WORKING PAPER

The Effect of Population Aging on Economic Growth, the Labor Force and Productivity

Nicole Maestas, Kathleen J. Mullen, and David Powell

RAND Labor & Population

WR-1063-1

August 2016

This paper series made possible by the NIA funded RAND Center for the Study of Aging (P30AG012815) and the RAND Labor and Population Unit.

RAND CORPORATION

For more information on this publication, visit www.rand.org/pubs/working_papers/WR1063-1.html

Published by the RAND Corporation, Santa Monica, Calif.

THE EFFECT OF POPULATION AGING ON
ECONOMIC GROWTH, THE LABOR FORCE AND PRODUCTIVITY

Nicole Maestas, Kathleen J. Mullen and David Powell

ABSTRACT

Population aging is widely assumed to have detrimental effects on economic growth yet there is little empirical evidence about the magnitude of its effects. This paper starts from the observation that many U.S. states have already experienced substantial growth in the size of their older population and much of this growth was predetermined by historical trends in fertility. We use predicted variation in the rate of population aging across U.S. states over the period 1980-2010 to estimate the economic impact of aging on state output per capita. We find that a 10% increase in the fraction of the population ages 60+ decreases the growth rate of GDP per capita by 5.5%. Two-thirds of the reduction is due to slower growth in the labor productivity of workers across the age distribution, while one-third arises from slower labor force growth. Our results imply annual GDP growth will slow by 1.2 percentage points this decade and 0.6 percentage points next decade due to population aging.

ACKNOWLEDGEMENTS

We are grateful to the Alfred P. Sloan Foundation Working Longer Program for grant funding. We thank David Cutler, Mary Daly, Edward Glaeser, Claudia Goldin, Larry Katz, Dan Wilson, and Robert Willis for valuable feedback, as well as participants of the 2014 SIEPR/Sloan Working Longer Conference at Stanford University and the Harvard Labor Economics Seminar for their many helpful comments.

The fraction of the United States population age 60 or older will increase by 21% between 2010 and 2020, and by 39% between 2010 and 2050 (Administration on Aging, 2014). This dramatic shift in the age structure of the U.S. population—itself the effect of historical declines in fertility and mortality—has the potential to negatively impact the performance of the economy as well as the sustainability of government entitlement programs, and could result in a decline in consumption for the population as a whole.

The potential macroeconomic and fiscal effects of population aging have been widely acknowledged and a number of studies have sought to forecast the effects of aging on future economic performance (e.g., Cutler et al., 1990; Borsch-Supan, 2003; Vogel, Ludwig, and Börsch-Supan, 2013; National Research Council, 2012; Sheiner, 2014). There are, however, few empirical estimates of the *realized* effect of aging on economic growth. This is a critical gap in knowledge. While demographic change is relatively easy to forecast on account of its predetermined nature, the ensuing economic adjustments—by firms, individuals, and policymakers—are not similarly deterministic. It is thus impossible to forecast the path of economic growth without making assumptions about the economic adjustments that may dampen or amplify the effects of predetermined changes in demography. It is similarly difficult to gauge the appropriate amount of policy intervention to counteract the economic and fiscal effects of population aging.

In this paper, we present empirical elasticities that summarize the realized economic response to the aging of the U.S. population since 1980. Our analysis begins with the observation that population aging is already long underway and has been playing out with varying degrees of intensity across different regions of the country. In some areas, the population has been aging at rates on par with those expected in the near future. Between

1980 and 2010, the growth rate in the population ages 60+ was above 30% for six states, similar to the projected national growth rate for 2010 to 2040. Over the same time period, three states experienced *reductions* in the fraction of their population 60 or above.

We leverage this variation in the rate at which U.S. states are aging to estimate the effect of aging on the rate of state growth in per capita Gross Domestic Product (GDP), the state labor force participation rate, and measures of labor productivity. To account for other factors that drive both the rate of state population aging and state economic outcomes, such as migration, we use the predetermined component of a state's age structure—its age structure 10 years prior—as an instrumental variable for its changing age structure. We use this variation in predictable aging to estimate a causal impact of aging on GDP growth.

Our estimates imply that 10% growth in the fraction of the population ages 60 and older decreases growth in GDP per capita by 5.5%. Decomposing GDP per capita into its constituent parts—GDP per worker and the employment-to-population ratio—we find that two-thirds of the reduction in GDP growth is driven by a reduction in the rate of growth of GDP per worker, or labor productivity, while only one-third is due to slowing labor force growth. This finding runs counter to predictions that population aging will affect economic growth primarily through its impact on labor force participation, with little effect on average productivity (National Research Council, 2012; Burtless, 2013). In addition, we find that the decline in productivity growth does not only reflect changes in the age composition of the pool of workers (who are on average older in states that age faster). Instead, evidence that population aging slows earnings growth across the age distribution suggests that it leads to declines in the average productivity of workers in *all* age groups, including younger workers. Importantly, these spillover effects do not appear to be driven by selection on the extensive labor supply margin, as we find population aging does not affect the employment rate of younger workers.

Our paper contributes an essential piece of evidence to the literature on the macroeconomic effects of changes in population age structures. Although not focused on aging per se, most relevant to our paper are a pair of studies by Feyrer (2007, 2008) that estimate the realized effect of changes in the age distribution of workers on changes in total factor productivity using a panel of OECD and low-income countries between 1960 and 1990.[1] Feyrer concluded that the relationship between worker age and total factor productivity has an inverse-U shape; specifically, productivity growth increases with the proportion of workers ages 40-49 and decreases as the proportion who are older rises. In its review of the literature, the National Research Council's *Committee on the Long-Run Macroeconomic Effects of the Aging U.S. Population* concluded that the pattern of age coefficients reported in the Feyrer papers was sensitive to specification, and unlikely to be true (National Research Council, 2012). The Committee concluded that productivity effects were likely to be negligible, but called for further research on the issue. Similar to the Committee's view, Burtless (2013) argued that since the earnings of older workers have been rising in comparison to younger workers, even as the older population share has grown, there is little evidence that the aging of the U.S. workforce has hurt economic productivity.[2]

---

[1] Feyrer (2008) also estimated models of changes in wage growth on changes in the age distribution of the workforce at the state and metropolitan levels using U.S. data; however the estimates were sensitive to empirical specification and generally not statistically significant.

[2] Other studies in the growth literature have considered the importance of the "dependency ratio" without focusing on population aging specifically. Bloom, Canning, and Sevilla (2003) examine the implications of a

There are two advantages to our empirical approach. First, by comparing the economic experiences of U.S. states with different aging trajectories, we are able to leverage counterfactual estimates of what would have happened to output, employment and productivity if the population had aged faster or slower. Our approach yields an elasticity of economic growth with respect to population aging that incorporates the economic response to demographic changes, and which thus may be useful to predict future impacts on economic growth as population aging continues to unfold. Second, examining economic units *within* the same country allows us to hold constant the effects of national pension systems, labor market institutions and cultural retirement norms that may interact with population aging in cross-country studies. Our estimates should therefore be interpreted as the relationship between population aging and economic growth holding the national policy environment constant. Consequently, our research design does not capture "indirect" effects of population aging on the federal budget (e.g., rising Medicare expenditures) or the effects of the federal policy response—as distinct from state policy responses—to aging (e.g., tax increases to fund Social Security benefits). While indirect federal-level effects are certainly of interest, they are separate considerations and can be recovered through other methods.

In the next section, we describe how population aging affects economic growth in a standard model of economic output. In Section II, we show the variation in population aging across states between 1980 and 2010. This is followed by our empirical strategy in Section III. We present our results in Section IV and conclude in Section V.

---

changing age structure for economic growth in developing countries. Kögel (2005) measures the effect of changes in the *youth* dependency ratio on total factor productivity. More recently, Aksoy et al. (2015) model the effects of demographic changes on long run economic growth accounting for endogenous fertility, education and innovation.

I. How Population Aging Affects Economic Growth

Figure 1 shows the percent of the U.S. population ages 60 and older between 1900 and 2000, and the projected percent through 2050. The figure illustrates how the population has aged nearly continuously over the last century. The only decade in which the population did not age was the 1990s when the baby boom passed through the middle of the age distribution. The U.S. population is projected to continue aging, at a relatively faster rate through 2030 (due again to the baby boom), and at a slower rate thereafter.

The size of the U.S. population and its age distribution at any point in time are the result of historical trends in birth rates, mortality rates, and immigration rates. U.S. population aging today results from the sharp decline in the birth rate in the 1960's, which marked the end of the Baby Boom, and the long-running decline in mortality rates. Immigration can offset these demographic forces to some degree, but has not been of sufficient magnitude to reverse population aging.

But how do these demographic forces affect economic growth? Consider a general representation of aggregate economic output and its subcomponents. Let the production of a state economy be represented by the function $y_{st} = F[\Omega_{st}, k_{st}, \ell_{st}]$, where y_{st} is per capita output at time *t* in state *s*, Ω_{st} is the (per capita) stock of ideas or technology, k_{st} is an index of physical capital per person, and ℓ_{st} is the per capita effective labor input.

The effective labor input depends on the employment rate in the economy and the human capital of the workforce, and both of these components are potentially shaped by the population age structure. Among individuals, labor supply behavior varies by age and over time. Similarly, human capital, which derives from cognition and health as well as investments in formal schooling and work experience (Mincer, 1974; Becker, 1975), varies over the individual life cycle, and across birth cohorts. Thus, we incorporate age-specific employment and human capital into the expression for the effective labor input: $\ell_{st} = p_t(a_{st})\theta_t(a_{st})$, where the function $p_t(a_{st})$ is the number of workers per person (i.e., the employment rate) at time *t* and depends on the older population share, represented by a_{st}. The function $\theta_t(a_{st})$ is the human capital (productivity) of the labor force and also depends on the older population share.

