Demographics and Productivity*

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This Draft: August 21, 2002

Abstract

This paper examines the impact of workforce demographics on aggregate productivity. The age structure of the workforce is found to have a significant impact on aggregate productivity. A large cohort of workers aged 40 to 49 is found to have a large positive impact on productivity. Out of sample predictions of output growth from 1990 to 1995 predict 17% of actual output growth differences across a sample of 108 countries. The results suggest a partial explanation for the productivity slowdown in the seventies and the boom in the nineties. This paper estimates that US productivity growth in the seventies was 2% lower than trend due to the entry of the baby boom into the workforce. As the baby boomers entered their forties in the nineteen eighties and nineties, productivity growth rebounded. Japanese demographics predict almost the opposite pattern, with high growth in the seventies followed by low growth in the nineties. Demographics can also explain part of the productivity divergence between rich and poor nations between 1960 and 1990.

Keywords: Productivity, human capital, demographics, slowdown.
JEL Classification: E23,O30,O47

*I am grateful to Doug Staiger, Andrew Bernard, Amitabh Chandra, Eric Edmonds, Lennart Erickson and David Weil for their helpful comments and advice. All errors are my own.

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Introduction

This paper will explore the impact of workforce demographics on productivity. Given the outpouring of empirical growth papers over the last decade, the effect of demographics has been relatively neglected. When demographics are considered, the focus tends to be on the dependency ratio (the ratio of workers to non-workers), not on the internal demographic composition of the workforce. This is unfortunate, because demographic measures have several characteristics which sidestep many of the difficulties that bedevil other variables used in the empirical growth literature.

First, there is microeconomic evidence to suggest that the age structure of the workforce is important in explaining output differences. Second, demographics have significant time series variation. The post war baby boom in the United States and other nations significantly affected the age structure of the workforce. This time series variation allows for exploiting the panel nature of the data, a luxury not available to most productivity affecting variables. Third, workforce demographics are strongly predetermined. The current age structure of the workforce was determined roughly twenty years ago and should be exogenous with respect to current productivity movements.

The combination of time series variation and exogeneity is extremely rare in the empirical growth literature. For most variables which change over time, like trade, investment and schooling, the direction of causality is difficult to determine. Variables which are plausibly exogenous, such as geographic measures, tend to lack time series variation. Another useful characteristic of workforce demographics is their predictability. Unlike most time series variables we use to look at growth, we can predict what the workforce will look like in twenty years in any country.

Using a large panel of countries, this paper will show that changes in workforce demographics have a strong and significant impact on the growth rate of productivity. Changes in the proportion of workers between the ages of 40 and 49 turns out to be particularly important in explaining productivity growth. A 5% increase in the size of this cohort over a ten year period can lead to 1.7% higher productivity growth in each year of the decade. The results are quite robust to specification changes and appear to have predictive power. An out of sample prediction of output growth from 1990 to 1995 predicts 17% of the actual variation.

The results can explain a large portion of the productivity slowdown of the seventies and the subsequent boom in the nineties. The entry of the baby boom into the workforce in the seventies led to an increase in the size of the cohort in their twenties and a reduction in annual productivity growth by $1-2\%$. As the boom reached their forties in the eighties and nineties, demographics suggest that productivity growth rebounded to $1-2\%$ higher than trend. The results of this paper suggest that the high productivity growth of the nineties is not sustainable. The size of the cohort aged 40-49 has peaked and the children of the baby boom will begin entering the workforce this decade. Both trends suggest that productivity growth will be slow in the first decades of the millennium.

Interestingly, Japan has very different demographic movements compared to the US that correspond very closely to Japan's rise in the seventies and crash in the nineties. Japan experienced an earlier and shorter post war baby boom than the US. In contrast to the US productivity slowdown, demographic changes added 1-2% to annual Japanese productivity growth between 1970 and 1990. In the nineties this demographic trend reversed. The results of this paper suggest that Japan's dismal performance in the nineties is partially due to demographics.

Demographics may also help to explain broader cross country productivity differences. Productivity levels in poor countries tend to be low in part because their workforces are very young. Productivity movements between rich and poor nations appear to be connected to relative demographic shifts. There is some evidence of productivity divergence between the rich and poor nations between 1960 and 1990. During the same time period, the rich nations have had aging workforces while the poorest nations have seen their workforces get younger.

The paper will proceed as follows. Section 1 reviews the existing literature. Section 2 discusses the microeconomic evidence related to the age structure of the population and suggests reasons why there may be important externalities that go unobserved in the micro evidence. Section 3 turns to the data to find evidence of these externalities. Section 4 discusses the implication of these results. Section 5 concludes.

1 Literature Review

Recent work in the empirical growth literature has shown the limits of the neoclassical growth model's ability to explain cross country income differences. Recent work by Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999) emphasize the importance of productivity differences and suggest that only half of cross country income differences can be explained by differences in physical and human capital accumulation.

Factor accumulation variables like schooling, investment, and population growth rates are undoubtedly important in explaining cross country output differences. These variables have several properties that make them natural candidates for empirical studies. They are relatively well defined and measured and vary over time. There is microeconomic variation in the accumulable factors, so we can turn to microeconomic evidence to inform us about private returns to capital and education. The Solow growth model provides a clear theoretical road map for thinking about factor accumulation. Most of the early empirical growth studies, such as Barro (1991) and Mankiw, Romer and Weil (1992) focused on factor accumulation.

Unfortunately, the problem of endogeneity in factor accumulation variables is nearly impossible to overcome, leading researchers away from growth regressions and toward an accounting approach which utilizes the microeconomic evidence on returns to investment.[1] This accounting approach is largely based on an updated version of Solow (1957). In

[1] Caselli, Esquivel and Lefort (1996) uses a GMM estimator to deal with endogenous factor accumulation. The results are roughly compatible with the growth accounting literature.

the Solow framework, variables not related to factor accumulation but which shift the productivity function appear as a residual and are famously labelled 'a measure of our ignorance.'

Variables that appear to be related to productivity, like institutions or geography present a different set of problems. These variables tend to have an indirect effect on output, so measurement is difficult. There is no clear theoretical basis for considering these variables.[2] Many of these variables, like geography, lack time series variation so they are only informative about persistent productivity differences. Some productivity variables also create causality concerns. Is high productivity due to good institutions or are good institutions a luxury enjoyed only by high productivity countries?

Despite the difficulties, several useful studies have appeared recently exploring productivity differences. Hall and Jones (1999) and Acemoglu, Johnson and Robinson (2001) emphasize the importance of institutions. Frankel and Romer (1999) show that trade has a positive effect on growth. These papers all use instrumental variables to solve the problem of endogeneity. Due to the lack of time variation in their instruments, these papers are limited to an examination of long run productivity differences.

Demographic data combine a number of useful qualities of other variables used in growth studies. There is micro evidence indicating that experience is important. There is significant time series variation in demographics. The age structure of the workforce is strongly predetermined. Surprisingly, demographic change has been relatively neglected in the empirical growth studies of the previous decade. Of the sixty variables considered by the two million regressions of Sala-i-Martin (1997), the only demographic characteristics included are population growth rate and the ratio of workforce size to population size. In a recent comprehensive survey of the empirical growth literature, Durlauf and Quah (1999) cite only Barro and Lee (1994) on the subject of the demographic structure of the population.

The focus of the work that has been done on demographics has largely focused on the

[2]While there is no lack of theory about the importance of institutions, geography, etc., none is as grounded and clear as the neoclassical growth model.

ratio of workers to non-workers in the economy, commonly referred to as the dependency ratio. In addition to the papers cited in the previous paragraph, Bloom, Canning and Sevilla (2001) find that increases in the size of the working age population can produce a "demographic dividend" to economic growth. Kögel (2001) finds a relationship between total factor productivity and the dependency ratio.

This paper is interested in the internal composition of the workforce, not the size of the workforce relative to the population. There is some previous work that moves a step in this direction by looking at the entire distribution of the population, not just the dependency ratio. In an empirical study of US states, Persson (2002) finds that the age structure of the population affects total factor productivity. Weil (1994) examines saving rates by age cohort and finds that workers in their late fifties save more than other cohorts. This paper differs from these two works in focusing on the age structure of the workforce, rather than the entire population.

Sarel (1995) finds a significant effect of the age structure of the population on output in a cross section of countries. Due to its use of cross country data, Sarel (1995) is the more closely related to this paper, but differs in several ways. First, this paper focuses on productivity, not output. By focusing on productivity, it is possible to distinguish between the impact of demographics on factor accumulation and the impact on productivity. The productivity channel turns out to be very important. There are also several econometric differences. Sarel (1995) assumes that the relationship between age and output is a quadratic function. This paper allows the age effects to vary in a less restrictive way. The regressions in Sarel (1995) are performed in a convergence framework including a lagged output term as an explanatory variable without any other controls. Since the age structure of the population will vary over time in a very structured way (the size of the group aged 30-35 today is roughly the same as the group aged 25-30 five years ago) it is not clear how to interpret the results of a regression including lagged dependent variables.

2 Mincerian Wage Regressions and Productivity

Many papers, including Barro (1991), Mankiw et al. (1992) and Benhabib and Speigel (1994) have found strong correlations between schooling and growth. However, the issue of causality has always been vexing, and attempts to find a casual link between schooling and economic performance have largely been disappointing. This has led to the current trend of utilizing microeconomic evidence on human capital to inform us about aggregate effects of schooling.

