Innovation in an Aging Economy*

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Abstract

The US and other developed nations have experienced two concurrent phenomena over the previous two decades: Slow productivity growth and rapid workforce aging. In this paper I argue that both phenomena are linked through a demand channel. Following an instrumental variable strategy I provide evidence for a causal link between workforce aging and lower innovation. I then investigate the mechanisms leveraging export data and find that commuting zones exposed to aging international demand reduce their innovation activities. Jointly this evidence suggests that demand for innovation is a key channel linking workforce aging to lower innovation.

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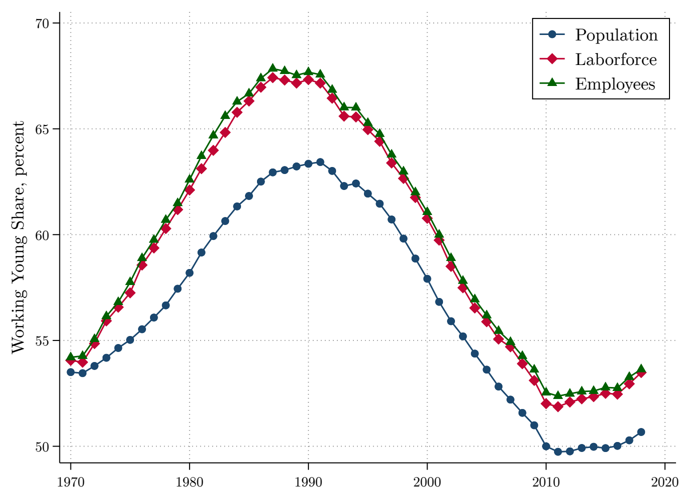
1 Introduction

The US and other developed nations have experienced two concurrent phenomena over the previous two decades: Slow productivity growth and rapid workforce aging. In this paper I argue that both phenomena are linked through a demand channel. In other words, aging economies produce less productivity growth as there is less demand for the associated innovation.

The scale of workforce aging in the US over the previous three decades is noticeable. In Figure 1 I plot the share of people aged 25-44 among those aged 25-64, a measure I will refer to as Working Young Share (WYS), for the US population, labor force, employees. Between 1990 and 2010 the WYS for the US population has decreased from 63% to 50% with similar declines in absolute terms for the labor force and employees, i.e. the US workforce has become significantly older. The UN projects the low WYS to persist in the medium to long-run (United Nations, 2019).

Figure 1: The US workforce aged rapidly since 1990



Note: This figure shows the WYS for the US population, laborforce and employees based on the CPS ASEC samples. The WYS is defined as the share of age 25-44 subjects among those aged 25-64.

At the same time and as documented in Gordon (2016) and Syverson (2017), productivity growth has slowed down considerably over the last two decades, which at times has been linked to a simultaneous decline in business dynamism (Andrews et al., 2016). While there is a growing literature attempting to explain the slow down in productivity growth, few papers have explicitly linked it to demographics and workforce aging in particular (Teulings and Baldwin, 2014).

In this paper, I present empirical evidence that directly links workforce aging to slow productivity growth. Within a local labor market I find that the WYS is significantly associated with a lower share of R&D employment in the workforce and less patenting per capita. To address potential endogeneity issues arising from local shocks driving the WYS and other local outcomes I pursue an instrumental variable strategy that leverages historical birth-rates as exogenous drivers of workforce age composition. The results support a causal link between local workforce aging and innovation.

I further investigate the channel through two complementary approaches. Firstly, I show that the before mentioned link between local workforce aging and R&D employment is at least partly driven by within age-group occupation patterns, which casts doubt on a simple supply side explanation relying on the comparative advantage of younger workers in R&D tasks. Secondly, I provide direct evidence for a demand-side channel by combining data on local industry composition, export destinations, and international workforce aging. I find that local labor markets exposed to workforce aging of its export partners reduce their R&D employment and produce fewer patents per worker. To strengthen the demand interpretation I show that this is not present when considering import partners instead.

Together these results suggest that workforce aging is linked to a decrease in innovation activity at least partly via a demand channel. I argue that these results are qualitatively in line with an endogenous growth model with costly technology adoption and overlapping generations of workers. In the model, older workers are less likely to adopt new technologies as they have less time remaining in the labor market and thus lower benefits from labor productivity enhancing investments. Via a composition effect, this channel suggests that an economy with a lower WYS will have lower average technology adoption rates and thus lower demand for new technologies. This lack of demand resultingly reduces investments in the creation of new technologies and thus productivity growth. As a result, economies with aging workforce are associated with slower economic growth.

I provide two pieces of suggestive evidence in line with this mechanism. Firstly, I show that older workers were indeed slow to adopt the computer during the 1990s.

Secondly, I show that local labor markets with a larger WYS of local workforce or exports experience higher employment and wages, but mostly so for young workers. This finding is in line with the model described above as the new technologies developed in light of a high WYS raise the labor productivity for adopting workers, which tend to be young on average.

This paper contributes to four lines of research. Firstly, I contribute to the growing literature on the recent slowdown in US productivity growth. The existing literature has documented a significant slowdown in productivity growth since at least 2005 together with low investment since around 2000 and explored a range of potential contributing factors.[1] I add to this literature by highlighting the contribution of labor force aging.

Secondly, the paper is closely related to the literature on the macroeconomic impact of aging, which has primarily focused on public finances and aggregate savings with three notable exceptions.[2] Firstly, Aksoy et al. (2019) allow for differential research productivity across age groups in their study on the macroeconomic impacts of aging. Secondly, Feyrer (2007) and Maestas et al. (2016) provide evidence that labor force aging is associated with slower productivity growth at the state level. Finally, Acemoglu and Restrepo (2022) highlight workforce aging as a key contributor to the current wave of automation and automation innovation. I complement this literature by providing direct evidence of a demand effect of workforce aging on innovation and highlighting technology adoption as a potential driving force.

Thirdly, my paper speaks to the growing literature on firm dynamics and demographics by highlight workforce composition as an important force impacting firm creation linked to innovation. Hopenhayn et al. (2018), Karahan et al. (2019) and Peters and Walsh (2021) argue that the declining labor force growth rate, which is tightly linked to workforce aging, has contributed to declining firm dynamism. In a similar line of inquiry, Engbom (2020) argues that age composition shifts contributed to declining job transition rates, unemployment rates, and entrepreneurship. His mechanism relies on older workers being better matched to their current employment

[1] Gordon (2016), Syverson (2017), and Philippon and Gutiérrez (2017) document slow productivity growth and investment. See e.g. Brynjolfsson et al. (2019); Bloom et al. (2020); Akcigit and Ates (2021); Aghion et al. (2022); Liu et al. (2022) for complementary mechanisms explaining these facts.

[2] See the papers in Teulings and Baldwin (2014) and Eggertsson et al. (2019).

and thus less likely to consider outside options such as entrepreneurship. My analysis complements the existing literature by highlight the important of demand instead of supply side factors when considering the impact of workforce aging on economic dynamism as represented by innovation.

Finally, I contribute to the literature connecting age to innovation and entrepreneurship by highlighting the demand-side implication of workforce aging on innovation. The existing literature documents that individual research and entrepreneurship productivity peaks around age 40-50, which would suggest that workforce aging should have a positive contribution to aggregate entrepreneurship and R&D productivity.[3] In contrast, Derrien et al. (2020) find that local labor markets with a higher share of young workers record higher patenting rates. I contribute to the discussion on age and innovation by highlighting labor force composition as a driver of new technology demand instead of focusing supply via the inventor or entrepreneur herself.

The remainder of this paper is structured as follows: Section 2 introduces the data and main empirical specification followed by the results in Section 3. Section 4 discusses technology adoption as a mechanism linking local workforce aging to innovation and Section 5 concludes. Appendix A provides further detail on the data as well as summary statistics. Additional robustness check are reported in Appendix B. Appendix C provides an endogenous growth model with costly technology adoption and overlapping generations that is the basis of the discussion in Section 4, while Appendix D reports evidence on worker age and the adoption of the computer.

2 Data

2.1 Data Sources

My analysis links a range of data sources across time and space to investigate the impact of workforce aging on local innovation. My unit of analysis are 1990 US commuting zones (CZs) for decadal observations from 1980 to 2010 (Tolbert and Sizer, 1996). CZs are consistent geographic areas that are designed to capture a local labor market and are the standard geography considered in the literature on

[3] See Akcigit et al. (2017), Jones (2010), and Jones and Weinberg (2011) for papers on scientific productivity and Azoulay et al. (2020) for entrepreneurship and entrepreneurial success.

local labor markets.[4] Unless otherwise noted, I map geographies to CZs using the crosswalks developed in Autor and Dorn (2013).

I construct employment- and population-based measures using the 1980, 1990, and 2002 decadal Censuses and the 2010-12 3-year ACS from IPUMS (Ruggles et al., 2020). For all employment-based measures I follow the literature in focusing on full-time full-year (FTFY) workers, i.e. those reporting to have worked at least 40 weeks last year with at least 35 hours per week (Acemoglu and Autor, 2011). I measure occupations using the consistent occupational codes developed in Autor and Dorn (2013).

I complement the Census data with data on local patenting from Berkes (2016), which is based on USPTO PatentsView. I map patents to CZ via the inventor's county of residence. For patents with multiple inventors, I split the credit for a patent in equal parts. I construct 5-year forward-citations via the patent citations file and define the technology class of a patent as its primary CPC sub-section. Forward-citations are citations received by a patent. As conventional in the literature, I record patents in the year of the patent application.[5]

I collect data on births by county from 1900 onwards by combining historical censuses, data from the NBER Vitality Statistics, and the Surveillance, Epidemiology, and End Results (SEER) program, and map them to CZs using the crosswalk developed in Eckert et al. (2018) and the crosswalk in Autor and Dorn (2013).[6]

Finally, I obtain local employment by industries using the 2010-12 County Business Pattern and exports by 6-digit NAICS in 2000 from the Census Foreign-Trade Statistics. For each of these data sources, I average values across years to guard against year-to-year fluctuations. I also obtain data on population size by age group by country from the UN database.

2.2 Measuring local innovation activity

I create two measures of local innovation activity that capture innovation inputs and outputs respectively. Using the Census, I proxy for local investments in innovation

[4] See e.g., Autor and Dorn (2013); Autor (2014).

[5] See e.g. Kogan et al. (2017); Terry et al. (2021)

[6] In accordance with the terms of use of the Vital Statistics of the US as digitized by the NBER, I acknowledge indirect financial support from NIA grant P30-AG012810 through the NBER.

using the share of full-time full year (FTFY) workers in R&D occupations in percent. I define the latter to be workers in natural sciences, engineering, social sciences, and computer science.[7] I consider this to be a reasonable proxy for local investment in innovation given that labor constitutes about 66.9% of total R&D cost according to the NSF's Business R&D and Innovation Survey and is thus an integral part of total R&D expenses. I will refer to this variable as R&D employment.

I complement this measure of innovation investments via a measure of realized inventions based on citation-weighted patents. For this I firstly create a citation-based weight for each patent measuring the citations received received relative to an average patent in the last 5 years and same technology class. I then aggregate this measure up to the CZ, splitting weights by inventor when necessary to have a measure of citation-weigthed patents at the CZ for a given year. Finally, I normalize citations-weighted patents by size of the local workforce to get citations-weighted patents per 1000 workers, which is my second innovation measure. The normalization ensures that values are comparable across CZs and follows the literature on local innovation. (Terry et al., 2021)

2.3 Approach

Following the growing literature on local labor markets I investigate this link using a simple first-difference specification for a local labor market g at time t:

$$\Delta Y_{g,t} = \alpha_g + \gamma_t + \Delta X_{g,t} + \varepsilon_{g,t}, \tag{1}$$

where $Y_{g,t}$ and $X_{g,t}$ are measures of innovation and workforce aging respectively and Δ is the 10-year change in the variable.[8] Estimating a difference specification safeguards against permanent differences across CZs driving my results and allows me to flexibly control for CZ-specific trends. In line with existing literature, I weigh observations by the size of the CZ's working age population in 1980.

Throughout I will focus on the WYS as my measure of workforce aging, which

[7] Based on the consistent occupational codes developed in Autor and Dorn (2013), I classify four broad categories of occupations as R&D workers: natural scientists (codes 68-83), social scientists (166-169), computer scientists (64-65, 229-233), and engineers (44-59).

[8] See e.g. Autor and Dorn (2013); Autor et al. (2013); Terry et al. (2021) for papers using similar specifications.

is defined as the ratio of the population age 25-44 to the population age 25-64 for a reference geography. The reference geography will be either the local CZ or the average over foreign nations to which a CZ is exposed via exports. I will discuss the measure and its construction in greater detail together with the associated results.

3 Results

In this section, I present results from three separate strands of investigation. Firstly, I document a link between local workforce aging and innovation. While this is an important first step, it is difficult to distinguish between supply and demand side channels in this context. I address this issues by constructing two measure of workforce aging that are explicitly linked to the demand faced by a CZ by leveraging export exposure. I find a strong relationship between workforce aging of demand and local innovation. A result suggesting that demand-side factors matter for the link between workforce aging and innovation.