To illustrate how changes in these components affect output growth, we differentiate the production function and rearrange terms to express the percent change in per capita output growth in terms of production elasticities[3] and percent changes in each factor of production:

$$\frac{dy_{st}}{y_{st}} = \eta_\Omega \frac{d\Omega_{st}}{\Omega_{st}} + \eta_k \frac{dk_{st}}{k_{st}} + \eta_\ell \frac{d\ell_{st}}{\ell_{st}},$$

where $\eta_\Omega = \frac{\partial F(\Omega_{st}, k_{st}, \ell_{st})}{\partial \Omega_{st}} \frac{\Omega_{st}}{F(\Omega_{st}, k_{st}, \ell_{st})}, \eta_k = \frac{\partial F(\Omega_{st}, k_{st}, \ell_{st})}{\partial k_{st}} \frac{k_{st}}{F(\Omega_{st}, k_{st}, \ell_{st})}$, and

$$\eta_\ell = \frac{\partial F(\Omega_{st}, k_{st}, \ell_{st})}{\partial \ell_{st}} \frac{\ell_{st}}{F(\Omega_{st}, k_{st}, \ell_{st})}.$$

Using the definition of ℓ, and letting the *a* superscript designate elasticities with respect to the older population share, we have:

$$\frac{dy_{st}}{y_{st}} = \eta_\Omega \frac{d\Omega_{st}}{\Omega_{st}} + \eta_k \frac{dk_{st}}{k_{st}} + \eta_\ell \left[\eta_\theta^a + \eta_p^a\right] \frac{da_{st}}{a_{st}}, \qquad (1)$$

for $\eta_\theta^a = \frac{d\theta_t(a_{st})}{da_{st}} \frac{a_{st}}{\theta_t(a_{st})}$ and $\eta_p^a = \frac{dp_t(a_{st})}{da_{st}} \frac{a_{st}}{p_t(a_{st})}$.

[3] We denote the elasticities as constant across state and time. There could be heterogeneity in these measures and our empirical analysis will explore whether (some of) these elasticities change over time. Our discussion below will also consider reasons why these elasticities may change over time.

Equation (1) shows how the relationship between output growth and growth in the older population share depends on three key elasticities. First, this relationship is a function of η_ℓ, the elasticity of production with respect to the economy's effective labor supply. This production elasticity with respect to labor is itself a function of the stocks of capital and technology. Second, growth in the older population share affects production growth through η_θ^a, the elasticity of labor productivity with respect to the older share. Finally, the relationship is governed by η_p^a, the elasticity of labor force participation with respect to the older share. Thus, changes in the older population share can impact the effective labor supply of the economy through two channels: by changing the fraction of the population that works and by affecting the productivity composition of the workers in the labor force. Productivity here can also include intensive margin labor supply changes as the population ages, though we will separate intensive labor supply from per-hour efficiency in our empirical analysis. The model places little structure on the relationship between the older population share and production, but we specify these particular elasticities because they are the essential components of the labor input. As noted above, the model allows the labor input to in turn affect production through interactions with the stocks of capital and technology since $\frac{\partial F(\Omega_{st}, k_{st}, \ell_{st})}{\partial \ell_{st}}$ includes these factors. Consequently, there are no assumptions here that the relationship between labor and production is independent of capital and technology.

The effects of population aging on both labor force participation and productivity are not simply mechanical functions of the age profiles in labor supply and productivity. Older workers may be complements or substitutes for younger workers such that changes in the older share may affect the economy's productivity and labor supply through interactions with younger workers. The model's human capital function makes no claims about these interactions, though we provide empirical evidence about the relationship between changes in the older share and changes in labor outcomes at younger ages.

II. Data

To construct measures of the age structure in a state, we obtain state population counts by age from the 1980, 1990, and 2000 Census Integrated Public Use Microdata Series (IPUMS) and the 2009-2011 American Community Surveys (ACS) (Ruggles et al., 2015). Due to the relatively small size of the ACS, we combine the 2009-2011 samples to construct a "2010 Census."[4] In addition to population counts, the Census and ACS contain individual-level data measuring employment status, hours worked and labor earnings in the preceding calendar year. We aggregate these data to the state-year level to obtain the state employment rate, total hours worked and total labor earnings. To facilitate sub-analyses by sector, we construct a parallel set of population and labor market measures at the level of two-digit industry, state and year. [5]

To measure aggregate output, we acquire GDP by state and year from the Bureau of Economic Analysis (BEA). State GDP is defined as "the value added in production by the labor and capital located in a state," measured in dollars. These data "provide a

[4] Alternatively, we could have used state-level population statistics from the Census. However, we chose to construct our population size and labor supply measures from the same individual-level data in order to minimize differences arising from differences in data aggregation procedures. Using these noisier measures of state-level population should not affect the consistency of our estimates but may increase our standard errors.

[5] We use the 1990 Census Bureau industrial classification scheme, which is consistently reported in IPUMS for all years since 1950.

comprehensive measure of a state's production" (BEA, 2006).[6] The state GDP data also include industry-specific output measures, which we use to study the differential impacts of aging on different sectors of the economy. Because the annual labor outcomes from the Census and ACS refer to the previous year (i.e., 1979 in the 1980 Census), we match GDP data from the year preceding the indicated Census year (i.e., 1979, 1989, 1999 or 2009).[7] However, for ease of exposition, we refer to the Census years when indexing by time below.

The BEA also collects state-level data on total employee compensation, which includes wages and salaries paid to employees as well as noncash benefits. Wages and salaries are the primary component of employee compensation and include overtime pay, sick and vacation pay, severance pay, incentive payments (e.g., commissions, tips, and bonuses), and voluntary contributions to deferred compensation plans. Noncash benefits include in-kind benefits and employer contributions to pension plans, health insurance, and social insurance programs. We use the BEA employee compensation data as a measure of *full* labor compensation in a state, and as a complement to the Census earnings data.[8]

We construct 10-year growth rates by state for all of our analysis variables. These data are presented in Table 1, where growth in a variable as of Census year t refers to the percent change between $t\text{-}10$ and t. The top panel shows all Census years pooled, while the

---

[6] An advantage of using aggregate production instead of consumption data is that GDP includes asset income, which can be used to compensate for declines in consumption.

[7] There is still a slight misalignment between state and year for the labor outcomes since, before 2000, the Census only included information on state of residence in the current year. For 2000 and 2010 it is possible to aggregate labor outcomes by state of residence in the previous year. We conducted robustness checks of our main regressions for 2000-2010 using the aligned and misaligned measures, respectively, and found that this did not affect our results. These estimates are shown in Appendix Table A.5 and discussed below

[8] One limitation of the BEA measure of total compensation is that it does not include compensation for the self-employed. Adding in labor earnings for the self-employed using the Census and ACS has little effect on the results.

lower panels show the data decade by decade. There is significant variation across states in the size and growth rate of the 60+ population in all years. In the pooled sample, the fraction ages 60+ ranges across states and Census years from 0.095 to 0.313, with mean 0.24 and standard deviation 0.029. The 10-year growth rate of the fraction 60+ ranges from -9% to 47%, with mean 4% and standard deviation 8%. Economic growth also varies substantially across states and years. In the pooled state-year sample, the 10-year growth rate in GDP per capita ranges from -12% to 131%, with mean 55% and standard deviation 26%. Productivity growth, measured as the 10-year growth rate in GDP per worker, ranges from -8% to 117%, with mean 55% and standard deviation 19%. Finally, labor force growth, the other component of growth in GDP per capita, ranges from -10% to 9%, with mean -0.3% and standard deviation 4%.

To shed light on the regional patterns underlying the variation summarized in Table 1, we also present choropleth maps of the state variation in population aging that occurred decade by decade. [9] Between 1980 and 1990 (Figure 2A), there was relatively fast growth in the older population in the West and in the Rust Belt. At the same time, 15 states, including the large states of California, Texas, Florida, and New York, experienced a *contraction* in the relative size of their older population. Between 1990 and 2000 (Figure 2B) the majority of states experienced declines in the relative size of their older populations, with just 12 small states seeing weakly positive growth. However, between 2000 and 2010 (Figure 2C) the growth rate of the older population was above 15% in 20 states, including the northern Pacific and Mountain states, and nearly all of the South Atlantic states. Only 4 states—Florida, North Dakota, South Dakota, and the District of

[9] Note Hawaii and Alaska are not shown in Figures 2A-2C, but are included in our analysis sample.

Columbia—experienced less than 5% growth during this period. Florida is notable in that by this time it *already* had a relatively high older population share.

If age-specific migration and mortality patterns were entirely independent of economic changes, then it would be useful to compare the economic outcomes of states that experienced fast population aging to states that experienced slow population aging. But economic changes can themselves shape the population age structure by affecting contemporaneous patterns of migration and mortality, and thus any association between economic growth and population aging at the state level is unlikely to represent the causal impact of population aging. As we detail in the next section, we address this issue with a research design that makes use of the fact that population age structures are to an extent the result of historical demographic patterns (e.g., fertility trends). Our research design leverages the *predetermined* components of the population age structure for identification in order to circumvent these confounding sources.

III. Empirical Strategy

To obtain an estimable specification for the differentiated production function in equation (1), we note that differentiating

$$\ln y_{st} = \eta_{\Omega} \ln \Omega_{st} + \eta_k \ln k_{st} + \eta_{\ell}[\eta_{\theta}^{a} + \eta_{p}^{a}]\ln a_{st}$$

would give equation (1). Since technology and capital at the state level are unobserved, we model their effects with state and time fixed effects. Specifically, let $\alpha_s + \gamma_t + \varepsilon_{st} =$ $\eta_{\Omega} \ln \Omega_{st} + \eta_k \ln k_{st}$. This permits growth over time while also allowing states to have different levels of capital and technology. We also allow for state-specific output shocks, modeled as ε_{st}. Our identifying assumption will be that our instrumental variable is uncorrelated with these shocks, and this assumption is discussed later. We take first-differences and include additional control variables to arrive at the following estimable specification:

$$\ln y_{s,t+10} - \ln y_{st} = \varphi_t + \beta\left[\ln\left(\frac{A_{s,t+10}}{N_{s,t+10}}\right) - \ln\left(\frac{A_{st}}{N_{st}}\right)\right] + X'_{st}\delta_t + \left(\varepsilon_{s,t+10} - \varepsilon_{st}\right), \qquad (2)$$

where y_{st} is an economic outcome (e.g., GDP per capita) for state s in Census year t, A is the number of individuals aged 60 and older, N represents the total population aged 20 and older, and X contains a set of time-varying control variables whose influence is also allowed to vary over time.[10] We include in X the initial (period t) two-digit industry composition of the state labor force (specifically, the log of the fraction of workers in each industry) to account for initial conditions that may predispose states to particular growth paths.[11] The log-difference specification for both dependent and independent variables normalizes comparisons of growth across states with different initial population shares and yields an easily interpretable elasticity, β. When presenting our main results, we will show that our results are robust to different functional forms.

Our main outcome of interest is growth in GDP per person aged 20 and older. To understand the mechanisms driving changes in GDP growth, we also examine specific decompositions of GDP per capita. First, we decompose GDP per capita into two components: GDP per worker (labor productivity) and the fraction of people working. This decomposition enables us to assess how much of the effect of population aging on economic growth operates through changes in labor force growth as compared to changes in productivity growth.

---

[10] $\varphi_t \equiv \gamma_{t+10} - \gamma_t$.

[11] In complementary work, we find that an area's initial industry structure predicts changes in labor outcomes (see Maestas, Mullen and Powell, 2013).