Mincerian wage regressions show that workers with more schooling and more experience receive higher wages. If workers earn their marginal product, then the wage differential described by the Mincer evidence is a measure of the productivity difference between workers caused by different levels of schooling and experience. The canonical Mincer wage regression takes the following form.

$$log(wage) = \alpha + \beta_1 * schooling + \beta_2 * experience + \beta_3 * experience^2 + \epsilon \tag{1}$$

Bils and Klenow (2000) collect a sample of these coefficients estimated for 52 countries. For the US, one estimate taken from Krueger and Pischke (1992) is

$$log(wage) = \alpha + 0.093 * schooling + 0.032 * experience - 0.00048 * experience^2 \tag{2}$$

According to these estimates, an additional year of schooling in the US increases the wage by 9.3%.[3] Experience has diminishing returns, with each addition year of experience increasing the wage by some amount less than 3.2%

If workers earn their marginal product, then the Mincer wage regressions should inform us about productivity differences between workers. The coefficients from these regressions can then be used to look at aggregate human capital differences. In the previous example,

[3] While there is cross country variation in the coefficient estimates, the US estimates are roughly representative. Bils and Klenow (2000) find coefficients on schooling as high as 0.28 (Jamaica) and as low as 0.024 (Poland). The majority of coefficients, however, fall between 0.05 and 0.15.

an additional year of schooling increased a worker's wage by roughly 10%. We can then look to the aggregate data and conclude that each year added to the *average* years of schooling in a population should increase aggregate output by 10%. Klenow and Rodriguez-Clare (1997) conclude that schooling differences, when viewed through the lens of the Mincer evidence, cannot explain the majority of cross country income differences.

The cross country growth literature has tended to focus on years of schooling as the relevant variable of interest. Since we are turning to the Mincer evidence for guidance, it seems natural to examine the role of experience. Klenow and Rodriguez-Clare (1997) and Bils and Klenow (2000) examine cross country differences in experience and show that they play a relatively minor role.[4]

According to the micro evidence, worker productivity in the US rises with age into the fifties then falls somewhat for workers in their sixties. The Mincer evidence implies that there is about a 50% difference between the productivity of twenty years old workers and fifty year old workers. For the aggregate data, this implies that an economy with a large cohort of young workers will have lower productivity than an economy with an large cohort of older workers.[5]

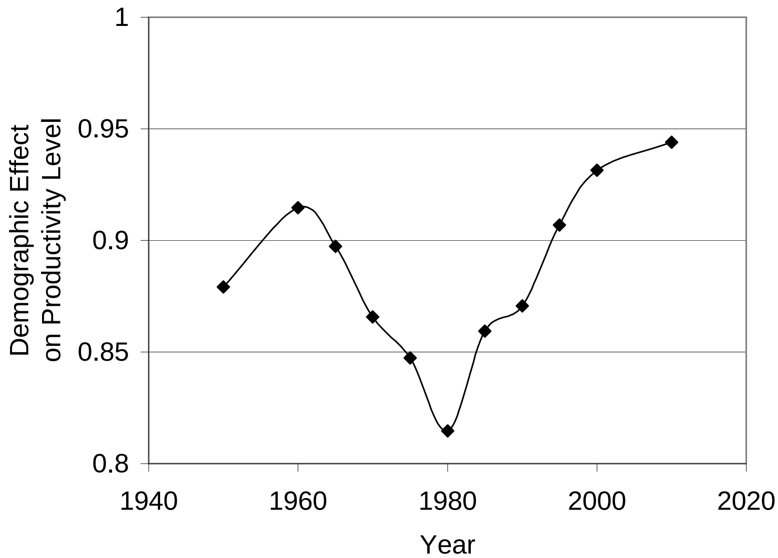
In order to make comparisons, it is useful to have a demographic reference distribution. Consider an economy with a stable population where workers enter the workforce at twenty and retire at sixty five. Over time, this will result in stable workforce demographics with a uniform distribution of ages from twenty to sixty five. Because the US has a growing population, the US demographic distribution has always been younger than a country with stable demographics. Figure 1 shows the US productivity level between 1960 and 2010 relative to an identical country with a stable demographic distribution.

In every year, the US has a less experienced workforce than the reference population and

[4]In fact, because experience is reduced by higher levels of education (you must defer experience while in school), education and experience tend to work in opposite directions. Including experience tends to reduce the proportion of cross country income differences that can be explained by overall human capital differences.

[5]Assuming, of course that productivity is measured in a way that does not account for differences in human capital through experience.

Figure 1: The Mincer Effect of Experience on the Productivity Level in the US

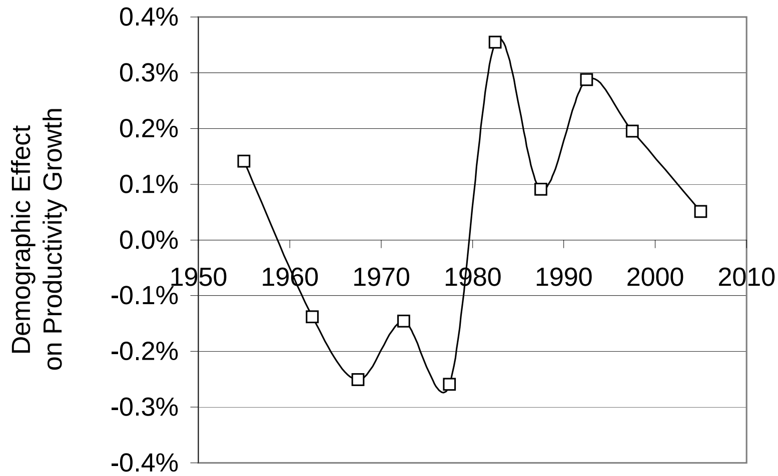


therefore lower productivity. As the US workforce grew younger during the seventies, the Mincer evidence suggests that productivity fell by about ten percent. As the baby boom cohort aged, the workforce grew more experienced and by 1990 the aggregate effect of experience returned to the levels of 1960. Figure 2 shows the impact of changing workforce demographics on US productivity growth. Suppose that there is constant trend growth in productivity.[6] Figure 2 shows the deviations from trend growth induced by demographic changes.

The Mincer evidence implies that productivity growth was reduced by about 0.2% from trend in the seventies due to demographic changes. As the baby boom aged through the eighties and nineties, their increasing experience made them more productive. The Mincer evidence suggests that productivity growth was above trend in the eighties and nineties by 0.1 to 0.3%. These results indicate that demographics may be a useful predictor of productivity growth. However, the magnitudes implied by the Mincer evidence appear to be too small to explain more than a small portion of US productivity movements.

[6]The estimation section of the paper does not make this assumption.

Figure 2: The Mincer Effect of Experience on Productivity Growth in the US



2.1 Externalities to Human Capital

The Mincer evidence may not tell the entire story at the aggregate level. The micro evidence, based on wage data, only captures the private return to experience and education. It may be that the social returns are higher than the private returns. Externalities to schooling and experience may mean that the Mincer coefficients are understating the aggregate productivity effects.[7]

Suppose that productivity changes are driven by individuals engaged in innovative activity. The Mincer coefficients on experience are unlikely to capture the full societal gains from innovation for several reasons. Recall that the Mincer regressions rely on wage data. Many wage surveys limit the maximum wage that can be reported. More importantly, for many individuals the majority of the benefits of their innovative activity may come in non wage forms, such as rising equity. This is particularly true of self employed workers.

A more important issue is the ability of firms to capture the full surplus created by

[7]The importance of externalities to education has long been emphasized beginning with the theoretical work of Nelson and Phelps (1966). It has, however, been difficult to show that these externalities exist empirically. Panel growth regressions such as Caselli et al. (1996) take into account country specific productivity effects and try to deal with the endogeneity of schooling relative to output. These regressions fail to find coefficients on schooling consistent with large externalities. In a study of US states, Acemoglu and Angrist (2000) also fail to find evidence of large externalities to education. Aiyar and Feyrer (2002) find evidence of dynamic externalities to human capital that act over long time periods.

innovation. In many innovative industries, a large proportion of productivity increases show up in consumer surplus, through lower prices. Take for example, the chip making industry. Suppose that an innovative firm implements a new technology to reduce the cost of manufacturing memory chips, giving them a competitive advantage. Other firms will respond with similar innovations (potentially benefitting from the example of the first firm). Prices fall and industry profits are the same as before the innovation. The societal benefit from the innovation shows up largely in the form of falling prices, not in the profits of the firm.

This paper will concern itself with the impact of the age structure of the workforce on aggregate productivity. If productivity growth is driven by innovation, then the ages at which workers are generating and implementing new ideas may be important. Lehman (1953) finds that creative output in science and invention varies substantially by age. There is some variation among disciplines, but Lehman finds that peak productivity tends to be in the interval between ages 30 and 40. If there is indeed an age effect in idea generation, having a larger cohort of workers in the peak idea generating ages should result in more rapid production of new ideas and new technologies. As an extreme example, consider the world of academic mathematics, where a significant portion of the innovative ideas are produced by people between the ages of twenty five and thirty five.[8] If the world were like a mathematics department, we would expect to see more new ideas being produced in countries with a large cohort of young workers.

While creative output is one potential channel through which age may impact productivity, it may not be the most relevant for cross country comparisons. For most of the countries in the world, it is not idea creation that matters so much as idea adoption. The distinction between idea creation and adoption is an important one because there are two distinct ways to think about the impact of the age distribution on productivity. If idea creation is important, then changes in the age distribution will have permanent growth effects. To take the example of the mathematics department, a department with a large

[8] Lehman (1953), p. 8

cohort aged twenty five to thirty five will generate more good ideas, raising productivity growth in every year that the department has this demographic composition.

