invested less in computers and have lower R&D expenditures.

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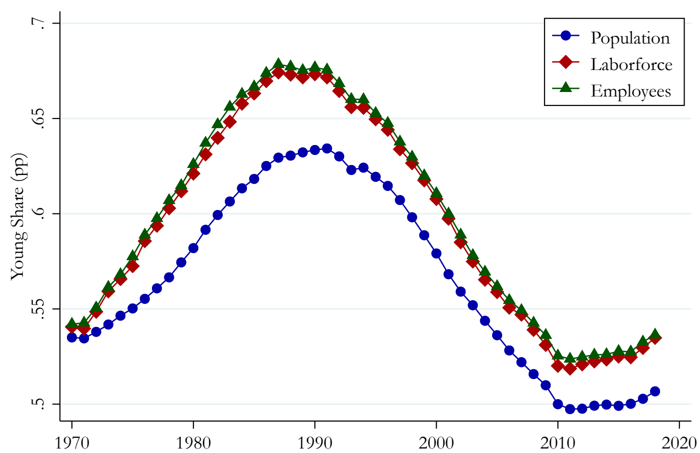
# 1 Introduction

The US workforce has been aging rapidly since 1990. Figure 1.1 plots the working young share (WYS) defined as the share of age 25-44 subjects among those aged 25-64 for the US population, labor force, and employees. The WYS peaks around 1990 followed by a rapid decline until 2010. The difference from peak to through constitutes more than 10 percentage points for all three measures highlighting the scale of demographic change.[1] OECD projections predict this change to persist with a long-run WYS around 52.5%.

Figure 1.1: Historical and Projected Shares of Young Among Working Age Population




Note: Author's calculations based on IPUMS CPS ASEC samples. Young share is defined as the share of age 25 to 44 among the population aged 25 to 64 years.

Workforce aging and the associated population aging has received some attention due to its potential implications on public finances, aggregate savings, and labor force participation.[2] Figure 1.2 highlights that an additional channel might be important: Technology adoption. Panel (a) plots the share of employees working with a computer as well as the average number of tasks performed by users by age in 1989. There is a clear downwards slope past age 40 in both measures highlighting that older workers were both less likely to use a computer and less proficient when using it.

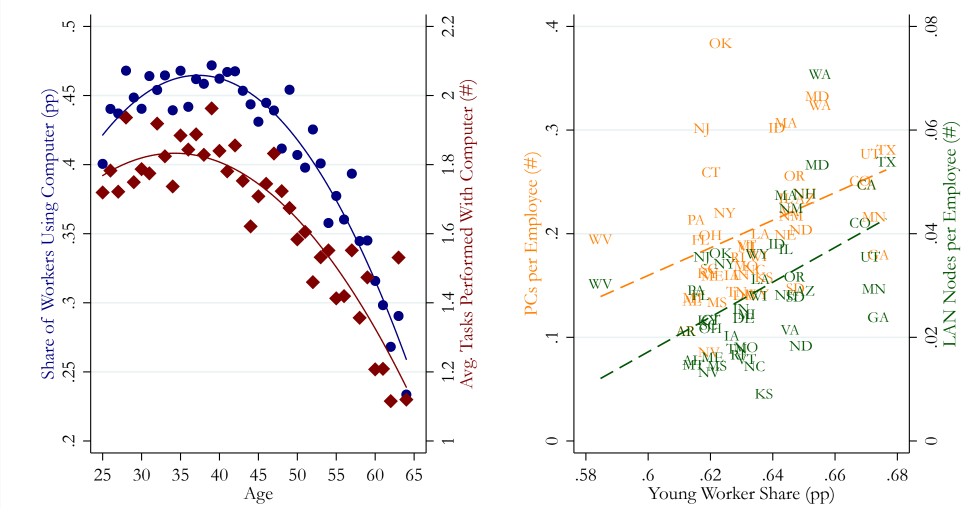
This has potential aggregate implications as highlighted in Panel (b). A simple scatter of the WYS against the overage number of computers or LAN nodes per employee across US states for the 1991 to 1993 period reveals a strong positive correlation. In other words, states with a younger workforce invested more in computer and associated equipment per employee likely boosting their productivity.[3]

[1]Note that the curves for labor force and employment are higher in general due to higher labor force attachment of the young.

[2]For example, Robert Gordon's article in Teulings and Baldwin (2014) identifies population aging as a key factor contributing to low growth after the Great Recession due to retirement and labor force participation. Similarly, Paul Krugman (in the same publication) identifies a slowdown in the workforce growth as a potential contributing factor to the low interest environment that is associated with "secular stagnation".

[3]Brynjolfsson et al. (2002) document that the adoption of computers and IT in general was associated with significant productivity gains during the 90s and early 2000s.

Figure 1.2: Computer Adoption by Age and Age Composition Early Sample




(a) Workers in 1989 (b) Establishments in 1991-93

Note: Figure displays adoption of the computer by workers and establishments in the early sample. Adoption by workers by age is measured from the CPS October supplement using the share of workers directly using PCs at work and the average tasks performed with a computer when used. The plotted line show the quatratic fit. Computer adoption by establishments by state is measured from the Harte-Hanks dataset using the number of computers or LAN nodes per worker. The young worker share is defined as the share of age 25-44 residents among age 25-64 residents measured from the NBER SEER files. Lines plot linear fit.

This naturally raises the question of whether workforce aging has contributed to the recent slowdown in productivity growth and investment through its impact on technology adoption. I bolster this claim by carefully documenting cohort effects in technology adoption by workers. Using the computer as a case study, I find strong cohort effects during the peak adoption period from 1989 to 2003, which are not driven by selection in to industries or occupations nor by educational attainment differences across cohorts.

Motivated by this evidence I build an endogeneous growth model with overlapping generation and costly technology adoption for workers. The latter naturally gives rise to age effects in technology adoption due to differences in the remaining time in the labor market. In the model, an aging population results in a lower average adoption rate of new technologies due to pure compositional effects. Resulting, the economy invests less in the capital associated with new technologies, dampening investment overall and reducing the associated profits for new equipment producers. This in turn dampens the incentive to develop new varieties in the first place and thus reduces aggregate investment in R&D and productivity growth.

I test the model's predictions following a local labor market approach focusing on investment in computers and R&D across US commuting zones (CZs). Using an instrumental variable strategy and detailed establishment level data on IT purchases, I show that a declining WYS leads to lower investment in computers per employee. Furthermore, I show that a lower WYS leads to lower R&D expenditures at the CZ level as measured by the share of employment in R&D occupations and the associated wage bill. Both findings are in line with the model's predictions and suggest that the overall decline in the WYS might have contributed to the observed slowdown in US productivity growth and investment.

This paper contributes to three lines of research areas. Firstly, I contribute to the growing literature on the recent slowdown in US productivity growth. Gordon (2016) and Syverson (2017) document a significant slowdown in productivity growth since at least 2005 and Philippon and Gutiérrez (2017) have argued that investment has been low since around 2000. A growing literature on this has explored various channels including declining competition induced by the IT revolution (Aghion et al., 2019) or low interest rates (Liu et al., 2019), declining diffusion of innovations across the economy (Akcigit and Ates, 2019), declining innovation productivity (Gordon, 2016; Bloom et al., 2019) and adoption lags (Brynjolfsson et al., 2019).I add to this literature by highlighting the impact of labor force aging through technology adoption as a factor and thereby giving a natural explanation for potential adoption lags discussed in Brynjolfsson et al. (2019).

Secondly, the paper is closely related to the larger literature on the macroeconomic impact of (labor force) aging, which has primarily focused on public finances and aggregate savings (Teulings and Baldwin, 2014; Aksoy et al., 2019). I add to this by focusing on the production side implications and adding technology adoption as a key factor instead of e.g. labor force participation rates. This is similar to Acemoglu and Restrepo (2018) who highlight workforce aging as a key contributor to the current wave of automation. Their model links automation to demographics as machines substitute for middle-aged workers that become increasingly scarce due to workforce aging. In contrast, I focus on worker augmenting technologies and the associated life-cycle pattern of human capital investments.

Note that the workforce aging in the US is at least partly linked to a slowdown in the labor force growth rates, which has been the focus of Karahan et al. (2019) and Hopenhayn et al. (2018). Both papers explore the impact of a slow down in the labor force growth rate on firm dynamics in a heterogeneous firm framework and conclude that the declining labor force growth rate has been a significant driver of the slowdown in the firm entry rate and average firm size, while being unrelated to the productivity slowdown. While my framework also predicts a slow down in the creation of new firms, this is directly linked to overall productivity growth. Furthermore, my framework highlights labor force composition instead of pure labor force size as a key channel. I confirm this empirically by highlighting that changes in the workforce composition change the share of employees engaged in R&D activities, both of which are independent of workforce size.

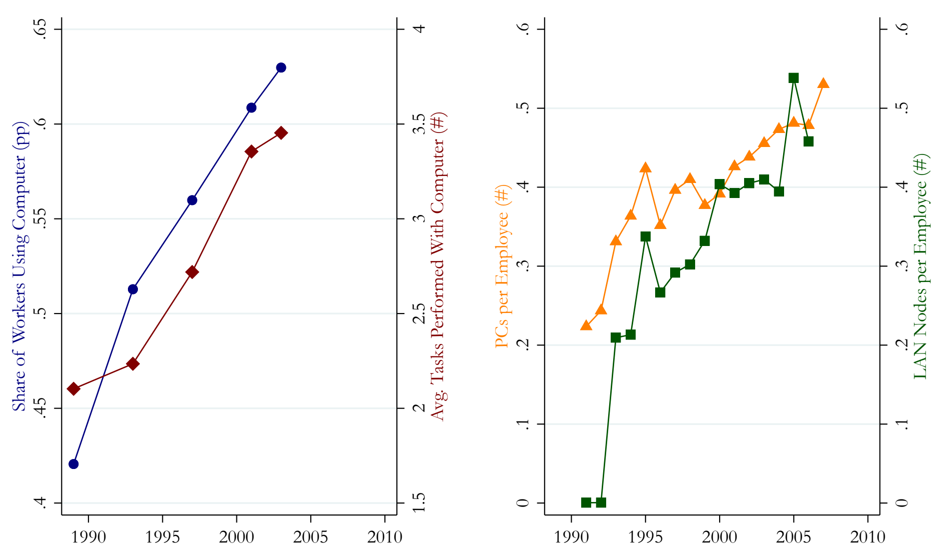
Closely related to this is Engbom (2019), who attributes declining job transition rates, unemployment rates, and entrepreneurship to population aging. In his model, older workers are less likely to switch jobs or engage in entrepreneurship as they are more productivity in their current jobs and thus face higher opportunity costs. A shift toward an older population thus leads to static gains via better matches on averages and dynamic losses via lower entrepreneurship. In contrast, I highlight explicit technology adoption choices by workers and associated investments in new technologies by firms that are absent in his framework, but appear empirically important. Furthermore, his framework does not have a role for R&D other than entrepreneurship and thus cannot account for the empirical evidence presented in this paper.

Finally, I contribute to the literature on aging, innovation and entrepreneurship. Akcigit et al. (2017), Jones (2010), and Jones and Weinberg (2011) find that innovation productivity appears to be peaking post age 45. Similarly, Azoulay et al. (2020) find that entrepreneurship and entrepreneurial success appear to peak around age 40-50. In contrast, Derrien et al. (2018) find that local labor markets with a higher share of young workers record higher patenting rates. My paper contributes to this discussion by highlighting labor force composition as a driver of new technology demand instead of focusing supply via the inventor or entrepreneur herself. Note that this insight is principally orthogonal to the observation that inventor and entrepreneurial success peaks during later ages, however, it also implies that aging effects on innovation are more complicated than pure composition effects based on inventor or entrepreneurial productivity.

## 2 Evidence on the Adoption of Computers

To motivate the focus on technology adoption as a key channel through which demographic change impacts aggregate productivity, I investigate the adoption of computers in the workplace during the 1990s. I investigate adoption at the worker level using the CPS. Arguably, the personal computer was the most important recent innovation in this period impacting firm productivity and labor market demand for skills across a wide range of industries (See e.g. Brynjolfsson et al. (2002); Bresnahan et al. (2002)).

Figure 2.1: Computers Were Rapidly Adopted During The 1990s




(a) Workers (b) Establishments

Note: Figure displays adoption of the computer by workers and establishments during the 1990s and early 2000s. Adoption by workers is measured from the CPS October supplement using the share of workers directly using PCs at work and the average tasks performed with a computer when used. Computer adoption by establishments is measured from the Harte-Hanks dataset using the number of computers or LAN nodes per worker.

Panel (a) of Figure 2.1 shows that share of workers directly using a computer increased by about 20 percentage points during the sample period going from c. 43.3% to 63.8% highlighting the pervasiveness of the technology as well as its fast paced adoption during the 90s. In addition to pure extensive margin adoption, workers also performed an increasing number of tasks with the computer such as emails, spreadsheet analysis or graphic design.

Adoption by workers went hand-in-hand with adoption by establishments. As shown in Panel (b), computers per employee rose from c. 0.21 to 0.52 from 1991 to 2007 with wide adoption across industries and labor markets. Similarly, electronic communication and data sharing became essential to modern corporate culture as indicated by the sharp rise in LAN nodes per employee.

While adoption was wide spread, it was not necessarily uniform as discussed in the introduction. In the following I carefully document that older cohorts had lower adoption rates of the computer, which will motivate the model developed in the subsequent section.

Note that throughout this section I make the implicit assumption that it is valuable to know about the computer. I confirm that hold true for my sample in Appendix C.1.3 by showing that workers using computers earn higher hourly wages. More broadly, Brynjolfsson et al. (2002) and Bresnahan et al. (2002) show that the computer adoption boosted firm productivity during this period.

## 2.1 Approach

I substantiate the findings in Panel(a) of Figure 1.2 by exploring two regression specifications. The first is a linear probability model of whether the respondent directly uses a computer at work. In the second specification I use the number of tasks performed with a computer as the outcome variable and restrict the sample to respondents performing at least one task with a computer at work. This yields measure of intensity of use ranging from 1 to 6. The regression equation takes the form

$$Y_{it} = \sum_{a \in A} \gamma_a + \delta X_{it} + \varepsilon_{it}, \tag{2.1}$$

where $\gamma_a$ are cohort dummies. I convert year of birth cohorts into age in 1989 cohorts grouped into 5-year bins starting at age 10-14 and going up to age 60-64. Note that the former age group is 24 - 28 by 2003 and thus enters the labor market in later samples.

All specification include dummies for female, bachelor degree, graduate degree as well as full state, occupation, and industry fixed effects, each of which is interacted with the survey year. I am thus focusing entirely on the cross-sectional variation across cohorts and allow all other potential determinants to adjust year by year. Adding educational dummies is important as age groups differ in educational attainment, which could be a separate channel affecting technology take-up that is not at the core of this paper. Industry and occupational dummies ensure that the regressions do not capture pure sorting.[4]

[4] As shown in the regression tables in the appendix, sorting appears to be working against the cohort effects. In other words, older

Note that the focus here is on cohort and not age effects. While both coincide in cross-section, they differ in a panel structure. The idea behind focusing on cohort effects is to keep the set of individuals represented by the estimated coefficients constant. In other words, this asks "Does it matter how old a subject was when the computer was introduced?" as opposed to "Does the age of a worker matter for current use of a computer?". While the former is focused on the adoption decision, the latter potentially confounds it with life-cycle pattern in the use of technology and might be highly dependent on the age of the technology.

### 2.2 Data

The October supplement to the CPS for 1989, 1993, 1997, 2001 and 2003 asked respondents about their use of computers and internet at work and home. I limit my analysis to responses linked to use at work to capture differences in the adoption of productive technologies. I restrict the sample to employees between the age of 25 and 64 with at least a high school degree. The latter is meant to ensure that the computer was a relevant technology for the worker.

The survey asks whether the respondent directly used a computer at work as well as which tasks they performed with a computer. I use the former for the linear probability model and the latter for task index model. The list of tasks performed with the computer that are consistently available throughout the survey years include calendar/scheduling, databases or spreadsheets, desktop publishing or word processing, electronic mail and programming.[5] I do not consider tasks that were not consistently asked throughout the survey waves to ensure that the estimation is not capturing changes in the survey structure.

Besides the CIU specific variables, I use the age and gender of the respondent, state of residency, educational attainment (bachelor or graduate degree), occupation, and industry. [6] Throughout I use 5-year year-of-birth cohorts starting from 1924-28. [7] I will report the results throughout by transforming the cohort measure into age group in 1989 to aid interpretation.