Second, we further decompose the productivity component, GDP per worker, into three subcomponents: GDP per dollar paid to labor (i.e., GDP/earnings), earnings per hour worked (i.e., wage) and hours H per worker L (intensive labor supply). This decomposition of the productivity component tests for compensating adjustments in earnings, as opposed to changes in intensive margin labor supply. Since labor earnings may not fully reflect labor costs, we repeat the decomposition substituting BEA's measure of total labor compensation, which includes the value of in-kind benefits paid to workers. Overall, these decompositions provide a rich picture of the mechanisms driving the relationship between population aging and economic growth.

While equation (2) relates changes in state population aging to changes in state economic outcomes, changes in the age structure of a state may depend – in part – on factors related to economic growth. For example, economic decline could induce prime-aged workers to migrate out of the state while older workers may be more likely to stay given the smaller lifetime return to moving. Consequently, we would observe that aging states have less favorable economic outcomes, though this relationship is not causal.[12] Similarly, differential industry growth and decline across states may affect mortality rates and these mortality effects may not be uniform across all age groups, directly altering the age composition of states depending on their economic conditions.

To address these potential confounds, we use an instrumental variables strategy to estimate equation (2) that exploits the differential and *predictable* component of population aging across states over time. We first construct *national* census survival rates, defined as the ratio of the national population age $j+10$ in one Census to the cohort's

[12] There is some evidence that population aging itself may affect interstate migration; see Karahan and Rhee (2014).

population size in the prior Census (at age *j*).[13] We then multiply the number of individuals age *j* in the *state* in one Census by the age-specific *national* survival rate to predict the number of individuals age *j+10* in the *state* in the next Census. For example, to predict the number of 60 year olds in Alabama in 2000, we multiply the number of 50 year olds in Alabama in 1990 by the *national* ratio of 60 year olds in 2000 to 50 year olds in 1990. This approach uses initial state composition interacted with national level cohort changes and has the advantage of disregarding variation resulting from differential state-level migration and mortality for identification. The instrument is similar in spirit to the Bartik instrument (Bartik, 1991; Blanchard and Katz, 1992), which predicts local economic growth by interacting national industry-specific growth with initial local industry composition.

More precisely, the instrument is the predicted change between *t* and *t+10* in the log of the fraction of the state population 60+:

$$\ln\left(\frac{\hat{A}_{s,t+10}}{\hat{N}_{s,t+10}}\right) - \ln\left(\frac{A_{st}}{N_{st}}\right)$$

where $$\hat{A}_{s,t+10} = \sum_{j\geq 50} \underbrace{N_{jst}}_{\substack{\text{Total number}\\ \text{of people age}\\ j \text{ in state } s\\ \text{at time } t}} \times \underbrace{\frac{N_{j+10,t+10}}{N_{jt}}}_{\substack{\text{National growth}\\ \text{rate}\\ \text{of cohort age } j \text{ at time } t}}$$

and $$\hat{N}_{s,t+10} = \sum_{j\geq 10} N_{jst} \times \frac{N_{j+10,t+10}}{N_{jt}}.$$

The main source of variation used by the instrument is the variation across states in the relative size of their population ages 50-59. States with a large fraction of 50-59 years olds are predicted to experience relatively large increases in the number of older individuals.[14]

[13] Note our census survival ratios incorporate international (as opposed to interstate) migration.
[14] Some variation may also come from changes in the denominator *N*. That is, if the younger population is (predictably) growing faster in one state than in another, the first state will have less population aging by our

The variation in population aging that we exploit is predictable and observable by residents of the state before time *t*. In this manner, the instrument parallels population aging at the national level.

IV. Estimates and Mechanisms

A. Effect of Population Aging on Economic Growth

We begin with a visual depiction of our research design. In Figure 3A, each data point is an observation of the decadal change in a state, weighted by population size in the base year. The figure shows the strong negative association in the raw data between realized population aging and per capita GDP growth over the period 1980-2010. Figure 3B shows the first-stage relationship critical to our research design. Here, we see that realized population aging is strongly predicted by the predicted aging instrument. Finally, Figure 3C presents the visual reduced form relationship between the predicted aging instrument and subsequent economic growth.

Table 2 presents the coefficients summarizing these relationships after we include controls for state industry composition in the base year and time fixed effects. Panel A shows the ordinary least squares (OLS) estimates of equation (2) for the entire time period 1980-2010, and separately for each decade. The dependent variable is the change in log per capita GDP. The point estimates indicate that states experiencing growth in the fraction of individuals ages 60+ also experience slower growth in per capita GDP. Using the full sample, we estimate that a 10% increase in the fraction of the state population ages 60+ is associated with a decrease in economic growth of 8.3%. Contrasting this estimate with the much larger slope coefficient in Figure 3A reveals the importance of controlling for

metric *even if* the two states experienced the same (absolute or proportional) change in the number of older individuals.

time fixed effects. Limiting the sample to one ten-year difference at a time, we consistently find a large and statistically significant association.

As noted above, there are many reasons why state populations might age at different rates and economic growth itself could impact the state age structure by affecting migration decisions; this would bias the OLS estimate away from zero if younger workers move to faster growing places to pursue new job opportunities or, conversely, if older individuals move to slower growing places to take advantage of the lower cost of living. Similarly, if economic growth affects mortality rates, then this too may contribute bias. The direction of the bias is less obvious in this case since it depends on how any growth-induced mortality changes play out across the age distribution.

Panel B of Table 2 presents the reduced form relationship between our instrument—the predicted change in the log of the fraction of individuals 60+ in a state—and economic growth. We find that a 10% increase in the predicted fraction of the 60+ population decreases per capita GDP growth by 3.9%. Panel C shows the first-stage coefficient, conditioning on time fixed effects and controls for initial industry composition. The additional controls matter relatively less for the first-stage relationship between predicted and actual growth in the older population. For each 10% increase in predicted growth of the 60+ population, we find that a state actually experiences a 7.2% increase (compared to an implied 8.3% in Figure 3B).

Table 3 presents two-stage least squares estimates of the effect of population aging on economic growth for all decades pooled and separately, weighted and unweighted by base-year state population in the top and bottom rows, respectively. Using the full sample, we estimate that a 10% increase in the fraction of the population 60+ decreases economic growth by 5.5%. Our IV estimate is smaller in magnitude than the OLS estimate, consistent with systematic migration of younger individuals to faster growing areas. The difference between the OLS and IV estimates is marginally statistically significant (p=0.06). The IV estimates are largely unaffected by the weighting scheme. Without weighting, we estimate a statistically significant effect of 4.8%. While noisy, we find consistent results for each decade, regardless of weights.

While our specification models changes in per capita GDP as a function of changes in the older population share, economic growth may also be affected by changes at other points of the age distribution. Moreover, predicted increases in the 60+ population share may be correlated with predictable growth in the share of other age groups, suggesting the possibility of an omitted variable related to changes in other (correlated) age group shares. We can test for this possibility explicitly given that our instrumental variables strategy can be extended to predict growth in other age groups. To implement this, we include multiple age groups, one at a time, in our specification and, as before, estimate our main model using two-stage least squares, where the instruments are the predicted changes in each included age group using the same method to predict changes as before. The excluded age group is the 20-29 age group. The results are presented in Appendix Table A.1. We find that only growth in the 60+ population leads to a statistically significant decrease in growth in GDP per capita. When we include all other age groups, our estimate is nearly the same as before—a 10% increase in the fraction of the population aged 60+ is associated with a 5.9% decrease in the rate of economic growth. Including or excluding the other age groups has little effect on this estimate. Consequently, we conclude that separately identifying these other age groups is not necessary for consistent estimation in our context.[15]

We also test the robustness of our results to functional form assumptions. Silva and Tenreyo (2006) show that a logged dependent variable in a linear regression restricts the error term. The specification in equation (2) assumes that the error term is multiplicative in per capita GDP growth. Using an exponential specification and Poisson regression relaxes this assumption, allowing for both multiplicative and additive error terms. We replicate our main analysis using instrumental variables Poisson regression and present the results in Appendix Table A.2. We find similar results as before, suggesting that our estimates are not driven by functional form assumptions.

Similarly, we test whether our results are driven by specifying changes in the log of per capita GDP as a function of changes in the log of the older population share instead of changes in the level of the older population share. In Appendix Table A.3, we use changes in the level of the older share, estimating that each percentage point increase in the older share decreases per capita GDP growth by over 2%. Given that the mean older population share in the sample is 0.24, a 10% increase in the older share implies a reduction in per capita GDP growth of 4.9%, which is similar to our main estimate.

In Appendix Table A.4 we show that our main estimates are robust to the inclusion of region-year interaction terms, and therefore common regional shocks are not driving our results. Appendix Table A.5 shows that the one-year misalignment in when labor outcomes are measured in the Census compared to state of residence does not materially

[15] We have also estimated a version of Appendix Table A.1 in which we do not use a log transformation of our explanatory variables because the age groups are different sizes and thus a 10% increase in the size of the 60+ population is different than a 10% increase in the 40-49 population. These results are qualitatively similar to the results presented in Appendix Table A.1.

affect our estimates for the 2000-2010 period (the one period in which both the current and prior year's state of residence are available). The IV estimate increases in magnitude when we use the prior year's state of residence.

Finally, our instrumental variable strategy assumes that the initial age distribution of a state is not predictive of *trends* in economic output except through changes in the state age structure. We test this assumption in multiple ways in Appendix Table A.6. In Column (1), we present estimates using an instrument generated from the age distribution *20 years prior*, instead of 10 years. That is, we use the state age distribution in year *t-10* (instead of year *t*) to predict state-level population aging between *t* and *t+10*. Using the same method as before, we predict the fraction of the population ages 60+ in year *t* as well as in year *t+10* to construct the predicted change. The age distribution in year *t-10* should be disassociated with underlying economic trends between period *t* and *t+10*.[16] The Column (1) estimate is similar to the main estimate of this paper, suggesting that any pre-existing trends are uncorrelated with our instruments.

In Columns (2) and (3), we report estimates from a specification that controls for the initial (period *t*) log of per capita GDP in state *s* to account for trends in initial economic conditions. This control is potentially important given previous evidence of convergence across states (Barro and Sala-i-Martin, 1992). Because of the biases associated with estimating a specification with a lagged dependent variable, we use the GMM estimator introduced in Arellano and Bond (1991). In Column (2), we present estimates using the Arellano-Bond estimator. The estimate is larger in magnitude than the main estimate of

[16] Alternatively, we could predict changes in the age structure in a state based on the period *t* age structure for individuals born in that state, not those living in the state at time *t*. Unfortunately, there is no first stage for this instrument as it is not correlated with changes in a state's age structure due to the high levels of migration out of individuals' state of birth before age 50.

the paper, though we cannot reject that the two estimates are equal (p-value=0.12). Column (3) replicates Column (2) but also includes the lagged industry employment share variables as additional controls. Again, the estimate increases in magnitude, though we cannot reject the equality of the Column (2) and Column (3) estimates (p-value=0.26).[17] The results shown in Appendix Table A.6 strongly suggest that underlying trends are not driving our results.