Organizations (or countries) that increase productivity by producing new ideas are different than organizations that adopt ideas generated elsewhere. Idea generators operate at the technological frontier at all times because they define the frontier. The rate of new idea creation determines the rate of expansion of the frontier.

For technology adopters, the technological frontier is a given. Nothing an adopter does impacts the rate of expansion of the frontier and adopters are always operating below the frontier. The relevant question is how far below the frontier they are operating. If age structure affects the rate of technology adoption, then favorable demographic shifts may make a country more effective at implementing ideas generated elsewhere. This allows the country to get closer to the frontier and in the short run this means more rapid productivity growth. However, in the long run growth will be determined by the movement of the frontier which is exogenous from the point of view of the adopter. It seems apparent that most countries in the world are technology adopters.

There is microeconomic evidence that age matters in the adoption of technology. Weinberg (2002) finds that both experience and age matters for technology adoption. Among high school graduates, technology adoption complements experience while among college graduates, technology adoption complements youth. This evidence points toward a tension between youth and experience. Since schooling tends to be concentrated early in life, young workers have the advantage of more recent human capital.[9] It may also be that younger workers are less bound by tradition and more likely to take risks. Young workers, on the other hand, lack human capital in the form of experience.

Entrepreneurial activity is one way in which new technologies are introduced into the economy. Using survey data produced by the Global Entrepreneurship Monitor (GEM) project Zacharakis, Reynolds and Bygrave (1999) suggest that the level of entrepreneurial activity is related to the age structure of the population. In a survey spanning ten OECD

[9]Chari and Hoenhayn (1991) find that technologies diffuse slowly due to vintage human capital effects.

counties they find that the majority of those involved in start-ups are 25-44 years old.[10] They also find that the proportion of adults in these "entrepreneurial years" have a correlation of 0.7 with overall start-up rates. If we believe that entrepreneurs play a major role in technological change, having a large cohort of workers in their prime entrepreneurial years may lead to more rapid productivity growth.

Other evidence points to the relative youth of innovators. Inc Magazine has a yearly survey of the 500 fastest growing companies in the US. In the 2001 survey, the median age of an Inc 500 CEO was 42 [11]. There is a gap between the beginning of entrepreneurial activity and the rapid growth required to join the Inc 500. The average age when Inc 500 CEO's started their companies was 34 and the average age of the companies that they managed was 8 years.

Though the evidence presented in this section is quite anecdotal, it suggests several things. First, age seems to matter in both generating ideas and engaging in entrepreneurial activity. Second, the ages at which these activities peak appears to be well below the age at which wages peak.[12]

3 The Effect of Workforce Demographics

The evidence from wage regressions suggests that demographic measures should be related to aggregate output and aggregate productivity.[13] The micro evidence, however, suggests that the impact will be relatively small in the absence of productive externalities. This section will test econometrically for these externalities.

Demographic measures have nice econometric properties compared to other explanatory

[10] The GEM project is rapidly expanding to other countries, including some non OECD countries such as India and Brazil. Findings on the age structure of entrepreneurship appears to be very similar across all countries, including LDC's.

[11] This is considerably younger than the average age of 56 for Fortune 500 CEO's.

[12] According to the results from Krueger and Pischke (1992), the wage peak in the US occurs in the early fifties.

[13] By productivity, I am referring to productivity measures that do not already account for experience differences.

variables in the growth literature. It is widely accepted that many variables commonly included in growth regressions are endogenous. That is, it is very difficult to determine whether growth causes schooling or the other way around.[14] The same is true for investment and population growth. Demographic metrics, on the other hand, are predetermined with a lag of over twenty years. Therefore, it seems reasonable to think that changes in demographic measures are exogenous with respect to contemporaneous productivity movements.

3.1 Estimation

Log productivity in country i at time t, $a_{i,t}$, is assumed to be a function of a time invariant country fixed effect, f_i, a time trend common to all countries, μ_t, and a vector of explanatory variables $x_{i,t}$.

$$a_{i,t} = f_i + \mu_t + \beta x_{i,t} + u_{i,t} \tag{3}$$

Productivity is calculated as a Solow residual. I assume a Cobb-Douglas production function taking physical capital, human capital from schooling, and productivity as inputs.

$$y_{i,t} = k_{i,t}^{\alpha}(A_{i,t}\ h_{i,t})^{1-\alpha} \tag{4}$$

where $y_{i,t}$ is output, $k_{i,t}$ is capital per worker, $h_{i,t}$ is human capital per worker, and $A_{i,t}$ represents productivity. Capital's share of output, α is assumed to be 1/3.[15] The human capital production function is assumed to have a Mincer form

$$h_{i,t} = e^{\phi(s_{i,t})} \tag{5}$$

where $s_{i,t}$ is the average years of schooling in country i at time t and $\phi(s)$ is an increasing

[14] The working paper title of Bils and Klenow (2000)

[15] Gollin (2002) shows that capital's share is roughly equal across counties.

function that is assumed to be piecewise linear with decreasing returns to scale. The coefficients are taken from Psacharopoulos (1994), which surveys the literature on returns to schooling.[16] The production function can be solved for the productivity term.[17]

$$logA_{i,t} = \frac{1}{1-\alpha} logy_{i,t} - \frac{\alpha}{1-\alpha} logk_{i,t} - logh_{i,t} \tag{6}$$

Since productivity is a Solow residual, it tends to take on the statistical properties of output. Therefore, serial correlation in the error term is a potential problem only partially mitigated by the fact that productivity is measured at 5 year intervals. Serial correlation should not affect the consistency of the parameter estimates, but will result in misstated standard errors. In order to deal with this, I exploit the panel structure of the data and cluster standard errors by country. This allows for an arbitrary covariance structure within each country and should produce consistent estimates of the standard errors as long as productivity is not a unit root process.

To deal with the possibility of a unit root, estimation is done both in levels and first differences. If productivity follows a random walk, the error term will have the following structure.

$$u_{i,t} = u_{i,t-1} + \epsilon_{i,t} \tag{7}$$

Productivity growth will be stationary with i.i.d. errors. Taking first differences of (3)

$$\Delta a_{i,t} = \mu_t + \beta \Delta x_{i,t} + \epsilon_{i,t} \tag{8}$$

yields a regression equation in productivity growth where Δ is the first difference operator. Since serial correlation is also possible in the differenced regression, errors will be clustered

[16] The choice of coefficients follows Hall and Jones (1999). For the first four years of schooling the return to schooling in sub-Saharan Africa, 13.4 percent, is used. For schooling from four to eight years the world average return to schooling, 10.1 percent, is used. For schooling beyond 8 years the OECD return to schooling, 6.8 percent, is used. The precise method of calculating human capital from schooling turns out to be unimportant for the following results.

[17] The productivity measure being used here takes into account differences in human capital in the form of schooling, but not differences in human capital that are due to experience.

by country.

The dependent variable is the log of the productivity residual. The regressors are the proportion of the workforce by age group, with W10 indicating workers between 10 and 19, W20 workers between 20 and 29, etc. W60 indicates workers older than 60 years of age. Since these variables are proportions, the sum of all the age groups is one for each country year pair. For this reason, one group is excluded. I choose to exclude W40 because the forty year old age group generally has the highest coefficient when included. By excluding W40, significant coefficients on the other age groups indicate that they are significantly different from the implied zero coefficient on W40.

As discussed in the previous section, demographics are assumed to have a level effect, not a growth effect. That is, the level of productivity is assumed to be a function of workforce demographics. The growth rate of productivity is assumed to be a function of *changes* in workforce demographics. Two countries with static, but different workforce demographics will have different levels of productivity, but a share a common growth rate.

3.2 Data

The data on workforce composition are from two sources. The International Labor Organization (ILO) has compiled cross country data on the number of workers by five year age groups spanning age ten to age sixty five. These are available at ten year intervals starting in 1960. The UN has similar data for the total population for five year intervals. The data are transformed in two ways. First, in order to reduce the number of coefficients being estimated, the age categories are collapsed to ten year groups. Second, the data are normalized by population and workforce size. The regressor W30 therefore indicates the proportion of the workforce between ages 30 and 39. The workforce numbers are only available at ten year intervals while output and human capital data are available at five year intervals. I therefore use the population data from the UN to impute the intermediate values for the workforce.[18]

Data for output are from the Penn World Tables, adjusted to exclude income from mining and oil.[19] Data for capital per worker are from Easterly and Levine (2000).[20] The schooling data used to calculate human capital stocks are from Barro and Lee.

Two different samples are used, a large sample which includes all countries for which data exists, excluding oil exporters. The second sample is limited to the OECD. The data for each sample make up a panel at five year intervals from 1960 to 1990.

3.3 Results

Table 1 describes the results of regressing the log level of productivity on workforce demographic measures. The model is estimated using country fixed effects with a full set of time dummies. Table 2 describes the results of estimating the model in differences, both with and without a full set of country dummies. Without country dummies, the estimation is equivalent to the regressions in levels with country fixed effects reported in Table 1. Adding a set of country dummies allows for different productivity trend growth in each country in the sample.

