Workforce Aging and Industry-level Productivity

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Abstract

This study tests two hypotheses regarding the relationship between workforce aging and industry-level productivity growth using panel data on 24 industries in 21 countries for the period 1985–2005. Our first model, based on the assumption that the employment of young workers generates industry-level external economies of scale, shows that total factor productivity growth will have a greater decline in industries that depend more on young workers when the growth rate of young workforce declines. Our second model, based on deferred payment contracts, shows that measured total factor productivity growth will have a greater decline in industries that depend more on young workers when the growth rate of the share of young workforce declines. Our dataset supports the first model. When the growth rate of prime-age workforce (aged between 30 and 49) falls, productivity growth rates in industries that are highly dependent on prime-age workers tend to fall compared to other industries. The effect seems to be quantitatively large.

Keywords: total factor productivity, prime-age workers, young labor intensity, external economies of scale, deferred payment

JEL codes: J11, O40, O41

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I. Introduction

Population aging has been the subject of vast economic research. Various aspects of population aging have been studied: effects on saving and investment, pension and public debt sustainability, industrial structure, poverty rate, health costs, housing prices, economic growth, and so on.

Studies on the relationship between the age structure of population and economic growth have largely focused on dependency ratio—the ratio of non-working-age to working-age population. Persson and Malmberg (1996), Bloom, Canning, and Sevilla (2001), and Kögel (2005) are some examples. They find that an increase in the ratio of children or the old to the working-age population negatively affects the growth in the output per capita or total factor productivity (TFP henceforth). Using data on US states, Maestas, Mullen, and Powell (2016) revealed that a high proportion of the old in the population has negative effects on income. However, Acemoglu and Restrepo (2017) fail to find such effects in cross-county data.[1]

In contrast, studies on the effects of population aging on aggregate productivity through workforce aging are relatively scarce. A change in the age structure of workers, as opposed to that in the dependency ratio, can have a direct impact on aggregate productivity because the individual productivity of workers varies over their life cycle. Workers' productivity increases with the accumulation of experience over time, but their physical or mental abilities start declining at some stage in life. (Lehman, 1953; Dixon, 2003, Skirbekk, 2004; Jones, 2010; and Börsch-Supan and Weiss, 2016) Recently, there has been a rise in econometric studies on the relationship between workforce aging and aggregate productivity growth. Feyrer (2007) uses country-level panel data to estimate the relationship between the shares of various age groups in the workforce and TFP, and finds a positive association between the share of workers aged 40–49 years and TFP. Liu and Westelius (2016) confirm his finding using data on Japanese prefectures. Aiyar, Ebeke and Shao (2016) find a negative correlation between the share of workers aged 55–64 years and TFP growth across European countries. They estimate that from 2014 to 2045, workforce aging could reduce annual TFP growth by 0.2 percentage points in European countries, and much more in Southern and Central European countries where

[1] Their measure of aging captures both population aging and workforce aging, and, thus, their study straddles the literature on population aging and that on workforce aging discussed below.

workforce aging is expected to be more pronounced.

This study differs from previous studies on workforce aging and TFP growth in two aspects. First, we derive estimation equations from simple general equilibrium models, enabling a sharper interpretation of estimation results. Second, we study the relationship between workforce aging and TFP growth at industry level.

It is important to note that TFP does not have to fall with workforce aging, even if the average productivity of workers deteriorates. If aggregate labor input is accurately measured by taking into account the different qualities of workers at different ages, TFP measured by growth accounting should not be affected by changes in the age distribution of workers. A study by Sarel (1995) is among the first to incorporate the inverse-U-shaped relationship between individual productivity and worker age in the measurement of aggregate labor input for growth accounting. Now, many studies on growth accounting, including the EU KLEMS database on which the current study relies, capture the differing qualities of workers in the calculation of aggregate labor input by distinguishing labor types in terms of age and educational attainment and using workers' relative wages as a quality adjuster. Therefore, in such data, a negative correlation between workforce aging and measured TFP growth would emerge only when systematic discrepancies exist between workers' contributions and their wages.

In this paper, we propose two simple models where those discrepancies arise, and test them using data on advanced countries. Our first model is based on the assumption that young workers generate industry-level external economies of scale. Under industry-level external economies of scale, an increase in the production scale of an industry raises the productivity of all firms in the industry through knowledge spillovers. These types of externalities, called Marshallian externalities, have been the subject of intense research in many fields of economics. The twist of our model is the assumption that externalities arise only from the production activities of young workers. Lehman (1953), Skirbekk (2004), Jones (2010), and many others note that individual performance in creative or innovative activities tends to decline sharply around the age of 50 years or even earlier. Because the spillover of knowledge would be intense when it is of recent vintage, we expect that external economies, if any, mostly originate from the activities of younger workers. These assumptions lead to our first hypothesis: TFP growth in industries that depend more on young workers relatively rises when the growth rate of young workforce increases.