B. Decomposing the Effect—Labor Force and Productivity Growth

While the literature concurs that population aging is likely to lead to slower growth in GDP per capita due to slower labor force growth, there is little evidence to suggest how population aging might affect aggregate productivity. Table 4 decomposes GDP per capita into these two components and separately estimates the effect of population aging on GDP per worker and the number of workers per capita. Column (1) reproduces the total effect of population aging on growth in GDP per capita. By construction, the estimated effects of population aging on growth in GDP per worker (Column 2) and growth in workers per capita (Column 3) sum to the total effect in Column (1).

We find that, as expected, population aging decreases labor force growth (Column 3). Specifically, a 10% increase in the fraction of the population 60+ leads to a 1.7% decrease in the growth rate of workers per capita. However, population aging has an even larger effect on productivity growth; a 10% increase in the fraction of the population 60+ leads to a 3.7% decrease in the rate of growth in GDP per worker.

To decompose the productivity effect further, we use the following identity:

---

[17] Similarly, we cannot statistically reject that the Column (3) estimate is equal to the main estimate of this paper.

$$\ln\left(\frac{GDP}{N}\right) = \ln\left(\frac{GDP}{\text{Earnings}}\right) + \ln\left(\frac{\text{Earnings}}{H}\right) + \ln\left(\frac{H}{L}\right) + \ln\left(\frac{L}{N}\right),$$

where the components are defined as:

1) $\frac{GDP}{\text{Earnings}}$ = output per dollar paid to labor

2) $\frac{\text{Earnings}}{H}$ = earnings per hour worked (wage)

3) $\frac{H}{L}$ = hours per worker (intensive margin of labor supply)

4) $\frac{L}{N}$ = fraction of population working (extensive margin of labor supply)

We then estimate equation (2) separately for the 10-year log difference of each component. The results are shown in Table 5. The estimate in the top row of column (1) indicates that growth in the older population share has little effect on the number of hours worked per worker, or intensive margin labor supply. Rather, column (2) shows that a 10% increase in the older share reduces GDP per hour worked by 3.4%. Because the intensive margin effect is small, the effect of population aging on growth in GDP per hour worked (column 2 in Table 5) is nearly the same as the effect of population aging on growth in GDP per worker (column 2 in Table 4). Thus the estimated productivity effect is not explained by reductions in the average number of hours worked.

Next, in columns (3) and (4) of Table 5 we test whether the effect of population aging on productivity growth reflects changes in the marginal product of labor. If workers are paid proportional to their marginal product of labor, then earnings should adjust in response to changes in productivity. If such adjustments are occurring, then the decline in productivity growth should be reflected in earnings per hour worked[18] and the effect of

[18] We use total earnings divided by total hours worked in a state, which is equivalent to a weighted (by hours) average of individual hourly wages.

population aging on GDP per dollar earned should be zero. Our findings in columns (3) and (4) of Table 5 support these hypotheses. A 10% increase in the fraction of the population 60+ decreases growth in the average wage by a statistically significant (p<0.05) 2% (column 4), and decreases GDP per dollar earned by a statistically insignificant 1.4% (column 3). The estimates in columns (3) and (4) sum to the estimate in column (2) by construction. Thus, the decomposition points to changes in the marginal product of labor as the primary source of the decline in productivity growth.

Since labor earnings may not fully reflect labor costs due to benefits, we repeat the decomposition substituting BEA's measure of total labor compensation for labor earnings, presented in the bottom row of Table 5. In these models, we find an even stronger negative effect of population aging on growth in the average wage when it includes monetary and in-kind benefits. Our estimates imply that a 10% increase in the fraction of the population 60+ leads to a statistically significant (p<0.01) 3.3% decrease in growth in average compensation per hour worked and a statistically insignificant 0.1% decrease in growth in GDP per dollar of labor compensation.

It is important to note that our productivity estimates represent the *combined effects* of all determinants of output per worker. Although output per worker can be decomposed to estimate the separate contributions of capital, labor and total factor productivity (Wong, 2001; Feyrer 2007), this approach requires data measuring the physical capital stock over time for the economic units of analysis. Unfortunately, no such government statistics on physical capital exist for U.S. states. That said, while in principle a state's physical capital stock may adjust to compensate for a smaller workforce or changes in output per worker, the fact that capital markets are integrated across U.S. states (in contrast to labor markets) means estimates from a state-based research design are unlikely to incorporate capital effects. Furthermore, because capital flows more freely than labor in response to supply and demand shocks (Kalemli-Ozcan et al., 2014; Bernard et al., 2013), any increases in the supply of capital investment due to population aging (since older individuals hold more wealth) are unlikely to accrue to the states in which they originate.

Overall, our decomposition exercise suggests that about 1/3 of the total effect of population aging on economic output growth operates through changes in labor force participation. We find little evidence that intensive margin changes are an important driver of the overall effect. The other 2/3 of the total effect is due to changes in GDP per hour worked. We show that this reduction in productivity growth is matched by a reduction in wage growth, which points to the existence of labor market adjustments that compensate for real losses in the marginal product of labor.

In the next sections, we explore potential mechanisms by which population aging leads to slower economic growth, and in particular slower growth in labor productivity. First, we estimate the effect of population aging on growth in GDP per capita at the industry level to test if the effects are concentrated in any particular industry or set of industries. Second, we examine the effects of population aging on employment and earnings for different age groups to investigate the role of spillover effects from older to younger workers.

C. Effects by Industry

It is possible that population aging affects different industries to varying degrees, depending on the age structure of their workforce, industry-specific skill demands or whether the industry produces tradable or nontradable goods or services. In addition, shifting consumption patterns with age may induce changes in demand for particular kinds of goods and services. For example, as people withdraw from the labor force they tend to reduce consumption of work-related goods and services and increase consumption of healthcare services (Hurd and Rohwedder, 2008; Hurst, 2008). Our state-based research design will capture these aging-induced product demand shifts to the degree the goods and services demanded by older individuals are mostly consumed in the state where they are produced. An example of such a service is health care, which in most instances must be consumed where it is produced.[19]

To explore this, we estimate equation (2) separately by industry. Although the dependent variable is based on industry-specific GDP per person in a state, population aging is measured at the state level as before. We present these industry estimates in Table 6. The first entry shows the effect of population aging on growth in output per capita of all *private* industries. This estimate is similar to our main estimate for total output per capita (private plus public sector) in column 1 of Table 4, and implies our main estimate is not driven by changes in public sector output. The rest of the entries in Table 6 show the estimated effects of population aging industry by industry. The largest effect arises in the construction industry. We estimate that a 10% increase in the fraction of the population 60+ decreases growth in construction output per capita by 8.6%. We also find a statistically significant aging-induced reduction in growth in Wholesale Trade, Retail Trade, Finance/Insurance, and Services. The estimate for Manufacturing is of similar magnitude, but imprecisely estimated. These patterns suggest that the decrease in overall economic growth cannot be explained by a reduction in the growth of one or a small number of

[19] As noted elsewhere, our research design does not capture changes in demand that drive production in other states (e.g., Internet sales) or that are dispersed uniformly across the national economy.

industries. Instead, it appears that population aging diminishes growth in most industries, with statistically inconclusive estimates for Agriculture, Mining,[20] and Transportation/Utilities.

D. Spillover Effects on Younger Age Groups

Workers in different age groups may be substitutes or complements to one another and therefore the productivity of one age group can depend on interactions with workers in other age groups. Such productivity spillovers could occur between older and younger workers if, for example, an older worker's greater experience increases not only his own productivity but also the productivity of those who work with him. In this section, we examine the effects of population aging on the employment and earnings growth of men and women in different age groups to investigate the role of spillover effects from older to younger workers.

First, we estimate equation (2) separately for men and women by ten-year age groups, where the dependent variable in each regression is the change in the log employment rate of the age-gender group. As before, the key independent variable in all models is the change in the log fraction of population ages 60+ (both genders combined), for which we instrument as above. The two-stage least squares estimates are shown in Table 7. We find little effect of population aging on employment growth in younger age groups, but larger reductions in employment growth in older age groups. The results suggest that an increase in the fraction of the population ages 60+ does not crowd out younger workers. Rather, these results imply that the slowdown in employment growth

[20] The Mining sector workforce is expected to age rapidly over the next several decades (Brandon, 2012), but because of its geographic concentration within just a few states, we lack statistical power to detect effects on economic growth.

induced by population aging was indeed concentrated among older individuals and, in particular, among older men. It is true, however, that as the population ages the workforce becomes older. Table 8 shows how population aging induces an increase in the *share* of the workforce that is 50 and older and a decrease in the share under 40.[21]

Table 9 presents the corresponding wage effects by age group and gender.[22] The outcome variable is the change in the log wage, which as before is defined as total labor earnings divided by total hours worked (by age group, gender, state, and year). Here, we find large effects of population aging on productivity growth among younger workers, as well as older workers. Our point estimates imply that a 10% increase in the fraction of population ages 60+ reduces productivity growth across the age distribution (through age 69), and for males and females alike, by 3-5%.

Our estimates reveal how population aging-induced changes in labor supply alter the productivity composition of the workforce. We find that population aging leads to slower average wage growth for workers ages 60-69, which implies that individuals in this age range who retire tend to be *more productive* on average than those who stay in the workforce, that growth in the number of older workers drives down wages for the older age group, or both. The reduction in wage growth for younger workers could arise from the loss of positive production spillovers from retiring older workers to their younger counterparts if the productive older workers are more likely to retire.[23] More generally, lower average productivity among older workers may affect younger groups if younger and

---

[21] Note our results illustrate that an aging-induced reduction in the younger employment *share* does not necessarily imply an aging-induced reduction in the younger employment *rate*.

[22] In this analysis, we cannot account for the full compensation costs since the BEA does not estimate compensation data by age group.

[23] Note the presence of negative wage growth effects across the age distribution is also consistent with efficiency losses arising from the "thinning" of labor markets in areas with faster population aging (Gan and Li, 2004).

older workers are complementary inputs in production, resulting in slower wage growth for both groups.

The relative productivity of older workers relative to younger workers may depend on work experience, health, education, and a host of other factors. Feyrer (2008) notes that typical estimates of the return to experience from Mincer wage regressions imply a 60 percent difference between the productivity of 20-year old and 50-year old workers. A case study of German car manufacturers found suggestive evidence that more experienced older workers were more productive than younger workers (Börsch-Supan et al., 2008).