### 2.3 Results

I present the main regression results graphically in this section and defer regression tables and additional robustness checks to Appendix C.

Panel (a) of Figure 2.2 plots the coefficients for specification (2.1). There is a clear monotone decrease in the age of the cohort in 1990, especially after the cohort aged 40-44 in 1989. Respondent aged 40-44 in 1989 had

workers tend to work in occupations that use the computer more intensively, flattening the overall cohort profile.

[5]"databases or spreadsheet" and "desktop publishing or word processing" are split into the individual items during the first three survey waves, but combined during the latter two. I aggregate both to have a consistent measure throughout.

[6]I use occupational codes that are standardized using the 1990 definitions as provided by IPUMS. For industry classifications, I use the code provided on David Dorn's data page to ensure consistent definitions.

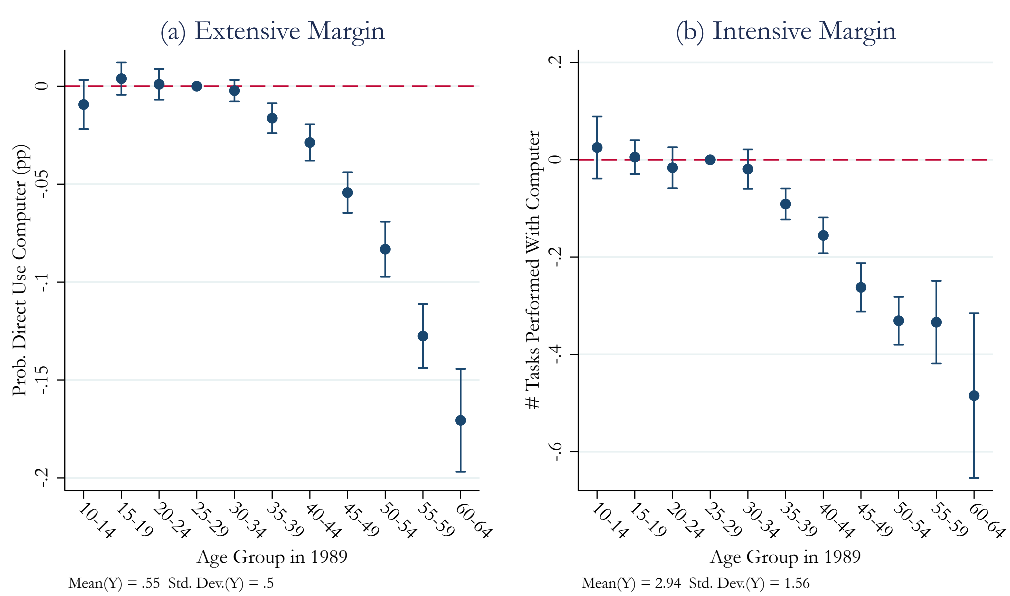
[7]Given my limited sample length, I have little power to distinguish between age and cohort effects. I show that cohort effects are the main driver of technology adoption as opposed to age effects in C. Note, also, that the non-parametric approach chosen is not subject to the Age-Cohort-Period identification challenge encountered when using linear effects.

Table 2.1: Summary Statistics for CPS CIU Sample

| | Obs. | Mean | Std. Dev. | Median | IQR | Q1 | Q3 |
|---|---|---|---|---|---|---|---|
| Computer Use | 238,150 | 0.609 | 0.488 | 1 | 1 | 0 | 1 |
| Tasks Performed With Computer | 106,443 | 3.219 | 1.521 | 3 | 2 | 2 | 4 |
| Female | 240,506 | 0.473 | 0.499 | 0 | 1 | 0 | 1 |
| College Degree | 240,506 | 0.349 | 0.477 | 0 | 1 | 0 | 1 |
| Graduate Degree | 240,506 | 0.120 | 0.325 | 0 | 0 | 0 | 0 |
| Age | 240,506 | 41.914 | 10.082 | 41 | 16 | 34 | 50 |

a 7.5% higher likelihood of working with a computer relative to the cohort age 55-59 in 1989. This effect size constitutes 15% of the sample mean and 14% of the sample mean. Aggregating the results up, the coefficients predict that average computer adoption would have been 1.5 percentage points lower in 1989 if the population age composition had resembled 2010 instead of 1989.

Figure 2.2: Regression Coefficients and Confidence Intervals for Main Specification




Note: Regressions control for sex, education, industry, occupation, and state, each interacted with survey year.
Extensive margin results estimated in linear probility model. Intesive margin results from linear regression on set of tasks performed conditional on performing at least one task. Regression apply CPS Computer and Internet Use Supplement sampli weights adjusted to weight survey years equally. Note that only age groups 25 to 50 are active in all years.
Standard errors clustered at industry level.

Panel (b) presents the results for the intensity of use conditional on using a computer. The pattern of coefficient is very similar to the overall use, highlighting that extensive and intensive margin are important. The gap between those aged 40-44 in 1990 and those 15 years older is around 0.2 tasks, which is a little less than 7% of the sample mean and 13% of the sample standard deviation respectively. Repeating the aggregation result from above predicts that employees would have had performed 0.045 tasks in 1989 if the population composition had resembled 2010, which would have implied a reduction of about 2%.

Overall, this evidence suggests significant cohort effects in usage and intensity of use. Interestingly, both measures suggest a relatively flat profile for cohorts aged 39 and younger in 1989. In Appendix C I report additional robustness checks adding 5-year age groups starting at 25-29 and up to 60-64 in my regressions. The results confirm the importance of cohort effects independent of life-cycle patterns. Breaking down the effects by education group and gender does not reveal any strong differences. There does not appear to be any catch-up of older cohorts across survey years, i.e. adoption progresses relatively uniformly across worker cohorts that remain in the labor market.

# 3 A Model of Demographic Change and Technology Adoption

Motivated by the evidence in the previous section, I develop a simple endogenous growth model featuring cohort effects and discuss the impact of demographic change on innovation and investment. The model builds on the standard expanding varieties growth model as in Romer (1990) and extends it in two directions. Firstly, I introduce demographics using a standard overlapping generations structure, and, secondly, technology adoption is made an explicit choice on part of workers.[8] The resulting model delivers strong predictions on the impact of population aging on output, investment, and R&D efforts, which I test the the subsequent section.

## 3.1 Environment

Time is discrete and indexed by $t$. For exposition purposes I will abstract from the consumption choice in the following and only focus on the labor market. I discuss in Appendix A.2 how the model can be closed, but this is not at the core of this paper. The primary effect of adding consumption and savings is to endogenize the interest rate $R_t$, which I will fix in the following to $R$. Equivalently, one can think of this economy as a being a small open economy, which can borrow or lend in international financial markets at gross interest rate $R$.

In each period two generations of workers are active in the labor market, juniors and seniors, with mass $L_{jt}$ and $L_{st}$ respectively. Workers adopt technology and supply labor inelastically in their chosen technologies. Technologies are equivalent to varieties in a standard Romer (1990) framework and I will use the terms interchangingly.

The final goods producer uses technology specific labor and equipment as inputs and acts as a price taker in output and input markets. The price of the final good is chosen as the numeraire. Equipment is supplied by specialized manufacturers. Manufacturers either acts as monopolists for their variety and produce using final good as sole input. Demand for equipment depends on workers' technology adoption choices.

[8] Technically, the model also features potential population growth as in Jones (1995). This affects the choice of innovation production function, which must ensure a Balanced Growth Path in the long run.

Finally, new technologies are produced by the innovation sector, which borrows at interest rate $R$ to finance it's expenditure on innovation and repays the debt using the generated monopoly rents.

### 3.1.1 Demographics

Workers enter the labor market as juniors and live for up to two periods. The mass of junior workers grows at constant rate $n$:

$$L_{jt+1} = (1+n)L_{jt}. \tag{3.1}$$

Between periods, juniors transition to senior status with probability $(1-p)$ and exit the economy otherwise. This captures life cycle dynamics in labor force participation as well as premature death. Seniors exit the labor market at the end of the period. Resulting, the mass of senior workers evolves according to

$$L_{st+1} = (1-p)L_{jt}. \tag{3.2}$$

The overall labor force is $L_t = L_{jt} + L_{st}$ and the share of young workers $s_t \equiv L_{jt}/L_t$ evolve according to

$$L_{t+1} = (1+n)L_t \qquad \text{and} \qquad s_t = s = \frac{1+n}{2+n-p}. \tag{3.3}$$

Note that the introduction of the death rate $p$ allows me to flexibly target a working young share while holding the population growth rate constant. In the following I will denote generations by $g \in \{j(unior), s(enior)\}$.

### 3.1.2 Technology Adoption and Labor Income

Technology adoption is a costly investment of time by the workers. Each period, households decide which technologies to adopt to form their skill set $A_{gt}$. Technologies adopted within the period are denoted by lower case $a_{gt}$. To save on notation I will not explicitly differentiate between the size of a set and the set itself. The skill set of a household evolves according to

$$A_{jt} = a_{jt} \qquad \text{and} \qquad A_{st} = A_{jt-1} \cup a_{st} \tag{3.4}$$

Technologies are adopted from the set of available technology, $A_t$, which in turn is composed of technologies from the previous period $A_{t-1}$ and newly available inventions $a_t$:

$$A_t = A_{t-1} \cup a_t. \tag{3.5}$$

Technology adoption costs differ across workers and technologies such as that each worker is subject to independent draws of learning costs across technologies. In particular, each technology has a type $n \in [0,1]$ indexing its adoption cost. The time-invariant distribution of (new and old) technology types is denoted by $F(n)$.[9]

[9] In practice, I will assume

$$F(n) = n^{\eta} \qquad \text{with} \qquad \eta > 0.$$

This yields tractable results derived below.

Adoption costs are additive such that worker $i$'s learning cost for newly adopted technologies, $h_{it}$, are given by

$$h_{it} = \varphi \int_{a_{it}} n_i(a) da, \tag{3.6}$$

where $n_i(a)$ is the type associated with technology $a$ for the particular worker. Note that $\varphi$ is simply a scaling parameter. The cost of learning is a function of the fraction of technologies learned and the underlying mass of technologies.

Worker supply one unit of labor inelastically for technologies in their skill set, such that worker $i$'s effective labor supply for technology $a$, $\ell_{it}(a)$ is given by

$$\ell_{it}(a) = \begin{cases} 1 & \text{if } a \in A_{it} \\ 0 & \text{otherwise.} \end{cases} \tag{3.7}$$

The discounted net labor income of a young worker at time $t$ (conditional on survival) is given by

$$\mathcal{W}_{it} = \int_{A_{it}} W_t(a) da - h_{it}(A_{it}) + \frac{1}{R_{t+1}} \left( \int_{A_{it+1}} W_{t+1}(a) da - h_{it+1}(a_{it+1}) \right). \tag{3.8}$$

I will assume perfect foresight throughout and, thus, focus on the problem of the young worker only as old workers will not want to adjust prior plans.

### 3.1.3 Final Good Producer

The final good $Y_t$ is produced by a perfectly competitive representative firm using labor $\ell_t(a)$ in conjunction with equipment, $k_t(a)$, for $a \in A_t$. Each technology is associated with a unique type of equipment.[10]

$$Y_t = \int_{A_t} \ell_t(a)^{1-\alpha} k_t(a)^{\alpha} da. \tag{3.9}$$

The price of the final good is normalized to 1. Equipment depreciates at rate $\delta$ and is immediately available in the purchase period such that

$$k_t(a) = i_t(a) + (1-\delta) k_{t-1}(a), \tag{3.10}$$

where $i_t(a)$ denoted the purchase of new equipment. Input prices labor, $W_t(a)$, and new equipment, $P_t(a)$, are

[10]Note that the standard expanding variety model is a special case of this production function, where all workers know about all technologies. In that case $\ell_t(a) = L_t$ and thus the production function is simplifies to

$$Y_t = L_t^{1-\alpha} \int_{A_t} k_t(a)^{\alpha} da,$$

which is the standard form as in Gancia and Zilibotti (2005).

taken as given by the final good producer. Its profits are given by

$$\begin{aligned} Y_t - \int_{A_t} \ell_t(a) W_t(a) da - \int_{A_t} i_t(a) P_t(a) da \\ \text{s.t.} \qquad k_t(a) = i_t(a) + (1-\delta) k_{t-1}(a). \end{aligned} \tag{3.11}$$

Note that the price of capital will always be determined by the price of new equipment in this environment due to population growth and depreciation. Adding depreciation affects the level and composition of investment, especially in terms of new versus old equipment, and thus has important implications for the interpretation of investment growth.[11]

### 3.1.4 Equipment Manufacturers

Each equipment type is produced by a monopolist producing with constant marginal costs $\psi$ in terms of the final good. I will embed market clearing for equipment directly and only refer to $i_t(a)$ throughout instead of differentiating between quantity produced and supplied. The manufacturer's profits are given by

$$\pi_t(a) = P_t(i_t(a)) i_t(a) - \psi i_t(a), \tag{3.12}$$

where $P_t(i_t(a))$ takes into account the demand by the final goods producer. I do not allow monopolists to take into account their impact on technology adoption in order to keep the framework tractable. As discussed in Appendix A, this does not affect the qualitative predictions of the model.

### 3.1.5 Innovation Sector

There is large set $I$ of perfectly competitive investments firms that invest in innovation to become a (temporary) monopolist for a new equipment variety. Firms invests $x_{it}$ per capita into innovation to create new set of blueprints $a_{it+1}$ according to the production function

$$a_{it+1} = \varphi_0 \left( \frac{X_t}{A_t} \right)^{\varphi_1 - 1} x_{it}, \tag{3.13}$$

where $X_t = \int_I x_{it} di$ is the aggregate investment in innovation per capita. Investment firms do not take into account their impact on $X_t$. The functional form is chosen to generate a robust balanced growth path in this economy and to avoid scale effects (Jones, 1995).[12] Intuitively, this states that the crowding out effect of investment in innovation does not depend on the level of investment per se, but on the level of investment relative to the stock of knowledge. In other words, for a given level of investment, there are less negative spillovers in a highly developed economy than in a less developed one.

[11] To see this, consider an economy without population growth and with constant capital labor ratio and constant adoption rates across equipment. If there is full depreciation, then the share of investment accounted for by new technologies will simply be the share of new technologies among all technologies. In contrast, if there is no depreciation, then new equipment will account for the entire investment.

[12] This also avoids any dependence on the household supply of funding other than through $R_{t+1}$.

The per capita value of a new innovation, $v_{t+1}(a)$ depends on the adoption by workers, which in turn depends on the associated adoption cost. The firm borrow at gross rate $R_{t+1}$ to finance their expenditures and maximizes the generated value:

$$L_{t+1}\left(\int_{a_{it+1}} v_{t+1}(a)da - \frac{R_{t+1}}{1+n}x_{it}\right) \tag{3.14}$$

Note that the first part can be decomposed in the mass of innovation times the expected value per innovation due to the continuum of varieties created.

#### 3.1.6 Equilibrium

**Definition 3.1.** *A "production side" Balanced Growth Path is a sequence of quantities (output, investment, workers, technology, R&D expenditure per capita), prices (tasks prices, equipment prices, interest rates), technology sets for worker types, and price functions $P_t(i_t)$ such that*

- *the mass of workers grows at constant rate $n$,*
- *output per capita, investment per capita, technology, and R&D expenditure per capita grow at constant rate $g$*
- *workers maximize life time income conditional on survival,*
- *equipment manufacturer maximize (current period) profits,*
- *the final goods producer maximizes profits, and*
- *investment firms maximize expected discounted profits.*

### 3.2 Equilibrium Characterization

I will throughout focus on a Balanced Growth Path style equilibrium with constant interest rate $R$ and constant growth rate of technology $g$. I will drop the time index $t$ for all variables that are constant along this path.

#### 3.2.1 Technology Adoption and Wages

The model's firm side is relatively standard and I will relegate most of the derivations to the Appendix. The core results for the worker problem is the task-wage:

$$W = (1-\alpha)\alpha^{\frac{2\alpha}{1-\alpha}}\psi^{\frac{-\alpha}{1-\alpha}} \tag{3.15}$$

Note that wages are lower in monopolized industries as the monopolist lowers quantities for increase the price of the equipment. Furthermore, they are not time dependent due to the constant marginal cost of producing equipment.

The first core result is that young workers adopt new technologies at a higher rate than old workers:

**Lemma 3.1.** Young worker adopt a higher share of new technologies than old workers. Furthermore, their total skill set is larger than that of old workers.