Tables 1 and 2 return remarkably similar results. In all six estimations, the coefficients on W10, W20, and W30 are significant at the 5% level. This suggests that countries with a large proportion of workers in their teens, twenties and thirties are significantly less productive than countries with large cohorts in their forties. In two of the three estimations on the full sample, the coefficients on W50 and W60 are also significant. The demographic measures are jointly significant at the 1% level in all the reported regressions. The inclusion of country dummies in the differenced estimates does not significantly alter the demographic

[18] Imputations are generated by a two stage process. In the first stage, the variable to be imputed is regressed on all the available population demographic data (P10, P20, ... , P90) and a full set of country dummies. The coefficients from the first stage are used to predict the missing values.

[19] This correction is taken from UN national accounts data, as collected in Aiyar and Feyrer (2002). Because the regressions in this paper exclude oil exporting countries, the corrections are quite minor and have very little impact on the results

[20] Their calculations, in turn, are based on the Penn World Tables 5.6. Both are available from the World Bank website (http://www.wordbank.org/research/growth).

Table 1: The Effect of Workforce Age Structure on Productivity

Sample	Nonoil	OECD
Country Dummy	Yes	Yes
	OLS	OLS
	LogA	LogA
W10 imputed	-5.069**	-5.536**
	(1.549)	(1.197)
W20 imputed	-2.296*	-2.226*
	(1.126)	(0.863)
W30 imputed	-2.571*	-3.728**
	(1.085)	(0.987)
W50 imputed	-2.670*	-1.813
	(1.107)	(1.071)
W60 imputed	-6.249**	-2.374
	(1.615)	(2.158)
year==1965	-0.041	0.042
	(0.051)	(0.058)
year==1970	0.195**	0.224**
	(0.038)	(0.054)
year==1975	0.076	0.175*
	(0.064)	(0.070)
year==1980	0.144*	0.248**
	(0.055)	(0.064)
year==1985	-0.018	0.223**
	(0.079)	(0.075)
year==1990	-0.034	0.262**
	(0.080)	(0.085)
Constant	11.554**	11.412**
	(0.818)	(0.465)
Observations	572	147
Countries	85	21
R-squared	0.90	0.84

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

Table 2: The Effect of Changes in the Workforce Age Structure on Productivity Growth

Sample	Nonoil	OECD	Nonoil	OECD
Country Dummy	yes	yes	no	no
	OLS	OLS	OLS	OLS
	ΔLogA	ΔLogA	ΔLogA	ΔLogA
ΔW10 imputed	-3.505*	-2.835*	-4.094**	-3.425**
	(1.340)	(1.032)	(1.109)	(0.744)
ΔW20 imputed	-3.599**	-3.114**	-3.681**	-3.175**
	(1.247)	(1.012)	(1.114)	(0.716)
ΔW30 imputed	-4.065**	-1.808*	-3.450**	-2.041**
	(1.351)	(0.696)	(1.107)	(0.588)
ΔW50 imputed	-2.536*	-2.147+	-3.481**	-1.913*
	(1.002)	(1.058)	(0.903)	(0.797)
ΔW60 imputed	-1.737	-2.496	-3.210**	-2.371+
	(1.135)	(1.463)	(1.032)	(1.164)
year==1965	-0.144**	0.133**	0.080*	0.111**
	(0.037)	(0.041)	(0.037)	(0.032)
year==1970	-0.190**	0.183**	0.134**	0.186**
	(0.055)	(0.057)	(0.039)	(0.053)
year==1975	-0.250**	0.007	-0.016	-0.008
	(0.035)	(0.043)	(0.032)	(0.030)
year==1980	-0.233**	0.014	0.051+	0.015
	(0.029)	(0.041)	(0.027)	(0.040)
year==1985	-0.346**	0.020	-0.103**	0.004
	(0.026)	(0.028)	(0.032)	(0.021)
year==1990	-0.285**	0.031	-0.021	0.026
	(0.028)	(0.027)	(0.027)	(0.023)
Observations	487	126	487	126
Countries	85	21	85	21
R-squared	0.29	0.63	0.15	0.54

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

results.[21]

The differences between the age groups are extremely large. According to the Table 2 nonoil (column three) estimates, a five percentage point shift from the thirty year age group to the forty year age group results in over a 17% increase in productivity.[22] Supposing this shift occurred over a 10 year period, this would add approximately 1.7 percentage points to productivity growth in each year. This impact is over thirty times larger than the Mincer evidence would suggest.

3.4 Robustness

The coefficients are extremely robust to changes in estimation method. Tables 1 and 2 present the results from estimating in levels and differences using the imputed results. Table 3 describes regressions using the workforce demographics at ten year intervals and therefore avoids imputing values. Since I am not using the population demographic data to impute the missing years it is possible to use the population data as an instrument for the workforce data. Though the composition of the population is strongly predetermined, you might be concerned that labor force participation rates are endogenous. Instrumenting the workforce statistics on population will solve this problem.

The coefficients are less precisely estimated than for the imputed sample, but tell much the same story. For the full sample, workers in their twenties and sixties are significantly less productive than workers in their forties. The OLS estimates and the 2SLS estimates are not significantly different from each other.

Table 4 reports the results of differenced regressions on output rather than productivity. The change to output per worker allow me to extend the panel to 1995 and increase the number of countries. The coefficients are very similar to those from the productivity regressions. The next section will examine the regressions on output in more detail.

[21] The country dummies are jointly significant in all the reported regressions.

[22] Demographic shifts of this size, while not the norm, are present in the data. Between 1980 and 1990, the proportion of workers in the US aged between 40 and 49 rose by 4.6%.

Table 3: The Effect of Workforce Composition on Productivity

Sample	Nonoil 2SLS	OECD 2SLS	Nonoil OLS	OECD OLS
	LogA	LogA	LogA	LogA
W10	-8.030**	-5.776**	-4.731*	-7.249**
	(2.058)	(1.899)	(1.820)	(1.677)
W20	-3.154*	-2.460+	-1.247	-1.031
	(1.274)	(1.369)	(1.815)	(1.066)
W30	-3.312*	-3.066	-1.936	-3.327*
	(1.436)	(1.855)	(1.682)	(1.402)
W50	-3.446*	-0.073	-1.443	-1.854
	(1.474)	(2.537)	(1.993)	(1.714)
W60	-7.015**	-5.475	-5.007*	-1.178
	(2.510)	(3.872)	(2.380)	(2.575)
year=1970	0.199**	0.235**	0.196**	0.207**
	(0.042)	(0.076)	(0.040)	(0.066)
year=1980	0.111*	0.148	0.135*	0.176*
	(0.054)	(0.101)	(0.057)	(0.081)
year=1990	-0.105	0.156	-0.028	0.181
	(0.094)	(0.120)	(0.089)	(0.118)
Constant	10.988**	10.403**	11.539**	10.235**
	(0.904)	(0.956)	(1.142)	(0.925)
Observations	337	84	337	84
Countries	86	21	86	21
R-squared	0.90	0.85	0.90	0.86

Standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 4: The Effect of Workforce Composition on per Worker Output

Sample	Nonoil	OECD	Nonoil	OECD
Country Dummy	yes	yes	no	no
	OLS	OLS	OLS	OLS
	ΔLog(gdpw)	ΔLog(gdpw)	ΔLog(gdpw)	ΔLog(gdpw)
ΔW10 imputed	-2.522**	-2.151**	-4.195**	-3.057**
	(0.644)	(0.524)	(0.672)	(0.610)
ΔW20 imputed	-2.103**	-1.875**	-3.049**	-1.874**
	(0.589)	(0.462)	(0.630)	(0.452)
ΔW30 imputed	-2.111**	-1.096*	-2.567**	-1.537**
	(0.593)	(0.423)	(0.614)	(0.463)
ΔW50 imputed	-1.492*	-1.454**	-2.562**	-1.559**
	(0.580)	(0.457)	(0.588)	(0.430)
ΔW60 imputed	-1.408*	-1.692+	-2.949**	-1.295
	(0.698)	(0.870)	(0.731)	(0.841)
year==1965	0.105**	0.122**	0.060**	0.135**
	(0.028)	(0.020)	(0.022)	(0.020)
year==1970	0.173**	0.212**	0.237**	0.244**
	(0.034)	(0.031)	(0.022)	(0.034)
year==1975	0.063*	0.049*	0.033	0.070**
	(0.028)	(0.021)	(0.021)	(0.016)
year==1980	0.122**	0.088**	0.162**	0.135**
	(0.025)	(0.021)	(0.018)	(0.020)
year==1985	-0.026	-0.007	-0.044*	0.004
	(0.024)	(0.013)	(0.020)	(0.012)
year==1990	0.005	0.043*	0.010	0.076**
	(0.024)	(0.017)	(0.017)	(0.020)
year==1995	-0.001	-0.010	-0.010	0.015
	(0.007)	(0.023)	(0.019)	(0.024)
Observations	708	154	708	154
Countries	108	22	108	22
R-squared	0.51	0.87	0.33	0.77

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

3.5 Factor Accumulation and Demographics

The previous section establishes that demographics have a large impact on productivity. It is also possible that demographic change will impact growth through factor accumulation. This section will examine the impact of demographics on factor accumulation.