3.1 Local Workforce Aging and Innovation

I firstly investigate the importance of local workforce aging within a commuting zone. Let $\texttt{Pop}_{g,a,t}$ be the age a population in CZ g and year t, then the WYS is defined as

$$\texttt{WYS}_{g,t} = \frac{\sum_{a=25}^{44} \texttt{Pop}_{g,a,t}}{\sum_{a=25}^{64} \texttt{Pop}_{g,a,t}} \times 100. \tag{2}$$

Table A.1 reports summary statistics for changes in the local WYS. In line with Figure 1, the WYS has declined on average in my sample by 2.78 percentage points per decade. Notably, this decline has been relatively uniform across CZs. The unconditional standard deviation of changes in the WYS is around 6 percentage points, while it is only 1.7 percentage points once we take out year fixed effects. This difference will become important when interpreting the results.

A natural concern with estimating (1) in this context is reverse causality due to short-term shocks to local activity. For example, innovation might be positively correlated with other measures of labor market opportunities, which in turn could disproportionately attract young, more mobile workers. On the other hand, it could be the case that environments with a lot of innovation have high cost of housing, which might make them less attractive to young workers. It is thus not entirely clear ex-ante in which direction the bias would go.

To solve this problem I will rely on an instrumental variable strategy leveraging historical births following a growing literature on demographics and macroeconomics.[9] In particular, I define a hypothetical population $\widehat{\texttt{Pop}}_{g,a,t}$ as the share of total births in CZ g at time $t-a$ times the total US population of age a at time t:

$$\widehat{\texttt{Pop}}_{g,a,t} = \frac{\texttt{Births}_{g,t-a}}{\sum_g \texttt{Births}_{g,t-a}} \times \left(\sum_g \texttt{Pop}_{g,a,t} \right). \tag{3}$$

From this measure I then construct the hypothetical WYS using equation (2). The resulting hypothetical working young share relies on variation in historical birth rates and thus isolates a demographic component of the WYS. One way to think about this is as if people never moved and were subject to identical mortality risks across CZs. By construction, the instrument is not related to other contemporaneous economic fluctuations that are not driven by the WYS itself.

Identification Assumption (Local WYS)**.** *Conditional on year and CZ fixed effects, changes in the local WYS instrument are only linked to innovation via the local WYS.*

Note that the instrument directly addresses the concern of differential worker mobility towards opportunities or properties of innovation environments that differentially affect young workers. The instrument does not address concerns that link birth rates to other characteristic of the CZ. For example, if there are differences in fertility rates across educational and ethnic groups, then this would be picked up by the instrument. I will later investigate this concern directly in a “bad control” exercise inspired by Angrist and Pischke (2009).

Table 1 reports the first stage results. Column (1), which controls for a range of initial conditions, finds a strong relationship between the instrument and the WYS. A one percentage point increase in the hypothetical working young share is associated with an 0.78 percentage point increase in the actual WYS. This is not particularly surprising as the aggregate WYS and hypothetical WYS coincide by construction.

[9]See e.g. Engbom (2020); Acemoglu and Restrepo (2022); Shimer (2001); Karahan et al. (2019); Derrien et al. (2020)

Table 1: Predicting the WYS from Births

	(1)	(2)	(3)
		$\Delta\texttt{WYS}$	
$\Delta\widehat{\texttt{WYS}}$	0.771***	0.168***	0.213***
	(0.022)	(0.032)	(0.035)
F statistic	552	42.5	37.2
Initial conditions	✓	✓	
CZ FE			✓
Year FE		✓	✓
Observations	2,166	2,166	2,166

Note: Inital conditions include the college, non-white, working young, and female share of the population as well as the metropolitan share and working age population size in 1980. CZ observations weighted by 1980 working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Once we control for year fixed effects in column (2), the coefficient drops significantly, but remains statistically and economically highly significant. Adding CZ fixed effects in column (3) does not materially affect the regression coefficient. The final first stage is strong with an F statistic around 31 and a 1 percent increase in the hypothetical WYS is linked to a 0.2 percentage points increase in the actual WYS.

With a strong instrument at hand we can then investigate the effect of local workforce aging on local R&D employment and patenting, which are reported in Table 2. Panel A reports the results for R&D employment. Controlling only for initial conditions in columns (1) and (2), we find a significant correlation between the WYS and R&D employment. A one percentage point increase in the WYS is associated with a 0.04 and 0.03 percentage point increase in the R&D employment share for the OLS and IV specification respectively. These results diverge once we add year and commuting zone fixed effects in column (3)-(4) and (5)-(6) respectively. While OLS results half in magnitude and become insignificant, IV results increase substantially. The IV coefficient from the full specification suggests that a one percentage point increase in the local WYS leads to a 0.19 percentage point increase in local R&D employment, equivalent to c. 0.25 standard deviations. The results for local

Table 2: Local Workforce Aging and Innovation

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
A. Employment	**Δ R&D employment**					
ΔWYS	0.038***	0.033***	0.021	0.153***	0.023	0.170***
	(0.005)	(0.007)	(0.018)	(0.052)	(0.022)	(0.040)
B. Patenting	**Δ Citation-weighted patents**					
ΔWYS	0.037***	0.033***	0.019*	0.078**	0.023	0.092**
	(0.003)	(0.004)	(0.011)	(0.035)	(0.014)	(0.036)
F statistic		1,275		27.4		37.2
Initial conditions	✓	✓	✓	✓		
CZ FE					✓	✓
Year FE			✓	✓	✓	✓
Observations	2,166	2,166	2,166	2,166	2,166	2,166

Note: Inital conditions include the college, non-white, working young, and female share of the population as well as the metropolitan share and working age population size in 1980. First stage F statistics reported. CZ observations weighted by 1980 working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

patenting, as presented in Panel B, mirror those for local employment. In the full specification in (6), a one percentage point increase in the WYS leads to 0.1 more citation weighted-patents per 1000 workers or 0.2 standard deviations.

Naturally, the question arises as to which channel is driving the results. One possibility is that young workers are more likely to be employed in R&D occupations and, thus, a positive relationship arises mechanically. This could be the case, for example, if younger workers have a comparative advantage in R&D occupations. On the other hand, young workers might have a higher demand for new technologies giving local firms and incentive to develop them. One channel giving rise to such a phenomenon is technology adoption, which I discuss in greater detail in Section 4 and the Appendix. Thus, from a theoretical perspective, young workers could create both supply and demand for new technologies, which renders the interpretation of local workforce aging results ambiguous.

One immediate concern that we can address directly in this specification is the mechanical relationship between workforce age and R&D employment. For this I con-

Table 3: Local Workforce Aging and Innovation — Composition-adjusted Results

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
	Δ R&D employment at 1980 age distribution					
ΔWYS	0.299***	0.268***	0.103*	0.614***	0.097	0.673***
	(0.012)	(0.013)	(0.055)	(0.124)	(0.065)	(0.144)
F statistic		1,275		27.4		37.2
Initial conditions	✓	✓	✓	✓		
CZ FE					✓	✓
Year FE			✓	✓	✓	✓
Observations	2,166	2,166	2,166	2,166	2,166	2,166

Note: Inital conditions include the college, non-white, working young, and female share of the population as well as the metropolitan share and working age population size in 1980. First stage F statistics reported. CZ observations weighted by 1980 working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

struct an alternative measure of R&D employment that first calculates employment rates within-age groups and then uses the local age composition in 1980 to aggregate them up to the CZ level. This alternative measure thus exclusively captures the evolution of local R&D employment within age groups.

As Table 3 reports, these within age group changes in R&D employment turn out to be more sensitive to changes in the WYS, while we would have expected a 0 effect across specifications if the effect was purely mechanical. We can thus conclude that the causal link between local workforce aging and innovation is not driven exclusively by a mechanical link between age and employment in R&D occupations. One way to understand the differences in magnitude between both measures is that older workers are actually more likely to work in R&D occupations, i.e. the mechanical effect works against finding a positive coefficient in my baseline specification. Mechanically, this implies that the within group changes documented in Table 3 need to be larger than the overall employment changes in 2. This result suggests that demand factors as a potential driver, which I will investigate next.

Overall, the difference between the OLS results and IV results for the local WYS in Tables 2 and 3 is quite striking. A possibility is that these results are driven by reserve causality via a cost of living channel as suggested earlier. In general, the stark difference between OLS and IV is something also observed in Shimer (2001) and Engbom (2020), who use similar instruments, and, thus, this issue is known to the literature.

3.2 Workforce Aging of Demand and Innovation

The demand for new technologies is likely to extend beyond the local labor market. Many product inventions aim for a (inter)national market and even process innovations are likely shared across plants for multi-plant firms and across firms via technology transfers. Thus, we need a wider definition of a market rather than a local commuting zone. Optimally, I would like to construct the WYS of the market that firms in a CZ face, however, this data is not directly available. Instead I will focus on international demand via exports as a source of variation in the WYS driving local innovation decisions. While direct commuting zone export data is not available, once can construct a proxy for workforce aging of international demand via industry-level exports and local industry employment. Let $\mathtt{WYS}_{c,t}$ be the WYS in country c and $\mathtt{Emp}_{g,i}$ be the employment of industry i in CZ g as measured in the County Business Patterns, then I calculate the industry level exposure as

$$\mathtt{WYS}_{i,t}^{Trade,Ind} = \sum_{c} \left(\frac{\mathtt{Exports}_{c,i}}{\sum_j \mathtt{Exports}_{c,j}} \right) \times \mathtt{WYS}_{c,t}. \tag{4}$$

I then map the industry-level measure back to the CZ using employment weights:

$$\mathtt{WYS}_{g,t}^{Trade} = \sum_{i} \left(\frac{\mathtt{Emp}_{g,i}}{\sum_{j \neq i} \mathtt{Emp}_{g,j}} \right) \times \mathtt{WYS}_{i,t}^{Trade,Ind}. \tag{5}$$

We can interpret the resulting regression as a reduced form for estimating the effect of workforce aging of international demand on local innovation. Variation in the resulting proxy comes from the fact that US industries are differentially exposed to other countries' workforce aging and that CZ are in turn differentially exposed to US industries.

Identification Assumption (International demand)**.** *Changes in the WYS across countries and as mapped to CZ via industry export and the CZ employment composition only affect a CZ due to changes in the foreign WYS itself.*

In particular, I want to rule out that changes in the international WYS reflect other demand shocks that have an independent effect on innovation. Given that the WYS is defined at the national level, it appears unlikely that demand shocks simultaneously drive demand and the WYS. Thus, while confounding demand shocks might be a larger concern at a local level, they are not at a national level. On the other hand, one might be concerned that there are other channels at play that simultaneously influence US innovation and the WYS. For example, young countries tend to be poorer and less developed giving them overall lower demand for US innovation. Note, however, that I am focusing on changes in the WYS, which ignores level differences. Finally, by construction I am ruling out any dynamic effects of exports and employment composition by fixing them over time.

One possibiliy that I cannot entirely rule out is that the WYS itself is linked to international demand via an independent channel. For example, it might be the case that younger workers have a higher likelihood of engaging in international trade, e.g. due to lower language barriers. In this case, a larger international WYS is directly linked to larger demand in general and not to innovation specific demand. I am not aware of any specific evidence on a similar channel in the trade literature and, thus, do not consider this to be a particular likely threat.

Table 4 confirms a strong link between workforce aging of international demand and innovation. Results are relatively stable across columns and I thus focus on the most conservative specification in column (3) in my discussion. A one percentage point increase in the WYS of international demand is linked to a 0.1 percentage point higher R&D employment rate and 0.11 more forward-citations per 1000 workers.

3.3 Discussion and Robustness

My results show a strong relationship between innovation and the WYS based on local workers and international trade. When faced with an aging demand, CZs invest less in innovation and produce less of it. This is an important insight given the rapid workforce aging observed for developed nations and the US in particular. A couple of observations deserve further discussion, though.

Table 4: Workforce Aging for Trading Parters and Innovation

	(1)	(2)	(3)
A. Employment	**Δ R&D employment**		
$\Delta \texttt{WYS}^{Trade}$	0.087***	0.070**	0.100***
	(0.010)	(0.035)	(0.034)
B. Patenting	**Δ Citation-weighted patents**		
$\Delta \texttt{WYS}^{Trade}$	0.083***	0.092***	0.118***
	(0.005)	(0.011)	(0.015)
Initial conditions	✓	✓	
CZ FE			✓
Year FE		✓	✓
Observations	2,166	2,166	2,166

Note: Inital conditions include the college, non-white, working young, and female share of the population as well as the metropolitan share and working age population size in 1980. CZ observations weighted by 1980 working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

General equilibrium effects. For the local WYS we observe that adding year fixed effects raises the estimated coefficients significantly. One interpretation of this is that the first column incorporates general equilibrium effects or other aggregate shocks, while specifications with year fixed effects don't. Mechanically, we observe large changes in the WYS across all CZs over time, while change in innovation are not as pronounced. Taking out year fixed effects allows the model to abstract from these baseline macro facts and focus primarily on local variation. This raises the question of why this local variation is so much more potent. A natural explanation is reallocation. The partial equilibrium response could potentially capture reallocation across CZs and industries towards those with high technology demand as induced by the WYS, while abandoning CZs and industries with relative low WYS. This interpretation implies that simple calculation using the most stringent coefficients times the overall decline in the aggregate WYS could lead to misleading results. Alternative consideration such as aggregate crowding out and changes in relative prices would lead to similar conclusions. Nonetheless, the coefficients still imply an important and prominent role for the WYS.