Until recently, this experience-productivity advantage was in part offset by the higher educational attainment of younger workers compared to older workers. But as a result of the secular growth in educational attainment through the 1970's (Goldin and Katz, 2007), completed education among 65 year olds is rising dramatically, from 10.1 years in 1980 to an expected 13.3 years in 2020. The subsequent slowdown in educational attainment means that, in sharp contrast, completed education among 25 year olds is rising very little, from 13.3 years in 1980 to a projected 13.9 years in 2020. The net result is that the average older worker is now nearly as educated as the average younger worker.

Age-related health differences may also offset part of the experience-productivity advantage, owing to the higher prevalence of disability with age. However, trends in health suggest this too may be lessening as obesity-related disabilities disproportionately affect younger cohorts (Freedman et al., 2013). Perhaps the biggest open question pertains to the age profile of cognition and its effect on work productivity. While some aspects of cognition decline gradually over the adult lifespan (e.g., processing speed), others hold steady until late life (e.g., knowledge) (Verhaegen and Salthouse, 1997), and there is considerable heterogeneity in the timing of decline across individuals (Hartshorne and Germine, 2015). Most intriguingly, cohort improvements in cognitive functioning point to a process of cognitive aging that is itself highly plastic (Staudinger, 2015).

These age and cohort patterns in human capital acquisition and decumulation point to the possibility of heterogeneity in the effects of population aging on economic growth over time. Appendix Tables A.7-A.9 present the employment and wage effects by age and gender for each decade between 1980 and 2010. We find that the negative spillover effects on wages of younger workers were strongest in the 1980s—when employment rates among older men were at their lowest point ever, when the human capital gap between older and younger workers was closing rapidly, and prior to the proliferation of desktop computers and the Internet.[24] Since then, employment rates among older men and women have risen, and the diffusion of technology has changed the skill demands of many jobs.

While further research is needed to identify the exact mechanisms at work, our findings foretell a further slowdown in productivity growth reflecting not only compositional differences in the workforce but also real productivity losses among individuals across the age spectrum. At the same time, greater investment in human capital development throughout the lifecycle coupled with policies and practices that encourage employment at older ages could prevent these losses to some degree.

V. Discussion and Conclusion

As the populations of developed countries become older than ever before, a persistent question has been what impact will this unprecedented demographic change have on consumption standards? Noting that population aging has been long underway in

[24] We do find some weak evidence of crowd out in employment of younger workers in the 1980s.

the U.S., and that changes in the population age structure of the U.S. were largely predetermined by historical trends in fertility and mortality, we use variation in the rate of population aging across U.S. states over the period 1980-2010 to estimate the economic impact of aging on state output per capita. Over this time period and across states, we observe substantial variation in population aging, including aging rates comparable to rates forecasted for the United States in the near future.

Our estimate of the elasticity of growth with respect to aging is that a 10% increase in the fraction of the population ages 60+ decreases growth in GDP per capita by 5.5%. Between 1980 and 2010, the older share increased by 16.8%. Thus our estimate implies that per capita GDP growth over the same time period was 9.2% lower than it otherwise would have been absent population aging. This corresponds to a 0.3 percentage point decrease in the annual rate of growth over a time period when the average growth rate was 1.8 percentage points.

Between 2010-2020 the older share of the U.S. population is expected to rise by 21%. Thus our estimate indicates population aging will reduce per capita GDP growth during the current decade by 11%. Annualizing this rate, population aging will be responsible for a 1.2 annual percentage point decrease in per capita GDP growth, relative to the growth rate with no change in the national share 60+. Between 2020-2030, the older population share will rise by 11%, implying an annual reduction in growth of 0.6 percentage points.[25] Assuming that the counterfactual growth rate is 1.88% (the growth rate between 1960 and 2010), our estimates imply that growth will slow to 0.68% this decade and 1.28% next decade.

---

[25] Between 2030-2050, the older population share will rise by just 2%.

Our estimates are larger than those predicted by the National Research Council (2012). The Council predicted a slowdown in growth in GDP per capita of 0.33-0.55 percentage points per year relative to a long-run rate of growth in GDP per capita of 1.88%. The explanation for the difference between our estimate and theirs, is that the Council assumed population aging would primarily affect labor force growth and not productivity growth. Our estimate of the effect of population aging on labor force growth alone is similar to their estimate of the total effect of population aging.

In fact, for the 1980-2010 period, about 2/3 of the total effect of population aging on growth in GDP per capita arose from slower productivity growth, while 1/3 was due to slower labor force growth, with labor supply effects concentrated entirely among older workers. The slowdown in productivity growth applies across the age distribution and includes younger workers. We interpret this as indicating that older and younger workers are complements in production, and so the productivity of the older workforce affects the productivity of younger workers. This pattern could also arise from a loss of positive productivity spillovers from older to younger workers if productive older workers are more likely to exit the labor force. We find little evidence that our estimated effect is driven by any particular industry or set of industries.

While our results suggest moderate reductions in economic growth associated with population aging at the state-level, it is worth recalling that our estimates do not account for any effects at the national level that may compensate for or exacerbate the slowdown in output growth.[26] Population aging may induce broader general equilibrium effects that we

[26] The National Research Council also did not account for general equilibrium effects of population aging on the federal budget that might lead to changes in tax policy, so this is not a source of difference between our estimate and their forecast.

cannot capture in a state-based research design, such as changes in federal tax policy.[27] As a result, our estimates do not preclude even larger effects of population aging on per-capita economic growth in the United States in the coming decades. On the other hand, further improvements in human capital coupled with greater labor force participation at older ages could temper these effects, as well as reduce the magnitude of changes in federal tax policy that will be required to address them.

[27] But note our research design does capture the effects of state policy responses.

References

Administration on Aging (2014). "Projected Future Growth of the Older Population." U.S. Department of Health and Human Services. http://www.aoa.gov/Aging_Statistics/future_growth/future_growth.aspx (accessed on October 3, 2014).

Aksoy, Yunus, Henrique S. Basso, Tobias Grasl and Ron P. Smith (2015). "Demographic Structure and Macroeconomic Trends," Manuscript, available on REPEC https://ideas.repec.org/p/bbk/bbkefp/1501.html.

Arellano, Manuel and Stephen Bond (1991). "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations." *The Review of Economic Studies*, 58(2), 277-297.

Barro, Robert J and Xavier Sala-i-Martin (1992). "Convergence." *Journal of Political Economy*, 100(2), 223-251.

Bartik, Timothy J (1991). *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Becker, G.S. (1975). "Human capital and the personal distribution of income: an analytical approach" in *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*, 2nd edition. New York: National Bureau of Economic Research.

Bernard, A. B., Redding, S. J., & Schott, P. K. (2013). "Testing for factor price equality with unobserved differences in factor quality or productivity." *American Economic Journal: Microeconomics*, *5*(2), 135-163.

Blanchard, Oliver Jean and Lawrence F. Katz (1992). "Regional Evolutions." *Brookings Papers on Economic Activity*, 1992(1): 1-75.

Bloom, David, David Canning, and Jaypee Sevilla (2003). *The demographic dividend: A new perspective on the economic consequences of population change*. RAND Corporation.

Börsch-Supan, Axel (2003). "Labor market effects of population aging." *Labour* 17.s1: 5-44.

Börsch-Supan, A., I. Duezguen and M. Weiss (2008). "Labor productivity in an aging society." In D. Broeders, S. Eijiffinger and A. Houben, eds. *Frontiers in Pension Finance and Reform*, Cheltenham, U.K.: Edward Elgar, pp. 83-96.

Brandon, Clifford N. (2012). "Emerging Workforce Trends in the U.S. Mining Industry." Englewood, CO: Society for Mining, Metallurgy, and Exploration. https://www.smenet.org/docs/public/EmergingWorkforceTrendsinUSMiningIndustry1-3-12.pdf (accessed May 20, 2015).

Bureau of Economic Analysis (2006). "Gross Domestic Product by State Estimation Methodology." U.S. Department of Commerce. http://www.bea.gov/regional/pdf/gsp/GDPState.pdf (accessed October 1, 2014).

Burtless, Gary (2013). "The impact of population aging and delayed retirement on workforce productivity." Center for Retirement Research at Boston College Working Paper No. 2013-11.

Cutler, D. M., Poterba, J. M., Sheiner, L. M., Summers, L. H., & Akerlof, G. A. (1990). An aging society: opportunity or challenge? *Brookings Papers on Economic Activity*, 1-73.

Feyrer, James (2007). "Demographics and productivity." *The Review of Economics and Statistics* 89, no. 1: 100-109.

Feyrer, James (2008). "Aggregate evidence on the link between age structure and productivity." *Population and Development Review*, pp. 78-99.

Freedman VA, Spillman BC, Andreski PM, Cornman JC, Crimmins EM, Kramarow E, Lubitz J, Martin LG, Merkin SS, Schoeni RF, Seeman TE, Waidmann TA. (2013). "Trends in late-life activity limitations in the United States: an update from five national surveys." *Demography*, 50(2): 661-671.

Gan, Li and Qi Li (2004). "Efficiency of Thin and Thick Labor Markets." NBER Working Paper No. 10815.

Goldin, C., and Katz, L. F. (2007). Long-Run Changes in the Wage Structure: Narrowing, Widening, Polarizing/General Discussion. *Brookings Papers on Economic Activity*, (2), 135.

Hartshorne, Joshua K. and Laura T. Germine (2015). "When Does Cognitive Functioning Peak? The Asynchronous Rise and Fall of Different Cognitive Abilities Across the Life Span." *Psychological Science*, March 13, 2015, 1-11.

Hurd, M. D., & Rohwedder, S. (2008). "The retirement consumption puzzle: actual spending change in panel data." National Bureau of Economic Research Working Paper #w13929.

Hurst, E. (2008). "The retirement of a consumption puzzle." National Bureau of Economic Research Working Paper #w13789.

Kalemli-Ozcan, S., Reshef, A., Sørensen, B. E., & Yosha, O. (2010). "Why does capital flow to rich states?" *The Review of Economics and Statistics*, *92*(4), 769-783.

Karahan, Fatih and Serena Rhee (2014). "Population Aging, Migration Spillovers, the Decline in Interstate Migration." Federal Reserve Bank of New York Staff Report No. 699.

Kögel, Tomas (2005). "Youth dependency and total factor productivity." *Journal of Development Economics* 76, no. 1: 147-173.