*Proof.* All proofs are deferred to the Appendix. □

I will denote the average adoption rate of junior and senior households respectively by $a_j$ and $a_s$ and the adoption rate for new technologies by $a_g^N$ for $g \in \{j, s\}$. Note that adoption rates across households are identical due to the iid distribution of adoption costs. Furthermore, adoption rates for equipment will be identical conditional on their market structure in $t-1$,$t$ and $t+1$.[13]

To simplify the analysis in this section, I will make a strong assumption about technology benefits that effectively implies that young workers adopt all technologies, while old workers only selectively adopt.

**Assumption 3.1.** *The model parameter satisfy*

$$1 > \frac{W}{\varphi} \geq \frac{1}{1 + 1/R}. \tag{3.16}$$

Note that we can always find values for $\varphi$ or $\psi$ to achieve this as $R > 0$. The left inequality states that there are at least some technologies where ratio of benefits to cost is smaller than one for senior workers, while the right guarantees that the benefits are always large enough for the juniors to exceed the highest adoption costs.

**Lemma 3.2.** Suppose that Assumption 1 holds, then technology adoption rates for junior and senior workers are given by

$$a_j = a_j^N = 1, \qquad a_s = \frac{1 + a_s^N g}{1+g} \qquad \text{and} \qquad a_s^N = \left(\frac{W}{\varphi}\right)^\eta. \tag{3.17}$$

Furthermore, overall technology adoption rate for all and for new technologies, $a$ and $a^N$ respectively, are given by

$$a = \frac{1 + a^N g}{1+g} \qquad \text{and} \qquad a^N = 1 - s_s(1 - a_s^N). \tag{3.18}$$

The expression for overall technology adoption clarifies that the channel through which old workers affect overall adoption is through new technologies only.

Before discussing the impact of technology adoption on firm profits and innovation, I want to briefly comments on the nature of labor compensation in this model. One natural concern arising from $a_s < a_j$ is that this implies that wages are downward sloping in age in cross section. In particular, gross labor compensation satisfies

$$\int_{A_{jt}} W_t(a) da = A_t W < A_t W \left(\frac{1 - a_j g}{1+g}\right) = \int_{A_{st}} W_t(a) da,$$

[13] In particular, there will be potentially three different adoption rates for each type of equipment. One for new equipment, one for equipment flipping from monopoly to perfect competition, and one for equipment with competitive market structure in the current and previous period.

where $A_{jt}$ and $A_{st}$ are the skill sets of a random junior and senior worker respectively.[14] This is, however, not the full picture as is does not take into account the adoption costs of technology, as is stated in the next Lemma.

**Lemma 3.3.** Net labor compensation is strictly increasing in age in cross section and life cycle. Furthermore, the life cycle profile is flattening in the growth rate of technology.

The core insight into this results is twofold. Firstly, junior workers face adoption costs for technologies that old workers have already adopted. As workers only have to pay adoption costs once for a given technology, this naturally reduces net compensation for young workers relative to old workers. Secondly, old workers adopt new technologies to maximize within period net-earnings due to their limited horizon. Thus, any additional adoption by young workers will be costly in the current period for the benefit of future earnings. Together, both factors guarantee that net-income from the labor market is upwards sloping in cross section and over the life cycle.

Note, however, that this is not meant to capture the entire life cycle of labor earnings. In particular, the model misses any learning-by-doing effects or pure experience considerations that are likely at the heart of the increasing life cycle profile observed empirically.

### 3.2.2 Profits and Innovation

Profits per worker ($L_t$) for new equipment manufacturers with monopoly power are given by

$$\pi_t^N = \pi^N = \pi a^N, \quad \text{where} \quad \pi = \left(\frac{1-\alpha}{\alpha}\right)\alpha^{\frac{2}{1-\alpha}}. \tag{3.19}$$

Note that this is the standard expression as in e.g. Gancia and Zilibotti (2005) except for the technology adoption term $a^N$. For existing technologies, profits per worker are given by

$$\pi_t^E = \pi^E = \pi. \tag{3.20}$$

Note that this is slightly higher as existing technologies are adopted by all workers by Assumption 1. The value of a new invention, $V_t^N$, is then given by the present discounted value of future profits:

$$V_t^N = \pi^N L_t + \sum_{s=1}^{\infty}\left(\frac{1}{R}\right)^s \pi^E L_{t+s}. \tag{3.21}$$

Note that this is only well defined if the interest rate is larger than the population growth rate, which I will assume in the following.

**Assumption 3.2.** *The gross interest rate satisfies*

$$R > 1 + n. \tag{3.22}$$

[14] Note that $\int_{A_{it}} W_t(a)da$ will be identical for any worker of the same cohort due to the iid adoption cost distribution.

With this assumption we can solve for the value per capita of a new innovation,$v_{t+1}^N$ as

$$v_t^N = v^N = \pi^N + \left(\frac{1+n}{R-(1+n)}\right)\pi^E. \tag{3.23}$$

With this in mind, we can solve the problem of the innovators. The problem is linear such that the distribution of innovation activity across firms is not determinate, nonetheless, the overall growth rate is well defined due to the innovation externalities. Note that aggregating across innovators we have

$$a_{t+1} = \int_I a_{it+1}di = \varphi_0 A_t \left(\frac{X_t}{A_t}\right)^{\varphi_1}. \tag{3.24}$$

Combined with the solution to the firm's problem and value of innovation, this yields the next Lemma.

**Lemma 3.4.** The BGP growth rate $g$ and expenditures on innovation per capita $X_t$ are strictly increasing in the adoption rate of new technologies and consequently in the young share.

In equilibrium, the growth rate $g$ is increasing in the innovation efficiency $\phi_0$, decreasing in the population adjusted discount rate $R/(1+n)$, and increasing in the value of new innovations $v^N$. All of these effects are standard. The only new insight is that $v^N$ is increasing in the technology adoption rate and therefore in the share of young workers in the economy.

$$g \equiv \frac{a_{t+1}}{A_t} = \varphi_0^{\frac{\varphi_1}{1-\varphi_1}}\left(\frac{1+n}{R}\right)^{\frac{\varphi_1}{1-\varphi_1}}(v^N)^{\frac{\varphi_1}{1-\varphi_1}}. \tag{3.25}$$

This insight carries over directly to aggregate expenditure on innovation per capita:

$$X_t = A_t\varphi_0^{\frac{\varphi_1}{1-\varphi_1}}\left(\frac{1+n}{R}\right)^{\frac{1}{1-\varphi_1}}(v^N)^{\frac{1}{1-\varphi_1}}. \tag{3.26}$$

### 3.2.3 Output and Investment

Finally, we can aggregate up to derive aggregate investment $I_t = \int_{A_t} i_t(a)da$ and output. I will define net-output as production net of learning costs. Furthermore, total consumption in this economy is net-output minus investment costs.

$$Y_t^N = Y_t - \int_i h_{it}di \qquad \text{and} \qquad C_t = Y_t^N - \psi I_t \tag{3.27}$$

**Lemma 3.5.** Conditional on the set of available technologies, output and investment are strictly increasing in the young share, while net-output and consumption are strictly decreasing in it.

It warrants to briefly explore both results separately. Total output in this economy is given by

$$Y_t^N = A_t L_t\left[a\left(\frac{\alpha^2}{\psi}\right)^{\frac{\alpha}{1-\alpha}} - \frac{\varphi\eta}{1+\eta}\left(1 - s_s\left(1 - \frac{g}{1+g}a_s^{\frac{1+\eta}{\eta}}\right)\right)\right]. \tag{3.28}$$

The crucial thing to notice is that the share of seniors operates through two separate channels in this equation. Firstly, the average technology adoption rate $a$ is decreasing in the senior share due to their lower adoption rate of new technologies. This decreases net-output. On the other hand, the senior share also decrease the resources used for learning as they already know about old technologies and adopt new technologies at a lower rate. To see why the latter channel always dominates, consider new and old technologies separately. It is immediate that old workers have an advantage in old technologies as both generations know about them, but only juniors face the adoption costs.

Now consider new technologies. We know that young workers adopt them at a higher rate than old workers, however, they only do so because of future benefits. Old workers only take into account current benefits and thus maximize the current net-output they produce. As a result, young workers' net-output from new technologies is also lower than that from old workers. Resulting, old workers have higher net-output for old and new technologies and thus overall net-output is increasing in the old share conditional on the state of technology.

The economics for investment are slightly different as the adoption cost do not impact investment choices.

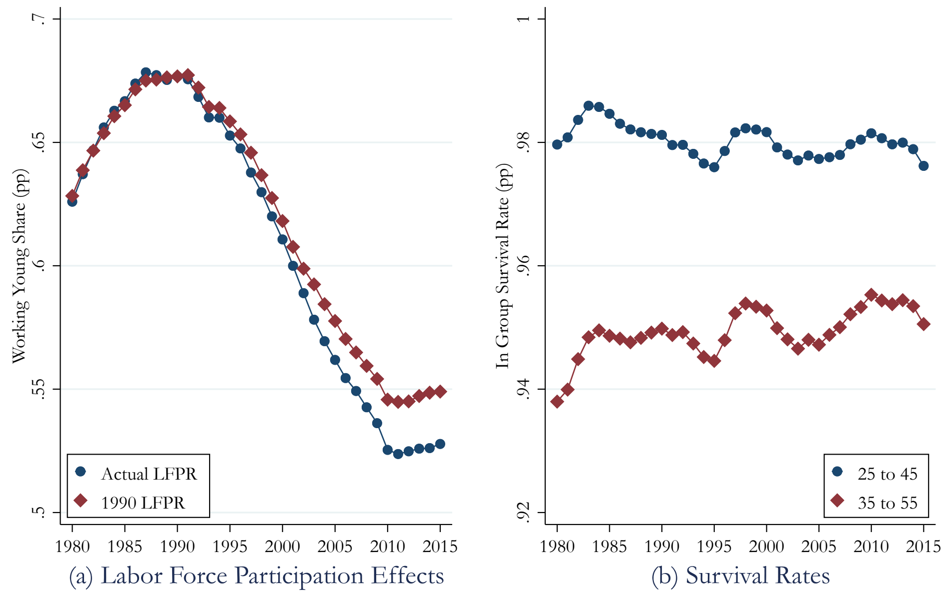
$$I_t = A_t L_t \left(\frac{\alpha}{\psi}\right)^{\frac{1}{1-\alpha}} \left[\frac{g}{1+g}\alpha^{\frac{1}{1-\alpha}} a^N + \frac{1}{1+g}\left(\frac{n+\delta}{1+n}\right) + \frac{g}{(1+g)^2}\left(\frac{1-\delta}{1+n}\right)\left(1-a^N\right)\right]. \tag{3.29}$$

Note, however, that there also is a delayed investment channel due to adoption of technologies by junior workers that had not been adopted by senior workers in the previous period. Nonetheless, the adoption channel always dominates and investment is decreasing in the senior share due to their impact on the adoption rate of new technologies.

Proposition 3.1 summarizes the core predictions of the model.

**Proposition 3.1.** *A decrease in the share of junior workers in the economy will lead to a reduction in output, investment, and R&D expenditure per capita conditional on the current level of technology. Furthermore, it will reduce the BGP growth rate of technology and, thus, the growth rate of investment, consumption, and output in the economy as well.*

Note that this suggests that the demographic change observed in the last 10-15 years could have contributed to the slow down in productivity growth. Before testing the model's predictions in the next section, I want to briefly discuss the origin on demographic change in the US. As discussed in Karahan et al. (2019) and Engbom (2019), this change is primarily driven by lower fertility rates, i.e. by a lower $n$ within the model framework. Figure 3.1 highlights this point.




Note: Panel (a) plots the observed Working Young Share in the ASEC CPS sample against a counterfactual holding labor forc participations rates by age constant at 1990 levels. The right panel plots survival rates by age based on the United States Morta Database. The survival rates are calculated as the ratio of 45(55) year old relative to their underlying population at age 25(35).

Figure 3.1: US Mortality Rates and Labor Force Participation during 1980-2015

Panel (a) plots the WYS in the US labor force versus the hypothetical working young share if labor force participation rates by age had remained constant since 1990. As the figure highlights, this would have dampened the transition and not accelerated it.[15] Furthermore, Panel (b) shows that survival rates among the working age population have remained roughly constant. Together, both indicated that $p$ has no moved much and, thus, have not been a key driver of demographic changes.

# 4 Evidence from Local Labor Markets

## 4.1 Data and Approach

I test the model's prediction for investment in new equipment and innovation by linking establishment level data on on investment in computers and commuting zone level R&D investment to broader workforce characteristics in the local labor market. I measure local R&D investment based on the employment in occupations typically associated with research and development activities. For both measures I then ask whether local investment in new equipment and R&D grew relatively faster for commuting zones with slower workforce aging.

Building on Autor and Dorn (2013) I use commuting zones as my definition of a local labor market and map counties and Public Use Micro Areas to commuting zones using the crosswalks provided by David Dorn on his personal data page.[16] A commuting zones are a partition of counties based on in commuting patterns across

[15] The dampening is primarily due to lower LFPRs for young workers.

[16] See `https://www.ddorn.net/data.htm`

county borders and are developed to capture the relevant labor market for workers within a commuting zone (Tolbert and Sizer, 1996). While their definition has changed over time due to changing commuting patterns, I follow Autor and Dorn (2013) in mapping counties to 1990 commuting zones throughout.

#### 4.1.1 Local Labor Market Demographics

To measure local labor market demographics I rely on the Working Young Share (WYS) in the local labor market as my key summary statistic, which is defined as

$$WYS_{CZ,t} = \frac{\text{Population Age 25-44}_{CZ,t}}{\text{Population Age 25-64}_{CZ,t}}.$$

This is meant to capture broad demographic trends within the working age population. I show in Appendix C.2.4 that I get qualitatively and quantitative similar results when using the average age within the age 25 to 64 population. This indicates that results will be robust to changing the exact measure of workforce aging.

Naturally, one might be concerned about the endogeneity of the WYS in local labor markets. I address this concern using an instrumental strategy laid out in more detail below. I will discuss potential endogeneity concerns for each regression separately below.

Finally, I measure the working young share either from the Census directly (for R&D regressions) or using the Survey of Epidemiology and End Results provided by NBER (for establishment level regressions). The advantage of the former is that I measure this from the same data as my outcomes, while the latter is available annually from 1968 onwards and thus allows me to exactly time the firm investment data described below.

#### 4.1.2 Fertility Instrument

I will instrument for the WYS using county level births from 1920 to 2000 following an expanding literature on demographics in macroeconomics.[17]. The idea is to construct the equivalent of the WYS, but assuming that there is no mobility across Commuting Zones. In other words, I construct the working young share as if people live forever in their place of birth and there is no in or out migration. For a given commuting zone, the instrument is constructed as

$$WYS^{Birth}_{CZ,t} = \frac{\sum_{s=25}^{44} \text{Births}_{CZ,t-s}}{\sum_{s=25}^{64} \text{Births}_{CZ,t-s}}.$$

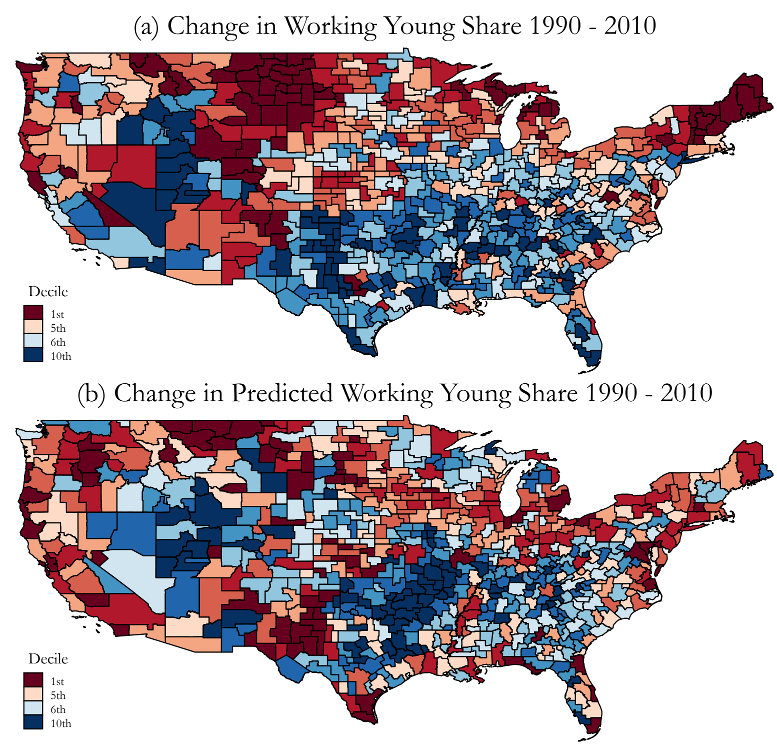
Note that the instrument relies on data that is realized at least 25 years before the actual observation. The exclusion restriction thus become that, conditional on the covariates, the instrument is only related to the outcome variable of interest through its impact on the working young share. Relevance in turns relies on attachment to place of birth or other moving costs that keep people in the places that they were born in.