Our second model is based on deferred payment contracts à la Lazear (1979). Under deferred payment contracts, wages for the younger workers are set at a level lower than their productivity level and at a higher level for the older workers. This wage profile increases the costs of being caught shirking and, thus, induces young workers to increase their efforts. When the qualities of workers at different ages are adjusted by their relative wages in the calculation of aggregate labor input, the presence of deferred payments causes the growth of aggregate labor input to be underestimated when the share of younger workers in the workforce increases; this results in an overestimation of measured TFP growth. This phenomenon leads to our second hypothesis: the growth rates of (mis-)measured TFP in industries that depend more on young workers relatively rises when the growth rate of the share of young workforce increases.

The two hypotheses can be tested using a difference-in-differences framework. We use panel data composed of 24 industries in 21 countries that is observed for four quinquennial periods between 1985 and 2005. Data on TFP and the age profile of workers by industry are taken from the EU KLEMS Database, March 2008 (Timmer et al., 2007). It is frequently claimed that country-level panel data can be relied upon to identify a correct causal relationship between productivity and the age structure of population. Population is probably the most exogenous variable with time series variation that economists can find for growth studies. By instrumenting employment levels on lagged population, as many of the aforementioned studies do, we can avoid the endogeneity problems caused by changes in participation rates and migration induced by TFP variations. However, endogeneity may remain even after using lagged population as instruments. For example, population aging can lead to higher taxation to finance increased social expenditures, which may slow down TFP growth. Omitting policy variables in regressions can lead to biases. Applying a difference-in-differences method to industry-level panel data can reduce endogeneity problems present in aggregate models.

We find that our dataset supports the first hypothesis, but not the second one. When the growth rate of prime-age workforce (workers between 30 and 49) increases, TFP growth rates in industries that are highly dependent on prime-age workers tend to increase relative to other industries. This effect is robust to changes in estimation methods and samples. The effect also seems to be quantitatively large. When the growth rate of prime-age workforce increases by 1 percentage point, TFP growth rates in industries that belong to the top tercile in terms of prime-age worker share increase by 0.5 percentage point relative to the bottom tercile industries. Our second hypothesis is not supported. We do not find any robust correlation between the relative TFP growth rates of industries and changes in the share of prime-age workforce.

This paper is organized as follows. Section II proposes two simple general equilibrium models, from which we derive testable hypotheses on the relationship between workforce aging and industry-level productivity growth. Section III tests the hypotheses using industry-level panel data constructed from the EU KLEMS Database. Section IV concludes the study.

II. Worker Age Profile and Total Factor Productivity

A pure labor economy produces N goods using L and H, which denote low-age labor and high-age labor, respectively. At any moment, the supply of both is inelastic. The representative household maximizes the following Cobb–Douglas utility function.

$$U = \sum_i \beta_i \log C_i \tag{1}$$
$$s.t.\ \ \sum_i P_i C_i \leq\ WL + R\ H.$$

β_i's are all positive and $\sum_i \beta_i = 1$. C_i denotes the consumption of good i $(= 1, \dots, N)$ and P_i is its price. W and R are the wage rates for low-age labor and high-age labor, respectively.

Our first model is based on industry-level external economies of scale. We assume that knowledge spillovers among firms in an industry induce their productivity level to rise with the industry's production scale, while each firm in the industry has no individual influence on the productivity level. These types of scale economies are dubbed as Marshallian externalities, following the analysis of Marshall (1890), who observes that the concentration of firms producing linked products in an industrial cluster allows easier recruitment of skilled labor and rapid exchange of commercial and technical information. Industry-level external economies of scale have been the subject of intense research in many fields of economics. They were formally analyzed by Chipman (1970) in a general equilibrium model. They have been widely studied as a source of comparative advantage in international trade, as exemplified by Ethier (1982), Krugman (1995), and Kucheryavyy, Lyn, and Rodriguez-Clare (2016). Their role in spatial agglomeration has been extensively examined in economic geography studies, such as Glaser et al. (1992), and Henderson, Kuncoro, and Turner (1995). Arrow (1962) and Romer

(1986) are influential examples that extend the notion to economy-wide externalities to obtain increasing returns in aggregate production.