Demand or trade linkages. It is natural to ask what happens if I use measures of imports instead of exports. One concern might be that the regressions reflect some broader spillovers along the supply chain that is not necessarily linked to demand. Table B.4 reports the international trade results using imports instead of exports. The full specification now has a precisely estimated zero for employment and a significant negative coefficient for patenting. This highlights that my results are specific to exports, in line with the demand interpretation.

Age-composition vs population growth. Another issue of interpretation is the disentanglement of age composition and population growth, which are mechanically linked. To see this, suppose that there are only two generations alive at each point in time: young and old. Old workers leave the economy at the end of each period, while fraction $1-p$ young workers survive and become old. The size of the young generation grows at rate n. It is straight-forward to verify in this context that the overall population grows at rate n as well, while the WYS is given by

$$\texttt{WYS} = \frac{1+n}{2+n-p}.$$

It follows immediately that population growth and WYS are mechanically linked in the long-run. Furthermore, one can show that short-run fluctuation in p also link to short-run fluctuations in population growth. Thus, it is difficult to distinguish effects of the WYS and population growth separately.

That being said, I try to address this issue by controlling for the growth rate of the population within the young generation for this purpose I define

$$\texttt{Pop Gr}_{g,t} = \left(\left(\frac{\sum_{a=25}^{34} \texttt{Pop}_{g,a,t}}{\sum_{a=35}^{44} \texttt{Pop}_{g,a,t}} \right)^{\frac{1}{10}} - 1 \right) \times 100. \tag{6}$$

I construct an instrument for this variable using the same approach as for the WYS:

$$\widehat{\texttt{Pop Gr}}_{g,t} = \left(\left(\frac{\sum_{a=25}^{34} \widehat{\texttt{Pop}}_{g,a,t}}{\sum_{a=35}^{44} \widehat{\texttt{Pop}}_{g,a,t}} \right)^{\frac{1}{10}} - 1 \right) \times 100. \tag{7}$$

For the international demand, I use the same mapping as for the WYS to calculate the commuting zone level variable:

$$\texttt{Pop Gr}_{g,t}^{Trade} = \sum_i \left(\frac{\texttt{Emp}_{g,i}}{\sum_{j \neq i} \texttt{Emp}_{g,j}} \right) \times \sum_c \left(\frac{\texttt{Exports}_{c,i}}{\sum_j \texttt{Exports}_{c,j}} \right) \times \texttt{Pop Gr}_{c,t}. \tag{8}$$

Table 5 reports the results for local WYS. As with the WYS, the instrument is strong with an F statistic above 20 in the full specification, while the F statistic is above 50 for the WYS. Population growth itself has a positive impact on innovation as measured by R&D employment and patenting as documented in column (4). Importantly, the coefficients on the WYS are stable and significant when including population growth in the specification. The effect of the local WYS on innovation thus appears to be distinct from pure population growth.

Table 5: Workforce Aging vs Population Growth

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
A. Employment			**Δ R&D employment**			
Δ`WYS`	0.023	0.170***			0.008	0.166***
	(0.022)	(0.040)			(0.023)	(0.037)
Δ`Pop gr`			0.142***	0.239***	0.140***	0.133**
			(0.026)	(0.073)	(0.027)	(0.061)
B. Patenting			**Δ Citation-weighted patents**			
Δ`WYS`	0.023	0.092**			0.018	0.089**
	(0.014)	(0.036)			(0.016)	(0.033)
Δ`Pop gr`			0.051**	0.152*	0.046**	0.095
			(0.020)	(0.089)	(0.022)	(0.074)
F stat. Δ WYS		37.2				55.2
F stat. Δ Pop. gr.				40.1		23.6
Observations	2,166	2,166	2,166	2,166	2,166	2,166

Note: All regressions control for CZ and year fixed effects. CZ observations weighted by 1980 working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

I reach a similar conclusion when looking at the WYS of international demand. Appendix Table B.1 shows that the coefficient on $\texttt{WYS}^{Trade}$ is stable when controlling for population growth.

Bad control. One concern with the instrumental variable strategy is that the instrument be reasonably constructed yet unluckily reflect other drivers that are associated with birth rates and have a separate effect on innovation. I investigate this in a bad control exercise, where I first estimate the first stage and then use the predicted values in combination with other covariates to investigate the robustness of my estimates. A stable coefficient on the WYS should strengthen our confidence in the estimate (Angrist and Pischke, 2009).

$$\Delta Y_{g,t} = \alpha_g + \gamma_t + \beta \mathtt{WYS}^{Pred}_{gt} + \delta \Delta X_{g,t} + \varepsilon_{g,t} \tag{9}$$

I consider three confounders: gender, ethnic, and educational composition. Appendix Table B.3 confirms that neither the share of women, non-whites, or workers with bachelor degree explain the relationship between the WYS and innovation. The coefficient remains virtually unchanged when adding all three variables.

Additional robustness checks. I conduct a range of additional robustness checks and report them in Appendix B. Firstly, I verify that my results are not driven by geographically correlated shocks by adding year×state fixed effects to the full specification. Appendix Table B.5 confirms that results for all three level of aggregation go through in this very stringent specification. Secondly, I report my main results unweighted and weighted by the beginning of period population in Appendix Tables B.6 and B.7. The results are practically unaffected for the local WYS, while they are smaller in magnitude, but still significant, in the unweighted specifications for export demand. Thus, the qualitative conclusion is unaffected by weighting. Finally, Appendix Table B.2 reports results for alternative patenting measures and confirms that my baseline choice is not driving the result. The only exception is raw patenting for the local WYS, which is positive, but insignificant.

4 Technology Adoption As a Potential Driver

A natural question at this point is how to think about a demand channel linking innovation and workforce aging. Existing theory and evidence linking aging and innovation mostly focus on supply side mechanisms. For example, Engbom (2020) posits that an older workforce will be less willing to switch jobs on average due to better matching between employees and employers. This makes it harder for innovative startups to hire workers and thus reduces growth. Similarly, Derrien et al. (2020), Jones (2010); Jones and Weinberg (2011) and Azoulay et al. (2020) investigate whether young workers have a comparative advantage in innovation and entrepreneurship.

The most prominent exception to this focus on supply side drivers is Acemoglu and Restrepo (2022), who argue that an aging population induces more automation-related innovation as automation is a substitute for young workers. In their model, production can either be done with young workers or with capital, while older generations work in managerial tasks. A reduction in young workers makes production inputs scarce and thus raises the return to automation. As noted by the authors themselves, however, the rise in automation is accompanied by a reduction in human centered innovation leading the implications for overall innovation ambiguous. This theory thus cannot directly explain the evidence presented above.

In Appendix C I propose an alternative theory that can qualitatively explain my findings. The theory argues that older workers will be less inclined to adopt new technologies as they have less time remaining in the labor market and, thus, less to gain. As a result, an economy with an older workforce will have a lower demand for new technologies and thus lower profits for firms creating them. Linking new technologies to innovation completes the link between workforce aging and innovation and leads to the prediction that workforce aging should lead to a decline in innovation due to a market size effect.

Appendix D presents some direct evidence on the link between technology adoption and age. In line with the predictions of the model described above, older workers adopted the computer in the workplace at lower rates at the dawn of the computer age. Furthermore, age differences dissipated over time as the computer became an old technology. This suggests that technology adoption could indeed be an empirically relevant channel linking workforce aging and innovation.

Here, I want to present some additional suggestive evidence focusing on the impact of the WYS on wages and employment across age groups. For this, I construct wages and employment at the CZ level for all workers as well as for young and old workers separately, where I define the latter as age 25-44 and age 45-64 respectively. I then explore the impact of changes in the WYS on changes in log employment and wages using the same estimation equation as for R&D employment.

As documented in Table 6, the local WYS is directly linked to increasing employment, but only for young workers. Furthermore, while the WYS is linked to higher wages in general, it is especially so for young workers. This finding is at odds with a simply supply side interpretation as the results would suggest that an exogenous increase in the supply of younger workers is linked higher wages, while standard supply and demand arguments would suggest lower wages. On the other hand, this is very much in line with the adoption channel described above: younger workers have a higher demand for new technologies as they adopt them more, which increases their wages. The employment results on the other hand suggest that the new technologies also attract more young workers, potentially due to their comparative advantage in using them.

Table 6: Workforce Aging, Employment, and Wages

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
A. Employment			**Δ Employment**			
Δ`WYS`	0.202***	0.286***	0.337***	0.393***	-0.106*	-0.055
	(0.059)	(0.077)	(0.048)	(0.064)	(0.055)	(0.070)
B. Wages			**Δ Wages**			
Δ`WYS`	0.089***	0.142***	0.118***	0.218***	0.087***	0.085*
	(0.021)	(0.049)	(0.021)	(0.049)	(0.018)	(0.044)
Workers	All	All	Young	Young	Old	Old
CZ FEs	2,166	2,166	2,166	2,166	2,166	2,166

Note: All regressions control for CZ and year fixed effects. CZ observations weighted by 1980 working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Appendix Table B.8 confirms the same pattern for the WYS of international demand. The documented patterns are linked to demand and not supply in line with the interpretation suggested above.

5 Conclusion

Over the last three decades the US has experienced fast workforce aging together with a slowdown in productivity growth. This paper argues that both phenomena are linked through a demand channel. Exploiting variation in the local exposure to workforce aging and following an instrumental variable strategy I show that CZs experiencing faster aging have invested less in R&D and have produced fewer inventions as measured by employment and patenting respectively.

I investigate the channel through which both phenomena are linked via a range of complementary approaches and conclude that demand side factors appear to be important. Firstly, I rule out a purely mechanical effect of workforce aging by holding fixed the age composition in a CZ when calculating R&D employment and confirm that I still find a strong positive link with the WYS. This suggests that comparative advantage channels do not fully explain the main result. Secondly, I directly construct an alternative measure of the WYS based on demand faced by a CZ leveraging local industry composition and export statistics. Aging of international demand as measured via workforce aging by export partners is strongly linked to reduction in local R&D employment and innovation. Together, these results confirm that the demand side of workforce aging is a key channel of the aging to innovation link.

Finally, I propose a theory centered on technology adoption that can rationalize the documented demand side effects. Older workers have lower technology adoption rates due to their limited time remaining in the workforce. Consequently, there will be less demand for new technologies in an aging economy and thus less incentives to innovate. This theory qualitatively explains the documented findings, while most existing theories focus on supply-side explanations that would struggle to fit the evidence.

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Appendix

A Data

A.1 Data construction

Patenting measures. I construct citations weights for a patent as follows the 5-year forward citations divided by the average 5-year forward citations of granted patents with applied for in $t - 4$ to t with the same primary CPC subsection. I split a patent equally if it has multiple inventors and assign each part to the CZ of the inventor. The total citation-weighted patents for a CZ is then simply the sum over the weighs times the splitting factors for all patents applied for in a given year by inventors residing in the CZ. To guard against outliers years I take the average of this measure over the $t - 1$ to $t + 1$ horizon. I normalize this value by the working age population in thousands via the Census.

Missing values. I impute missing values as 0. This applies to results for patenting and international trade based results. Results are robust to instead dropping the respective values.

Instrument. I construct historical births at the county level from three separate sources. Firstly, for the 1901-1939 period I rely on historical full-count census for 1910, 1920, 1930, and 1940.(Ruggles et al., 2020) For each decade I impute annual births using the age 0-9 population. The number of imputed births in a county in 1925 is thus the population born in 1925 as recorded in the 1930 census. Note that this naturally does not account for mortality up to age 5, an issue that I will discuss when detailing the actual construction of the instrument. For the 1940-67 period, I obtain births by county directly from the Vital Statistics of the US as digitized by the NBER. Finally, from 1967 onwards I use the age 0 population recorded in the SEER data as my measure of births.[10] I map historical county-level birth to modern

[10] The digitized Vital Statistics of the US and SEER data are available here and here via the NBER.

CZs using the crosswalks developed in Eckert et al. (2018) and Autor and Dorn (2013).