[17] See e.g. Shimer (2001), Acemoglu and Restrepo (2018), Derrien et al. (2018), Engbom (2019), and Karahan et al. (2019)

For the year 1920 to 1939, births are imputed based on the 1920 to 1940 Censuses, 1940 births per county, and infant survival rates from the 1930 mortality statistics. From 1940 to 1968 births by county are based on the NBER Vitatlity statistics and from 1969 onwards from the NBER CDC SEER data. Relative population sizes are adjusted using 1980 survival rates across ages published by the US Social Security Administration. Construction details are deferred to Appendix B.

Figure 4.1 plots the actual changes and predicted changes in the WYS across US CZs for the 1990 to 2010 period by decile of the overall distribution. The rural Northeast and commuting zones around the Dakotas have experienced the strongest decline in the WYS, while the South as well as the region around Nevada and Utah appear to have been least effects. Note also that changes in the predicted WYS is not particularly favorable to large urban centers such as the Bay Area, Boston, or New York. Thus, my identification strategy is not going to rely on predicting these growing urban hubs correctly.

Figure 4.1: Change in WYS vs Predicted WYS 1990-2010




### 4.1.3 Computer Investments by Establishments

I investigate the adoption of the computer by establishments across the US using data from Harte Hanks using Personal Computers (PCs) per employee as measure of investment in recent equipment. Harte Hanks (HH) is a multinational company that collects IT data via phone interviews and sells them to large IT firms. My data consists of a panel of 109k establishments for the years 1992, 1997, 2002, and 2007 with a total of 260k observations in 415 CZs.[18] I focus on long differences (5-years) to reduce measurement error and ensure that my explanatory variable captures meaningful variation.

I estimate 4.1 using 5-year differences for establishment $i$ and controlling commuting zone trends $\alpha_{CZ(i)}$ and overall time fixed effects $\gamma_t$. The model's core prediction is $\beta > 0$, i.e. firms in younger labor markets have a higher adoption rate of computers as measured by their PC stock per employee. I further introduce 4-digit industry trends to investigate in how far these difference are driven by industry structure.

$$\Delta \ln \left( \frac{\text{Computer}_{it}}{\text{Employment}_{it}} \right) = \alpha_{CZ(i)} + \gamma_t + \beta \Delta WYS_{CZ(i),t} \times 100 + \delta X_{it} + \varepsilon_{it} \tag{4.1}$$

There are at least three concerns with the OLS formulation of that equation that are likely biasing potential results downwards. Firstly, as highlighted in Kaplan and Schulhofer-Wohl (2017) young people are more mobile in general and thus more likely to move towards opportunity. Thus, if young people move towards places that have high adoption rates early on, while leaving behind places that are catching up in terms of computer adoption, one can mechanically achieve a negative coefficient in equation 4.1. On the other hand if young workers are able to correctly predict positive shocks to firms and move to place that had not been booming in $t-1$, but are booming in $t$, then $\beta$ would be upwards biased. My results below indicate that the former effect appears to be stronger.

Secondly, young workers are likely to select into young firms, which often tend to be credit constrained. Thus, $\beta$ might be downwards biased due to financial constraints that limit adoption. I show in Appendix C that larger firms appear to be more sensitive to the WYS in line with this idea, however, I do not have strong measures of firm finances and am thus unable to directly control for this using firm level data. Furthermore, using firm controls might be insufficient to address omitted variable bias coming from selection into nascent industries or products that might be credit constrained beyond the extend measurable through baseline firm characteristics such as total employment.

Finally, the local labor market is likely to be an imprecise proxy for the workforce that is truly relevant for the firm. Resulting, $\beta$ will be biased towards zero due to measurement error. This could be quite substantial given that the the median firm size in the sample is 100 employees, while the median CZ has 825k people in working age. Note, however, that the measurement error from the perspective of relevant population is likely to be correlated for instrument and endogenous independent variable, thus, it is unclear how strong any downwards biased addressed by the instrument would be.

To address the concerns outline above, I follow the instrumental variable strategy detailed in the previous section. Without going into too much detail, the instrument is increasing magnitudes throughout the results presented below. This appears to be a broader finding in the literature reliant on this instrument and is also discussed in Shimer (2001) and Engbom (2019).

[18] For a detailed introduction to Harte Hanks see the data section in Bloom et al. (2016).

### 4.1.4 Local R&D Expenditures

Finally, I confirm the model's prediction for investment in R&D using the US Census and ACS for 1990, 2000, and 2010. The interval is selected to match the availability of my instrument, which only starts in 1985, as well as to capture the large shift in employment composition documented in 4.1, which took place between 1990 and 2010.

I construct two main measures of local R&D intensity, share of employment in R&D and total labor cost of R&D, and investigate the impact of the WYS on both. I focus on employment and labor costs as direct measures of total R&D expenditures at the local are not available to the best of my knowledge. Note, however, that labor costs are a key driver of R&D expenditures and, thus, should be an effective proxy. According to the NSF's Business R&D and Innovation Survey, labor had a cost share of 66.9% for domestic R&D in US companies in 2015 (National Science Foundation and Statistics, 2018). Note that while labor intensity differs across industries, my main local will be on changes in R&D measure and not on levels, which should somewhat address this potential concern.

As in the computer investment regression I focus on long differences and use the change in the share of R&D employment and the growth rate in R&D expenditure as core outcome variables. I will focus on the former in my exposition as employment is relatively precisely measured with the Census, but earning might not if they include e.g. non-pecuniary benefits, deferred payments, or other incentives that are not directly captured by labor income.

I measure R&D employment as all full-time full-year (FTFY) employees that fall into two broader occupational groups: Scientist and Engineers. I use the consistent occupation definitions developed in Autor and Dorn (2013) to ensure that occupations are comparable across Censuses and the ACS. A list of all occupation codes used in this definition is provided in Appendix B. The focus on FTFY workers is meant to ensure that nominator and denominator give an accurate picture of the local employment structure. I present robustness results using all employment and find that this does not materially affect the magnitude of the estimated effect.

To measure R&D expenditure I simply use all labor income for workers in R&D occupations. As a robustness check I consider different definitions of R&D employment including widening the sample to all workers and specifically restricting to private sector employees and non-academic workers.

For both outcome variables I estimate 4.2 to confirm $\beta > 0$ as the model predicts.

$$\Delta Y_{CZ,t} = \alpha_{CZ} + \gamma_t + \beta \Delta WYS_{CZ,t} + \varepsilon_{it} \tag{4.2}$$

Similar to the computer adoption case, one might be concerned with the endogeneity of the working young share. As discussed above, moving towards opportunity and self selection into young firms could naturally lead to a downwards bias in these regressions. I follow the same instrumental strategy outlined above to address this issue.

## 4.2 Results

### 4.2.1 Computer Investments by Establishments

Table 4.1 reports the estimated coefficients for 4.1. Odd columns report OLS results and even columns the associated IVs. Unsurprisingly, the raw coefficient for OLS and IV is positive, reflecting a declining WYS and a slowdown in computer adoption over the period. Time-fixed effects dampen both coefficients significantly, as one might suspect. The OLS coefficient is not significant anymore, while the IV coefficient remains highly significant. Thus, commuting zones with a higher WYS see higher adoption levels, or, more precisely, commuting zones that grow old more slowly see faster adoption. The IV coefficient remains economically meaningful with a standardized coefficient size of 6%.

Column (6) confirms that these effects are not merely driven by commuting zone trends. Note that this quite restrictive given that my instrument only have 4 observations per commuting zone. Finally, I confirm that these results are not driven by industry composition differences in column (8). Adding industry time trends does not appear to change the coefficient size materially and it remains significant at the 5% level.

Table 4.1: Computer Adoption by Firms: Main Results

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Second Stage** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** |
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| WYS ($\Delta$) | 0.1298*** | 0.1430*** | 0.0025 | 0.0562*** | 0.0011 | 0.0366** | -0.0003 | 0.0360** |
| | (0.010) | (0.022) | (0.004) | (0.015) | (0.008) | (0.015) | (0.008) | (0.015) |
| **First Stage** | | **WYS ($\Delta$)** | | **WYS ($\Delta$)** | | **WYS ($\Delta$)** | | **WYS ($\Delta$)** |
| WYS Instr. ($\Delta$) | | 0.2735*** | | 0.1567*** | | 0.2246*** | | 0.2242*** |
| | | (0.024) | | (0.022) | | (0.028) | | (0.028) |
| Stand. coeff. | 0.14 | 0.15 | 0.00 | 0.06 | 0.00 | 0.04 | -0.00 | 0.04 |
| F-stat (1st) | | 132.70 | | 48.79 | | 62.13 | | 62.50 |
| Year FEs | No | No | Yes | Yes | Yes | Yes | Yes | Yes |
| CZ FEs | No | No | No | No | Yes | Yes | Yes | Yes |
| NAICS4 FEs. | No | No | No | No | No | No | Yes | Yes |
| Obs. | 132,066 | 132,066 | 132,066 | 132,066 | 132,066 | 132,066 | 132,051 | 132,051 |

*Note:* This table reports the coefficient estimates for the OLS and first and second stage IV regressions of changes in the CZ-level young worker share on log changes in the establishment level computers per employee at the 5-year horizon. Odd columns present OLS results, while even columns present the coefficients for the instrumental variable specification. The top panel reports the second stage or OLS results and the bottom panel first stage resuts. The reported F-statistics is the Sanderson-Windmeijer multivariate F-test of excluded instruments. WYS refers to the working young share, which is defined as the share of age 25-44 among the age 25-64 population. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

Overall, the results confirm the model's prediction that younger (local) economies invest more in recent technologies. I confirm that there results are not qualitatively changed by weighting commuting zones in Appendix

C.2. The coefficient is basically unaffected by weighting observations by initial commuting zone population and is materially larger when weighting observations by initial firm employment. The latter is in line with the idea that small firms might be financially constraint and thus unable to take advantage of the technical know how of a young workforce. In further results I show that the estimated coefficient is marginally larger in the tradable sector. This confirms that the effect works through the workforce and not the consumer side of the local economy.[19]

Finally, I confirm that the results are driven by the young share and not by potential confounders in Table 4.2. Column (1) reports the baseline second stage. I add the growth rate of the working age population in column (2) and highlight that this is not driving the results. The coefficient on the predicted young share remains approximately constant. Similarly, the coefficent is practically unaffected by adding changes in other demographic variables that could be associated with a higher young share such as the female share or non-white share. Finally, I add more detailed industry fixed effects in column (4) and confirm that the results are not driven by granular industry trends.

Table 4.2: Computer Adoption by Firms: Bad Control

| Indepent Variable | (1)<br>**Comp. per Emp. ($\Delta ln$)** | (2)<br>**Comp. per Emp. ($\Delta ln$)** | (3)<br>**Comp. per Emp. ($\Delta ln$)** | (4)<br>**Comp. per Emp. ($\Delta ln$)** |
|---|---|---|---|---|
| Δ WYS (Predicted) | 0.0360** | 0.0343** | 0.0380** | 0.0350** |
| | (0.015) | (0.016) | (0.015) | (0.016) |
| Workforce Growth Rate | | -0.6869*** | -0.9303*** | -0.9497*** |
| | | (0.187) | (0.219) | (0.219) |
| Δ Female Share | | | -0.0541** | -0.0543** |
| | | | (0.023) | (0.023) |
| Δ Non-white Share | | | 0.0311*** | 0.0311*** |
| | | | (0.010) | (0.010) |
| Year FEs | Yes | Yes | Yes | Yes |
| CZ FEs | Yes | Yes | Yes | Yes |
| Industry FEs | NAICS4 | NAICS4 | NAICS4 | NAICS6 |
| Obs. | 132,051 | 132,051 | 132,051 | 131,901 |

*Note:* This table reports the coefficient estimates for OLS regressions of changes in the predicted CZ-level young worker share and other control variables on log changes in computers per employee at the establishment level. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

### 4.2.2 Local R&D Investment

Table 4.3 reports the results for R&D employment share. The effect is sizable, especially once we control for aggregate trends. The IV coefficient with year fixed effects in column (4) is about three times as large as the associated OLS coefficient in column (3). This effect size is also quantitatively large with a standardized coefficient of 0.47. Adding commuting zone trends increases the estimated coefficient by around one third. Finally,

[19] Interestingly, I do not find any significant results for the service sector or tradeable services, however, this might simply be driven by the computer being a non-factor in the former and a necessity in the latter.

when I restrict R&D employment to scientists and engineers only, the effect size is markedly larger in absolute and standardized terms. This might be due to a too inclusive definition of R&D employment in the first place.

My preferred specification in column (6) indicates that a ten percentage point increase in the young share leads to a 1.6 percentage point increase in the share of R&D personal, which is around 20% of the average R&D employment share.

Table 4.3: Local R&D Employment: Main Results

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Second Stage** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** |
| | OLS | IV | OLS | IV | OLS | IV |
| Dpop_wy | 0.0492*** | 0.0020 | 0.0132 | 0.1955*** | 0.0565*** | 0.2581*** |
| | (0.008) | (0.147) | (0.009) | (0.048) | (0.014) | (0.064) |
| **First Stage** | | **WYS (Δ)** | | **WYS (Δ)** | | **WYS (Δ)** |
| Δ WYS (Instr.) | | 0.0290** | | 0.1090*** | | 0.1455*** |
| | | (0.014) | | (0.014) | | (0.027) |
| Std. coeff. | 0.17 | 0.01 | 0.04 | 0.66 | 0.19 | 0.88 |
| F-stat (1st) | | 4.25 | | 57.26 | | 29.83 |
| Year FEs | No | No | Yes | Yes | Yes | Yes |
| CZ FEs | No | No | No | No | Yes | Yes |
| Obs. | 1,444 | 1,444 | 1,444 | 1,444 | 1,444 | 1,444 |

*Note:* This table reports the coefficient estimates for the OLS and first and second stage IV regressions of changes in the CZ-level young worker share on the share of workers in R&D employments among Full-Time Full-Year employees. Odd columns present OLS results, while even columns present the coefficients for the instrumental variable specification. The top panel reports the second stage or OLS results and the bottom panel first stage resuts. The reported F-statistics is the Sanderson-Windmeijer multivariate F-test of excluded instruments. WYS refers to the working young share, which is defined as the share of age 25-44 among the age 25-64 population. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

As a robustness check, I change the set of industries and R&D employees consider. Table 4.4 reports the associated results for the IV specification. Column (1) repeats column (2) in Table 4.3. Column (3) widens the set of workers to all employees instead of Full-Time Full-Year only. The coefficient is reduced by a little more than 50%, however, the standardized coefficient is barely affected. Columns (3) and (4) restrict the measure to private sector and non-academic R&D workers respectively. The coefficient is statistically indistinguishable from the baseline. This confirms that the effects are truly driven by private sector investment in R&D activities.

Finally, I restrict my employment measure to tradeables only in column (5). The standardized coefficient falls by about half, but remains highly significant. The overall dampening might be driven by averaging over commuting zones with and without tradeable base, where the latter is not affected at all. This is particularly relevant to tradeables as they tend to be geographically highly concentrated. I test this in unreported results and find that the coefficient doubles and the standardized coefficient exceeds 1 once I restrict the sample to CZ with at least 0.5% tradable R&D share.[20]

[20] The same restriction leaves the baseline coefficient effectively unaffected.