Recall that productivity is calculated as a Solow residual based on a Cobb Douglas production function,

$$y_{it} = k^{\alpha}(A_{it}h_{it})^{1-\alpha} \tag{9}$$

which can be rewritten as

$$y_{it} = \left(\frac{K}{Y}\right)_{it}^{\frac{\alpha}{1-\alpha}} A_{it}h_{it} \tag{10}$$

laking logs of both sides

$$log(y_{it}) = \frac{\alpha}{1-\alpha} log\left(\frac{K}{Y}\right)_{it} + log(A_{it}) + log(h_{it}) \tag{11}$$

Equation 11 provides a guide to decomposing movements in output. By construction, all output differences across countries and time must come from differences in one of the three right hand side variables.[23] The capital term is (K/Y), not capital per worker, because the capital output ratio correctly captures differences in capital accumulation that are not attributable to productivity differences.[24] The $log(h)$ term captures human capital from schooling, leaving $log(A)$ as a Solow residual. The previous section concentrated on

[23] I continue to assume that α is the same in all countries at all times.

[24] To see the relationship between productivity and capital per worker, start with the Solow model with neutral technological progress:

$$y_{i,t} = A_{i,t}\ f(k_{i,t}) \tag{12}$$

$$\dot{k}_{i,t} = s_i A_{i,t} f(k_{i,t}) - (n_i + \delta)k_{i,t} \tag{13}$$

where $f(k_{i,t})$ is a neoclassical production function with decreasing returns to capital per worker, $A_{i,t}$ is an exogenous productivity parameter, $k_{i,t}$ is capital per worker, n_i is population growth, and δ is depreciation. We can state the requirements for a steady state where $\dot{k}_{i,t} = 0$.

$$(n_i + \delta)\ k^*_{i,t} = A_{i,t}\ f(k^*_{i,t})\ s_i \tag{14}$$

It can be shown that the steady state level of capital per worker, $k^*_{i,t}$ is an increasing function of the productivity level $A_{i,t}$. A shock to productivity will therefore produce an increase in the steady state level the relationship between demographics and $log(A)$, ignoring factor accumulation. Table 5 shows the results of regressing output and each of the components of output on the demographic variables. For each of the regressions the sample is composed of the nonoil countries. The results for the OECD sample are similar.

By design, the coefficients on the three components of output sum to the coefficient on output. The relative magnitudes of the coefficients indicate the importance of demographics for each of the components of output. The most striking feature of this table is the overwhelming importance of the productivity channel. The productivity coefficients are uniformly an order of magnitude higher than the factor coefficients.

Demographics have the expected impact on capital stocks. For the capital output ratio, large cohorts younger than 40 and older than 60 are correlated with a lower stock of capital. The significant coefficient on W50 indicates that a large cohort of workers in their fifties increases the level of the capital stock. The coefficient on W50 is significantly higher than the coefficients on all the other age categories. This is consistent with life cycle models of saving. Workers in their fifties are at their peak earning years and will therefore be at their peak saving rates.[25]

The coefficients on the human capital regression are somewhat less clear. Having a large cohort of workers in their forties appears to impede human capital accumulation. Large cohorts in their twenties and fifties correlate with increasing human capital stocks. Human capital will therefore move in the opposite direction from productivity in response to demographic change. Increases in the number of workers in their forties will increase productivity, but will tend to inhibit human capital growth. Because of the much larger coefficients on productivity, the productivity affect will dominate.

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of capital per worker. On the other hand, the steady state level of the capital-output ratio,

$$\left(\frac{K}{Y}\right)^{*}_{i,t} = \frac{k^{*}_{i,t}}{A_{i,t}\ f(k^{*}_{i,t})} = \frac{s_i}{n_i + \delta} \tag{15}$$

is not a function of the productivity level.

[25] Weil (1994) finds similar evidence that the age structure of the population affects savings rates.

Table 5: Decomposing The Effect of Workforce Composition

	Δlog(gdpw)	Δlog(A)	$\frac{\alpha}{1-\alpha}\Delta log(K/Y)$	Δlog(h)
ΔW10 imputed	-4.222**	-4.094**	-0.348	0.141
	(0.766)	(1.109)	(0.459)	(0.194)
ΔW20 imputed	-3.201**	-3.681**	-0.167	0.547**
	(0.792)	(1.114)	(0.351)	(0.199)
ΔW30 imputed	-3.373**	-3.450**	-0.241	0.230
	(0.808)	(1.107)	(0.344)	(0.194)
ΔW50 imputed	-2.420**	-3.481**	0.647+	0.516+
	(0.726)	(0.903)	(0.379)	(0.264)
ΔW60 imputed	-3.075**	-3.210**	-0.141	0.276
	(0.791)	(1.032)	(0.324)	(0.215)
year==1965	0.073**	0.080*	-0.008	0.002
	(0.027)	(0.037)	(0.015)	(0.007)
year==1970	0.217**	0.134**	0.036*	0.046**
	(0.027)	(0.039)	(0.015)	(0.007)
year==1975	0.057*	-0.016	0.048**	0.026**
	(0.025)	(0.032)	(0.013)	(0.006)
year==1980	0.147**	0.051+	0.036**	0.051**
	(0.019)	(0.027)	(0.011)	(0.007)
year==1985	-0.026	-0.103**	0.048**	0.033**
	(0.024)	(0.032)	(0.014)	(0.006)
year==1990	0.022	-0.021	-0.012	0.059**
	(0.020)	(0.027)	(0.010)	(0.005)
Observations	487	487	487	487
Countries	85	85	85	85
R-squared	0.37	0.15	0.17	0.49
ΔW joint p-value	0.00	0.00	0.16	0.08

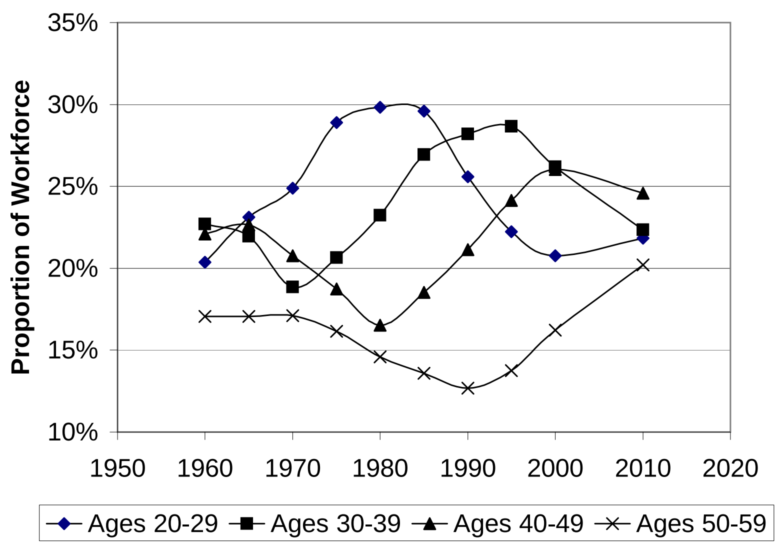
Standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

4 Implications

4.1 US Productivity

The previous section makes the case that there are large externalities to having a large group of workers in their forties. This has potentially large implications for the US since the US workforce has undergone (and is still undergoing) a massive demographic transition since the late sixties. This transition is described in Figure 3. In 1960, the proportion

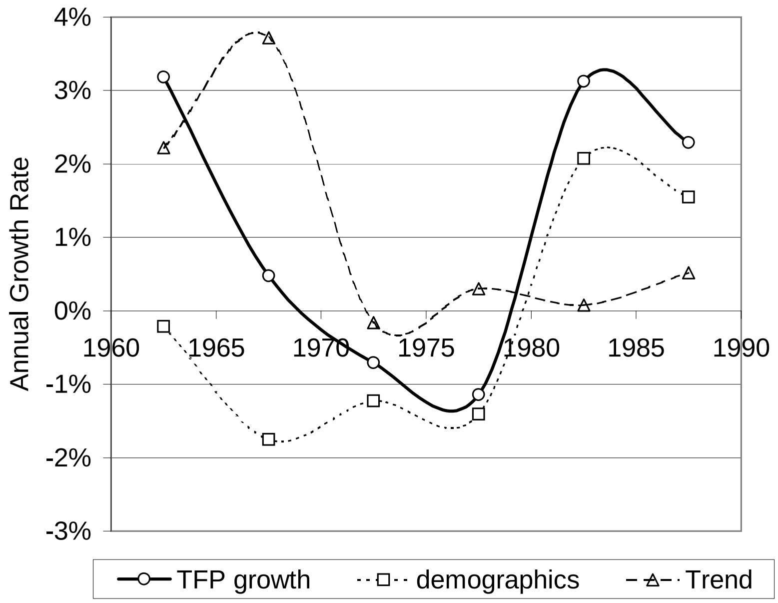
Figure 3: US Workforce Demographics



of workers in the US economy in their twenties, thirties, and forties was relatively equal at between 20 and 25%. As the baby boom entered the workforce in the seventies, these proportions changed dramatically. By 1980, the proportion of workers in their twenties had risen by ten percentage points to almost 30% of the workforce. At the same time, the proportion of workers in their forties fell to 17% from a high of 22%. From 1980 on this trend reverses as the baby boom ages. By 2000, workers in their forties outnumber workers in their twenties.