I complement the data on births with data on the actual population size across age groups for the US from the NBER SEER data. The hypothetical population of age a at time t in CZ g is then the number of births in time $t-a$ divided by the total imputed births for the cohort times the actual population size of age a for the US in the particular year:

$$\widehat{\texttt{Pop}}_{g,a,t} = \frac{\texttt{Births}_{g,t-a}}{\sum_g \texttt{Births}_{g,t-a}} \times \left(\sum_g \texttt{Pop}_{g,a,t} \right). \tag{A.1}$$

By construction, this instrument gets the aggregate evolution of population groups correct, but uses historical births to distribute them across space. I aggregate this hypothetical measure across age groups to obtain the hypthetical WYS using the same formula as for the actual WYS itself:

$$\widehat{\texttt{WYS}}_{g,t} = \frac{\sum_{a=25}^{44} \widehat{\texttt{Pop}}_{g,a,t}}{\sum_{a=25}^{64} \widehat{\texttt{Pop}}_{g,a,t}}. \tag{A.2}$$

A.2 Summary statistics

Table A.1: Summary statistics

Variable	**Mean**	**SD**	**Within-year SD**
Δ R&D emp. (%)	0.492	0.829	0.666
Δ Age-adjusted R&D emp. (%)	-1.153	3.329	1.457
Δ Citation-weighted patents	-0.018	0.528	0.387
Δ Unbiased Citation-weighted patents	-0.040	0.553	0.399
Δ Unadjusted Citation-weighted patents	-0.021	0.569	0.445
Δ Patents	0.043	0.252	0.199
Δ Innovators	0.135	0.374	0.291
$\Delta\mathtt{WYS}$	-2.976	5.912	1.730
$\Delta\widehat{\mathtt{WYS}}$	-3.821	6.802	3.262
$\Delta\mathtt{WYS}^{Trade}$	-1.758	2.695	0.488

Note: R&D employment in percentage points. Patenting values are per 1,000 workers. Final column residualizes variable with respect to year before calculating standard deviation. CZ observations weighted by 1980 working age population. See text for variable description.

B Robustness

Table B.1: Workforce Aging vs Population Growth — Trade

	(1)	(2)	(3)
A. Employment	**Δ R&D employment**		
$\Delta\texttt{WYS}^{Trade}$	0.100***		0.072**
	(0.034)		(0.034)
$\Delta\texttt{Pop gr}^{Trade}$		-0.384***	-0.370***
		(0.060)	(0.059)
B. Patenting	**Δ Citation-weighted patents**		
$\Delta\texttt{WYS}^{Trade}$	0.118***		0.111***
	(0.015)		(0.014)
$\Delta\texttt{Pop gr}^{Trade}$		-0.118***	-0.095**
		(0.041)	(0.040)
Observations	2,166	2,166	2,166

Note: All regressions control for CZ and year fixed effects. CZ observations weighted by 1980 working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Table B.2: Workforce Aging and Innovation — Alternative patenting measures

	(1)	(2)	(3)	(4)	(5)
A. Local			**Δ Innovation measure**		
ΔWYS	0.092**	0.083**	0.098***	0.027	0.057**
	(0.036)	(0.040)	(0.035)	(0.018)	(0.027)
B. Exports			**Δ Innovation measure**		
ΔWYS^{Trade}	0.118***	0.121***	0.129***	0.027***	0.049***
	(0.015)	(0.019)	(0.017)	(0.006)	(0.008)
Innovation measure	Baseline	Unadjusted	Unbiased	Patents	Inventors
Observations	2,166	2,166	2,166	2,166	2,166

Note: Column (1) reports the baseline results for comparison, column (2) uses raw Citation-weighted patents as weights, column (3) only counts citation from non-involved innovators, and column (4) does not ajust for citations at all. Finally, column (5) uses the number of inventors active in a CZ instead of patents. All regressions control for CZ and year fixed effects. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Table B.3: Workforce Aging, Employment, and Wages

	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
A. Employment	**Δ R&D employment**			
$\texttt{WYS}^{Pred}$	0.170***	0.169***	0.177***	0.166***
	(0.038)	(0.037)	(0.034)	(0.036)
Δ Non-white		0.005	0.006	0.008
		(0.010)	(0.011)	(0.010)
Δ Female			-0.124***	-0.074**
			(0.033)	(0.031)
Δ College				0.155***
				(0.028)
B. Patenting	**Δ Citation-weighted patents**			
$\texttt{WYS}^{Pred}$	0.092***	0.091***	0.093***	0.090***
	(0.032)	(0.032)	(0.031)	(0.031)
Δ Non-white		0.003	0.003	0.004
		(0.006)	(0.006)	(0.006)
Δ Female			-0.028	-0.014
			(0.024)	(0.026)
Δ College				0.043**
				(0.016)
Observations	2,166	2,166	2,166	2,166

Note: All regressions control for CZ and year fixed effects. CZ observations weighted by 1980 working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Table B.4: Workforce Aging for Trading Parters and Innovation — Import Robustness

	(1)	(2)	(3)
A. Employment		**Δ R&D employment**	
$\Delta \texttt{WYS}^{Trade}$	0.079***	-0.056*	0.003
	(0.009)	(0.030)	(0.033)
B. Patenting		**Δ Citation-weighted patents**	
$\Delta \texttt{WYS}^{Trade}$	0.073***	-0.063***	-0.081***
	(0.006)	(0.019)	(0.024)
Initial conditions	✓	✓	
CZ FEs			✓
Year FEs		✓	✓
Observations	2,166	2,166	2,166

Note: Inital conditions include the college, non-white, working young, and female share of the population as well as the metropolitan share and working age population size in 1980. CZ observations weighted by 1980 working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Table B.5: Workforce Aging and Innovation — Results with State × Year FEs

	(1)	(2)
A. Employment	**Δ R&D employment**	
$\Delta\texttt{WYS}$	0.396***	
	(0.065)	
$\Delta\texttt{WYS}^{Trade}$		0.101***
		(0.028)
B. Patenting	**Δ Citation-weighted patents**	
$\Delta\texttt{WYS}$	0.163***	
	(0.036)	
$\Delta\texttt{WYS}^{Trade}$		0.077***
		(0.018)
Type		
Observations	2,157	2,157

Note: All regressions control for CZ and state× year fixed effects. CZ observations weighted by 1980 working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Table B.6: Workforce Aging and Innovation — Unweighted results

	(1)	(2)
A. Employment	**Δ R&D employment**	
ΔWYS	0.163***	
	(0.035)	
ΔWYS^{Trade}		0.073***
		(0.014)
B. Patenting	**Δ 5-year Citation-weighted patents**	
ΔWYS	0.076***	
	(0.019)	
ΔWYS^{Trade}		0.043***
		(0.008)
Observations	2,166	2,166

Note: All regressions control for CZ and year fixed effects. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Table B.7: Workforce Aging and Innovation — Alternative weight

	(1)	(2)
A. Employment	**Δ R&D employment**	
$\Delta \texttt{WYS}$	0.160***	
	(0.027)	
$\Delta \texttt{WYS}^{Trade}$		0.098***
		(0.029)
B. Patenting	**Δ Citation-weighted patents**	
$\Delta \texttt{WYS}$	0.076***	
	(0.018)	
$\Delta \texttt{WYS}^{Trade}$		0.117***
		(0.020)
Observations	2,166	2,166

Note: All regressions control for CZ and year fixed effects. Regressions weighted by beginning of period working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Table B.8: Workforce Aging, Employment, and Wages — Trade

	(1)	(2)	(3)
A. Employment		**Δ Employment**	
$\Delta\texttt{WYS}^{Trade}$	0.322***	0.245**	0.028
	(0.092)	(0.092)	(0.088)
B. Wages		**Δ Wages**	
$\Delta\texttt{WYS}^{Trade}$	0.227***	0.275***	0.193***
	(0.047)	(0.047)	(0.043)
Workers	All	Young	Old
CZ FEs	2,166	2,166	2,166

Note: All regressions control for CZ and year fixed effects. CZ observations weighted by 1980 working age population. Standard errors clustered at the state level. See text for variable description.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

C Aging, Technology Adoption, and Growth

This section develops an endogenous growth model that features a direct link between workforce aging and innovation via a demand channel. This feature allows it qualitatively to capture some of the patterns documents in Section 3. The model builds on the standard expanding varieties growth model as in Romer (1990) and extends it in two directions.[11] Firstly, I introduce demographics using a standard overlapping generations structure, and, secondly, technology adoption is made an explicit choice on part of workers.

C.1 Environment

Time is discrete and indexed by t. The economy features four types of agents. Households work, learn about technologies, and face a standard savings-consumption choice. The final goods sector in turn hires workers and buys equipment at competitive prices to produce the final good. Equipment is produced by specialized monopolists using the final good. Finally, new equipment varieties, which I will refer to as new technologies, are produced by an innovation sector, which borrows from households and repays them using profits generated by the associated equipment manufacturers. The final good is chosen as the numeraire.

I will denote the set of available technologies and new inventions as A_t and a_t respectively. The stock of technologies evolves cumulatively by adding new inventions:

$$A_t = a_t + A_{t-1}. \tag{C.1}$$

Households. The representative household maximizes

$$\sum_{s=0}^{\infty} \beta^s (1+n)^s \ln(c_{t+s}), \tag{C.2}$$

where β is the time discount factor, n is the population growth rate, and c_t is per capita consumption.[12]

[11]See Gancia and Zilibotti (2005) for an introduction to expanding variety growth models.

[12]Log utility is chosen to keep the exposition simple and can be replaced by a CRRA utility

The household derives income from interest r_t on savings b_t and wages w_t, and spends it on savings, consumption, and technology adoption h_t. Technology adoption is linked to labor income and will be discussed in detail below. I focus on per capita values throughout to simplify the exposition. The budget constraint is given by

$$(1+n)b_{t+1} = (1+r_t)b_t + w_t - h_t - c_t. \tag{C.3}$$

Savings are restricted to be non-negative, $b_{t+1} \geq 0$.

The household is composed of two generations, young and old. The old generation exits the economy at the end of each period. It is replaced by the current young generation, whereof a share $1-p$ survives across periods. The young generation is replaced by a new young generation whose size grows at rate n. The setup gives rise to a constant share of young workers in the economy, denoted by s_y:

$$s_y = \frac{1+n}{2+n-p} \tag{C.4}$$

The analysis below focuses on comparative statics with respect to the population growth rate n and abstracts from transition dynamics induced by time-varying birth rates. Comparative statics for n are the appropriate analysis when considering the US. As discussed in Engbom (2020) and Karahan et al. (2019), the demographic patterns in Figure 1 are primarily driven by declining fertility rates.

Technology adoption is modeled as a costly, one-off investment on part of the household. Each period the representative household is confronted with the set of available technologies and decides for each worker which additional technologies to adopt. There is no forgetting, so a worker will be able to use a skill for the rest of her life once learned. Furthermore, workers can supply one unit of labor for all technologies in their skill set, so a larger skill set translates into a larger effective labor supply.

For technology $a \in A_t$ let $\ell_t(a)$ be the share of workers in the economy that have adopted the technology and $\ell_{gt}(a)$ be the share of workers of age group g that have adopted the technology. The former is then simply a weighted average of the latter:

function without changing the main results. I will throughout assume $\beta(1+n) < 1$ to ensure effective discounting on part of the household.

$$\ell_t(a) = s_y \ell_{yt}(a) + (1 - s_y)\ell_{ot}(a). \tag{C.5}$$

Labor supply earns technology-specific wage $W_t(a)$. Per capita labor earnings are given by

$$w_t = s_y \int_{A_t} \ell_{yt}(a) W_t(a) da + (1 - s_y) \int_{A_t} \ell_{ot}(a) W_t(a) da \tag{C.6}$$

Knowledge does not come for free, however. All technologies are subject to per worker learning costs, which are i.i.d. distributed across technologies and workers, and constant over time for a particular technology-worker combination. I will denote the distribution by $F(n)$, where n is the cost of adopting a particular technology in terms of final goods. Workers do not differ in their inherent learning ability. Thus, I abstract from any considerations of reduced learning ability over the life-cycle or similar mechanisms.[13]

From the perspective of the household, workers in a given cohort look identical except for the technology adoption costs. Furthermore, I will show below that in equilibrium we will have $W_t(a) = W_t$ such that technologies will look identical from the perspective of a worker apart from their adoption costs. This facilitates the analysis greatly, as we can focus on adoption costs only.

Cohorts enter the economy with a blank slate and, thus, available technologies are indistinguishable to them apart from their adoption costs. We can thus think of the household's optimization problem as choosing a threshold type n_{yt} such that young workers adopt all technologies with cost type $n \leq n_{yt}$. The total adoption costs per young worker h_{yt} and effective labor supply for a technology $\ell_{yt}(a)$ are thus given by

$$h_{yt} = A_t \int_0^{n_{yt}} n dF(n) \quad \text{and} \quad \ell_{yt}(a) = F(n_{yt}). \tag{C.7}$$

The formulation takes advantage of homogeneous adoption costs, which guarantee that the share of adopters is identical across available technologies.[14]

Consider the old generation next. A crucial difference is that they have already

[13] It is straight-forward to incorporate them and they amplify the existing mechanism, however, to the best of my knowledge, there does not exist strong evidence to support these mechanisms.