Table 4.4: Local R&D Employment: Alternative Measures

| Second Stage | (1) R&D Empl. Share (Δ) | (2) R&D Empl. Share (Δ) | (3) R&D Empl. Share (Δ) | (4) R&D Empl. Share (Δ) | (5) R&D Empl. Share (Δ) |
|---|---|---|---|---|---|
| D.WYS | 0.2539*** | 0.2708*** | 0.2955*** | 0.3061*** | 0.1070 |
| | (0.064) | (0.060) | (0.088) | (0.071) | (0.108) |
| **First Stage** | **WYS (Δ)** | **WYS (Δ)** | **WYS (Δ)** | **WYS (Δ)** | **WYS (Δ)** |
| D.WYS (Instr.) | 0.1457*** | 0.1457*** | 0.1457*** | 0.1457*** | 0.1457*** |
| | (0.027) | (0.027) | (0.027) | (0.027) | (0.027) |
| Std. coeff. | 0.87 | 1.00 | 0.78 | 0.98 | 0.19 |
| F-stat (1st) | 29.95 | 29.95 | 29.95 | 29.95 | 29.95 |
| Year FEs | Yes | Yes | Yes | Yes | Yes |
| CZ FEs | Yes | Yes | Yes | Yes | Yes |
| Outcome Sample | Baseline | All Employed | Private Sector | Non-Academic | Tradables |
| Obs. | 1,444 | 1,444 | 1,444 | 1,444 | 1,444 |

*Note:* This table reports the coefficient estimates for the first and second stage IV regressions of changes in the CZ-level young worker share on various measures of the share of workers in R&D employment. The baseline measure considers only Full-Time Full-Year employees. The top panel reports the second stage results and the bottom panel first stage resuts. The reported F-statistics is the Sanderson-Windmeijer multivariate F-test of excluded instruments. WYS refers to the working young share, which is defined as the share of age 25-44 among the age 25-64 population. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

Table 4.5: Local R&D Employment: Tradable Industries

| Second Stage | (1) R&D Empl. Share (Δ) | (2) R&D Empl. Share (Δ) | (3) R&D Empl. Share (Δ) | (4) R&D Empl. Share (Δ) |
|---|---|---|---|---|
| D.WYS | 0.1070 | 0.1288 | 0.3256*** | 0.5581** |
| | (0.108) | (0.108) | (0.112) | (0.253) |
| **First Stage** | **WYS (Δ)** | **WYS (Δ)** | **WYS (Δ)** | **WYS (Δ)** |
| D.WYS (Instr.) | 0.1457*** | 0.1594*** | 0.1702*** | 0.1099*** |
| | (0.027) | (0.029) | (0.033) | (0.041) |
| Std. coeff. | 0.19 | 0.24 | 0.64 | 1.12 |
| F-stat (1st) | 29.95 | 29.74 | 26.49 | 7.20 |
| Year FEs | Yes | Yes | Yes | Yes |
| CZ FEs | Yes | Yes | Yes | Yes |
| Man. Share 1990 | All | Top 90% | Top 75% | Top 50% |
| Obs. | 1,444 | 1,298 | 1,080 | 740 |

*Note:* This table reports the coefficient estimates for the first and second stage IV regressions of changes in the CZ-level young worker share on the share of FTFY workers in R&D employment in the tradable sector and splits the sample based on the share in manufacturing employment in the commuting zone in 1990. The top panel reports the second stage results and the bottom panel first stage resuts. The reported F-statistics is the Sanderson-Windmeijer multivariate F-test of excluded instruments. WYS refers to the working young share, which is defined as the share of age 25-44 among the age 25-64 population. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

I further investigate the robustness of my results by adding “bad controls”. As Table 4.6 highlights, the results are not driven by potential confounders such as workforce growth, different educational achievement across cohorts, or population composition.

Column (1) reports the baseline second stage results. I add workforce growth in column (2) to address the potential confounding of growing workforce and young workforce as discussed in Karahan et al. (2019). The coefficient size is effectively unchanged. Note that the positive coefficient on the workforce growth rate is in line with model's prediction as $n$ has a separate positive effect due to the market size growth. Column (3) confirms that differential educational attainment across cohorts does not drive the results either. Finally, I confirm that other compositional differences across cohort are not driving my results either in column (4). The coefficient remains within a standard deviation of the original coefficient and highly significant.

Table 4.6: Local R&D Employment: Alternative Mechanisms

| **Indepent Variable** | (1)<br>**R&D Empl. Share (Δ)** | (2)<br>**R&D Empl. Share (Δ)** | (3)<br>**R&D Empl. Share (Δ)** | (4)<br>**R&D Empl. Share (Δ)** |
|---|---|---|---|---|
| D.WYS (Predicted) | 0.254*** | 0.252*** | 0.259*** | 0.241*** |
| | (0.062) | (0.062) | (0.062) | (0.061) |
| Workforce Growth Rate | | -0.006 | -0.006 | -0.005 |
| | | (0.004) | (0.004) | (0.004) |
| D.College degree among FTFY (pp) | | | 0.065*** | 0.065*** |
| | | | (0.014) | (0.013) |
| D.Non-whites (pp) | | | | -0.025*** |
| | | | | (0.009) |
| D.Married (pp) | | | | -0.050*** |
| | | | | (0.015) |
| D.Female (pp) | | | | -0.050 |
| | | | | (0.034) |
| Year FEs | Yes | Yes | Yes | Yes |
| CZ FEs | Yes | Yes | Yes | Yes |
| Obs. | 1,444 | 1,444 | 1,444 | 1,444 |

*Note:* This table reports the coefficient estimates for OLS regressions of changes in the predicted CZ-level young worker share and other control variables on changes in share of workers in FTFY R&D employment. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

I confirm that the employment results translate to labor cost in Table 4.7. As with employment, I focus on FTFY workers and use the growth rate in total expenditure on FTFY R&D workers as outcome variable. The results are qualitatively similar to the employment regressions once I include time fixed effects. The negative IV coefficient in column (2) is entirely driven by aggregate trends and flips the sign once I include a linear trend.

Table 4.7: Local R&D Expenditure: Main Results

| Second Stage | (1) R&D Exp. ($\Delta ln$) OLS | (2) R&D Exp. ($\Delta ln$) IV | (3) R&D Exp. ($\Delta ln$) OLS | (4) R&D Exp. ($\Delta ln$) IV | (5) R&D Exp. ($\Delta ln$) OLS | (6) R&D Exp. ($\Delta ln$) IV |
|---|---|---|---|---|---|---|
| D.WYS | 5.006*** | -23.030 | 2.258*** | 8.728*** | 5.458*** | 4.930 |
| | (0.563) | (16.428) | (0.555) | (2.838) | (0.785) | (3.753) |
| **First Stage** | | **WYS ($\Delta$)** | | **WYS ($\Delta$)** | | **WYS ($\Delta$)** |
| D.WYS (Instr.) | | 0.029** | | 0.109*** | | 0.146*** |
| | | (0.014) | | (0.014) | | (0.027) |
| Std. coeff. | 0.24 | -1.12 | 0.11 | 0.43 | 0.27 | 0.24 |
| F-stat (1st) | | 4.35 | | 57.40 | | 29.95 |
| Year FEs | No | No | Yes | Yes | Yes | Yes |
| CZ FEs | No | No | No | No | Yes | Yes |
| Obs. | 1,444 | 1,444 | 1,444 | 1,444 | 1,444 | 1,444 |

*Note:* This table reports the coefficient estimates for the OLS and first and second stage IV regressions of changes in the CZ-level young worker share on log changes in R&D expenditure as measured by wages for FTFY R&D personnel. Odd columns present OLS results, while even columns present the coefficients for the instrumental variable specification. The top panel reports the second stage or OLS results and the bottom panel first stage resuts. The reported F-statistics is the Sanderson-Windmeijer multivariate F-test of excluded instruments. WYS refers to the working young share, which is defined as the share of age 25-44 among the age 25-64 population. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

The coefficient in the full specification in column (6) indicates that a one percentage point decrease in the WYS leads to a 6.0% decline in local expenditure on R&D employees.

## 4.3 Understanding Sources of Variation

Table 4.8: Local R&D Employment: Regional Fixed Effects

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Second Stage** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** |
| D.WYS | 0.2539*** | 0.3281*** | 0.2873*** | 0.3533* |
| | (0.064) | (0.122) | (0.111) | (0.183) |
| **First Stage** | **WYS (Δ)** | **WYS (Δ)** | **WYS (Δ)** | **WYS (Δ)** |
| D.WYS (Instr.) | 0.1457*** | 0.0861*** | 0.0911*** | 0.0638*** |
| | (0.027) | (0.021) | (0.023) | (0.022) |
| Std. coeff. | 0.87 | 1.12 | 0.98 | 1.21 |
| F-stat (1st) | 29.95 | 16.14 | 15.78 | 8.53 |
| Year FEs | Yes | Yes | Yes | Yes |
| CZ FEs | Yes | Yes | Yes | Yes |
| Interaction FEs | None | Region x Year | Division x Year | State x Year |
| Obs. | 1,444 | 1,444 | 1,444 | 1,440 |

*Note:* This table reports the coefficient estimates for the first and second stage IV regressions of changes in the CZ-level young worker share on the share of FTFY workers in R&D employment and add regional time fixed effect interactions. The top panel reports the second stage results and the bottom panel first stage resuts. The reported F-statistics is the Sanderson-Windmeijer multivariate F-test of excluded instruments. WYS refers to the working young share, which is defined as the share of age 25-44 among the age 25-64 population. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

### 4.3.1 Period-by-Period Effects

Table 4.9: Local R&D and Self-Employment: Year-by-Year

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Second Stage** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **Self-Empl. Share (Δ)** | **Self-Empl. Share (Δ)** | **Self-Empl. Share (Δ)** |
| D.WYS | 0.1940*** | 0.0493 | 0.3283*** | 0.1791 | 0.6149*** | -0.2254 |
| | (0.047) | (0.041) | (0.091) | (0.119) | (0.234) | (0.176) |
| **First Stage** | **WYS (Δ)** | **WYS (Δ)** | **WYS (Δ)** | **WYS (Δ)** | **WYS (Δ)** | **WYS (Δ)** |
| D.WYS (Instr.) | 0.1093*** | 0.1698*** | 0.0821*** | 0.1093*** | 0.1698*** | 0.0821*** |
| | (0.014) | (0.029) | (0.025) | (0.014) | (0.029) | (0.016) |
| Std. coeff. | 0.66 | 0.21 | 1.07 | 0.21 | 0.63 | -0.32 |
| F-stat (1st) | 57.40 | 34.23 | 26.37 | 57.40 | 34.23 | 26.37 |
| Year FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Sample | Baseline | 1990-2000 | 2000-2010 | Baseline | 1990-2000 | 2000-2010 |
| Obs. | 1,444 | 722 | 722 | 1,444 | 722 | 722 |

*Note:* This table reports the coefficient estimates for the first and second stage IV regressions of changes in the CZ-level young worker share on the share of FTFY workers in R&D employment in the tradable sector and splits the sample based on the share in manufacturing employment in the commuting zone in 1990. The top panel reports the second stage results and the bottom panel first stage resuts. The reported F-statistics is the Sanderson-Windmeijer multivariate F-test of excluded instruments. WYS refers to the working young share, which is defined as the share of age 25-44 among the age 25-64 population. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

## 5 Conclusion

The US has experienced a large demographic shift since 1990 that is projected to continue. While 64% of the working age population were below age 45 in 1990, only 51% were in 2018 and only 52.5% are project to be in the medium term. This demographic change could have wide ranging impacts on the US economy.

In this paper I highlight one potential channel: Technology adoption. I show that older workers were less likely and able to work with the computer during the peak adoption period from 1989 to 2003 using the CPS. Motivated by this evidence I build a simple endogenous growth model with overlapping generations and technology learning cost for workers. The model suggests lower technology adoption rates among the older population due to the shorter remaining work life in line with CPS evidence. Furthermore, the model predicts that that population aging leads to lower average technology adoption rates and thus lower productivity levels, which in turn imply smaller markets for innovators. Resulting, an aging economy will feature less investment, innovative activity and output in the short run as well as lower productivity growth rates in the medium- and long-run.

I confirm the model's prediction regarding investment in new equipment and innovative activity using a local labor markets approach. I measure investment in new equipment by looking at computer stocks across US establishment in a large sample of US firms and find that establishments in aging labor markets are slower to adopt the computer. Furthermore, I shows that aging local labor markets record lower shares of R&D employment and R&D expenditure growth.

Overall, this suggests that population aging has contributed to the recent slowdown in productivity growth in the US. I leave a quantification of its contribution to future work.

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# A Model Appendix

## A.1 Derivations and Proofs

The following section provides the details to the model derivations as well as proofs omitted from the mail body.

### A.1.1 Wages, Prices and Household Labor Income

First order condition for the final producer's problem yield the standard factor demands:

$$P_t(a) = \alpha \left(\frac{k_t(a)}{\ell_t(a)}\right)^{\alpha-1} \qquad \text{and} \qquad W_t(a) = (1-\alpha)\left(\frac{k_t(a)}{\ell_t(a)}\right)^{\alpha}. \tag{A.1}$$

Note that I am implicitly assuming $i_t(a) \geq 0$ here, which is the relevant case here with positive population growth and depreciation.

Monopolists solves the profit maximization problem taking into account the equipment demand for monopolist price $P_t(a)$:

$$P_t = \frac{\psi}{\alpha}. \tag{A.2}$$

Equipment prices then determine the equipment labor ratio and as a result the skill wages in equation 3.15. Note that producers do not internalize their impact on adoption in this set up. This is done for analytic convenience only and will not qualitatively affect the results. In practice this will make demand more elastic and as a result reduce the monopolists optimal mark-up. An interesting implication for this framework is that markups would fall in for new technologies in an aging economy in this framework as older workers are generally more elastic in their response to prices.[21]
Will the skill wages in hand we can derive the first major implication of the framework, which I will repeat here:

**Lemma A.1.** Young worker adopt a higher share of new technologies than old workers. Furthermore, their total skill set is larger than that of old workers.

*Proof.* The proof for this is straight-forward and relies on simply comparing the value of technologies to different age groups. A young worker $i$ will adopt a given technology iff the benefits exceed the cost:

$$W_t(a) + \frac{1}{R}W_{t+1}(a) \geq \psi n_i(a) \tag{A.3}$$

[21] In particular, let $\varepsilon_a$ be the elasticity of adoption with respect to equipment prices:

$$\varepsilon_a \equiv -\partial \ln \ell_t(a)/\partial \ln P_t(a) \in (0, \infty),$$

Note that this value will always be positive as higher equipment prices reduce the optimal equipment labor ratio and thus the skill wages. The (static) optimal monopolist price then satisfies

$$P_t(a) = \frac{\psi(1+\varepsilon_a)}{\alpha+\varepsilon_a} \in \left(\psi, \frac{\psi}{\alpha}\right).$$

A younger population will be less sensitive to the current equipment price due to future benefits from adoption and, thus, $\varepsilon_a$ will decline in the young share. As a result, an aging economy will have lower markups for new technology firms in this framework.

The same holds true for an older worker, however, the benefits are lower:

$$W_t(a) \geq \psi n_i(a) \tag{A.4}$$

Given that $W_{t+1} > 0$ and $R_{t+1} \in (0, \infty)$, it follows immediately that for given adoption cost a young worker will always adopt the new technology if an old worker does, but not vice versa. The adoption rates for new technologies across age groups, $a^N_{jt}$ and $a^N_{st}$ are then simply given by

$$a^N_{jt} = F\left(\frac{W}{\varphi}(1 + 1/R)\right) \geq F\left(\frac{W}{\varphi}\right) = a^N_{st}. \tag{A.5}$$

To see why this carry over to all technologies, note first that task-wages are constant. It then follows immediately that the returns to early adoption of a particular skill are constant as well. Thus, any technology adopted early by senior workers (i.e. when they were junior) will also be adopted early by the subsequent generation. Furthermore, there is no late adoption of technologies as the benefits of technologies are strictly decreasing over the life cycle, while the costs are constant.

Thus, any technology adopted by senior workers is also in the skill set of junior workers with the same adoption cost. Given that adoption costs are iid across workers, this carries over immediately to average adoption rates. Finally, to guarantee that the skill set is strictly larger for younger workers, we need that adoption rates for older worker are strictly between 0 and 1. Together with a continuous distribution of adoption costs this completes the proof.

□

**Lemma A.2.** Net labor compensation is strictly increasing in age in cross section and life cycle. Furthermore, the life cycle profile is flattening in the growth rate of technology.

*Proof.* Consider first the cross-sectional statement and note that the total net compensation is simply the integral over the net compensation for each individual technology. Consider old technologies first. Both generations adopt them at rate $a_j$ during their junior period, however, only young face adoption costs in this period. It follows immediately that the net compensation for old technologies is strictly higher for older workers.

Now consider new technologies and note that the within period net compensation for a given worker type $i$ is $W_t(a) - \varphi n_i(a)$ regardless of whether the worker is junior or senior. Thus, the net benefit from new technologies that junior and senior both adopt is exactly the same. Now consider a technology that only young adopt. For these, the following has to hold true:

$$W_t(a) + \frac{1}{R_{t+1}} W_{t+1}(a) \geq \varphi n_i(a) > W_t(a) \tag{A.6}$$

The first inequality states that it must be profitable for the young worker to adopt the technology, while the second states that it must not be profitable for the old worker to adopt the technology. Note, however, that the second inequality also implies $W_t(a) - \varphi n_i(a) < 0$. Thus, the net contribution of the technology for this period is negative and hence senior workers get strictly higher net compensation from new technologies as well, as long as there are adoption differences.