The standard specification for industry-level external economies of scale is to write the production function as $Q_i = B_i L_i^{\phi_i} L_i$, where Q_i is the output of good i, L_i is labor input into good *i*, and $L_i^{\phi_i}$ captures external economies. $B_i L_i^{\phi_i}$ determines the TFP level of the industry, but each firm in the industry takes it as given. We tweak the model by adding a second type of labor, H_i, and assuming that it generates no externalities.

$$Q_i = B_i \left(L_i^{\phi_i} L_i\right)^{\alpha_i} H_i^{1-\alpha_i}, \tag{2}$$

where L_i is the employment of low-age labor in good *i* industry and H_i is the employment of high-age labor. High-age workers do not produce new knowledge that spills over to other firms in the industry, or their limited mobility prevents their knowledge being shared with other firms.

Utility maximization under (1) implies that $P_i C_i = \beta_i (WL + R\,H)$. Profit maximization under (2) requires that $\alpha_i\, P_i Q_i = W\, L_i$. $C_i = Q_i$ in equilibrium, and

$$\alpha_i \beta_i (WL + R\,H) = W\, L_i. \tag{3}$$

Summing both sides of (3) over i's, with the full employment condition $\sum_i L_i = L$, yields:

$$\textstyle\sum_i \alpha_i \beta_i\ (WL + R\,H) = W\, L. \tag{4}$$

Dividing (3) by (4), we arrive at

$$L_i = \frac{\alpha_i \beta_i}{\sum_i (\alpha_i \beta_i)}\, L. \tag{5}$$

Thus, $\dot{L}_i / L_i = \dot{L} / L$ under constant parameter values. Similarly, we can show that $\dot{H}_i / H_i = \dot{H} / H$. Let A_i be the observed TFP of good *i* industry. Its growth rate is calculated as a Solow residual:

$$\frac{\dot{A}_i}{A_i} = \frac{\dot{Q}_i}{Q_i} - \frac{W L_i}{P_i Q_i}\frac{\dot{L}_i}{L_i} - \frac{R H_i}{P_i Q_i}\frac{\dot{H}_i}{H_i} = \frac{\dot{Q}_i}{Q_i} - \alpha_i \frac{\dot{L}_i}{L_i} - (1-\alpha_i)\frac{\dot{H}_i}{H_i} = \frac{\dot{B}_i}{B_i} + \phi_i\, \alpha_i\, \frac{\dot{L}}{L}. \tag{6}$$

ϕ_i, which measures the strength of externality, may differ across industries. We assume that the deviation of ϕ_i from its mean ϕ is independent of α_i.[2] Because (6) holds in each country, we can write (6) as:

$$\frac{\dot{A}_{ik}}{A_{ik}} = \phi\, \alpha_i \frac{\dot{L}_k}{L_k} + \frac{\dot{B}_{ik}}{B_{ik}} + u_{ik}, \tag{7}$$

where k denotes a country and u_{ik} a random variable. We further assume that $\dot{B}_{ik}/B_{ik}$ can be decomposed into three parts: specific to industry *i*, specific to country *k*, and purely random. Thus, we can obtain the following estimation equation:

$$\begin{aligned} TFP\ Growth_{ik} = {} & \gamma_0. \\ & + \phi\ (\,low\text{-}age\ worker\ share_i \times low\text{-}age\ \ workforce\ growth_k) \\ & + \delta_i + \delta_k + \varepsilon_{ik}. \end{aligned} \tag{8}$$

δ_i and δ_k denote industry fixed effects and country fixed effects, respectively. ε_{ik} is a random variable. Thus, our estimation equation conforms to a difference-in-differences format popularized by Rajan and Zingales (1998). If ϕ is found to be significantly positive, we can say that there are positive externalities coming from the production activities of low-age workers, and the TFP growth rates in industries that have higher low-age worker shares rise more when the growth rate of low-age workforce increases.

Our second model is based on the assumption that low-age workers are paid less than the value of their marginal product, while high-age workers are paid more than the value of their marginal product. The seniority-based payment system that is frequently found in Japan and Korea is often associated with this type of compensation scheme. However, as Lazear (1979)

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[2] This condition is stronger than necessary. All that we need is that ϕ_i is not so negatively correlated with α_i that $\phi_i\, \alpha_i$ becomes negatively correlated with α_i.

argues, deferred compensation can result from a long-term labor contract in the workplace where workers' effort levels cannot be easily monitored. Young workers accept wages lower than their productivity in anticipation of higher wages later in their life. Firms can reduce the shirking by younger workers because getting caught shirking is costly under deferred payment contracts.