[14] If instead learning costs were identical across workers, optimal adoption would imply an all-or-nothing pattern for each technology without affecting the model's core predictions.

adopted technologies in the previous period for which they do not need to pay adoption costs again. Thus, old workers will only have to pay adoption costs for old technologies if they haven't learned about the technology yet, i.e. if the adoption threshold exceeds its counterpart from the previous period. For new technologies, on the other hand, old workers have to pay the full adoption costs. Again, the benefits of adopting a technology are independent of its invention date, such that the worker can simply set an adoption threshold n_{ot} with the associated costs h_{ot}:

$$h_{ot} = A_{t-1} \int_0^{n_{ot}} \mathbb{1}\{n_{yt-1} < n\} n dF(n) + a_t \int_0^{n_{ot}} n dF(n). \tag{C.8}$$

Note that the indicator guarantees that the technology has not been previously adopted by the generation. The associated labor supply then depends on the invention period as well. In particular, the adoption threshold for old technologies is the maximum of the previous period's adoption threshold and the current period's threshold. The adoption of new technologies is as in the baseline case for the young.

$$\ell_{ot}(a) = \begin{cases} F(\max\{n_{yt-1}, n_{ot}\}) & \text{if} \quad a \in A_{t-1} \\ F(n_{ot}) & \text{if} \quad a \in a_t. \end{cases} \tag{C.9}$$

Total technology adoption costs are the aggregate across generations:

$$h_t = s_y h_{yt} + (1 - s_y) h_{ot}. \tag{C.10}$$

In summary, the representative household makes technology adoption choices weighing current cost against current and future benefits, where the latter depend on wages to be earned from a particular technology. This naturally brings us to the production sector.

Final production. The final good y_t is produced by a 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.[15]

[15]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, $\ell_t(a) = 1$ and thus the production function simplifies to

$$y_t = \int_{A_t} k_t(a)^{\alpha} da.$$

$$y_t = \int_{A_t} \ell_t(a)^{1-\alpha} k_t(a)^\alpha da. \tag{C.11}$$

The final good producer takes equipment prices $P_t(a)$ and wages $W_t(a)$ as given and solves its standard profit maximization problem:

$$\max \quad y_t - \int_{A_t} W_t(a)\ell_t(a)da - \int_{A_t} P_t(a)k_t(a)da \qquad \text{s.t.} \quad \text{(C.11)}. \tag{C.12}$$

Equipment manufacturers. The blueprint for each technology is owned by an independent monopolist, who produces the associated capital good at constant marginal costs ψ in terms of the final good and sells it to the final producer at cost $P_t(a)$. To simplify the exposition I will assume that equipment fully depreciates each period. This assumption can easily be relaxed without changing any of the main results below.

Given full depreciation and market clearing, the equipment produced is the same as the equipment used and I will use the same notation. The monopolist takes into account its price effect on the demand by the final goods producer, but not the associated second-order effects on technology adoption by workers. This ensures that the analysis remains tractable. Resulting, the monopolist solves the static problem

$$\max P_t(a)k_t(a) - \psi k_t(a), \quad \text{s.t.} \quad P_t(a) = \alpha \left(\frac{\ell_t(a)}{k_t(a)}\right)^{1-\alpha}. \tag{C.13}$$

Innovation. The innovation sector is the key driver of economic growth by creating new technologies. The sector invest per capita resources x_t to generate new varieties a_{t+1} according to the simple linear production function:[16]

$$a_{t+1} = \varphi_0 x_t. \tag{C.14}$$

[16] Formulating the production function in per capita terms neutralizes strong market size effects from population growth (see e.g. Jones (1995a,b)). This simplifies the exposition greatly and allows me to focus on balanced growth path differences. The main results will still be in effect in a semi-endogenous growth setup, however, they will apply to the transition path of the economy instead of the balanced growth path. This is unlikely to change the short to medium term implications of the framework developed in this paper.

To simplify the exposition, I will directly assume that the innovation sector is governed by two equations. Firstly, equation (C.15) states the benefits of innovation per dollar invested have to be equal to the opportunity cost of investment, which is the economy's effective discount rate:[17]

$$\varphi_0 v_{t+1}^0 = \left(\frac{1+r_{t+1}}{1+n}\right), \tag{C.15}$$

where v_{t+1}^0 is the expected net present value of profits from a new invention and φ_0 the research productivity. Appendix C.4 shows that this can be motivated by a competitive innovation sector borrowing from the household to finance its innovation expenditures.

Secondly, the innovation sector distributes all profits to the bondholders in the economy, such that

$$r_t b_t = \int_{A_t} \pi_t(a) da. \tag{C.16}$$

The full distribution of income to bondholders can be motivated by assuming that the innovation sector does not have any equity initially and operates in perfect competition or with free entry. Due to the linear production function, this will imply zero profits and thus all income is paid to the lenders.

C.1.1 Market-clearing conditions

Finally, the economy is subject to two market-clearing conditions. Goods market-clearing requires that resources are either invested in learning, capital goods, and innovation or consumed.

$$y_t = \int_{A_t} \psi k_t(a) da + h_t + x_t + c_t. \tag{C.17}$$

Secondly, market clearing in the investment sector requires that savings equal investment in innovation:

$$x_t = (1+n) b_{t+1} - b_t. \tag{C.18}$$

[17]Population growth appears in this equation as profits scale with the population size.

C.1.2 Equilibrium

I next define a competitive equilibrium in this economy and a balanced growth path equilibrium. I will focus on the latter only in my analysis below.

Definition 1. *Given $\{A_0, a_0, n_{y-1}\}$, a Competitive Equilibrium is a sequence*

$$\{y_t, h_t, x_t, c_t, A_t, a_t, n_{yt}, n_{ot}, \{k_t(a), \ell_{yt}(a), \ell_{ot}(a), \ell_t(a), P_t(a), W_t(a)\}_{a \in A_t}, r_t\}_{t=0}^{\infty}$$

such that

(a) the representative household, the final good producer, and the producers of intermediate goods solve their maximization problems,

(b) the no-arbitrage condition in the investment sector holds,

(c) markets clear.

Definition 2. *A Balanced Growth Path is a competitive equilibrium such that consumption grows at constant rate g.*

C.2 Equilibrium Characterization

I will limit the equilibrium characterization to the core results that are necessary to understand the intuition of the model. Detailed derivations and proofs are provided in Appendix Section C.5.

Lemma C.1. *On any BGP, the interest rate satisfies $1 + r = \frac{1+g}{\beta}$. Furthermore, as long as $g \geq 0$, the effective discount rate of the economy satisfies $\frac{1+r}{1+n} > 1$.*

Technology adoption and wages. To simplify the analysis and abstract from corner solutions, I will assume that adoption cost follow a continuous distribution with unbounded support from above.

Assumption 1. *The cost distribution function satisfies $f(n) > 0$ for $n \in (0, \infty)$, where $f(n)$ is the pdf of $F(n)$.*

Lemma C.2. *On any BGP, tasks wages $\mathcal{W}$ are constant and identical across tasks. Furthermore, the adoption thresholds for young and old workers are constant over time and given by*

$$n_y = \mathcal{W}\left(1 + \frac{1-p}{1+r}\right) \quad \textit{and} \quad n_o = \mathcal{W}. \tag{C.19}$$

Firstly, note that constant wages per variety are a standard result in expanding variety models with constant marginal costs of production in the intermediary sector. In particular, the capital-labor ratios in the model, which determine the wages, are directly linked to the equilibrium price of the intermediary good, which in turn is supplied at a constant markup over marginal costs. Since the latter is constant and identical across equipment varieties, wages are as well.

The second part of the Lemma is a direct result of the first. As all technologies yield the same benefits, workers only differentiate between them according to their adoption costs. The benefits of adoption are then the expected, discounted wages earnings. The marginal adopted technology type equalizes cost and benefits. For the old generation, this implies that all technologies yielding weakly positive net income are adopted, while the young generation adopts technologies whose current and future expected, discounted benefits exceed current adoption costs.

Corollary C.1.

(a) Workers adopt technologies as early as possible or never.

(b) Old workers have lower technology adoption rates driven by threshold differences for new technologies.

(c) Take-home income is increasing in age over the life cycle and in the cross-section.

(d) Old technologies have higher aggregate technology adoption rates than young technologies.

Consider (a) first. The payoff from learning about a technology is strictly increasing in the number of periods that a given generation can use it in the labor market, while the adoption costs stay constant. Thus, it is always preferable to adopt a technology early if ever.

Part (b) links the insight of early adoption to differences in the availability of technologies over time. In particular, old workers adopted old technologies when they were young and, thus, due to the constant adoption threshold for each age group, young and old workers adopt the same share of old technologies. In contrast, old workers apply their current, lower adoption threshold to new technologies as they did not have the opportunity to learn about them previously. Via a simple composition effect across old and new technologies, this implies that old workers have lower aggregate technology adoption rates compared to young workers, who apply the same, high technology adoption threshold to all currently available technologies.

Note that higher aggregate technology adoption rates also imply larger skill sets for young workers. The latter might be perceived as a bug rather than a feature given the extensive evidence for increasing compensation over the life-cycle (See e.g. Lagakos et al. (2018)). While the model does not possess features that are likely important for life-cycle wage dynamics such as job-ladders or learning-by-doing, it still features an upwards sloping take-home income, which I define as gross income minus adoption costs, in cross-section and across the life-cycle as pointed out in part (c).

Two insights are driving this result. Firstly, old workers gain more from old technologies as they do not have to pay their adoption costs again. Secondly, old workers also gain more from new technologies as they adopt all new technologies that generate positive net cash flow in this period. On the other hand, young workers adopt some technologies with negative cash flow in the current period due to the benefits in the next period. As a result, old workers receive larger take-home income from the labor market.

Finally, and as pointed out in (d), technologies themselves are subject to a life-cycle pattern, which arise due to composition effects. Over time, low adoption generations, i.e. the initially old, are replaced by high adoption generations. Eventually, all active generations entered the economy when the technology was available and, thus, had the chance to adopt it when young. Therefore, for a given technology, the aggregate adoption rate has an upwards trajectory converging towards its long-run value, the adoption rate of young workers.

Firm Profits and the Value of Innovation. Having solved the worker problem, we can next turn our attention to the intermediary problem.

Lemma C.3. *Per capita profits for a variety are proportional to its adoption rate:*

$$\pi_t(a) = \tilde{\pi}\ell_t(a). \tag{C.20}$$

Similarly, the per capita value of a new variety is proportional to its discounted market size:

$$v^0 = \tilde{\pi}\left(\ell^N + \left(\frac{1+n}{r-n}\right)\ell^E\right), \tag{C.21}$$

where $\ell^N = s_y F(n_y) + (1-s_y)F(n_o)$ and $\ell^E = F(n_y)$ are the aggregate technology adoption rates for new and old technologies respectively.

Firstly, note that the formulation for profits is standard in the endogenous growth literature apart from the explicit acknowledgment of adoption rates as a driver of market size. The latter matter for per capita profits as the monopolist earns constant profits per adopter.

Market size effects for profits directly bleed into the value of a new innovation. The key insight from is formulation is that the adoption rate for new technologies only matters in the first active period as the technology becomes an old technology afterward. Note that the expansion of market size for old technologies is directly linked to the fact that they are adopted by young workers only. As a result, the workforce age composition matters for short-run profits, but not in the long run.

How does aging impact the model economy? Before understanding the effects of aging in the model, I quickly note that the BGP exists and is unique.

Proposition C.1. *There exists a unique balanced growth path equilibrium.*

To gain some insight into the model dynamics I will discuss a set of comparative statics exercises. I start by taking the WYS s_y as exogenous in partial equilibrium and then discuss how the intuitions developed for this simple scenario translate to general equilibrium.

Proposition C.2. *Holding the constant the interest rate and population growth rate, an exogenous decline in the WYS decreases the average adoption rate for new and overall technologies, (gross) output, and the value of new inventions.*

The important insight is that there are pure composition effects from the WYS pushing down technology adoption, output, and the value of new innovations. The next proposition highlights how these feed into general equilibrium.

Proposition C.3. *Holding constant the population growth rate, an exogenous decline in the WYS decreases the aggregate adoption rate for new and overall technologies, investment into new technologies relative to old technologies, the value of new inventions, the interest rate, and the economy's productivity growth rate.*

The key insight from the proposition is that the partial equilibrium results based on Proposition C.2 carry over into general equilibrium. In response to declining firm values, interest rates have to decline as well to satisfy the research arbitrage equation. Lower interest rates translate to lower productivity growth rates via the Euler equation. The overall mechanism is clear: Population aging reduces the technology adoption rate for new innovations via a simple composition effect. Declining adoption rates decrease the value of innovation and, thus, lead to a reduction in R&D investment. The resulting decline in innovation directly implies lower productivity growth rates.

Finally, the next proposition confirms that these predictions carry over to a decline in the working young share driven by declining population growth rates, which is the empirically relevant case for the US. The decline in fertility itself has first-order consequences via market size effects, which turn out to point in the same direction as the composition effects.

Proposition C.4. *A decrease in the population growth rate, which mechanically leads to a decrease in the WYS, decreases the aggregate adoption rate for new and overall technologies, investment into new technologies relative to old technologies, the value of new inventions, the interest rate, and the economy's productivity growth rate.*

What are the policy implications of an aging economy? Given the results above, the question arises of whether there is room for policy in this framework. To study this question, I introduce the social planner problem in Appendix C.3 and focus on its implications here:

Proposition C.5. *The social planner solution features higher technology adoption rates for older workers, a flatter life-cycle profile of adoption thresholds, and a higher productivity growth rate.*

Inefficiently low productivity growth rates are a ubiquitous feature of the endogenous growth literature as firms are unable to capture the full value of their innovation, e.g. because part of it is paid to workers in wages. Similarly, monopoly distortions feed into inefficiently low wages, which, in this framework, translate into inefficiently low adoption rates. Setting optimal capital-labor ratios immediately yields higher adoption rates. The adoption profile flattens as future resources generated by young workers are discounted at a higher rate due to faster economic growth, providing a countervailing force for young workers to the overall larger marginal product of technology adoption. Since old workers do not have future income, they are only subject to the pure increase in marginal product effect.