Given the results of the previous section, the connection between the demographic transition in the US and the productivity slowdown should be clear. As the baby boomers

Figure 4: The Demographic Effect on US Productivity Growth



entered their twenties in the seventies, productivity growth slowed as the size of the 40-49 cohort fell. As the boomers entered their forties beginning in about 1980, this caused an upsurge in productivity growth. Using the coefficients from the OECD sample in Table 2, Figure 4 plots actual US TFP growth, the time trend as estimated by the time dummies, and the change in productivity growth driven by demographic change.[26]

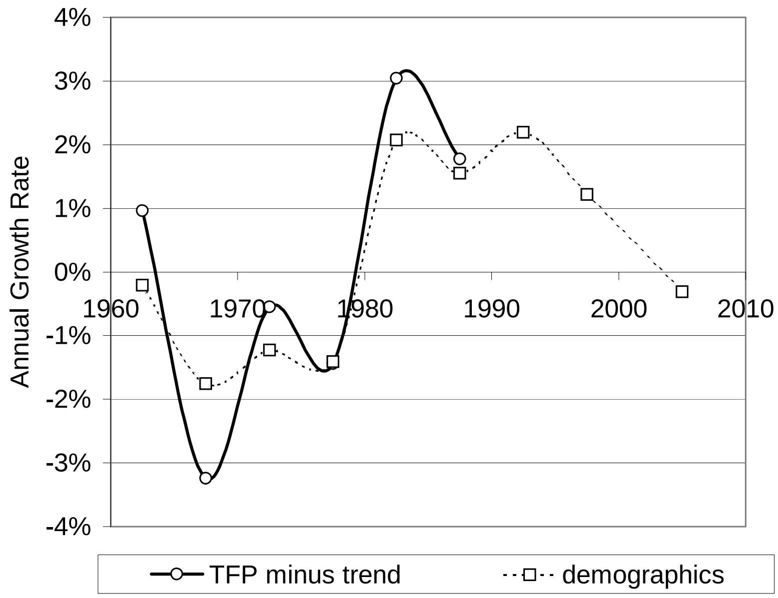
The solid line is the growth of the Solow residual for the US. There is a significant dip in the seventies and a rebound in the eighties. The dashed line with triangles is the common growth rate of productivity for the OECD sample as estimated by the time dummies in the fourth column of Table 2. Trend growth experiences a slowdown in the seventies and eighties compared to the sixties.

The dotted line with squares is the demographic effect on productivity growth calculated by using the estimates from Table 2 and demographic data for the US. These estimates are constructed so that static workforce demographics imply a 0% impact of demographics on

[26]The choice of particular samples or estimation methods makes little difference for the following figures and discussion. The OECD sample estimated in differences with no time dummies (Table 2, column 4) has the lowest standard errors . For the broader cross country comparisons that appear later in the paper, the nonoil sample estimated in differences with no time dummies is used (Table 2, column 3).

productivity growth. The effect of the baby boom's entry into the workforce is evident in the seventies, with demographics causing an estimated 1.6% drop in productivity growth between 1970 and 1980. As the boomers leave their twenties in the eighties, demographics predict growth higher than trend. Figure 5 shows more clearly the relationship between the demographic effects and TFP growth. In Figure 5, the common time trend is subtracted from the Solow residual to return non trend TFP growth. This figure also includes forward projections of the demographic impact on productivity growth.

Figure 5: The Demographic Effect on US Productivity Growth Projected Forward



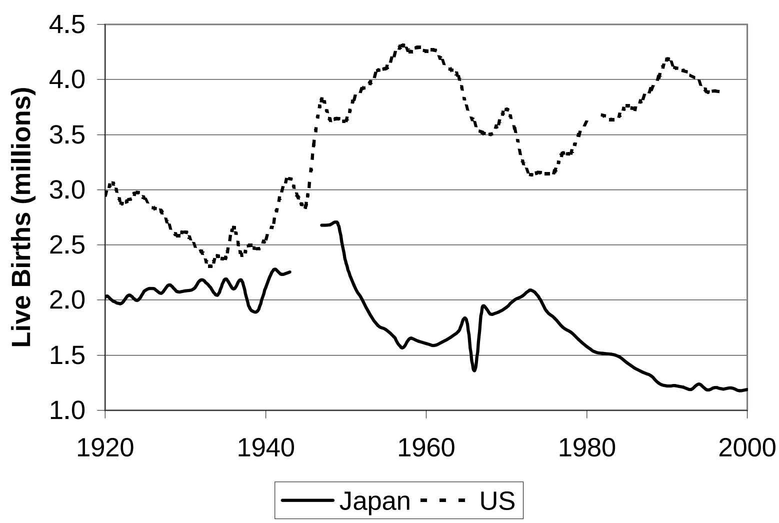
For 1980 through 2000 the model predicts productivity growth roughly 2% higher than trend as the baby boom is in its fourth decade. This prediction is quite consistent with the productivity revival that the US has experienced in the nineties. However, the model also predicts that this will not be sustained. Productivity growth rates in the nineties were driven by *changes* in demographics. For the last twenty years demographic changes have resulted in higher than usual productivity growth as the large baby boom cohort has aged. This period is about to end. The baby boom is about to leave the decade of their forties and move into their fifties. As they do so, productivity will grow more slowly.

The baby boom has been driving changes in the age structure of the US workforce for the last thirty years, but they are on the verge of leaving the workforce. As the baby boom exits the workforce, the main force driving US demographic change will be the children of the baby boom generation, the echo. The peak birth year for the baby boom was 1948. The peak birth year for the echo occurred almost thirty years later in 1990. As the echo begins to enter the workforce we should expect to see a productivity slowdown similar to the seventies. Because the echo cohort is not nearly as large as the baby boom cohort, the coming slowdown should be more mild than the slowdown in the seventies. However, for at least the next decade the entry of the echo will be combined with the aging of the boom to reduce productivity growth to almost 0.5% below trend.

4.2 The US and Japan

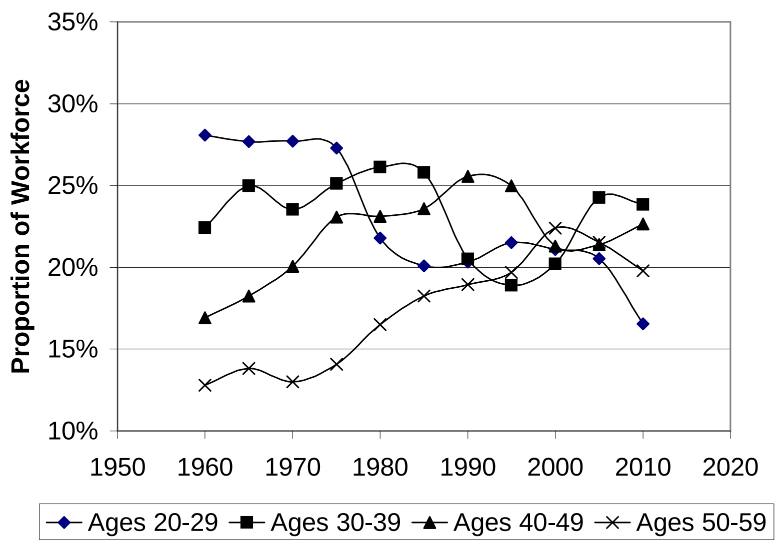
Relative demographic movements can also inform us about relative growth rates between different countries. The demographic composition of the Japanese workforce has differed greatly from the US in the postwar period. Figure 6 shows the number of live births in Japan and the US in the post war period. The most remarkable feature of this graph is the

Figure 6: Live Births in the US and Japan 1950-2000



degree to which US and Japanese birthrates move in opposite directions.[27] During the peak of the baby boom (around 1960), Japan was experiencing a local minimum in births. Japan had an upsurge in births during the mid seventies as the US was experiencing a significant slowdown. Consequently the Japanese workforce has very different demographic movements than the US. Figure 7 graphs the evolution of Japanese workforce demographics from 1960 to 2010. Japan has a steeply rising cohort of workers in their forties from 1960 to 1980, a

Figure 7: Japanese Workforce Demographics



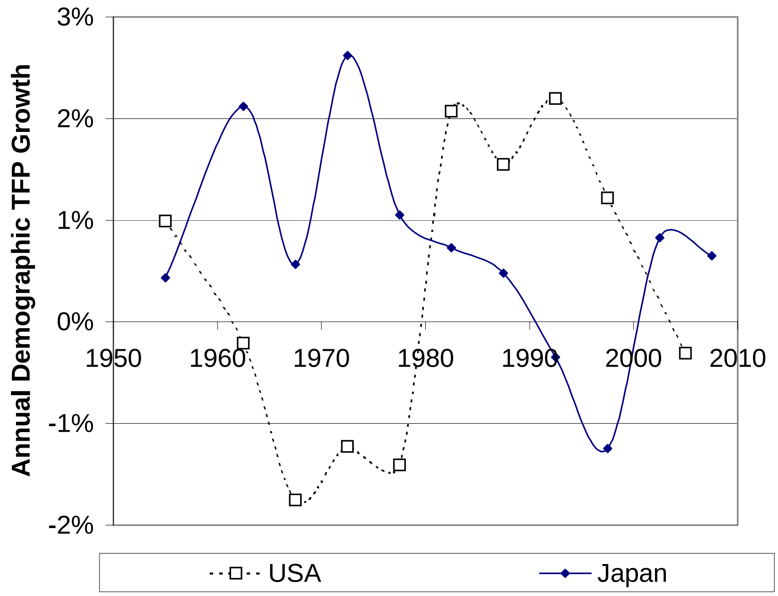
period when the US saw this cohort fall in size. From 1990 to 2000 the situation reverses.