Maestas, Nicole, Kathleen J. Mullen and David Powell. “The Effect of Local Labor Demand Conditions on the Labor Supply Outcomes of Older Americans.” RAND Working Paper #WR-1019, October 2013.

Mincer, Jacob A. (1974). “The Human Capital Earnings Function” in *Schooling, Experience, and Earnings*. Cambridge, MA: National Bureau of Economic Research, pp. 83-96.

National Research Council of the National Academies (2012). *Aging and the Macroeconomy: Long-Term Implications of an Older Population.* Washington, D.C.: The National Academies Press.

Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek (2015). *Integrated Public Use Microdata Series: Version 6.0* [Machine-readable database]. Minneapolis: University of Minnesota.

Sheiner, L. (2014). The Determinants of the Macroeconomic Implications of Aging. *The American Economic Review*, *104*(5), 218-223.

Silva, JMC Santos, and Silvana Tenreyro (2006). "The log of gravity." *The Review of Economics and Statistics* 88, no. 4: 641-658.

Staudinger, U. M. (2015). Images of aging: Outside and inside perspectives. *Annual Review of Gerontology & Geriatrics, 35*, 187-210.

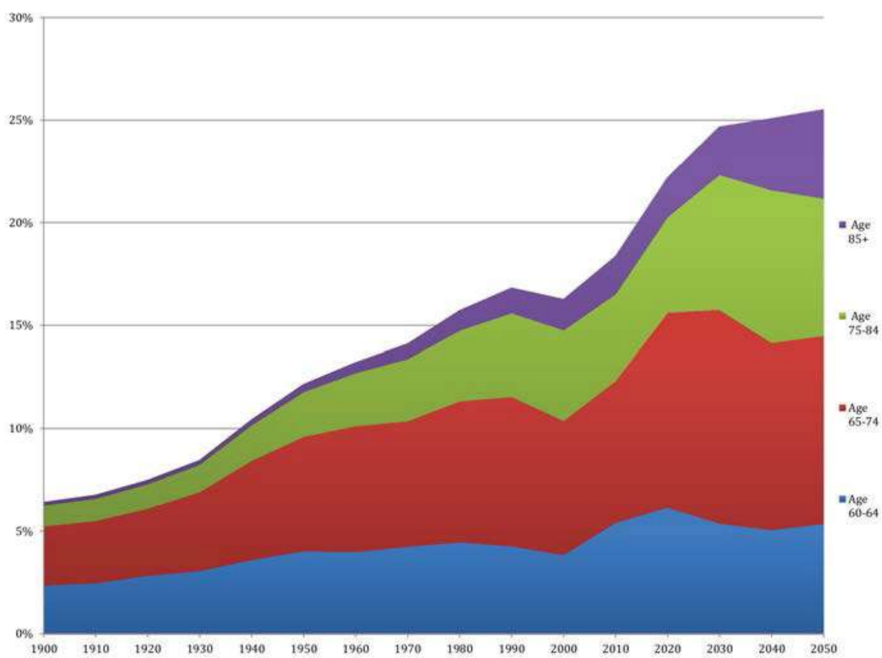
Verhaegen, P. and T.A. Salthouse (1997). “Meta-analyses of age-cognition relations in adulthood. Estimates of linear and nonlinear age effects and structural models.” *Psychological Bulletin*, 122(3): 231-249.

Vogel, E., Ludwig, A., & Börsch-Supan, A. (2013). “Aging and pension reform: extending the retirement age and human capital formation” (No. w18856). National Bureau of Economic Research.

Wong, W. K. (2001). The channels of economic growth: a channel decomposition exercise. *National University of Singapore Working Paper* #0101.

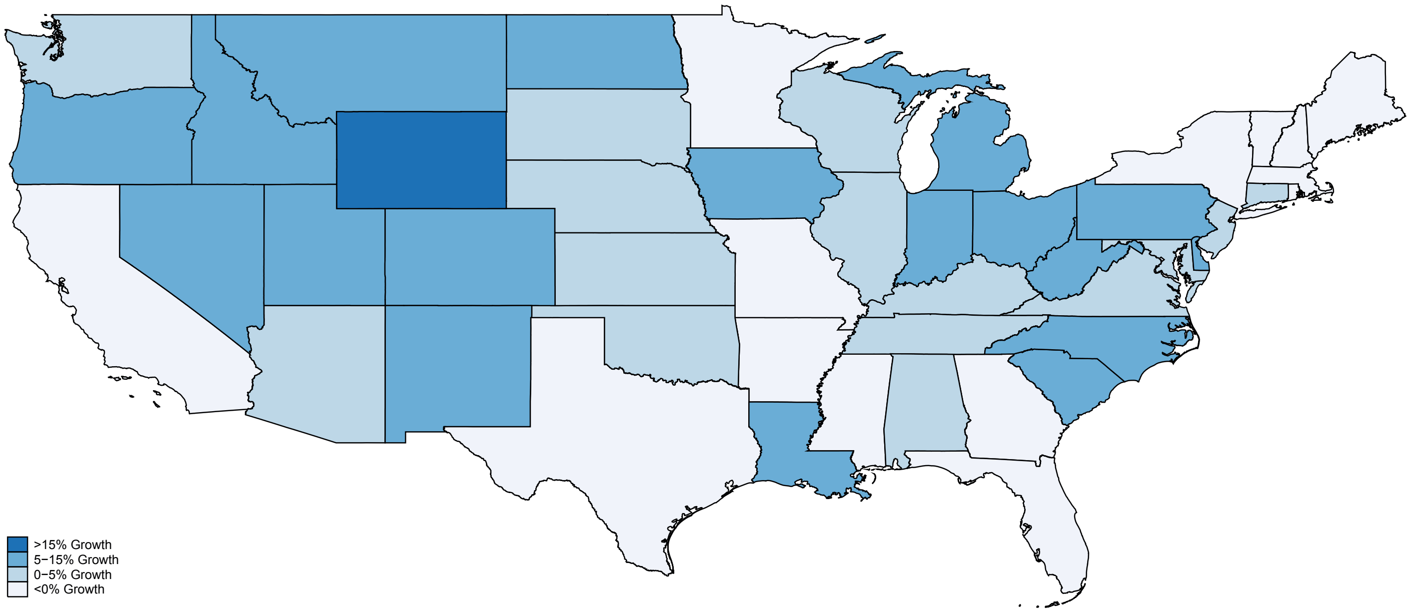
Figures

Figure 1: Percent of United States Population Age 60+: Actual and Projected – 1900-2050



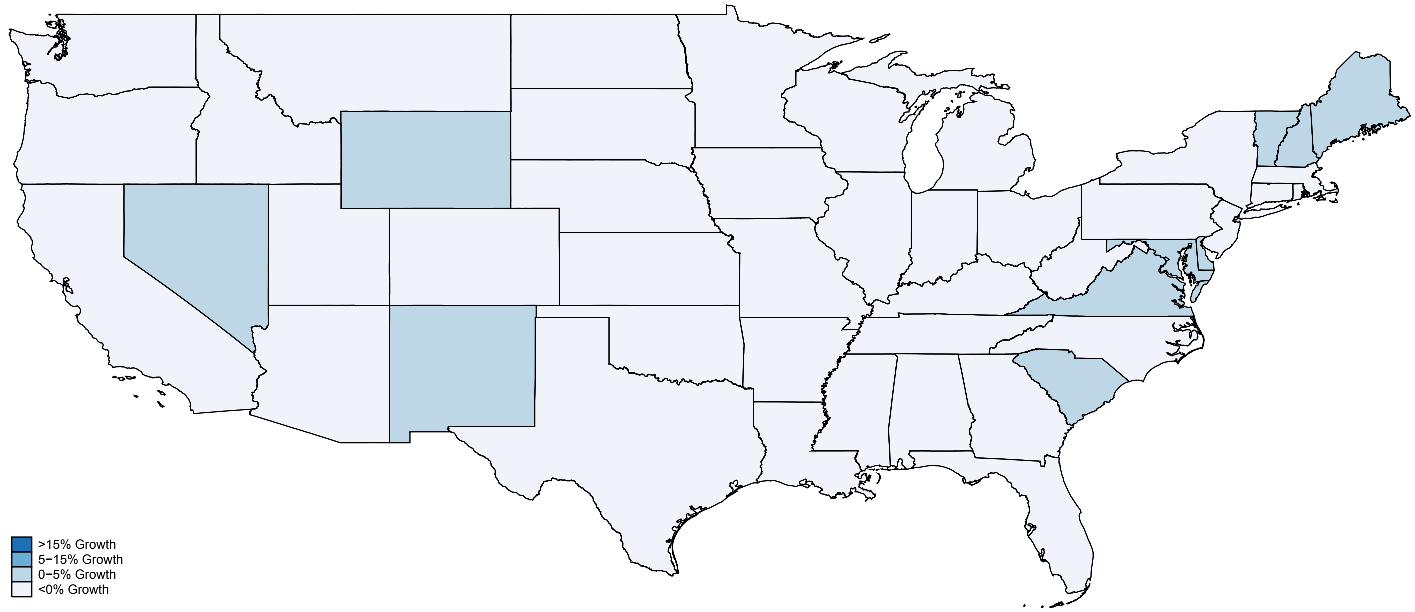
Source: U.S. Census Bureau, compiled by U.S. Administration on Aging.