Proposition C.6. *In the Social Planner Equilibrium, a decrease in the population growth rate, which mechanically leads to a decrease in the WYS, decreases the aggregate technology adoption rate as well as the economy's productivity growth rate.*

Proposition C.6 is the social planner equivalent to Proposition C.4 and highlights that the direction of the response to an aging population is the same across solution concepts. Thus, while adoption levels and innovation activity are sub-optimally low in the competitive equilibrium, its response to an aging population is not necessarily sub-optimal. The intuition for this result is that the forces leading to a declining productivity growth rate in the competitive equilibrium are still active in the social planner solution. Lower population growth rates lower the value of resources in the future. Furthermore, adoption rates decline as well due to changes in the relative weight of resources across periods, leading to a declining social value of innovation as well. Thus, while adoption levels and innovation activity are sub-optimally low in the competitive equilibrium, their responses to an aging population are not necessarily sub-optimal.

C.3 Social Planner Solution

Decision problem. The equations for the planner setup are provided below. I forgo proving that $n_y > n_o$ in equilibrium and directly impose it here. This is without loss of generality as there are no inefficiencies in the adoption conditional on factor rewards.

$$
\begin{aligned}
& \max \sum_{s=0}^{\infty} \beta^s (1+n)^s \ln(c_{t+s}), \\
\text{s.t.} \quad & \int_{A_t} \ell_t(a)^{1-\alpha} k_t(a)^{\alpha} da = \int_{A_t} \psi k_t(a) da + h_t + x_t + c_t \\
& \ell_t(a) = \begin{cases} s_y F(n_{yt}) + (1-s_{yt}) F(n_{yt-1}) & \text{if} \quad a \in A_{t-1} \\ s_y F(n_{yt}) + (1-s_{yt}) F(n_{ot}) & \text{if} \quad a \in a_{t-1}. \end{cases} \\
& h_t = s_y A_t \int_0^{n_{yt}} n dF(n) + (1-s_y) a_t \int_0^{n_{ot}} n dF(n) \\
& A_{t+1} = A_t + \varphi_0 x_t
\end{aligned}
$$

Naturally, we have to add the appropriate initial conditions on technology and previous adoption.

Definition 3. *A social planner equilibrium is a set of sequences*

$$\{y_t, h_t, x_t, c_t, A_t, a_t, n_{yt}, n_{ot}, \{k_t(a), \ell_{yt}(a), \ell_{ot}(a), \ell_t(a)\}_{a \in A_t}\}_{t=0}^{\infty}$$

such that the social planner maximizes its objective functions subject to its constraints and markets clear.

Definition 4. *A Balanced Growth Path for the social planner problem is a social planner equilibrium such that consumption grows at constant rate g.*

C.4 Motivating the Investment Sector

I briefly outline a investment sector problem that gives rise to the equations presented in the text. There is a representative investment firm producing new innovations with production function

$$a_{t+1} = \varphi_0 x_t.$$

To finance innovation, the firm borrows from the households at rate r_t such that its (discounted) profits from new investments are given by

$$\left(\frac{1+n}{1+r_t}\right) \mathbb{E}_t \left[\int_0^{a_{t+1}} v_{t+1}^0(a)da\right] - x_t,$$

where $v_{t+1}^0(a)$ is the value of new innovation a at time $t+1$, which equals the present discounted value of profits. Due to the linearity of the investment function and homogeneous adoption costs, it follows immediately that any interior solution needs to satisfy

$$\varphi_0 \left(\frac{1+n}{1+r_t}\right) v_{t+1}^0 = 1,$$

The second equation can be motivated by assuming that the sector is fully leveraged at $t = 0$. From the equation it follows immediately that the sector never builds equity such that $r_t b_t$ has to equal all the profits earned by the sector.

C.5 Derivations and Proofs

This section provides derivations and proofs omitted from the main text.

Production and Prices. First order condition for the final producer's problem yield the standard factor demands:

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

Monopolist solves the profit maximization problem taking into account the equipment demand for monopolist price $P_t(a)$, which in turn pins down the equilibrium capital-labor ratio $\mathcal{K}$ and equilibrium task wage $\mathcal{W}$ via the first order conditions of the final good producer:

$$P_t(a) = \mathcal{P} = \frac{\psi}{\alpha}, \quad \frac{k_t(a)}{\ell_t(a)} = \mathcal{K} \equiv \left(\frac{\mathcal{P}}{\alpha}\right)^{\frac{1}{\alpha-1}}, \quad \text{and} \quad W_t(a) = \mathcal{W} \equiv (1-\alpha)\mathcal{K}^{\alpha}.$$

Plugging in the definition of $\mathcal{K}$ and $\mathcal{P}$ yields the expression in Lemma 1 for the task wage.[18] Note that we can already solve for firm profits nd the value of a new invention conditional on household adoption:

$$\pi_t(a) = (P_t(a) - \psi)k_t(a) = (1-\alpha)\alpha^{\frac{1}{1-\alpha}}\mathcal{P}^{-\frac{\alpha}{1-\alpha}}\ell_t(a) = \alpha\mathcal{W}\ell_t(a).$$

The value of a new invention is then just the expected, discounted value of profits.

Household Decisions. With the skill wages in hand we can turn our attention to the household problem.

Proof of Lemma C.1. Note that this is the standard Euler equation result. In particular, the first order conditions of the household for b_{t+1} and c_t require

$$1 = \beta(1+r_t)\frac{c_t}{c_{t+1}}.$$

By definition of a BGP $c_t/c_{t+1} = 1/(1+g)$ and the first result follows. The second part follows by rearranging the Euler equations and noting that $\beta(1+n) < 1$. by assumption. Thus, as long as $g \geq 0$, we have effective discounting. □

Consider next the first order conditions for the adoption threshold of old workers. This does not have any inter-temporal implications and thus simply involves maximizing the net-resources for the household:

$$(1-s_y)f(n_{ot})\mathcal{W} = (1-s_y)f(n_{ot})n_{ot}.$$

[18] Note that $\partial\mathcal{W}/\partial\mathcal{P} < 0$, i.e. the equipment price set by the intermediary producer reduces the task wages via its impact on the capital-labor ratio. This will become important once we consider adoption rates by households. In particular, it will be the case that adoption is increasing in the tasks wage. As a result, the intermediary producer has an incentive to decrease prices as to increase the market size. I will abstract from this consideration, but note that this will naturally lead to a lower markup compared to the case considered here, but higher profits. Allowing the intermediary producers to take into account this impact makes the problem intractable.

The left hand side states the gross resources generated at the margin, which is the mass of workers times the mass of technologies at the threshold times the (constant) task wage. This has to be equal the cost at the margin, which are the mass of workers to which the threshold applies time the mass of technologies at the threshold (since the household has to pay for all of them) time the cost per technology at the threshold, which is the threshold itself. Following the assumption that $f(n_{ot}) > 0$, the condition simplifies to the constant adoption threshold in the text. Positive support ensures the the threshold is clearly defined and unique. Having $f(n) = 0$ for some n potentially gives rise to saddle points or sets of optimal thresholds.

Note that I've implicitly assumed that the marginal value of resources is positive and have already normalized by the mass of technologies around the threshold, which could be a_t or A_{t-1} given the threshold. Both terms will show up on both sides and thus do not influence the adoption threshold.

Next, consider the problem for choosing the adoption threshold for the young household. I will first take the derivative assuming that $n_{yt} > n_{ot}$ and then confirm this conjecture. Furthermore, I will highlight that assuming the opposite does not yield a solution in line with the conjecture.

The first order condition for s_{yt} can be derived as

$$s_y f(n_{yt}) f(n_{yt}) \mathcal{W} + \frac{\lambda_{t+1}}{\lambda_t}(1 - s_y) f(n_{yt}) \mathcal{W} = s_y f(n_{yt}) n_{yt}.$$

Firstly, note that the right hand side is the same as before. Secondly, consider the LHS. The first term is as for the old generation and represents current gains. The second term represents future gains from current adoption, appropriately discounted by the relative value of resources λ_{t+1}/λ_t, where λ_t is the Lagrange multiplier on the resource constraint. Furthermore, note that mortality risk is taken into account as the benefits only apply to a mass $(1 - s_y)$ of workers.

Plugging the Euler condition for the relative value of resources across periods and normalizing by s_y yields the expression for n_y in the text. Note that the expression satisfies $n_y > n_o$ as per our conjecture.

Now instead suppose $n_{yt} < n_{ot}$. Then the resulting first order derivative can be expressed as

$$s_y f(n_{yt}) f(n_{yt}) \mathcal{W} = s_y f(n_{yt}) n_{yt} - \frac{\lambda_{t+1}}{\lambda_t}(1 - s_y) f(n_{yt}) n_{yt}.$$

Firstly, note that the benefit are only current period, as the future adoption threshold being larger than the current one implies that the technology will be adopted tomorrow anyways and thus tomorrows benefits do not depend on today's action. On the other hand, the cost of adoption reflect both current period adoption costs as well as the savings made next period. In particular, adopting the technology today implies that the household doesn't have to pay for the adoption tomorrow. It is straight-forward to show that the associated adoption threshold with this first order condition violates $n_o > n_y$ and thus this can never be an equilibrium.

Proof of Lemma C.2. See derivations above. □

Proof of Corollary C.1. See derivations above for part (a).

For part (b) note that it follows immediately from (C.19) that young workers adopt new technologies at a higher rate. In particular, the adoption rate for new technologies for either generation is $F(n_y)$ and $F(n_o)$ respectively. Given that $n_y > n_o$ and $F(\cdot)$ is a strictly increasing function, the latter will always be larger. This carries over to the overall adoption rate via a simple composition effect. The share of adopted technologies among A_t for each age group, denoted by $\mathcal{A}^y$ and $\mathcal{A}^o$ respectively, is given by:

$$\mathcal{A}_y = \frac{A_t F(n_y)}{A_t} = F(n_y) \quad \text{and} \quad \mathcal{A}_o = \frac{A_{t-1} F(n_y) + a_t F(n_o)}{A_t} = \frac{1}{1+g} F(n_y) + \frac{g}{1+g} F(n_o).$$

Given that $n_o < n_y$, it follows immediately that $\mathcal{A}_y > \mathcal{A}_o$ for $g > 0$.

Next, consider part (c). The proof for the first part of this is straight-forward when considering the net income earned by a young worker. In particular, let w_{yt} the gross income of the young generation, then we can decompose the overall net income as

$$
\begin{aligned}
w_{yt} - h_{yt} =& A_t \int_0^{n_y} (\mathcal{W} - n) dF(n) \\
=& A_{t-1} \int_0^{n_y} (\mathcal{W} - n)\, dF(n) + a_t \int_0^{n_o} (\mathcal{W} - n)\, dF(n) + a_t \int_{n_o}^{n_y} (\mathcal{W} - n)\, dF(n)
\end{aligned}
$$

The first line states that the net income for young workers is the mass of available technologies times the integral over the net benefits from each adopted technology type. The second line splits this into the net benefits for technologies that the old generation adopted when young plus the net benefits of the new technologies adopted by the old in the current period plus the net benefits from new technologies adopted by the young, but not by the old. We can compare this to the same calculation for old workers:

$$
w_{ot} - h_{ot} = A_{t-1} \int_0^{n_y} \mathcal{W} dF(n) + a_t \int_0^{n_o} (\mathcal{W} - n)\, dF(n).
$$

Note that old workers do not have to pay the adoption cost for technologies adopted when they were young. The comparison across terms is quite straight-forward then. Old workers have a clear advantage in the first terms. The second term is the same for both and, finally, the third term for young workers is always negative. One can show this immediately by noting that $\mathcal{W} - n_o = 0$ by definition of the adoption threshold. Thus $\mathcal{W} - n$ is going to be negative for all $n > n_o$. The intuition is straight-forward. Old workers adopt all technologies that help them in the present. Thus, if there is a technology that young adopt, but old do not, then this technology cannot yield positive returns in the present. Note that the present discounted value is still going to be positive from the future income flow.

For the second part, note that the we can express the income of an old generation tomorrow as

$$
w_{ot+1} - h_{ot+1} = A_t \int_0^{n_y} \mathcal{W} dF(n) + a_{t+1} \int_0^{n_o} (\mathcal{W} - n) dF(n).
$$

It is trivial to show that this exceeds $w_{yt} - h_{yt}$.

Finally, for part (d) note that old technologies, i.e. technologies invented in the previous period, were adopted by the current old generation when they were young.