Figure 8 graphs the demographic effect on productivity growth for the US and Japan. The demographic effect maps roughly to the observed growth pattern between the US and Japan. Between 1960 and 1980, the US was experiencing worsening demographics and low productivity growth. The model suggests that $2-3\%$ of the differences between US and Japanese growth in the seventies was attributable to demographic shifts. In the nineties, this situation reverses. The US saw higher productivity growth due to demographic shifts while Japan experienced declining productivity growth.[28] Demographics can explain a 2-4%

[27]In 1966 there was a dramatic one year downturn of almost one half million births in Japan. Apparently, 1966 was the most recent "Year of the Fire Horse." According to Japanese superstition, girls born in the year of the Fire Horse will have very unhappy lives and most likely will kill their husbands.

[28]For the 1995-2000 period the model predicted that Japan would have the lowest growth rate of any nation with demographic data available.

Figure 8: The Demographic Effect on US and Japanese Productivity Growth



differential between the US and Japan during the nineties. The model predicts that relative growth rates are set to reverse once again in the coming decade. The US is about to enter a period of slower productivity growth while Japan should see a significant improvement in productivity growth relative to the nineties.

4.3 Out of Sample Predictions, 1990-1995

One of the nice features of demographic change is its predictability. The model should, in theory, allow us to predict future movements in productivity. To test this, out of sample projections of output growth for 1990-1995 were constructed using demographic data and the coefficients estimated using the 1960-1990 data. Figure 9 graphs these growth projections against actual growth in real GDP per worker for 1990-1995.

Table 6 presents the results of an OLS regression on the demographic predictions versus actual output growth in the 1990-1995 period. The point estimate for the coefficient is near one and is significant at the 1% level. Demographic changes appear to predict seventeen percent of the growth in real GDP per worker in the 1990-1995 period. The projections

Figure 9: Out of Sample Predictions of 1995 Output Growth

Table 6: Predicted Versus Actual Growth of Real per Worker GDP 1990-1995

	RGDPW growth
Prediction	0.811
	(0.207)
Constant	-0.002
	(0.020)
N	102
R^2	0.17

Robust standard errors in parentheses

are based on a regressions in differences including a country dummy so that cross country differences in trend growth are included in the prediction. Using predictions based on demographic measures alone (omitting the country dummies) produces similar results, with an R^2 of 0.12.

4.4 Cross Country Productivity Differences

The link between demographics and productivity growth can also provide insight into cross country productivity patterns. The demographic characteristics of the workforce differ greatly across regions and income levels. Figures 10 and 11 summarize the demographic profile of nations by region and income.

As these graphs show, the size of the demographic transition in North America is exceptional. The size of the post war baby boom was much larger in North America (US and Canada) than in Western Europe. In the Middle East & North Africa and Latin America the baby boom started later and ended less decisively. Sub Saharan Africa and South Asia have a baby boom that has not ended, with an increasing proportion of twenty year olds continuing into the future. The income group graphs mirror these results. The OECD is largely the same as Western Europe, while the low income group follows Sub Saharan Africa.

Figures 12 and 13 show the impact of these demographics on productivity growth along with detrended productivity growth by region and income level.[29] Countries with modest demographic changes see little impact of demographics on TFP growth. North America and Western Europe see large demographic TFP growth movements while Sub Saharan Africa and Latin America see little movement in demographic TFP growth.

Figures 14 and 15 illustrate the proportion of the workforce between the ages of 40 and 49 by region and income level. Two facts are immediately apparent. The poorer nations have a lower proportion of forty year old workers than the richer nations in every year. This will result in lower productivity in the poor nations throughout the sample. The second aspect of the graph is the trend. The wealthy nations saw a relatively static 40 year old cohort until about 1980. From 1980 until 2000 the proportion of 40 year olds increases dramatically. This is not true of the poor nations. Sub Sahara Africa, in particular, sees a substantial fall in the size of the 40 year old cohort.

This may have implications for "club convergence." Quah (1993) concludes that world income is moving toward a twin peaked distribution, with a cluster of rich countries and a cluster of poor countries. Countries in the middle of the income distribution appear to be transitioning to one of the extreme groups in the long run. The upper and lower income

[29] Detrended productivity growth for each group is the average change in the Solow residual minus the time dummies from the productivity regressions.