In total this implies that senior workers achieve a higher net compensation from old and new technologies, which implies that their overall net compensation, which is the sum of the two, has to be larger as well.

The result for the life cycle profile is trivial as well. Senior workers do not have to pay adoption costs for technologies adopted when junior, while the gross compensation remains constant. Furthermore, old workers gainfully adopt new technologies, adding to the slope of the life cycle profile.

Finally, we can turn to the effect of $g$ on earnings in the cross section. Firstly, note that we already know that old workers get a higher net benefit from new technologies by our discussion above. A larger share of new technologies will simply increase the mass of technologies with negative current contribution that are adopted by young workers and thus widen the gap in absolute terms, however, as I will show below, the effect is the opposite in relative terms.

Denote by $W_{st}$ and $W_{jt}$ the labor earnings of junior and senior workers. One can show that they satisfy

$$W_{jt} = A_{t-1}(1+g)Wa_j\left(\frac{1}{1+\eta}(1-\eta/R)\right) \tag{A.7}$$

$$W_{st} = A_{t-1}Wa_s\left(\frac{a_j}{a_s} + g\frac{1}{1+\eta}\right) \tag{A.8}$$

I will assume $R > \eta$ to ensure that net-labor income for young is positive.[22] Then, the ratio of labor income is given by

$$\frac{W_{st}}{W_{jt}} = \frac{a_s}{a_j}\frac{1}{1+g}\frac{\frac{a_j}{a_s}(1+\eta)+g}{1-\eta/R} \tag{A.9}$$

It follows then that

$$\frac{\partial \ln W_{st}/W_{jt}}{\partial g} = -\frac{1}{1+g} + \frac{1}{\frac{a_j}{a_s}(1+\eta)+g} < 0 \tag{A.10}$$

The inequality follows from $a_j \geq a_s$ and $\eta \geq 0$. This intuition follows from the simply logic that old workers have an advantage in old technology that vanishes in relative terms as old technologies get ever less important. □

**Lemma A.3.** The BGP growth rate $g$ and expenditures on innovation per capita $X_t$ are strictly increasing in the adoption rate of new technologies and consequently in the young share.

*Proof.* This trivially follows from the equations given in the text. □

[22] Technically, the correct assumption is $W > \varphi\frac{\eta}{1+\eta}$, which guarantees positive earnings even when all technologies are adopted. In this case, either $R > \eta$ or $a_j = 1$.

**Lemma A.4.** Conditional on the set of available technologies, output and investment are strictly increasing in the young share, while net-output and consumption are strictly decreasing in it.

*Proof.* Total output is simply given by

$$Y_t^N = A_t L_t a \left(\frac{\alpha^2}{\psi}\right)^{\frac{\alpha}{1-\alpha}} \tag{A.11}$$

It follows immediately that this is increasing in the young share as $\partial a / \partial s_j > 0$. The remainder follows from the equations in the main text. $\square$

## A.2 Closing The Model

The most immediate way to close the model is to simply assume the standard OLG utility structure with CRRA preferences. The problem for junior generation worker $i$ born at $t$ is then simply

$$\begin{aligned} &\max \frac{c_{it}^{1-\gamma} - 1}{1-\gamma} + \beta(1-p)\frac{c_{it+1}^{1-\gamma} - 1}{1-\gamma} \qquad \text{s.t.} \\ b_{it} = W_{it} - h_{it} - c_{it} \quad &\text{and} \quad c_{it+1} = W_{it+1} - h_{it+1} + R_{t+1} b_{it}, \end{aligned} \tag{A.12}$$

where $b_{it}$ are savings, and wages and technology costs are based on technology adoption sets $A_{it}$ and $A_{it+1}$.

First order conditions for $A_{it}$ can be simplified to

$$\frac{\partial h_{it}}{\partial A_{it}} = \frac{\partial W_{it}}{\partial A_{it}} + \frac{1}{R_{t+1}} \frac{\partial W_{it+1}}{\partial A_{it+1}}, \tag{A.13}$$

where I have use the fact that $A_{it+1} = A_{it} + a_{it+1}$. This confirms that, within this setup, households ignore the death probability and act as if they are maximizing their lifetime earnings conditional on survival, which motivates the assumption in the main text.

Alternatively, one could close the model with a representative consumer solving

$$\max \frac{C_t^{1-\gamma} - 1}{1-\gamma} + \beta(1-p)\frac{C_{t+1}^{1-\gamma} - 1}{1-\gamma} \quad \text{s.t.} \qquad C_t + S_t = \Pi_t L_{jt}(W_{jt} - h_{jt}) + L_{st}(W_{st} - h_{st}) + R_t S_{t-1}, \tag{A.14}$$

where $S_{t-1}$ are aggregate savings. Within this framework, the derivative with respect to the technology adoption set for junior workers is slightly different, as the household takes into account the death probability:

$$\frac{\partial h_{jt}}{\partial A_{jt}} = \frac{\partial W_{jt}}{\partial A_{jt}} + \frac{1-p}{R_{t+1}} \frac{\partial W_{st+1}}{\partial A_{st+1}}. \tag{A.15}$$

Note, however, that this does not affect the qualitative predictions of the model with respect to the junior share.

# B Data Appendix

## B.1 Census

Table B.1 reports the list of occupations and associated codes that were classified as R&D employment.

Table B.1: R&D Related Occupations

| occ1990dd code | Occupation title | Subcategory |
|---|---|---|
| 44 | Aerospace engineers | Engineers |
| 45 | Metallurgical and materials engineers | Engineers |
| 47 | Petroleum, mining, and geological engineers | Engineers |
| 48 | Chemical engineers | Engineers |
| 53 | Civil engineers | Engineers |
| 55 | Electrical engineers | Engineers |
| 56 | Industrial engineers | Engineers |
| 57 | Mechanical engineers | Engineers |
| 59 | Engineers and other professionals, n.e.c | Engineers |
| 64 | Computer systems analysts and computer scientists | (Computer) Scientists |
| 65 | Operations and systems researchers and analysts | (Computer) Scientists |
| 68 | Mathematicians and statisticians | (Natural) Scientists |
| 69 | Physicists and astronomists | (Natural) Scientists |
| 73 | Chemists | (Natural) Scientists |
| 74 | Atmospheric and space scientists | (Natural) Scientists |
| 75 | Geologist | (Natural) Scientists |
| 76 | Physical scientists, n.e.c. | (Natural) Scientists |
| 77 | Agricultural and food scientists | (Natural) Scientists |
| 78 | Biological scientists | (Natural) Scientists |
| 79 | Foresters and conservation scientists | (Natural) Scientists |
| 83 | Medical scientists | (Natural) Scientists |
| 166 | Economists, market and survey researchers | (Social) Scientists |
| 167 | Psychologists | (Social) Scientists |
| 169 | Social scientists and sociologists, n.e.c | (Social) Scientists |

## B.2 Fertility Instrument

The fertility instrument creates shares of working young (age 25-44) among the working age population (age 25 to 64) by county based on fertility. To do so, I use recorded births for 1940-68, age 0 population for 1969-2016 and imputed births based on state fertility and relative fertility rates across counties for 1920-39. I detail the approach for each time-period separately in the following.

### B.2.1 Births by county for 1920-39

There are no recorded births available for 1920-39 using either Census, NBER Vitality data or SEER data. To impute births by county I rely on Census data from IPUMS for population sizes in 1920, 1930 and 1940 by county, age 0 - 9 population at the state level and population at the state level as well as relative birth rates across counties from 1940-49.

Firstly, I impute population by county for 1921-1929 and 1931-39 by using population sizes in 1920,1930 and 1940 from the National Historical Geographic Information System (NHGIS), which is based on the Census, and assume constant geometric growth rates between census years.

Secondly, I use IMPUMS USA to estimate fertility rates by year by assuming that age 0-9 population was born within each state and using geometric smoothing for state population between Census years, i.e. my estimated fertility rate for Arkansas in 1921 is the age 9 population in Arkansas in the 1930 census divided by the geometric average of 1930 and 1940 population in Arkansas based on the IMPUMS USA.[23]

Finally, I use the relative fertility rates across counties from 1940 to 1949 (see below) to allocate births within states. Births for county $i$ in state $j$ are then calculated as

$$Births_{it} = Pop_{it} \times Fert_{i,1940-49} \times \frac{Births_{jt}}{\sum_{i \in j} Pop_{it} \times Fert_{i,1940-49}} \tag{B.1}$$

This formula basically allocates imputed births within a state based on relative fertility rates across counties in 1940-49 and current population. Time-series variation in this measure thus arises from state-level changes in births and population movements across counties.

### B.2.2 Births by county for 1940-68

For the 1940-69 period I rely on the "Vital Statistics Births" as provided by the NBER.[24] I do not transform the data apart from selection county level observations and mapping county names to county FIPS codes. The latter part requires some manual remapping of counties due to changing county definitions over the historical period. The main culprits for this are Alaska and Virginia. I drop Alaska in my analysis (due to overall inconsistent data across source) and generally map independent cities in Virginia (the main source of inconsistencies") to the county they are formed from.

### B.2.3 Births by county 1968 - 2016

For all other birth data I use age 0 population by county from the Surveillance, Epiemiology, and End Results program (SEER), which is provided by the NBER as well. As with the 1940-68 data, I map independent cities in Virginia to their county of origin.

[23] Clearly, this is an imperfect measure for several reasons including Child mortality, parents moving across state lines and non-smooth population movements across states. In principle, one could rely on the vital statistics rates from `https://www.nber.org/vital-stats-books/`, however, the data is only available in pdf format. In future iterations of this instrument I will consider using this data instead.

[24] Heidi Williams is credited with the compilation and, in accordance with the terms of use, I acknowledge financial support from NIA grant P30-AG012810 through the NBER.

### B.2.4 Mapping Counties to Commuting Zones

I map county level births to 1990 commuting zones to establish a consistent geographical definition. I use the mapping provided by Eckert et al. (2018), which is based on the geographic shapefiles of the census. The mapping changes with the Census, i.e. with redistricting. I aggregate births to commuting zone using the provided weights.

### B.2.5 Fertility Instrument

The final instrument is then constructed by simply aggregating births such that the working age population in a given industry $i$ at time $t$ is given by

$$Pop_{it}^{WA} = \sum_{s=25}^{64} Births_{it-s}, \tag{B.2}$$

and share of young is given by

$$Young_{it}^{WA} = \frac{\sum_{s=25}^{44} Births_{it-s}}{\sum_{s=25}^{64} Births_{it-s}}. \tag{B.3}$$

# C Empirical Appendix

## C.1 Computer Adoption by Workers

### C.1.1 Regression Tables

Table C.1: Regression Table for Computer Use At Work

| Indepent Variable | (1) Comp. Use At Work | (2) Comp. Use At Work | (3) Comp. Use At Work | (4) Comp. Use At Work | (5) Comp. Use At Work |
|---|---|---|---|---|---|
| Age 10-14 in 1989 | -0.026* | -0.028** | -0.010 | -0.011 | -0.009 |
| | (0.014) | (0.012) | (0.007) | (0.007) | (0.006) |
| Age 15-19 in 1989 | 0.008 | -0.003 | 0.002 | 0.002 | 0.004 |
| | (0.008) | (0.006) | (0.004) | (0.004) | (0.004) |
| Age 20-24 in 1989 | 0.003 | -0.004 | -0.001 | -0.001 | 0.001 |
| | (0.005) | (0.005) | (0.004) | (0.004) | (0.004) |
| Age 30-34 in 1989 | 0.009 | 0.006 | -0.003 | -0.003 | -0.002 |
| | (0.006) | (0.005) | (0.003) | (0.003) | (0.003) |
| Age 35-39 in 1989 | 0.005 | -0.009 | -0.016*** | -0.017*** | -0.016*** |
| | (0.010) | (0.007) | (0.004) | (0.004) | (0.004) |
| Age 40-44 in 1989 | 0.011 | -0.008 | -0.029*** | -0.029*** | -0.029*** |
| | (0.013) | (0.009) | (0.005) | (0.005) | (0.005) |
| Age 45-49 in 1989 | -0.025 | -0.034*** | -0.055*** | -0.055*** | -0.054*** |
| | (0.016) | (0.012) | (0.005) | (0.005) | (0.005) |
| Age 50-54 in 1989 | -0.066*** | -0.064*** | -0.084*** | -0.084*** | -0.083*** |
| | (0.017) | (0.014) | (0.007) | (0.007) | (0.007) |
| Age 55-59 in 1989 | -0.115*** | -0.112*** | -0.132*** | -0.131*** | -0.128*** |
| | (0.019) | (0.016) | (0.008) | (0.008) | (0.008) |
| Age 60-64 in 1989 | -0.167*** | -0.168*** | -0.181*** | -0.180*** | -0.171*** |
| | (0.024) | (0.021) | (0.015) | (0.015) | (0.013) |
| Year FEs | Yes | Yes | Yes | Yes | Yes |
| Gender/Educ. FEs | No | Yes | Yes | Yes | Yes x year |
| Ind./Occ. FEs | Nos | Nos | Yes | Yes | Yes x year |
| State FEs | No | No | No | Yes | Yes x year |
| Obs. | 225,021 | 225,021 | 225,021 | 225,021 | 225,005 |

*Note:* This table reports the regression coefficients for direct computer use at work. Outcome is an indicator variable with standard deviation .5 and mean .55. Age 25 in 1989 is the leave out category. Regressions use CPS Computer and Internet Supplement weights. All standard errors clustered at industry level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

Table C.2: Regression Table for Tasks Performed With Computer

| Indepent Variable | (1)<br>**Tasks Performed with PC** | (2)<br>**Tasks Performed with PC** | (3)<br>**Tasks Performed with PC** | (4)<br>**Tasks Performed with PC** | (5)<br>**Tasks Performed with PC** |
|---|---|---|---|---|---|
| Age 10-14 in 1989 | -0.012 | -0.019 | 0.038 | 0.035 | 0.025 |
| | (0.041) | (0.039) | (0.036) | (0.036) | (0.038) |
| Age 15-19 in 1989 | 0.008 | -0.011 | 0.017 | 0.016 | 0.005 |
| | (0.026) | (0.024) | (0.021) | (0.020) | (0.021) |
| Age 20-24 in 1989 | -0.006 | -0.023 | -0.011 | -0.011 | -0.016 |
| | (0.020) | (0.019) | (0.019) | (0.019) | (0.019) |
| Age 30-34 in 1989 | -0.020 | -0.016 | -0.013 | -0.015 | -0.019 |
| | (0.018) | (0.017) | (0.015) | (0.015) | (0.016) |
| Age 35-39 in 1989 | -0.084*** | -0.098*** | -0.083*** | -0.084*** | -0.091*** |
| | (0.019) | (0.017) | (0.014) | (0.013) | (0.014) |
| Age 40-44 in 1989 | -0.127*** | -0.148*** | -0.147*** | -0.147*** | -0.155*** |
| | (0.023) | (0.019) | (0.018) | (0.017) | (0.019) |
| Age 45-49 in 1989 | -0.233*** | -0.245*** | -0.250*** | -0.248*** | -0.262*** |
| | (0.027) | (0.025) | (0.023) | (0.022) | (0.022) |
| Age 50-54 in 1989 | -0.312*** | -0.304*** | -0.320*** | -0.322*** | -0.331*** |
| | (0.040) | (0.037) | (0.026) | (0.026) | (0.026) |
| Age 55-59 in 1989 | -0.301*** | -0.298*** | -0.317*** | -0.317*** | -0.334*** |
| | (0.041) | (0.040) | (0.040) | (0.040) | (0.038) |
| Age 60-64 in 1989 | -0.484*** | -0.487*** | -0.456*** | -0.455*** | -0.485*** |
| | (0.091) | (0.092) | (0.086) | (0.086) | (0.089) |
| Year FEs | Yes | Yes | Yes | Yes | Yes |
| Gender/Educ. FEs | No | Yes | Yes | Yes | Yes x year |
| Ind./Occ. FEs | Nos | Nos | Yes | Yes | Yes x year |
| State FEs | No | No | No | Yes | Yes x year |
| Obs. | 98,322 | 98,322 | 98,316 | 98,316 | 98,182 |

*Note:* This table reports the regression coefficients for tasks performed with a computer at work. Outcome is an index variable ranging from 1 to 6 with standard deviation 1.55 and mean 2.95. Age 25 in 1989 is the leave out category. Regressions use CPS Computer and Internet Supplement weights. All standard errors clustered at industry level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