Figure 2A: Growth Rate in Age 60+ Population by State: 1980-1990



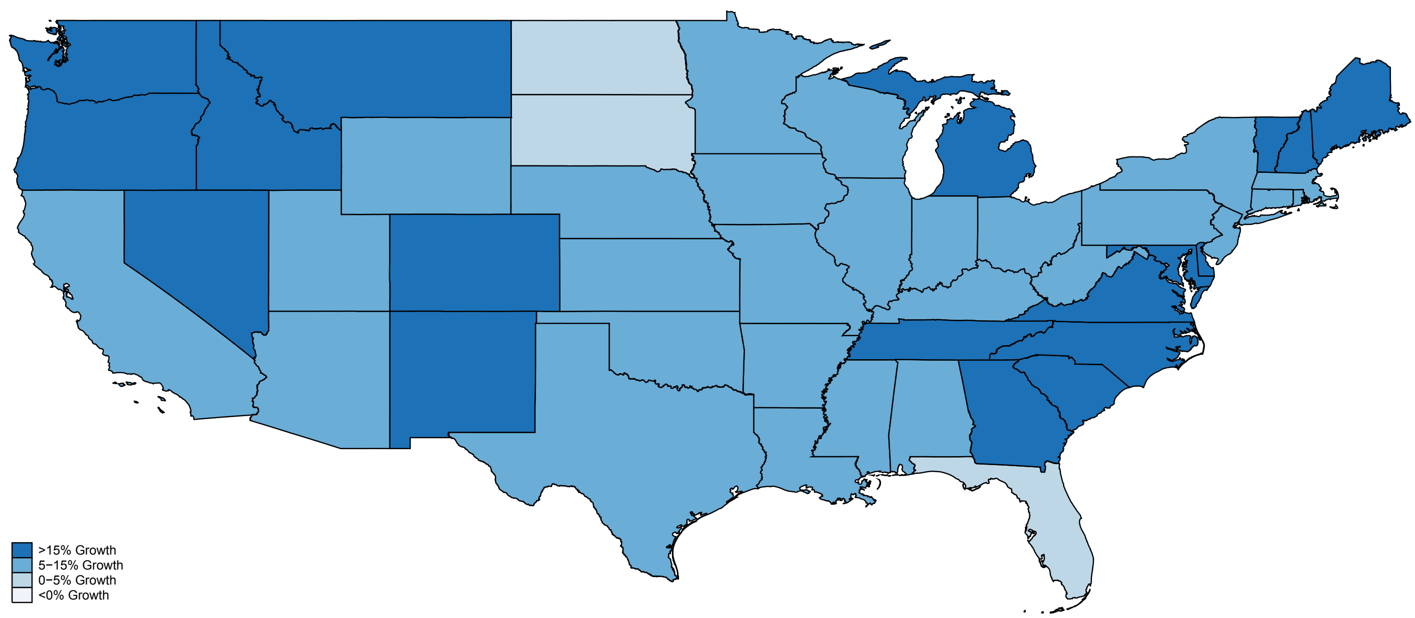
Notes: We use 1980 and 1990 Census data to construct the fraction of each state's population ages 60+. This map refers to the percentage change in this metric between 1980 and 1990.

Figure 2B: Growth Rate in Age 60+ Population by State: 1990-2000



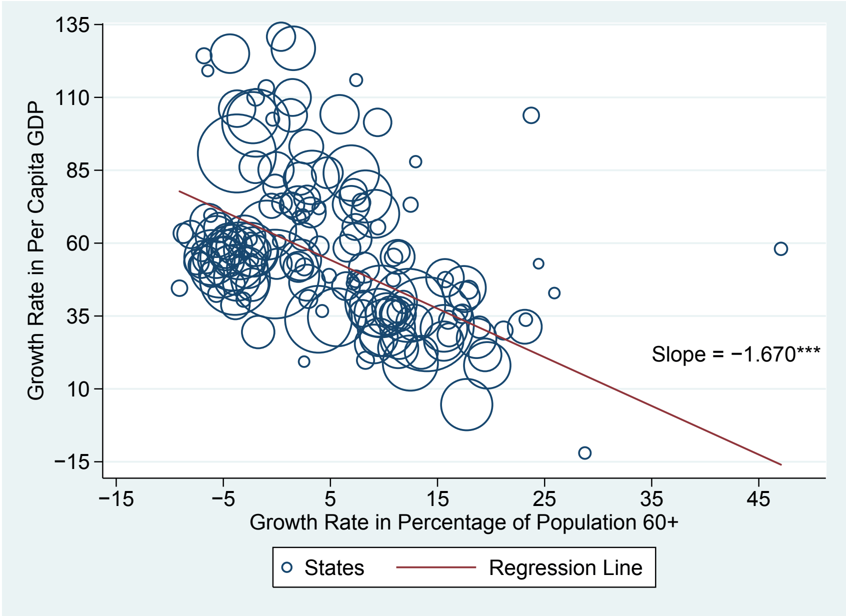
Notes: We use 1990 and 2000 Census data to construct the fraction of each state's population ages 60+. This map refers to the percentage change in this metric between 1990 and 2000.

Figure 2C: Growth Rate in Age 60+ Population by State: 2000-2010



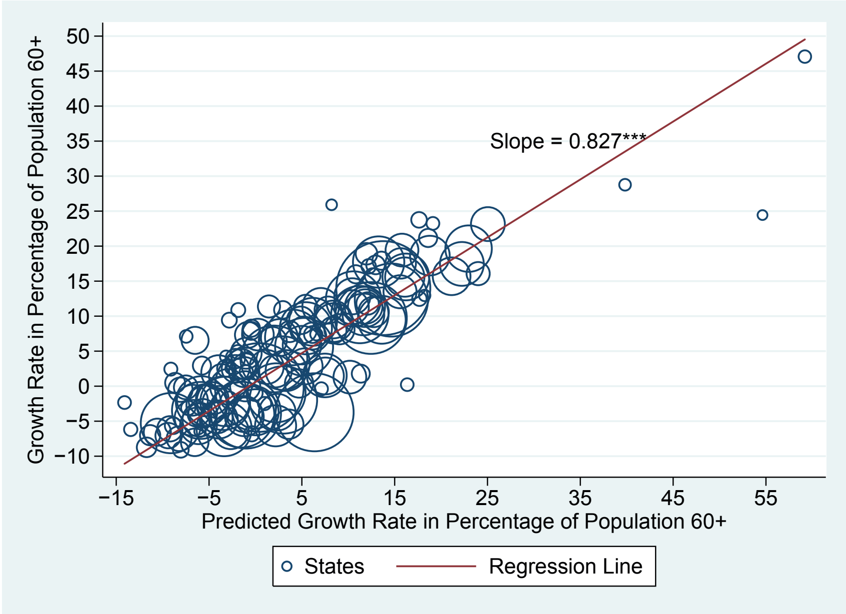
Notes: We use 2000 and 2010 Census data to construct the fraction of each state's population ages 60+. This map refers to the percentage change in this metric between 2000 and 2010.

Figure 3A: Relationship between Aging and Per Capita GDP Growth



Notes: Size of bubbles reflects state population size.

Figure 3B: Relationship between Predicted Aging and Observed Aging Growth



Notes: Size of bubbles reflects state population size.

Figure 3C: Relationship between Predicted Aging and Per Capita GDP Growth

Notes: Size of bubbles reflects state population size.

Tables

Table 1: Summary Statistics

	Mean	Standard Dev	Min	Max
1990, 2000, 2010 (N=153)				
Fraction of Population 60+	0.240	0.029	0.095	0.313
Percent Change in Fraction of Population 60+	4.258	7.901	-9.089	47.073
Predicted Percent Change in Fraction of Population 60+	4.445	8.338	-14.103	59.196
Percent Change in GDP per Capita	55.480	25.548	-12.001	130.816
Percent Change in GDP per Worker	55.277	19.425	-8.105	117.128
Percent Change in GDP per Dollar Earned	4.343	6.259	-27.825	30.941
Percent Change in GDP per Compensation Dollar	2.090	3.631	-25.977	17.660
Percent Change in Employment-to-Population Ratio	-0.314	4.225	-10.022	9.262
1990 (N=51)				
	Mean	Standard Dev	Min	Max
Fraction of Population 60+	0.236	0.030	0.095	0.313
Percent Change in Fraction of Population 60+	2.141	4.959	-6.802	25.911
Predicted Percent Change in Fraction of Population 60+	2.307	5.078	-9.113	54.631
Percent Change in GDP per Capita	87.702	18.672	42.872	130.816
Percent Change in GDP per Worker	78.780	15.498	38.674	117.128
Percent Change in GDP per Dollar Earned	0.095	3.346	-14.269	11.216
Percent Change in GDP per Compensation Dollar	3.354	3.187	-10.264	12.604
Percent Change in Employment-to-Population Ratio	4.887	1.961	-1.709	9.262
2000 (N=51)				
	Mean	Standard Dev	Min	Max
Fraction of Population 60+	0.228	0.028	0.123	0.297
Percent Change in Fraction of Population 60+	-3.066	3.122	-9.089	28.764
Predicted Percent Change in Fraction of Population 60+	-2.836	4.321	-14.103	39.822
Percent Change in GDP per Capita	53.087	7.594	-12.001	69.543
Percent Change in GDP per Worker	53.724	7.339	-8.104	73.158
Percent Change in GDP per Dollar Earned	0.804	4.168	-27.825	14.571
Percent Change in GDP per Compensation Dollar	0.674	4.131	-25.977	17.660
Percent Change in Employment-to-Population Ratio	-0.406	1.919	-6.392	3.117
2010 (N=51)				
	Mean	Standard Dev	Min	Max
Fraction of Population 60+	0.255	0.024	0.181	0.308
Percent Change in Fraction of Population 60+	12.324	4.678	0.219	47.073
Predicted Percent Change in Fraction of Population 60+	12.487	5.749	-1.898	59.196
Percent Change in GDP per Capita	32.955	9.985	4.599	87.947
Percent Change in GDP per Worker	38.677	8.133	16.249	87.025
Percent Change in GDP per Dollar Earned	10.706	3.810	3.366	30.941
Percent Change in GDP per Compensation Dollar	2.370	3.068	-7.499	17.042
Percent Change in Employment-to-Population Ratio	-4.208	2.259	-10.022	1.806

Unit of observation is state-year. There are 51 observations per year and 153 total. All percent changes refer to ten year changes: $\frac{X_t - X_{t-10}}{X_{t-10}}$.
"GDP per Dollar Earned" refers to GDP divided by total labor earnings.
"GDP per Compensation Dollar" refers to GDP divided by total compensation to employee (wages and in-kind benefits).