Figure 10: Demographics by Region

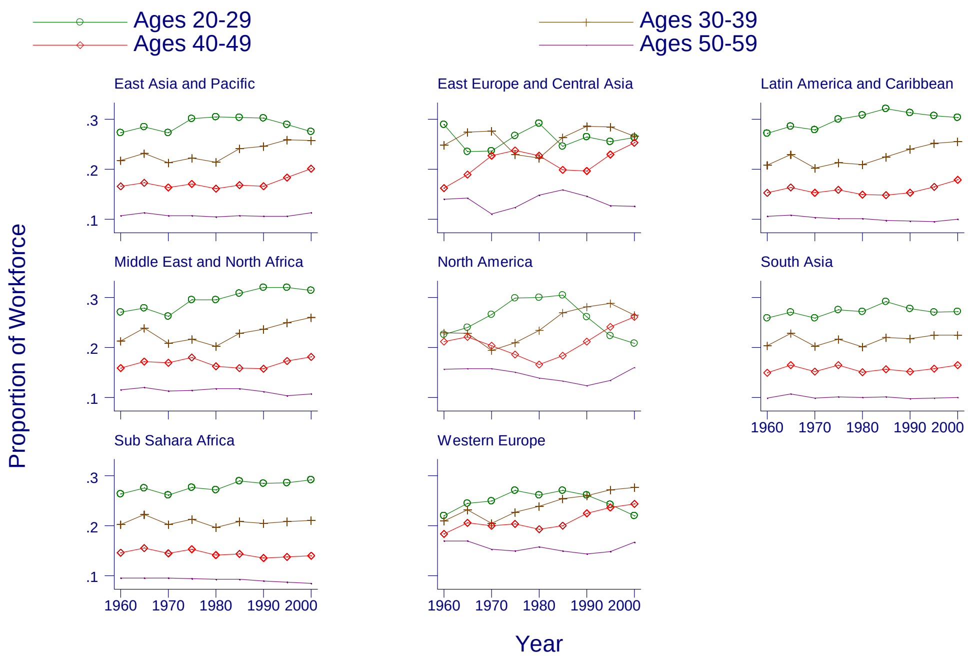


Figure 11: Demographics by Income Group

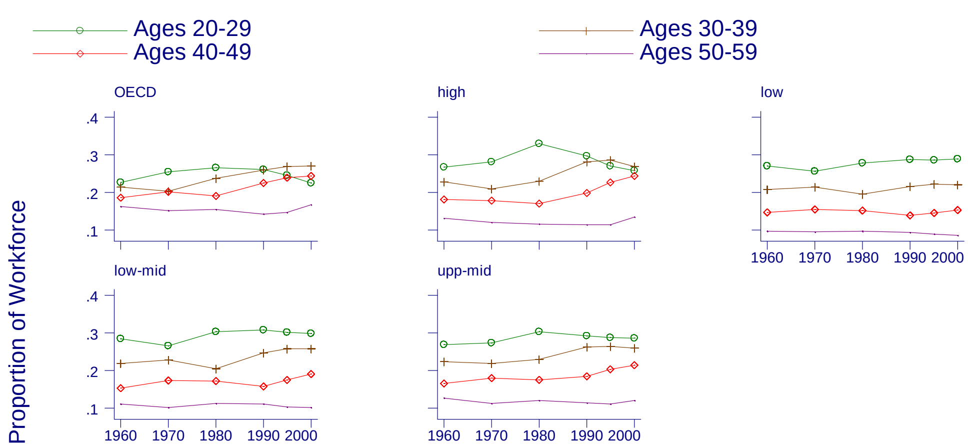


Figure 12: Actual and Demographic Productivity Growth by Region 1960-2020

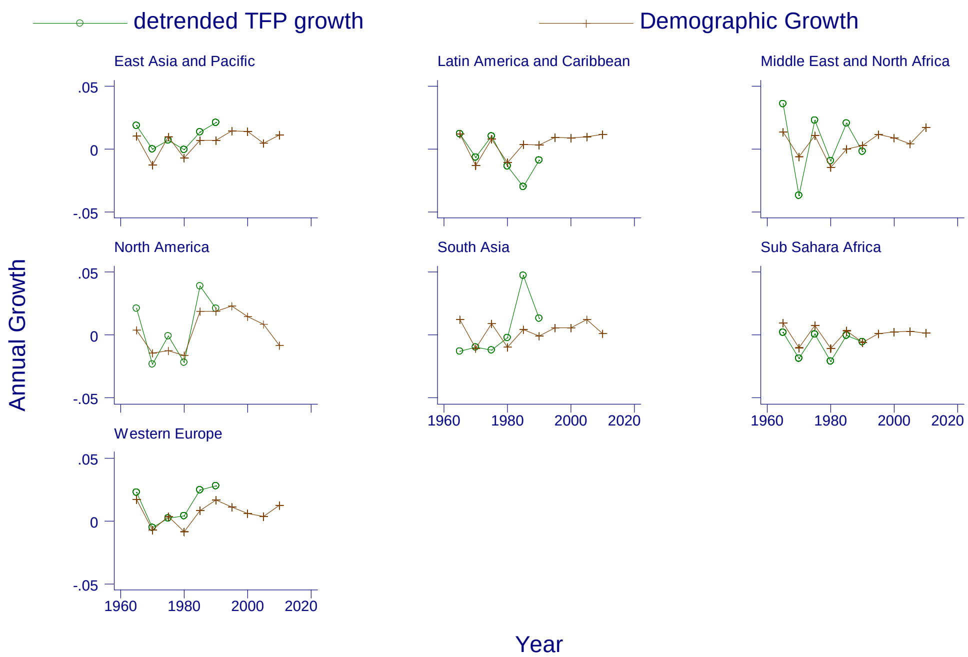


Figure 13: Actual and Demographic Productivity Growth by Income 1960-2020

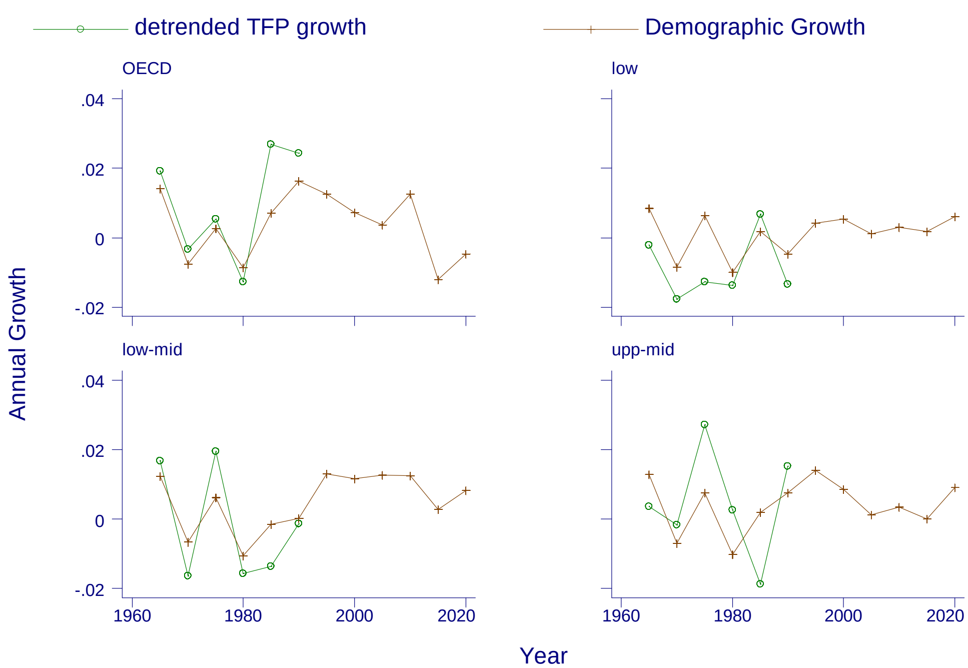


Figure 14: The Proportion of Workers Aged 40-49 By Region

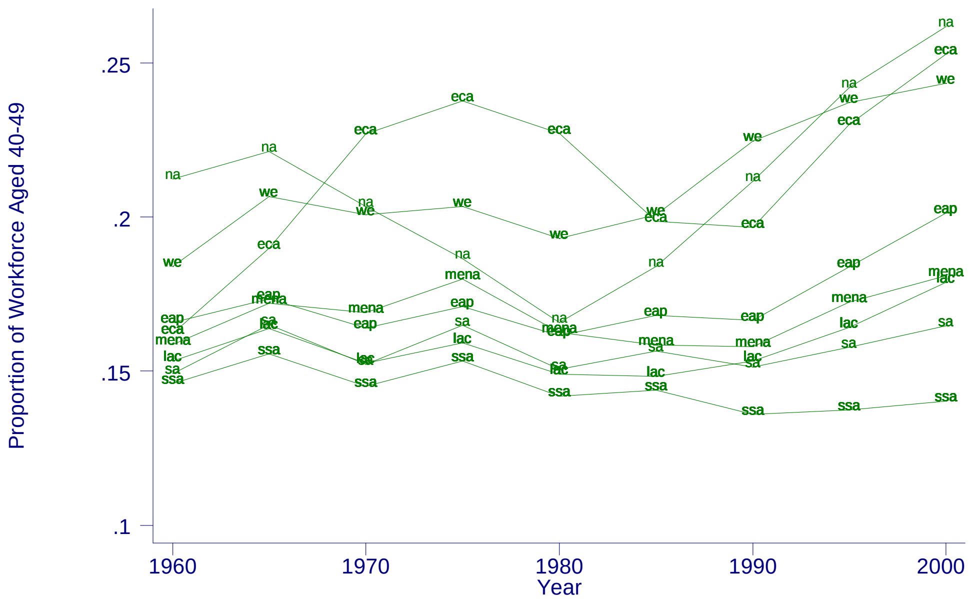
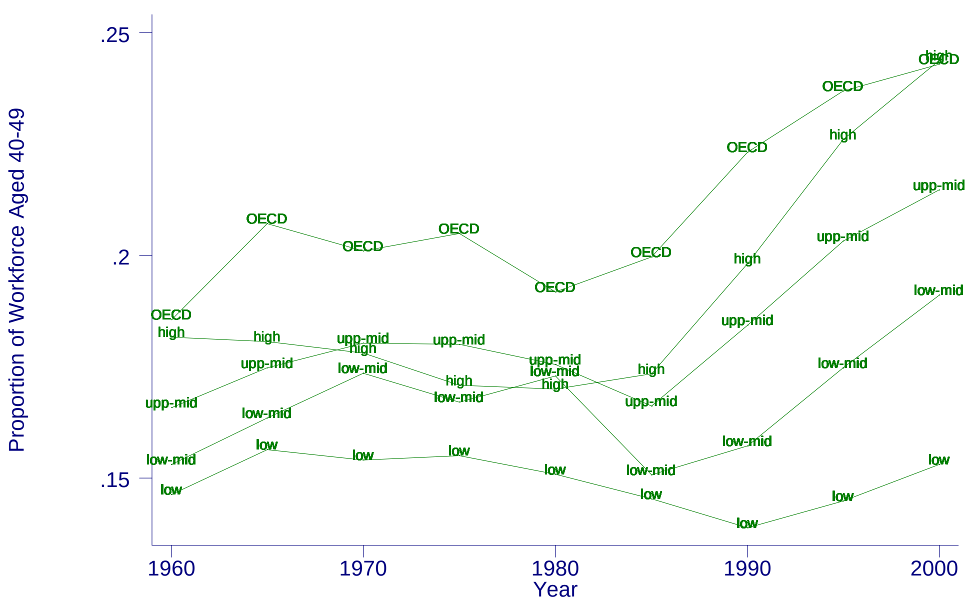
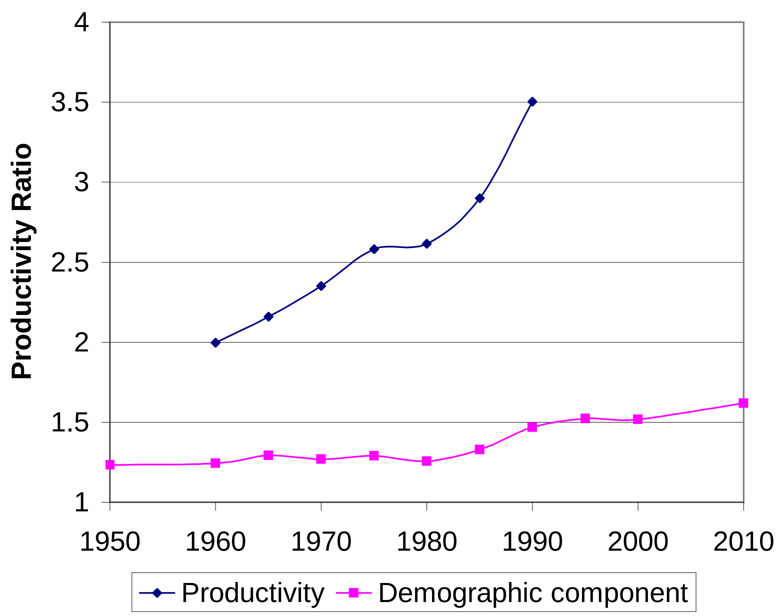


Figure 15: The Proportion of Workers Aged 40-49 By Income Group



clusters of countries are commonly referred to as convergence clubs. Feyrer (2001) finds that the existence of convergence clubs is largely being driven by productivity movements. Figure 16 shows the ratio of average productivity in the OECD to the average productivity of the low income group. A second line is plotted showing the demographic component of this gap.

Figure 16: OECD-Low income group productivity Ratio



This graph shows the divergence in productivity between the OECD and the low income nations. The ratio increases from about 2 in 1960 to nearly 3.5 in 1990. This divergence in productivity is mirrored in the demographic predictions, particularly after 1980. The ratio of the demographic component of productivity rises from 1.2 to 1.5 between 1960 and 2000.

5 Conclusion

The results presented in this paper show that workforce demographics are strongly correlated with productivity and output. Given the importance of productivity in explaining cross country income differences, this is a useful result. Unlike most of the variables used in the growth literature to study productivity, demographics have substantial time series variation. This allows us to gain insight into short run productivity phenomenon such as the US productivity slowdown and cross country movements.

The ability to predict forward is a particularly useful feature of this study. Work force demographics are quite predictable (at least in the near term) and the out of sample predictions for 1990-1995 suggest that informative projections of output growth are possible.

While emphasizing the importance of demographics, this paper does not present clear evidence of the mechanisms through which demographic change operates. The evidence on entrepreneurship is certainly suggestive, but by no means conclusive. There is enormous scope for microeconomic studies on the impact of age on technology adoption.

Most of the theoretical literature about demographics emphasizes the link between demographics and factor accumulation. While this link is certainly present, it is clear that the main channel through which demographics move output is the productivity residual. This paper suggests that there is theoretical work to be done on the age-productivity link.

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