Table C.3: Age vs Cohort Horserace for Computer Use At Work

| Indepent Variable | (1) Comp. Use At Work | (2) Comp. Use At Work | (3) Comp. Use At Work | (4) Comp. Use At Work | (5) Comp. Use At Work |
|---|---|---|---|---|---|
| Age 10-14 in 1989 | -0.023* | -0.027** | -0.017** | -0.017** | -0.013 |
| | (0.013) | (0.011) | (0.008) | (0.008) | (0.008) |
| Age 15-19 in 1989 | 0.006 | -0.004 | -0.005 | -0.005 | -0.000 |
| | (0.008) | (0.007) | (0.006) | (0.006) | (0.006) |
| Age 20-24 in 1989 | 0.001 | -0.006 | -0.004 | -0.004 | -0.002 |
| | (0.006) | (0.005) | (0.005) | (0.004) | (0.005) |
| Age 30-34 in 1989 | 0.007 | 0.004 | -0.001 | -0.001 | -0.001 |
| | (0.005) | (0.004) | (0.003) | (0.003) | (0.003) |
| Age 35-39 in 1989 | 0.006 | -0.007 | -0.010* | -0.011* | -0.012** |
| | (0.009) | (0.007) | (0.006) | (0.006) | (0.006) |
| Age 40-44 in 1989 | 0.016 | -0.003 | -0.021*** | -0.021*** | -0.021*** |
| | (0.011) | (0.010) | (0.008) | (0.008) | (0.008) |
| Age 45-49 in 1989 | -0.011 | -0.021 | -0.044*** | -0.044*** | -0.042*** |
| | (0.015) | (0.014) | (0.011) | (0.011) | (0.010) |
| Age 50-54 in 1989 | -0.042*** | -0.043*** | -0.068*** | -0.068*** | -0.066*** |
| | (0.016) | (0.016) | (0.012) | (0.012) | (0.012) |
| Age 55-59 in 1989 | -0.085*** | -0.085*** | -0.114*** | -0.114*** | -0.108*** |
| | (0.020) | (0.019) | (0.015) | (0.015) | (0.015) |
| Age 60-64 in 1989 | -0.112*** | -0.117*** | -0.151*** | -0.151*** | -0.138*** |
| | (0.025) | (0.024) | (0.024) | (0.024) | (0.023) |
| Age 30-34 | 0.011* | 0.008 | 0.002 | 0.002 | 0.003 |
| | (0.006) | (0.006) | (0.004) | (0.004) | (0.004) |
| Age 35-39 | 0.009 | 0.006 | -0.004 | -0.004 | 0.000 |
| | (0.008) | (0.008) | (0.006) | (0.006) | (0.006) |
| Age 40-44 | 0.004 | 0.003 | -0.009 | -0.010 | -0.005 |
| | (0.010) | (0.010) | (0.007) | (0.008) | (0.007) |
| Age 45-49 | 0.009 | 0.006 | -0.007 | -0.007 | -0.003 |
| | (0.012) | (0.012) | (0.009) | (0.010) | (0.009) |
| Age 50-54 | -0.006 | -0.006 | -0.015 | -0.016 | -0.014 |
| | (0.016) | (0.013) | (0.011) | (0.011) | (0.011) |
| Age 55-59 | -0.007 | -0.006 | -0.011 | -0.011 | -0.009 |
| | (0.017) | (0.015) | (0.012) | (0.012) | (0.013) |
| Age 60-64 | -0.044* | -0.043** | -0.028* | -0.028* | -0.029* |
| | (0.022) | (0.020) | (0.015) | (0.016) | (0.016) |
| Year FEs | Yes | Yes | Yes | Yes | Yes |
| Gender/Educ. FEs | No | Yes | Yes | Yes | Yes x year |
| Ind./Occ. FEs | Nos | Nos | Yes | Yes | Yes x year |
| State FEs | No | No | No | Yes | Yes x year |
| Obs. | 225,021 | 225,021 | 225,021 | 225,021 | 225,005 |

*Note:* This table reports the regression coefficients for direct computer use at work. Outcome is an indicator variable with standard deviation .5 and mean .55. Age 25 and Age 25 in 1989 are the leave out categories. Regressions use CPS Computer and Internet Supplement weights. All standard errors clustered at industry level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

Table C.4: Age vs Cohort Horserace for Tasks Performed With Computer

| Indepent Variable | (1) Tasks Performed with PC | (2) Tasks Performed with PC | (3) Tasks Performed with PC | (4) Tasks Performed with PC | (5) Tasks Performed with PC |
|---|---|---|---|---|---|
| Age 10-14 in 1989 | 0.036 | 0.020 | 0.086 | 0.085 | 0.073 |
| | (0.055) | (0.053) | (0.053) | (0.053) | (0.055) |
| Age 15-19 in 1989 | 0.026 | 0.008 | 0.045 | 0.045 | 0.038 |
| | (0.030) | (0.031) | (0.031) | (0.031) | (0.029) |
| Age 20-24 in 1989 | -0.006 | -0.020 | -0.003 | -0.002 | -0.005 |
| | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) |
| Age 30-34 in 1989 | -0.017 | -0.013 | -0.015 | -0.018 | -0.022 |
| | (0.020) | (0.019) | (0.018) | (0.018) | (0.019) |
| Age 35-39 in 1989 | -0.057* | -0.074*** | -0.069** | -0.071*** | -0.080*** |
| | (0.029) | (0.026) | (0.028) | (0.027) | (0.028) |
| Age 40-44 in 1989 | -0.057 | -0.080* | -0.093** | -0.097** | -0.107** |
| | (0.048) | (0.044) | (0.043) | (0.043) | (0.044) |
| Age 45-49 in 1989 | -0.103* | -0.112** | -0.138*** | -0.140*** | -0.158*** |
| | (0.055) | (0.052) | (0.050) | (0.050) | (0.051) |
| Age 50-54 in 1989 | -0.143** | -0.130** | -0.173*** | -0.180*** | -0.192*** |
| | (0.067) | (0.064) | (0.066) | (0.066) | (0.070) |
| Age 55-59 in 1989 | -0.087 | -0.074 | -0.125 | -0.131 | -0.151* |
| | (0.096) | (0.092) | (0.089) | (0.088) | (0.090) |
| Age 60-64 in 1989 | -0.205 | -0.190 | -0.206 | -0.211 | -0.244* |
| | (0.143) | (0.142) | (0.140) | (0.141) | (0.145) |
| Age 30-34 | 0.066** | 0.047* | 0.045* | 0.045* | 0.032 |
| | (0.027) | (0.026) | (0.024) | (0.024) | (0.025) |
| Age 35-39 | 0.085*** | 0.075** | 0.079*** | 0.081*** | 0.075** |
| | (0.032) | (0.031) | (0.030) | (0.030) | (0.031) |
| Age 40-44 | 0.071 | 0.069 | 0.080* | 0.083** | 0.077* |
| | (0.046) | (0.044) | (0.041) | (0.041) | (0.042) |
| Age 45-49 | 0.028 | 0.025 | 0.038 | 0.041 | 0.040 |
| | (0.054) | (0.052) | (0.049) | (0.049) | (0.052) |
| Age 50-54 | -0.011 | -0.014 | 0.009 | 0.013 | 0.009 |
| | (0.072) | (0.069) | (0.066) | (0.066) | (0.066) |
| Age 55-59 | -0.087 | -0.099 | -0.077 | -0.069 | -0.069 |
| | (0.085) | (0.081) | (0.076) | (0.076) | (0.079) |
| Age 60-64 | -0.186* | -0.211** | -0.168* | -0.162* | -0.162 |
| | (0.108) | (0.101) | (0.094) | (0.094) | (0.099) |
| Year FEs | Yes | Yes | Yes | Yes | Yes |
| Gender/Educ. FEs | No | Yes | Yes | Yes | Yes x year |
| Ind./Occ. FEs | Nos | Nos | Yes | Yes | Yes x year |
| State FEs | No | No | No | Yes | Yes x year |
| Obs. | 98,322 | 98,322 | 98,316 | 98,316 | 98,182 |

*Note:* This table reports the regression coefficients for tasks performed with a computer at work. Outcome is an index variable ranging from 1 to 6 with standard deviation 1.55 and mean 2.95. Age 25 and Age 25 in 1989 are the leave out categories. Regressions use CPS Computer and Internet Supplement weights. All standard errors clustered at industry level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

### C.1.2 Additional Results

Figures C.1, C.2, and C.3 provide a further breakdown of the results by educational attainment, gender and survey year. There is little evidence of diverging patterns across education or gender. Furthermore, the relative adoption rates across cohorts appears to be constant across survey years. Thus, adoption rates appear to increase uniformly across groups.

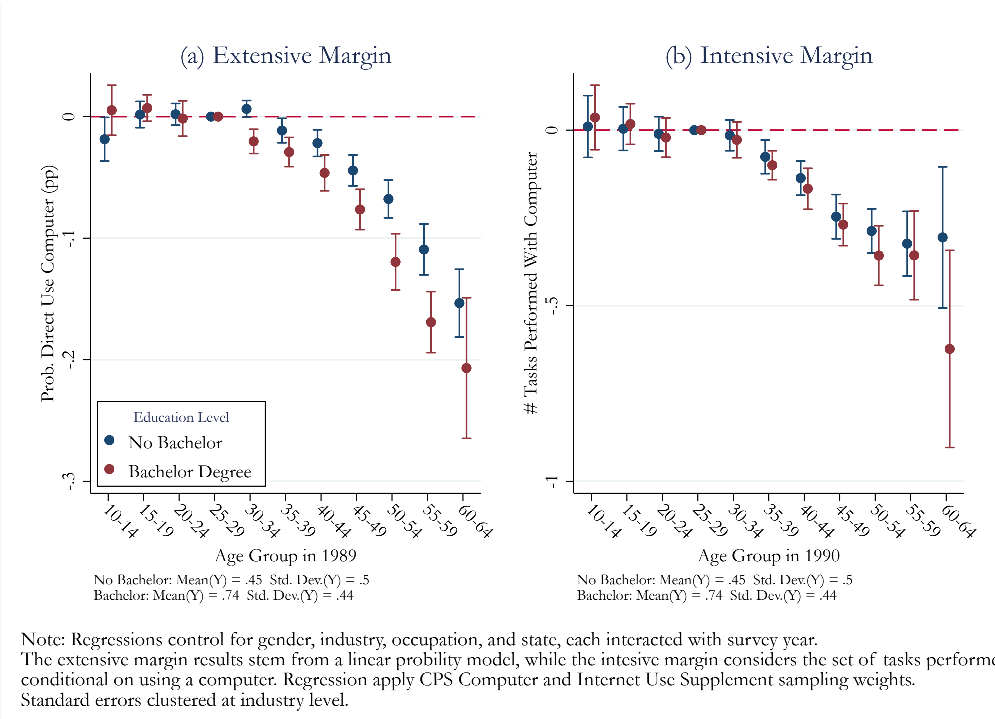



Figure C.1: Computer Use Results By Educational Attainment

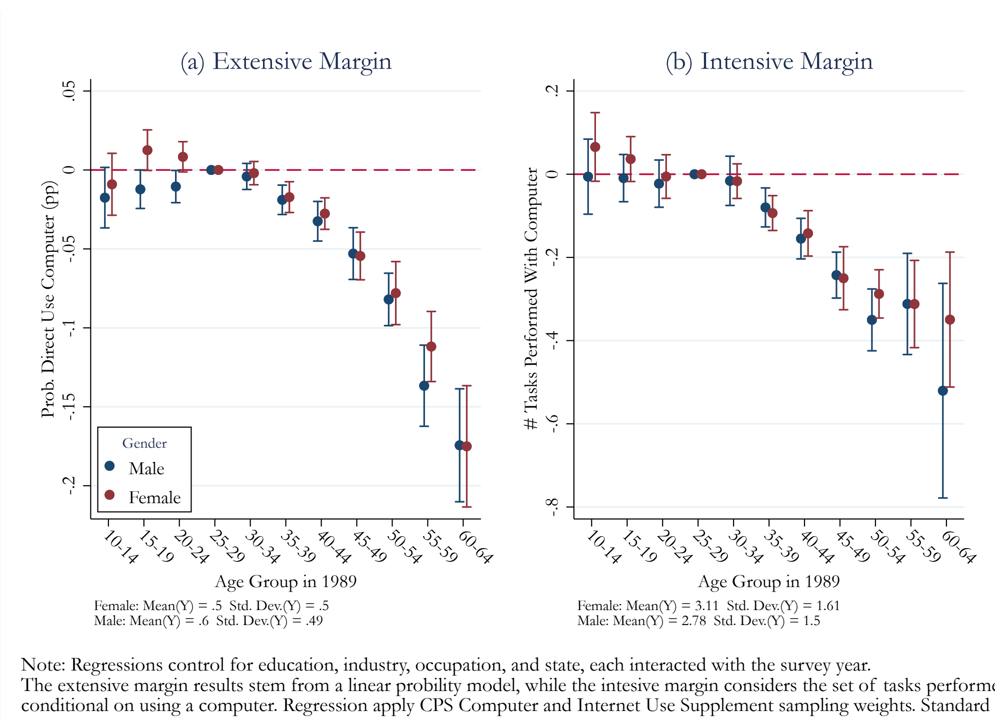
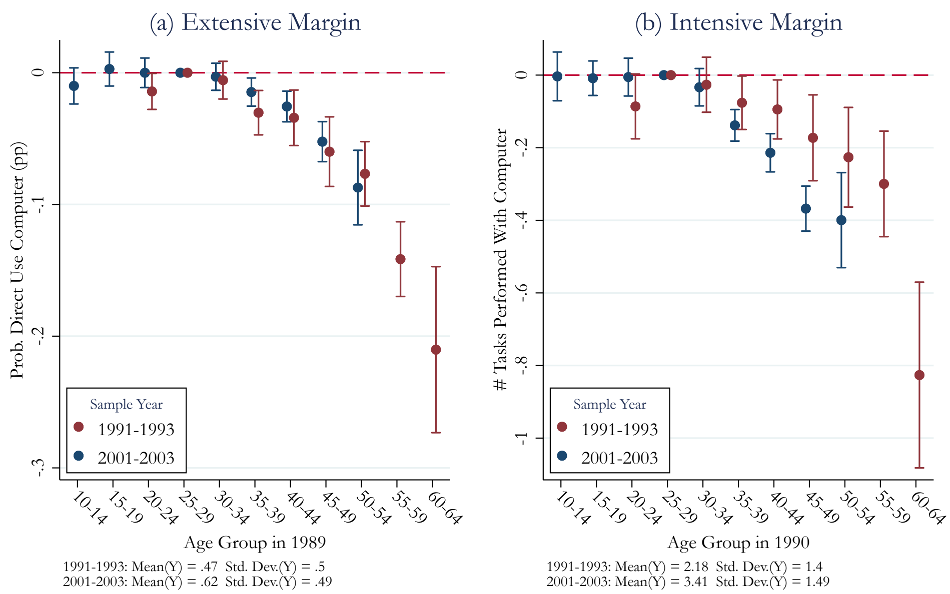



Figure C.2: Computer Use Results By Gender




Note: Regressions control for education, gender, industry, occupation, state and survey year. The extensive margin results stem from a linear probility model, while the intesive margin considers the set of tasks perf conditional on using a computer. Regression apply CPS Computer and Internet Use Supplement sampling weights. Standard e

Figure C.3: Computer Use Results By Survey Year

### C.1.3 Computer Use At Work and Wages

To confirm that both measures of computer use have economic meaning, I regress them on wages reported for the subsample of workers that also was part of the Merged Outgoing Rotations Group. The regression takes the form

$$\ln \text{Hourly Wage}_{it} = \gamma_t + \beta_1 \text{Computer Use}_{it} + \beta_2 \text{Tasks Performed With Computer}_{it} + \delta X_{it} + \varepsilon_{it}. \quad \text{(C.1)}$$

I interpret $\beta_1 > 0$ and $\beta_2 > 0$ as indicators that computer use at work is economically meaningful. I include age fixed effects, occupation, industry, state and time fixed effects in the main regression and investigate interactions with age as well as evolution over time. For the interaction with age I investigate if workers aged 44 and younger have higher associated "wage premia".

The results are reported in Table C.1.3 reports the results. Columns (1) and (2) investigate the relationship between computer use and wages one measure at a time, while column (3) introduces both at the same time. Both coefficients are positive and highly significant, confirming that the measure have independent importance. Column (6) reports the full specification. Using the computer at work is associated with a wage premium of about 4.1%, while each tasks performed with the computer is associated with an additional wage premium of 2%. For comparison, the gender gap and college premium are around 12% conditional on the same set of fixed effects.