Table 2: Results

Panel A:	**Ordinary Least Squares Estimates**			
Dependent Variable:	$\Delta \ln$ (GDP / N)			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{A}{N})$	-0.826***	-0.853***	-1.344***	-0.608***
	(0.140)	(0.220)	(0.332)	(0.208)
No. Obs.	153	51	51	51

Panel B:	**Reduced Form Estimates**			
Dependent Variable:	$\Delta \ln$ (GDP / N)			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{\hat{A}}{\hat{N}})$	-0.390***	-0.563**	-0.375	-0.306**
	(0.134)	(0.215)	(0.429)	(0.172)
No. Obs.	153	51	51	51

Panel C:	**First Stage Estimates**			
Dependent Variable:	$\Delta \ln$ (A / N)			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{\hat{A}}{\hat{N}})$	0.716***	0.627***	0.504***	0.865***
	(0.054)	(0.119)	(0.161)	(0.071)
No. Obs.	153	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 3: Instrumental Variable Estimates: Effect of Aging on GDP Growth

Dependent Variable:	Δ ln (GDP / N)			
	Weighted by Population			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{A}{N})$	-0.545***	-0.898**	-0.744	-0.354**
	(0.173)	(0.336)	(0.655)	(0.194)
No. Obs.	153	51	51	51
	Unweighted			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{A}{N})$	-0.478***	-0.361	-0.996***	-0.258**
	(0.161)	(0.319)	(0.369)	(0.152)
No. Obs.	153	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 4: Decomposing Main Effect

	(1)	(2)	(3)
Dependent Variable:	Δ ln(GDP / N)	Δln(GDP / L)	Δln(L / N)
$\Delta \ln(\frac{A}{N})$	-0.545***	-0.373**	-0.172***
	(0.173)	(0.161)	(0.047)
No. Obs.	153	153	153

Notation: L = number of workers

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. The coefficients presented in Columns (2) and (3) mechanically sum to the main effect presented in Column (1). Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 5: Decomposing the Productivity Effect

	Decomposing Δln(GDP/L)		**Decomposing Δln(GDP/H)**	
	(1)	(2)	(3)	(4)
Dependent Variable:	Δln(H/L)	Δln(GDP/H)	Δln(GDP/Earnings)	Δln(Earnings/H)
$\Delta\ln(\frac{A}{N})$	-0.031	-0.343**	-0.145	-0.197**
	(0.033)	(0.151)	(0.112)	(0.113)
No. Obs.	153	153	153	153
	(1)	(2)	(3')	(4')
Dependent Variable:	Δln(H/L)	Δln(GDP/H)	Δln(GDP/Compensation)	Δln(Compensation/H)
$\Delta\ln(\frac{A}{N})$	-0.031	-0.343**	-0.011	-0.331***
	(0.033)	(0.151)	(0.108)	(0.123)
No. Obs.	153	153	153	153

Notation: L = number of workers; H = total number of hours worked; Earnings = total labor earnings; Compensation = total compensation paid to workers.

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. The coefficients in Columns (3) and (4) mechanically add up to the effect estimated in Column (2). The coefficients in Columns (1) and (2) mechanically add up to the effect estimated in Column (2) of Table 4. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 6: Effect of Aging on Industry-Specific GDP

	Private Industries	Agriculture	Mining	Construction	Manufacturing	Transportation / Utilities
$\Delta\ln(\frac{A}{N})$	-0.590***	0.170	0.873	-0.860**	-0.361	-0.270
	(0.201)	(0.853)	(1.919)	(0.399)	(0.486)	(0.389)
	Wholesale Trade	Retail Trade	Finance / Insurance	Services	Public Admin	
$\Delta\ln(\frac{A}{N})$	-0.472**	-0.397**	-0.624**	-0.471**	-0.341**	
	(0.218)	(0.207)	(0.277)	(0.221)	(0.184)	

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. The outcome is the log of industry-specific GDP per person in the state. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 7: Age-Specific Labor Outcomes: Change in Log of Employment Rate

				Men			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.003	-0.014	0.015	-0.082*	-0.313***	-0.447**	-0.762***
	(0.045)	(0.027)	(0.022)	(0.043)	(0.117)	(0.200)	(0.278)
No. Obs.	153	153	153	153	153	153	153
				Women			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	0.018	-0.071	-0.026	-0.037	-0.241*	-0.132	-0.702*
	(0.050)	(0.045)	(0.050)	(0.059)	(0.124)	(0.269)	(0.411)
No. Obs.	153	153	153	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 8: Age-Specific Labor Outcomes: Change in Log of Employment Share

				Men			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.243***	-0.300***	0.096	0.399***	0.769***	0.728***	0.226
	(0.083)	(0.087)	(0.087)	(0.082)	(0.116)	(0.162)	(0.358)
No. Obs.	153	153	153	153	153	153	153
				Women			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.215***	-0.264***	0.176*	0.583***	1.097***	0.946***	0.133
	(0.080)	(0.096)	(0.100)	(0.085)	(0.112)	(0.271)	(0.493)
No. Obs.	153	153	153	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 9: Age-Specific Labor Outcomes: Change in Log of Wage

				Men			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.422***	-0.325***	-0.402***	-0.477***	-0.498***	0.129	0.429
	(0.150)	(0.119)	(0.113)	(0.096)	(0.107)	(0.261)	(0.507)
No. Obs.	153	153	153	153	153	153	153
				Women			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.342**	-0.404***	-0.376***	-0.433***	-0.324**	0.045	0.712
	(0.135)	(0.137)	(0.123)	(0.123)	(0.125)	(0.276)	(0.641)
No. Obs.	153	153	153	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Appendix

Table A.1: Effects of Other Age Groups

Dependent Variable:	Δ ln (GDP / N)			
Δ ln(Ages 30-39 / N)	-0.112			
	(0.192)			
Δ ln(Ages 40-49 / N)	-0.279	-0.261		
	(0.226)	(0.218)		
Δ ln(Ages 50-59 / N)	-0.104	-0.051	-0.063	
	(0.228)	(0.200)	(0.198)	
Δ ln(Ages 60+ / N)	-0.594***	-0.550***	-0.527***	-0.545***
	(0.191)	(0.153)	(0.164)	(0.173)
No. Obs.	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.2: Instrumental Variable Poisson Estimates: Effect of Aging on GDP Growth

Dependent Variable:	GDP / N			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{A}{N})$	-0.509***	-0.924***	-0.962**	-0.337**
	(0.129)	(0.283)	(0.453)	(0.136)
No. Obs.	153	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Period t GDP per capita is included as an offset (the coefficient is constrained to equal 1). Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.3: Logs vs. Levels

Dependent Variable:	$\Delta \ln$(GDP / N)	
$\Delta \ln(\frac{A}{N})$	-0.545***	
	(0.173)	
$\Delta(\frac{A}{N})$		-2.030**
		(0.828)
Implied Elasticity	-0.545	-0.485
No. Obs.	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year. "Implied Elasticity" in second column is calculated by evaluating at the sample means for both per capita GDP growth and growth in 60+ population share.

Table A.4: IV Estimates with Region-Year Interactions: Effect of Aging on GDP Growth

Dependent Variable:	$\Delta\ln(\text{GDP / N})$			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta\ln(\frac{A}{N})$	-0.585**	-0.690	-0.895	-0.447**
	(0.250)	(0.463)	(0.668)	(0.235)
No. Obs.	153	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies interacted with Census regions; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.5: Using Previous Year's State of Residence: 2000-2010

	OLS	Reduced Form	First Stage	IV
$\Delta\ln(\frac{A}{N})$	-0.634***	-0.348**	0.878***	-0.396**
	(0.204)	(0.174)	(0.070)	(0.192)
No. Obs.	51	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies interacted with Census regions; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year. For this table, $\Delta\ln(\frac{A}{N})$ (and the corresponding instrument) are generated using each individual's prior year state of residence. This information is first available in the 2000 Census.

Table A.6: Accounting for Trends

	(1)	(2)	(3)
$\Delta \ln(\frac{A}{N})$	-0.513***	-0.672***	-0.839***
	(0.180)	(0.244)	(0.160)
Instrument	20-year	10-year	10-year
Industry Lags	Yes	No	Yes
$\ln(GDP)_{st}$	No	Yes	Yes
No. Obs.	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Other variables included: year dummies and "Industry Lags" when noted. These are the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year. Column (1) uses an instrument generated using Census population data from year $t - 10$ (instead of year t). Column (2) controls for period t log of per capita GDP and estimates using Arellano-Bond estimation. Column (3) replicates Column (2) but also controls for the initial industry composition in each state.

Table A.7: Employment and Wages, 1980-1990

				Δln(Employment Rate), Men			
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	-0.129	-0.104*	-0.122***	-0.483***	-1.084***	-1.534***	-2.497***
	(0.087)	(0.059)	(0.040)	(0.108)	(0.262)	(0.376)	(0.924)
No. Obs.	51	51	51	51	51	51	51
				Δln(Employment Rate), Women			
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	-0.102	-0.201	-0.065	-0.146	-0.606**	-0.555	-2.365*
	(0.114)	(0.126)	(0.137)	(0.189)	(0.282)	(0.685)	(1.216)
No. Obs.	51	51	51	51	51	51	51
				Δln(Wage), Men			
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	-1.335***	-0.906***	-1.170***	-0.889***	-1.206***	0.432	1.831
	(0.451)	(0.252)	(0.276)	(0.256)	(0.423)	(0.685)	(1.515)
No. Obs.	51	51	51	51	51	51	51
				Δln(Wage), Women			
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	-1.118***	-1.205***	-1.047***	-1.000***	-1.159**	-0.326	0.722
	(0.388)	(0.324)	(0.274)	(0.342)	(0.466)	(0.654)	(1.291)
No. Obs.	51	51	51	51	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.8: Employment and Wages, 1990-2000

Δln(Employment Rate), Men							
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	0.066	0.059	0.075	0.172	0.157	0.452	2.550**
	(0.090)	(0.062)	(0.078)	(0.107)	(0.255)	(0.471)	(1.284)
No. Obs.	51	51	51	51	51	51	51

Δln(Employment Rate), Women							
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	-0.032	-0.032	-0.081	-0.043	-0.582*	0.155	0.62
	(0.146)	(0.132)	(0.116)	(0.179)	(0.299)	(0.513)	(0.979)
No. Obs.	51	51	51	51	51	51	51

Δln(Wage), Men							
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	0.124	-0.170	-0.115	-0.681**	0.072	0.262	2.755
	(0.306)	(0.249)	(0.269)	(0.269)	(0.366)	(0.692)	(2.176)
No. Obs.	51	51	51	51	51	51	51

Δln(Wage), Women							
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	0.036	-0.185	-0.349	-0.254	0.268	-0.054	-2.276
	(0.267)	(0.307)	(0.225)	(0.301)	(0.385)	(0.759)	(2.155)
No. Obs.	51	51	51	51	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.9: Employment and Wages, 2000-2010

	Δln(Employment Rate), Men						
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	0.031	0.002	0.056**	0.012	-0.126	-0.270	-1.167***
	(0.068)	(0.043)	(0.028)	(0.043)	(0.133)	(0.264)	(0.341)
No. Obs.	51	51	51	51	51	51	51
	Δln(Employment Rate), Women						
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	0.093	-0.024	0.013	0.016	0.054	-0.040	-0.411
	(0.079)	(0.038)	(0.027)	(0.044)	(0.154)	(0.320)	(0.545)
No. Obs.	51	51	51	51	51	51	51
	Δln(Wage), Men						
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	-0.198*	-0.112	-0.150	-0.210**	-0.378***	-0.062	-1.075
	(0.114)	(0.120)	(0.120)	(0.100)	(0.137)	(0.318)	(1.040)
No. Obs.	51	51	51	51	51	51	51
	Δln(Wage), Women						
	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89
$\Delta \ln(\frac{A}{N})$	-0.120	-0.112	-0.073	-0.235**	-0.152	0.255	1.801
	(0.111)	(0.113)	(0.105)	(0.119)	(0.154)	(0.329)	(1.500)
No. Obs.	51	51	51	51	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.