Furthermore, the current adopters are the young generation as well. This yields an economy with adoption rate of $F(n_y)$. In contrast, new inventions are first adopted by the current new and old generations. As a result, their adoption rate is simply $s_y F(n_y) + (1 - s_y)F(n_o)$. Given that $n_y > n_o$, this is smaller than $F(n_y)$. $\square$

The Value of New Innovations. Having determined technology adoption rates, we can turn our attention back to the value of innovation. Note that an invention is a new technology in its first period and an old afterwards. Thus, $\ell_t(a) = s_y F(n_y) + (1 - s_y)F(n_o)$ in its first period and $F(n_y)$ in all following periods. Thus, the (per capita) value of a new invention is given by

$$\begin{aligned} v^0 &= \sum_{s=0}^{\infty} \left(\frac{1+n}{1+r}\right)^s \mathbb{E}[\pi_{t+s}(a)|a \in a_t] \\ &= \alpha \mathcal{W} \left(s_y F(n_y) + (1 - s_y)F(n_o) + \sum_{s=1}^{\infty} \left(\frac{1+n}{1+r}\right)^s F(n_y) \right). \end{aligned}$$

Note that $(1+n)^s$ corrects for population growth. The formula in the text simply solves the infinite sum and rearranges terms.

Furthermore, note that by a similar calculation, we can determine the value of old technologies as

$$v^E = \alpha \mathcal{W} \left(\frac{1+r}{r-n}\right) F(n_y).$$

The only difference being that the adoption rate is constant for all periods.

Lemma C.4. *There exists a unique interest rate r that satisfies the research arbitrage equation. Furthermore, there exist $\underline{\varphi}_0$ such that $\forall \varphi_0 \geq \underline{\varphi}_0$, the equilibrium growth rate satisfies $g \geq 0$.*

Proof of Lemma C.4. Firstly, we can use our results in the previous lemmas to rearrange the research arbitrage equation to

$$\frac{1+n}{1+r} v_0 = \frac{1}{\varphi_0}.$$

Note that the RHS is constant in r. The LHS, in contrast, is strictly decreasing in r for two reasons. Firstly, and increase in r increases the discount rate, which lower the value of future profits. Since all terms are discounted, this has a strictly negative effect. Secondly, an increase in r also pushes down n_y, which further decreases the value of innovation. Given that all these effects are strict and point in the same direction, we have a strictly decreasing function in r on the LHS. In other words, if there exists an interest rate satisfying this condition, then it is unique.

To show existence, note that $\lim_{r \to n} \left(\frac{1+n}{1+r} v_0\right) \to \infty$ and $\lim_{r \to \infty} \left(\frac{1+n}{1+r} v_0\right) \to 0$. Thus, as long as $\varphi_0 \in (0, \infty)$, there exists an $r > n$ to satisfy this equation.

For the second part, note that since the LHS is decreasing in r and the RHS is decreasing in φ_0, there exist and implicit function $r(\varphi_0)$ that is strictly increasing in φ_0. We can then take advantage of Lemma 1 stating that

$$1 + g = \beta(1 + r(\varphi_0)),$$

to note that $\exists \underline{\varphi}_0$ such that $\beta(1 + r(\varphi_0)) > 1 \ \forall \varphi_0 > \underline{\varphi}_0$. □

Aggregates and Market Clearing. The no profit condition in the innovation sector as well as market clearing for savings imply a simplified budget constraint for households:

$$w_t + \pi_t = c_t + h_t + x_t,$$

where π_t denoted the aggregate profits. Note that $w_t + \pi_t = y_t - i_t$. Furthermore, by the research production function, we have $x_t = a_{t+1}/\varphi_0$. Denote by $\tilde{y} = y_t/A_t$ with similar definitions for other variables, then we can rearrange the resource constraint to

$$\tilde{y} = \tilde{c} + \tilde{i} + \tilde{h} + \frac{g}{\varphi_0}.$$

It is straight-forward to be shown that $\tilde{c} > 0$ on the balanced growth path. Furthermore, one can show that $\lim_{s \to \infty} \lambda_{t+s} = 0$ as $\lambda_{t+s} = \left(\frac{1+n}{1+r}\right)^s \lambda_t$, $\lambda_t > 0$ and $r > n$. Thus, the problem is well defined.

Finally, note that for any other balanced growth path equilibrium we have

$$\tilde{\lambda}_{t+s} = \tilde{\lambda}_t \left(\frac{1+n}{1+r}\right)^s = \tilde{\lambda}_t \left(\frac{\beta(1+n)}{1+g}\right)^s \tag{C.22}$$

By assumption (via $\varphi_0 \geq \underline{\varphi}_0$ and $x_t \geq 0$), we have $g \geq 0$. Since $\beta(1+n) < 0$ and $\tilde{\lambda}_t \geq 0$ (from $c_t \geq 0$), we have $\lim_{s\to\infty} \tilde{\lambda}_t \left(\frac{\beta(1+n)}{1+g}\right)^s \in (0, \infty)$. Thus, all other balanced growth path solutions are also well defined.

Main Results.

Proof of Lemma C.1. Firstly, note that Lemma C.4 shoes that there always exists and interest rate and thus a growth rate to satisfy the research arbitrage equation. I will focus on the case with a interest rate implying a positive growth rate here.

The derivations above further show that the balanced growth path constructed so far features positive consumption and thus is optimal among balanced growth paths with bounded utility.

What remains to be shown then is that the objective function is well defined on any balanced growth path. This is straight-forward. On a BGP we have $c_{t+s} = c_t(1+g)^s$, and thus

$$\sum_{s=0}^{\infty} ((1+n)\beta)^s \ln(c_{t+s}) = \ln(c_t) \sum_{s=0}^{\infty} ((1+n)\beta)^s + \ln(1+g) \sum_{s=0}^{\infty} ((1+n)\beta)^s s.$$

It is straight-forward to show that both terms are well defined and bounded for any $g \geq 0$. Thus, the objective function is well defined for any BGP equilibrium. This in turn implies that the equilibrium defined in the derivations above is as a matter of fact unique. Note that uniqueness follows from a unique r and thus g satisfying the research arbitrage equation. □

Proof of Proposition C.2. The proposition highlights the pure composition effects from an increase in the young share. The proof simply relies on $n_y > n_o$ and is omitted for brevity. Note that the output result follows from the fact that output is proportional to the average technology adoption rate. □

Proof of Proposition C.3. I will start the proof from the last point. Consider the research arbitrage equation:

$$\frac{1+n}{1+r}\alpha\mathcal{W}\left[\left(\frac{1+r}{r-n}\right)F(n_y)+(s_y-1)\left(F(n_y)-F(n_o)\right)\right]=\frac{1}{\varphi_0}.$$

It is straight-forward to show that an increase in s_y increases the LHS holding everything else equal, while leaving the RHS untouched. The only variable on the LHS that can respond to keep the equality is r. As per our earlier discussion, the LHS is strictly decreasing in r, thus we have that an increase in s_y needs to be offset by an increase in r. Furthermore, from the Euler equation, we know that an increase in r requires an increase in g, which completes the proof for the last bullet point.

For the third bullet point, note that since $\frac{1+r}{1+n}v_0$ is constant, but r is increasing, we need to have v_0 increasing in s_y.

The first and second bullet point are tightly linked. Let $\ell^N = s_y F(n_y) + (1 - s_y)F(n_o)$ and $\ell^E = F(n_y)$ be the economy wide adoption rates of new and old technologies respectively. We can express the value of a new innovation as

$$v^0 = \alpha\mathcal{W}\left(\ell^N + \sum_{s=1}^{\infty}\left(\frac{1+n}{1+r}\right)^s \ell^E\right)$$

From before, we know that $\partial v^0/\partial s^y > 0$. Furthermore, we know that $\partial r/\partial s_y > 0$ and thus $\partial \ell^E/\partial s_y < 0$. Thus, the only way to have $\partial v_0/\partial s_y > 0$ is $\partial \ell^N/\partial s_y > 0$. In other words, the direct effect has to be stronger than the general equilibrium force pushing against it. This proves the first bullet point.

Finally, the ration of investment in new technologies to investment in old technologies can be expressed as

$$\frac{\int_{a_t}\psi k_t(a)da}{\int_{A_{t-1}}\psi k_t(a)da} = \frac{g}{1+g}\frac{\ell^N}{\ell^E}$$

Since both factors are increasing in s_y, the overall term is as well. Note that total investment in new technologies, $a_t\ell^N\mathcal{K}$, is increasing in s_y as well. □

Proof of Proposition C.4. The proof for this follows the same steps as above and is omitted for brevity. Note, however, that the induced increase in r is larger as there are two channels at play in the innovation sector: Pure market size via population growth and composition changes via s_y. □

Social planner results. Throughout this section I will omit most of the algebraic intermediate steps for brevity. Detailed derivations are available upon request.

Firstly, note that the social planner will set a higher capital-labor ratio compared to the competitive solution due to the lack of monopoly pricing.

Lemma C.5. *On a social planner BGP, the social planner chooses a higher capital-labor ratio $\mathcal{K}^{SP}$ compared to the competitive equilibrium, which implies a higher implicit wage $\mathcal{W}^{SP}$. Furthermore, the planner chooses larger technology adoption threshold n_y^{SP} and n_o^{SP} compared to the competitive equilibrium due to larger implicit wage/ the larger marginal product of labor.*

Proof. Firstly, note that the standard first order conditions for capital imply

$$\frac{k_t(a)}{\ell_t(a)} = \mathcal{K}^{SP} \equiv \left(\frac{\psi}{\alpha}\right)^{-\frac{1}{1-\alpha}}.$$

Since $\alpha < 1$, we have $\mathcal{K}^{SP} > \mathcal{K}$. This is a direct implication of the monopoly friction. The monopolist reduces supply to maximize profits, while the planner chooses the social optimum. As a direct implication of lower capital-labor ratios, we have that the implicit wage or marginal product of labor is larger in the social planner solution

$$\frac{\partial y_t}{\partial \ell_t(a)} = \mathcal{W}^{SP} \equiv (1-\alpha)\left(\frac{\psi}{\alpha}\right)^{-\frac{\alpha}{1-\alpha}}$$

Again, it is straight-forward to see that since $\alpha < 1$, $\mathcal{W}^{SP} > \mathcal{W}$. This is important since it directly impacts optimal technology adoption. In particular, we have

$$n_y^{SP} = \mathcal{W}^{SP}\left(1 + \frac{\beta(1-p)}{1+g}\right) \quad \text{and} \quad n_o^{SP} = \mathcal{W}^{SP}$$

Note that $n_o^{SP} > n_o$ in general, while $n_y^{SP} > n_y$ conditional on g. It remains to be shown whether this will be the case once we endogenize g. Furthermore, note that we can make this comparison by plugging in the Euler equation for the competitive equilibrium in n_y. □

Lemma C.6. *The social planner chooses a higher equilibrium growth rate g^{SP} compared to the competitive solution.*

Proof. It is useful to make a couple of definitions first. Denote by λ_t^{SP} the Lagrange multiplier on the resource constraint. Furthermore, denote by ℓ_N and h_N the adoption rate and associated learning costs for a new variaty and by ℓ_E and h_E the associated values for existing varieties. One can then show that the first order conditions for x_t boil downs to

$$\frac{1}{\varphi_0} = \frac{\lambda_{t+1}}{\lambda_t}\left(\mathcal{W}^{SP}\ell_N - h_N\right) + \sum_{s=2}^{\infty}\frac{\lambda_{t+s}}{\lambda_t}\left(\mathcal{W}^{SP}\ell_E - h_E\right)$$

Note that the LHS denotes the unit costs of innovation, while the RHS denotes the benefits discounted to current marginal utility. These benefits are the net-gains from a new technology tomorrow plus the net-gains of an old technology starting in two periods. Note that investment costs are already taken into account in this formulation.

Plugging in the evolution of marginal products along the BGP, we have

$$\frac{1}{\varphi_0} = \frac{(1+n)\beta}{1+g}\left(\left(\mathcal{W}^{SP}\ell_N - h_N\right) + \sum_{s=1}^{\infty}\left(\frac{(1+n)\beta}{1+g}\right)^s\left(\mathcal{W}^{SP}\ell_E - h_E\right)\right)$$

Define the implicit value of innovations as

$$v_{SP}^0 = \left(\left(\mathcal{W}^{SP}\ell_N - h_N\right) + \sum_{s=1}^{\infty}\left(\frac{(1+n)\beta}{1+g}\right)^s\left(\mathcal{W}^{SP}\ell_E - h_E\right)\right).$$

Note that to show that $g^{SP} > g$, we need to show that $v_{SP}^0 > v^0$. To see why this is true, note that in the competitive market equilibrium, total generated resources from innovation are v^0 plus the net-present values of wages minus adoption costs. Note that the latter are strictly positive by the first order conditions of workers. Denote by v_P^0 the sum of both and by $v_{SP}^0(g)$ the social planner value associated with a growth rate as in the competitive equilibrium. It follows that $v^0 < v_P^0 \leq v_{SP}^0(g)$. The first inequality follows from positive net-income of workers and the second from the fact that (conditional on g), the social planner can always enact the competitive equilibrium solution. However, this implies

$$\frac{1}{\varphi_0} = \frac{(1+n)\beta}{1+g} v^0 < \frac{(1+n)\beta}{1+g} v^0_{SP}(g)$$

Note that the I've used the Euler equation for the expression for the competitive solution. Finally, since $\frac{(1+n)\beta}{1+g} v^0_{SP}(g)$ is strictly decreasing in g, the equilibrium with $\frac{1}{\varphi_0} = \frac{(1+n)\beta}{1+g} v^0_{SP}(g^{SP})$ needs to satisfy $g^{SP} > g$.