Finally, columns (7) and (8) indicate that the wage premium associated with tasks performed is somewhat larger for older workers and that this premium to using a computer is lower in the 2001-2003 period, i.e. declining over time.

Table C.5: Regression Results for Hourly Wage

| Indepent Variable | (1) Hourly Wage (log) | (2) Hourly Wage (log) | (3) Hourly Wage (log) | (4) Hourly Wage (log) | (5) Hourly Wage (log) | (6) Hourly Wage (log) | (7) Hourly Wage (log) | (8) Hourly Wage (log) |
|---|---|---|---|---|---|---|---|---|
| Computer Use | 0.185*** | | 0.094*** | 0.122*** | 0.037*** | 0.041*** | 0.030** | 0.060*** |
| | (0.029) | | (0.035) | (0.024) | (0.009) | (0.009) | (0.014) | (0.014) |
| Tasks Performed With Computer | | 0.061*** | 0.041*** | 0.028*** | 0.021*** | 0.020*** | 0.029*** | 0.018*** |
| | | (0.009) | (0.010) | (0.010) | (0.003) | (0.003) | (0.004) | (0.005) |
| Computer Use # Young | | | | | | | 0.016 | |
| | | | | | | | (0.016) | |
| Tasks Performed With Computer # Young | | | | | | | -0.013*** | |
| | | | | | | | (0.005) | |
| Computer Use # 2001-03 | | | | | | | | -0.033* |
| | | | | | | | | (0.017) |
| Tasks Performed With Computer # 2001-03 | | | | | | | | 0.005 |
| | | | | | | | | (0.005) |
| Year FEs | year | year | year | year | year | year | year | year |
| Age FEs | yes | yes | yes | yes | yes | yes | yes | yes |
| Edu./Gender FEs | no | no | no | yes | yes | yes | yes | yes |
| Ind./Occ. FEs | no | no | no | no | yes | yes | yes | yes |
| State FEs | no | no | no | no | no | yes | yes | yes |
| Observations | 27,674 | 27,674 | 27,674 | 27,674 | 27,668 | 27,668 | 27,668 | 27,668 |

*Note:* Standard errors in parenthesis. All standard errors clustered at occupation level. Weighted-regression using CPS Computer and Internet Use Supplement weights. Hourly wages are obtained from the Merged Outgoing Rotation Group.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.
Table generated on 9 Dec 2019.

## C.2 Local Investment and R&D Expenditures

### C.2.1 Aging Geographies

Figure C.4: Change in WYS vs Predicted WYS

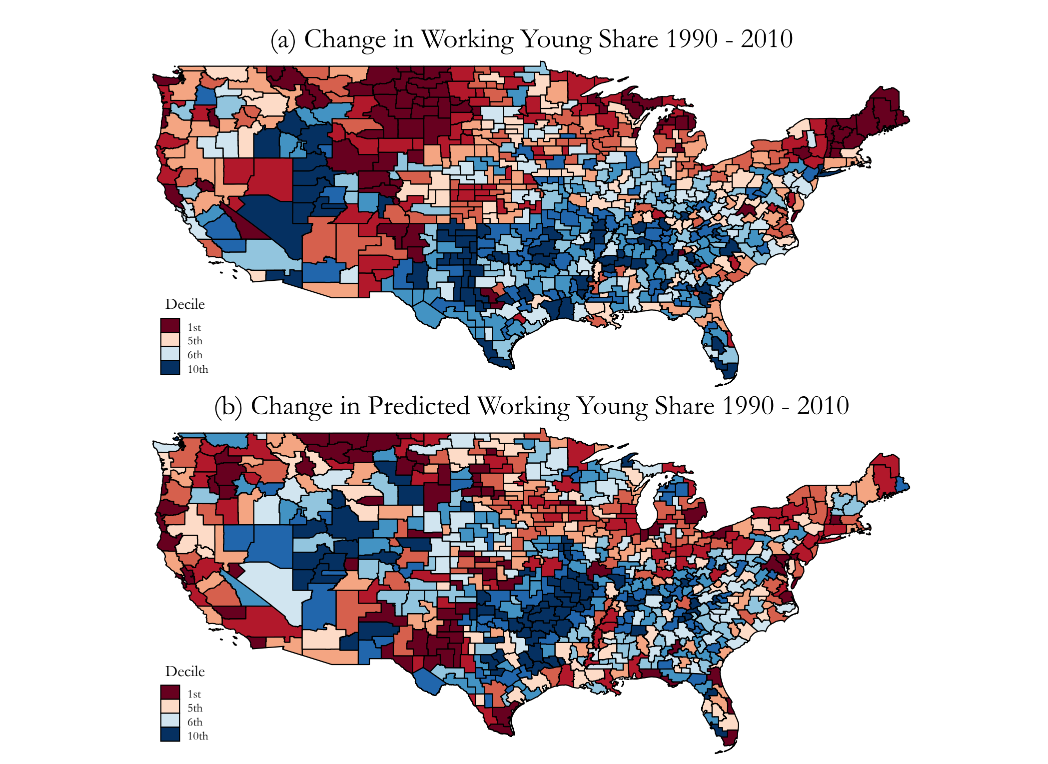



Table C.6: Top and Bottom 5 Commuting Zones by Changes in the Working Young Share from 1990 to 2010

| Rank | CZ FIPS Code | Included Geographies | Change in WYS (pp) | Predicted Change (pp) |
|---|---|---|---|---|
| 1 | 36000 | Provo-Orem, Utah | - 3.07 | 0.06 |
| 2 | 31503 | Laredo, TX | -4.73 | -18.1 |
| 3 | 05402 | Glasgow City, KY | -5.11 | -8.35 |
| 4 | 32403 | Snyder City, TX | -5.46 | - 19.85 |
| 5 | 32402 | Abilene, TX | -5.46 | -13.56 |
| 718 | 20402 | Nantucket County, MA | -27.40 | -6.84 |
| 719 | 20403 | Dukes County, MA | -27.40 | - 3.34 |
| 720 | 36401 | Craig City, CO | -26.65 | -8.40 |
| 721 | 34602 | Carbon County, WY | -23.28 | - 9.86 |
| 722 | 26402 | Fallon County, MT | -22.37 | -24.76 |

Table C.7: Top and Bottom 5 Commuting Zones by Predicted Changes in the Working Young Share from 1990 to 2010

| Rank | CZ FIPS Code | Included Geographies | Change in WYS (pp) | Predicted Change (pp) |
|---|---|---|---|---|
| 1 | 30000 | Russellville City, AR | -12.67 | 11.19 |
| 2 | 39301 | San Juan County, WA | -20.92 | 9.54 |
| 3 | 25104 | Heber Springs City, AR | -14.13 | 8.85 |
| 4 | 34002 | Idabel City, OK | -10.36 | 8.46 |
| 5 | 30501 | Woodward city, OK | -9.90 | 8.13 |
| 718 | 31401 | Odessa City, TX | -13.70 | -32.30 |
| 719 | 37902 | Mineral County, NV | -17.28 | -32.70 |
| 720 | 30701 | Roswell city, NM | -10.19 | -33.70 |
| 721 | 36901 | Brookings city, OR | -17.73 | -36.70 |
| 722 | 38501 | Moses Lake city, WA | -13.62 | -37.40 |

### C.2.2 Computer Investments by Firms

Table C.8: Computer Adoption by Firms: Weighting Robustness

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Second Stage** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** |
| | OLS | IV | OLS | IV | OLS | IV |
| WYS ($\Delta$) | -0.0003 | 0.0360** | 0.0097 | 0.1892*** | 0.0002 | 0.0354** |
| | (0.008) | (0.015) | (0.026) | (0.071) | (0.008) | (0.015) |
| **First Stage** | | **WYS ($\Delta$)** | | **WYS ($\Delta$)** | | **WYS ($\Delta$)** |
| WYS Instr. ($\Delta$) | | 0.2242*** | | 0.2036*** | | 0.2339*** |
| | | (0.028) | | (0.026) | | (0.030) |
| Stand. coeff. | -0.00 | 0.04 | 0.01 | 0.20 | 0.00 | 0.04 |
| F-stat (1st) | | 62.50 | | 61.88 | | 62.34 |
| Year FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| CZ FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| NAICS4 FEs. | Yes | Yes | Yes | Yes | Yes | Yes |
| Weighting | None | None | Employment | Employment | Population | Population |
| Obs. | 132,051 | 132,051 | 132,051 | 132,051 | 132,051 | 132,051 |

*Note:* This table reports the coefficient estimates for the OLS and first and second stage IV regressions of changes in the CZ-level young worker share on log changes in the establishment level computers per employee at the 5-year horizon. Odd columns present OLS results, while even columns present the coefficients for the instrumental variable specification. The top panel reports the second stage or OLS results and the bottom panel first stage resuts. The reported F-statistics is the Sanderson-Windmeijer multivariate F-test of excluded instruments. WYS refers to the working young share, which is defined as the share of age 25-44 among the age 25-64 population. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

Table C.9: Computer Adoption by Firms: Sample Robustness

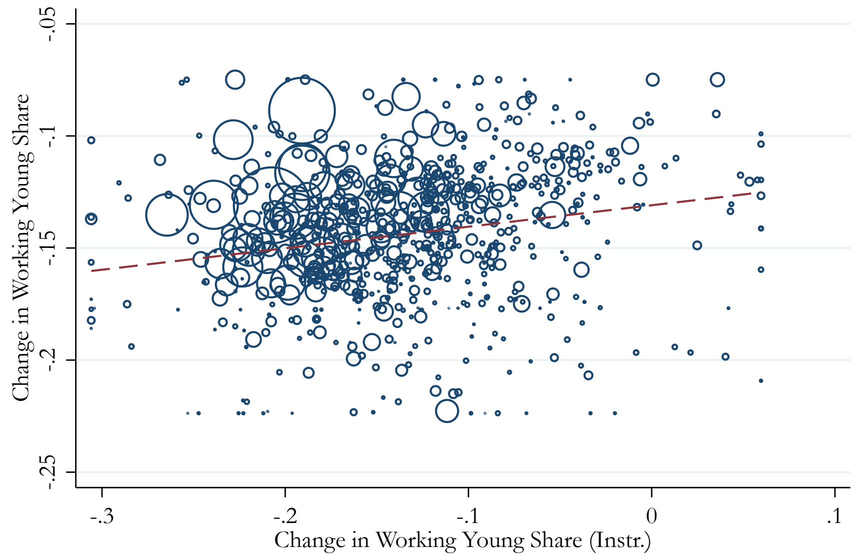
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Second Stage** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** | **Comp. per Emp. ($\Delta ln$)** |
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| WYS ($\Delta$) | -0.0003 | 0.0360** | -0.0005 | 0.0345* | -0.0098 | 0.0067 | -0.0132 | 0.0037 |
| | (0.008) | (0.015) | (0.008) | (0.019) | (0.013) | (0.024) | (0.013) | (0.026) |
| **First Stage** | | **WYS ($\Delta$)** | | **WYS ($\Delta$)** | | **WYS ($\Delta$)** | | **WYS ($\Delta$)** |
| WYS Instr. ($\Delta$) | | 0.2242*** | | 0.2151*** | | 0.2405*** | | 0.2456*** |
| | | (0.028) | | (0.026) | | (0.033) | | (0.032) |
| Stand. coeff. | -0.00 | 0.04 | -0.00 | 0.04 | -0.01 | 0.01 | -0.01 | 0.00 |
| F-stat (1st) | | 62.50 | | 68.79 | | 51.57 | | 58.18 |
| Year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| CZ FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| NAICS4 FEs. | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sample | Full | Full | Tradables | Tradables | Services | Services | Trade. Services | Trade. Services |
| Obs. | 132,051 | 132,051 | 68,242 | 68,242 | 48,265 | 48,265 | 32,012 | 32,012 |

*Note:* This table reports the coefficient estimates for the OLS and first and second stage IV regressions of changes in the CZ-level young worker share on log changes in the establishment level computers per employee at the 5-year horizon. Odd columns present OLS results, while even columns present the coefficients for the instrumental variable specification. The top panel reports the second stage or OLS results and the bottom panel first stage resuts. The reported F-statistics is the Sanderson-Windmeijer multivariate F-test of excluded instruments. WYS refers to the working young share, which is defined as the share of age 25-44 among the age 25-64 population. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

### C.2.3 Long-Run Changes in R&D Employees

Figure C.5: First Stage and Reduced Form Results for 1990 - 2010 Period




(a) 2SLS first stage regression


(b) OLS reduced form regression

Note: Commuting Zones level change over 1990 to 2010 period. N = 722.

### C.2.4 Changes in the Mean Age As Alternative Measure

Tables C.10 and C.11 replicate the main findings using the average age of the working age population as alternative measure of workforce aging. Compared to the baseline results, the estimated effects in terms of standardized coefficients are slightly larger and, especially for expenditures, somewhat more precisely estimated.

Note also that the IV estimate is significantly larger than the OLS coefficient as in the main text.

Table C.10: Local R&D Employment: Average Age of Working Age Population

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Second Stage** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** | **R&D Empl. Share (Δ)** |
| | OLS | IV | OLS | IV | OLS | IV |
| D.Avg. Age (Instr.) | -0.00132*** | -0.00277 | -0.00064* | -0.01088*** | -0.00216*** | -0.01565*** |
| | (0.000) | (0.002) | (0.000) | (0.002) | (0.001) | (0.003) |
| **First Stage** | | **Mean Age (Δ)** | | **Mean Age (Δ)** | | **Mean Age (Δ)** |
| D.Avg. Age | | 0.08128*** | | 0.11900*** | | 0.23868*** |
| | | (0.016) | | (0.017) | | (0.030) |
| Std. coeff. | -0.09 | -0.19 | -0.04 | -0.73 | -0.15 | -1.05 |
| F-stat (1st) | | 27.00 | | 50.56 | | 63.09 |
| Year FEs | No | No | Yes | Yes | Yes | Yes |
| CZ FEs | No | No | No | No | Yes | Yes |
| Obs. | 1,444 | 1,444 | 1,444 | 1,444 | 1,444 | 1,444 |

*Note:* This table reports the coefficient estimates for the OLS and first and second stage IV regressions of changes in the CZ-level average age among the working age population on the share of workers in R&D employments among Full-Time Full-Year employees, where the working age population is defined as age 25 to 64. Odd columns present OLS results, while even columns present the coefficients for the instrumental variable specification. The top panel reports the second stage or OLS results and the bottom panel first stage resuts. The reported F-statistics is the Sanderson-Windmeijer multivariate F-test of excluded instruments. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.

Table C.11: Local R&D Expenditure: Average Age of Working Age Population

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Second Stage** | **R&D Exp. ($\Delta ln$)** | **R&D Exp. ($\Delta ln$)** | **R&D Exp. ($\Delta ln$)** | **R&D Exp. ($\Delta ln$)** | **R&D Exp. ($\Delta ln$)** | **R&D Exp. ($\Delta ln$)** |
| | OLS | IV | OLS | IV | OLS | IV |
| D.Avg. Age (Instr.) | -0.147*** | 0.136 | -0.094*** | -0.600*** | -0.191*** | -0.582*** |
| | (0.028) | (0.167) | (0.027) | (0.132) | (0.047) | (0.130) |
| **First Stage** | | **Avg. Age (Δ)** | | **Avg. Age (Δ)** | | **Avg. Age (Δ)** |
| D.Avg. Age | | 0.081*** | | 0.119*** | | 0.239*** |
| | | (0.016) | | (0.017) | | (0.030) |
| Std. coeff. | -0.14 | 0.13 | -0.09 | -0.58 | -0.18 | -0.56 |
| F-stat (1st) | | 27.00 | | 50.56 | | 63.09 |
| Year FEs | No | No | Yes | Yes | Yes | Yes |
| CZ FEs | No | No | No | No | Yes | Yes |
| Obs. | 1,444 | 1,444 | 1,444 | 1,444 | 1,444 | 1,444 |

*Note:* This table reports the coefficient estimates for the OLS and first and second stage IV regressions of changes in the CZ-level average age among the working age population on log changes in R&D expenditure as measured by wages for FTFY R&D personnel, where working age is defined as age 25 to 64. Odd columns present OLS results, while even columns present the coefficients for the instrumental variable specification. The top panel reports the second stage or OLS results and the bottom panel first stage resuts. The reported F-statistics is the Sanderson-Windmeijer multivariate F-test of excluded instruments. All standard errors are clustered at the commuting zone level.

Standard Errors in Parenthesis. Significance levels: * 10% , ** 5%, *** 1%.