□

Proof of Proposition C.5. The proposition follows from the results above. □

Proof of Proposition C.6. To proof this result, it is convenient to rewrite the "research arbitrage equation" in terms of the resources generated for each generation:

$$\frac{1}{\varphi_0} = \left(\frac{(1+n)\beta}{1+g}\right) \left((1-s_y)\left(F(n_o)\mathcal{W}^{SP} - h_o\right) + s_y \sum_{s=0}^{\infty} \left(\frac{(1+n)\beta}{1+g}\right)^s \left(\left(1 + \frac{(1-p)\beta}{1+g}\right) \mathcal{W}^{SP} F(n_y) - h_y\right)\right)$$

From the optimal technology adoption choice if follows that

$$F(n_o)\mathcal{W}^{SP} - h_o = \int_0^{n_o} (n_o - n) dF(n) < \int_0^{n_y} (n_y - n) dF(n) = \left(1 + \frac{(1-p)\beta}{1+g}\right) \mathcal{W}^{SP} F(n_y) - h_y.$$

Thus, a decrease in s_y pushes down the right hand side and, thus, needs to be offset by a correspondingly lower growth rate. A decrease in n has the same effect and thus both forces push in the same direction.

The decline in the average technology adoption rate is due to the simple composition effect that is only partly offset by the decline in g. The proof for this is similar to the one for the competitive equilibrium and omitted here for brevity. □

D Evidence on the Age-Technology Adoption Nexus

The computer has arguably been the most important "new" production technology introduced in the 1990s and early 2000s. Earlier studies document its wide ranging impact on firm productivity and demand for skills across industries and occupations (Autor et al., 1998, 2003; Brynjolfsson et al., 2002; Bresnahan et al., 2002). Nonetheless, computer adoption was not uniform across workers and, as documented below, older workers' adoption rates significantly lagged their younger counterparts.

In this section, I carefully document that older cohorts had lower adoption rates of the computer at the workplace in the 1990s and early 2000s. The analysis expands on Friedberg (2003) by using a longer time frame, extended set of outcome variables, and a non-parametric regression approach controlling for a wider set of confounding factors such as occupation and industry choice. This evidence motivates the model developed in the subsequent section.[19]

D.1 Data

I investigate computer adoption at the workplace using the five CPS Computer and Internet (CIU) Supplement waves between 1989 and 2003. (Flood et al., 2020) 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 full-time employees between the age of 25 and 64 with at least a high school degree. This is intended to ensure that the computer was a relevant technology for the worker and that differences in effective labor supply are not driving my results.

I construct two measures of computer adoption by workers. Firstly, I consider a simple indicator measure of computer use at work, which I will refer to as computer adoption, which is based on the response to the question of whether the respondent uses a computer at work. Secondly, I construct a proficiency index by counting the number of tasks a worker performs with a computer at work conditional on working with it at all. The task index ranges from 1 to 6 and is only available for workers reporting computer use at work. 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.[20] 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

[19]See also Weinberg (2004); Aubert et al. (2006); Meyer (2007), and Schleife (2008) for related evidence on technology adoption across the lifecycle.

[20]"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.

structure. I will refer to this variable as the proficiency index.

Besides the CIU specific variables, I use the age and gender of the respondent, state of residency, educational attainment, occupation, and industry. 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.[21]. Throughout I use 5-year year-of-birth cohorts starting from 1924-28 and report the results by transforming the cohort measure into age groups in 1989 to aid interpretation. Table D.1 reports summary statistics.

Table D.1: Summary Statistics for CPS Sample

Variable	**Obs.**	**Mean**	**Std. Dev.**
PC Adoption	207,998	0.581	0.493
PC Proficiency	109,280	2.784	1.703
Age	207,998	41.013	9.934
Female	207,998	0.423	0.494
College Degree	207,998	0.341	0.474
Graduate Degree	207,998	0.125	0.330
White	207,998	0.846	0.361
Black	207,998	0.106	0.308
Asian	207,998	0.038	0.191

Note: This tables reports summary statistics for the CPS CIU sample. Observations are weighted by CPS CIU supplement weights.

D.2 Empirical Framework

I test whether older workers are less likely to adopt the computer by estimating a simple linear model for both outcome variables:

$$Y_{it} = \gamma_{a(i)} + \delta X_{it} + \varepsilon_{it}, \tag{D.1}$$

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

The variables of interest are cohort fixed effects γ_a, where a indicates a particular cohort. An observation is a worker i interviewed in year t. I include gender, education, state, occupation, and industry fixed effects interacted with the survey year. Adding education fixed effects accounts for differences in educational attainment across cohorts, which could be a separate channel affecting technology take-up that is not at the core of this exercise. Industry and occupational fixed effects ensure that the regressions do not capture pure sorting.[22]

Note that cohort and age patterns coincide in cross-section, but differ in a panel structure. Focusing on cohort patterns keeps the set of individuals represented by the estimated coefficients constant and, thus, 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 patterns in technology use.

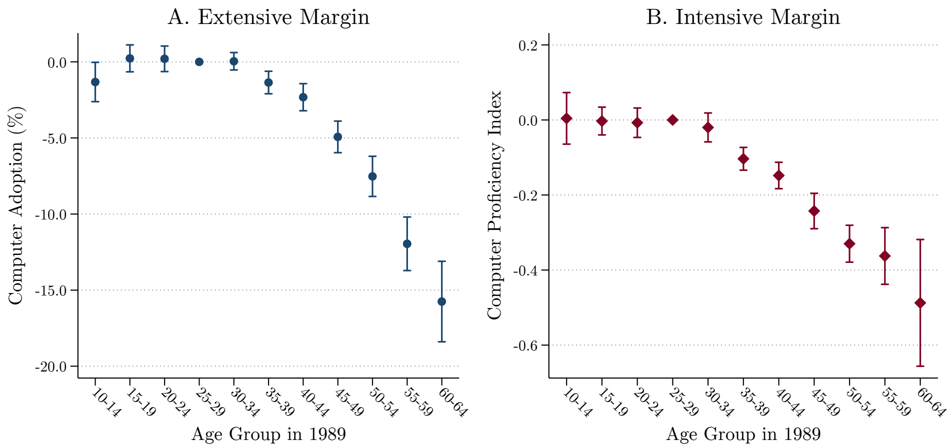
D.3 Results

Panel A of Figure D.1 plots the coefficients for technology adoption, while Tables D.3 and D.3 present the associated regression results. The pattern suggests a monotone decreasing technology adoption rate across cohorts, especially for those aged 40-44 and older in 1989. Panel B confirms a similar pattern for computer proficiency, highlighting that intensive and extensive margin are reinforcing each other. Respondent aged 40-44 in 1989 have a 7.5 percentage points (0.2 tasks) higher computer adoption rate (proficiency index) relative to the cohort age 55-59 in 1989, which constitutes 15% (7%) of the sample mean and 14% (13%) of the sample standard deviation.

In unreported results I confirm cohort patterns as the driving force as opposed to pure life-cycle patterns by simultaneously controlling for age. Furthermore, there does not appear to be any catch-up of older cohorts across survey years, i.e. adoption progresses relatively uniformly across cohorts remaining in the labor market. Finally, note that the CPS does not record employer size or age, which might contribute to the documented patterns if e.g. young firms have a higher technology adoption rate.

[22]Interestingly, the regression tables suggest that sorting appears to be working against the cohort patterns.Older workers tend to work in occupations that use the computer more intensively, flattening the overall cohort profile. This is in line with the evidence provided in Acemoglu and Restrepo (2018), who argue that older workers have a comparative advantage in "white-collar" occupations.

Figure D.1: Older cohorts were slow to adopt the computer



Notes: This figure reports the coefficient estimates for specification (D.1) for computer adoption and proficiency. Regressions include sex, education, industry, occupation, and state fixed effects interacted with survey year. Observations are weighted by CPS Computer and Internet Use Supplement sampling weights. Standard errors are clustered at the industry level.

However, it not necessarily clear that one would want to control for firm age given that the observed sorting of young workers to young firms might be partly driven by (joint) technology adoption decisions (Ouimet and Zarutskie, 2014). Furthermore, the evidence presented focuses on realized patterns, which might differ from "natural" patterns if e.g. employers respond to low technology adoption rates by old workers with more training (Bartel and Sicherman, 1998).

In conclusion, the evidence suggests that older workers adopted the computer at a lower rate in line with the idea that they might be slow to pick up new technologies in general.

Table D.2: Regression Table for Computer Use At Work

	(1)	(2)	(3)	(4)	(5)
			Computer Adoption (%)		
Age 10-14 in 1989	-2.076*	-2.789***	-1.119	-1.169	-1.323**
	(1.229)	(1.065)	(0.711)	(0.712)	(0.655)
Age 15-19 in 1989	0.751	-0.504	0.146	0.130	0.230
	(0.697)	(0.601)	(0.431)	(0.438)	(0.449)
Age 20-24 in 1989	0.457	-0.279	0.080	0.070	0.202
	(0.524)	(0.495)	(0.421)	(0.418)	(0.425)
Age 30-34 in 1989	1.307**	0.907*	0.048	0.014	0.041
	(0.654)	(0.493)	(0.299)	(0.295)	(0.290)
Age 35-39 in 1989	1.165	-0.306	-1.269***	-1.344***	-1.357***
	(1.045)	(0.684)	(0.375)	(0.368)	(0.376)
Age 40-44 in 1989	2.305	0.168	-2.253***	-2.317***	-2.322***
	(1.441)	(0.978)	(0.447)	(0.445)	(0.452)
Age 45-49 in 1989	-1.157	-2.255*	-4.979***	-4.985***	-4.929***
	(1.689)	(1.262)	(0.545)	(0.547)	(0.526)
Age 50-54 in 1989	-4.306**	-4.179***	-7.435***	-7.422***	-7.524***
	(1.807)	(1.464)	(0.646)	(0.647)	(0.670)
Age 55-59 in 1989	-9.081***	-8.938***	-12.237***	-12.138***	-11.953***
	(1.898)	(1.582)	(0.869)	(0.867)	(0.893)
Age 60-64 in 1989	-13.838***	-14.467***	-16.921***	-16.729***	-15.751***
	(2.690)	(2.249)	(1.481)	(1.474)	(1.342)
Gender/Educ. FEs		Yes	Yes	Yes	Yes x Year
Ind./Occ. FEs			Yes	Yes	Yes x Year
State FEs				Yes	Yes x Year
Obs.	207,998	207,998	207,998	207,998	207,983

Note: This table reports the regression coefficients for direct computer use at work. Outcome is an indicator variable taking values 0 and 100 with standard deviation 49.3 and mean 58.34. Age 25-29 in 1989 is the leave out category. Regressions use CPS Computer and Internet Supplement weights and control for year fixed effects. All standard errors clustered at industry level.

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

Table D.3: Regression Table for Tasks Performed With Computer

	(1)	(2)	(3)	(4)	(5)
			Computer Proficiency		
Age 10-14 in 1989	-0.082	-0.089*	-0.010	-0.013	-0.025
	(0.051)	(0.049)	(0.041)	(0.042)	(0.043)
Age 15-19 in 1989	-0.006	-0.035	0.009	0.008	-0.000
	(0.028)	(0.026)	(0.019)	(0.019)	(0.019)
Age 20-24 in 1989	-0.017	-0.039	-0.018	-0.019	-0.021
	(0.025)	(0.024)	(0.023)	(0.024)	(0.024)
Age 30-34 in 1989	-0.031	-0.025	-0.028	-0.030	-0.032
	(0.024)	(0.021)	(0.020)	(0.019)	(0.020)
Age 35-39 in 1989	-0.092***	-0.111***	-0.110***	-0.111***	-0.115***
	(0.026)	(0.021)	(0.017)	(0.017)	(0.018)
Age 40-44 in 1989	-0.104***	-0.135***	-0.157***	-0.159***	-0.164***
	(0.031)	(0.024)	(0.021)	(0.020)	(0.021)
Age 45-49 in 1989	-0.214***	-0.220***	-0.260***	-0.258***	-0.272***
	(0.037)	(0.033)	(0.027)	(0.027)	(0.026)
Age 50-54 in 1989	-0.318***	-0.305***	-0.351***	-0.354***	-0.357***
	(0.045)	(0.039)	(0.027)	(0.027)	(0.027)
Age 55-59 in 1989	-0.317***	-0.318***	-0.372***	-0.371***	-0.385***
	(0.046)	(0.048)	(0.051)	(0.051)	(0.049)
Age 60-64 in 1989	-0.486***	-0.485***	-0.505***	-0.505***	-0.498***
	(0.086)	(0.085)	(0.077)	(0.077)	(0.079)
Gender/Educ. FEs		Yes	Yes	Yes	Yes x Year
Ind./Occ. FEs			Yes	Yes	Yes x Year
State FEs				Yes	Yes x Year
Obs.	109,280	109,280	109,275	109,275	109,160

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 1.69 and mean 2.8. Age 25-29 in 1989 is the leave out category. Regressions use CPS Computer and Internet Supplement weights and control for year fixed effects. All standard errors clustered at industry level.

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