To capture deferred payment in a simple competitive equilibrium framework, we use the standard Cobb–Douglas production function:

$$Q_i = B_i\, L_i^{\alpha_i}\, H_i^{1-\alpha_i}. \tag{9}$$

However, we assume that firms tax the wages of low-age workers and subsidize the wages of high-age workers:

$$\tau_i\, \alpha_i\, P_i Q_i = W\, L_i, \tag{10}$$
$$\sigma_i\, (1-\alpha_i)\, P_i Q_i = R\, H_i. \tag{11}$$

$\tau_i < 1$, and $\sigma_i > 1$. In a competitive equilibrium, firms must have zero profits and $\tau_i\, \alpha_i + \sigma_i\, (1-\alpha_i) = 1$. Because $P_i C_i = \beta_i (WL + R\, H)$ by (1), and $C_i = Q_i$ in equilibrium,

$$\alpha_i\, \beta_i\, \tau_i (WL + RH) = W\, L_i, \tag{12}$$
$$(1-\alpha_i)\, \beta_i\, \sigma_i (WL + RH) = R\, H_i. \tag{13}$$

From these equations, we can easily obtain:

$$L_i = \frac{\alpha_i \beta_i \tau_i}{\sum_i (\alpha_i \beta_i \tau_i)}\, L, \tag{14}$$
$$H_i = \frac{(1-\alpha_i)\, \beta_i \sigma_i}{\sum_i ((1-\alpha_i)\, \beta_i \sigma_i)}\, H. \tag{15}$$

Thus, as before, $\dot{L}_i / L_i = \dot{L}/L$ and $\dot{H}_i / H_i = \dot{H}/H$ under constant parameter values. Using the equations above, we obtain

$$\frac{\dot{A}_i}{A_i} = \frac{\dot{Q}_i}{Q_i} - \frac{W\,L_i}{P_iQ_i}\frac{\dot{L}_i}{L_i} - \frac{R\,H_i}{P_iQ_i}\frac{\dot{H}_i}{H_i} = \frac{\dot{Q}_i}{Q_i} - \tau_i\,\alpha_i\frac{\dot{L}_i}{L_i} - \sigma_i(1-\alpha_i)\frac{\dot{H}_i}{H_i}$$
$$= \frac{\dot{Q}_i}{Q_i} - \tau_i\,\alpha_i\frac{\dot{L}_i}{L_i} - (1-\tau_i\,\alpha_i)\frac{\dot{H}_i}{H_i} = \frac{\dot{B}_i}{B_i} + (1-\tau_i)\,\alpha_i\frac{\dot{L}}{L} - (1-\tau_i)\,\alpha_i\frac{\dot{H}}{H}$$
$$= \frac{\dot{B}_i}{B_i} + (1-\tau_i)\,\alpha_i\left(\frac{\dot{L}}{L} - \frac{\dot{H}}{H}\right). \tag{16}$$

Because (16) holds in each country, assuming again that the deviation of τ_i from its mean τ is independent of α_i, we can write (16) as:

$$\frac{\dot{A}_{ik}}{A_{ik}} = (1-\tau)\,\alpha_i\left(\frac{\dot{L}_k}{L_k} - \frac{\dot{H}_k}{H_k}\right) + \frac{\dot{B}_{ik}}{B_{ik}} + u_{ik}. \tag{17}$$

Thus, the only difference from our first model is that now TFP growth rates rise more in industries that have higher shares of low-age workers when the growth rate of the share of low-age workforce increases, not when the growth rate of the absolute size of low-age workforce increases. We can write our second estimation equation as:

$$\begin{aligned}&TFP\ Growth_{ik} = \gamma_0.\\&+\phi\ (\ low\text{-}age\ worker\ share_i \times relative\ low\text{-}age\ \ workforce\ growth_k)\\&+\delta_i + \delta_k + \varepsilon_{ik}\ ,\end{aligned} \tag{18}$$

where relative low-age workforce growth is defined as the difference in the growth rates of low-age and high-age workforce. Because the ratio of low-age to high-age workforce is increasing in the ratio of low-age to total workforce, we can also use the difference between the growth rates of low-age and total workforce as an inverse measure of workforce aging. Indeed, Feyrer (2007), Liu and Westelius (2016), and many others use it as the measure of workforce aging, though they do not provide any theoretical justification.

III. Data and Estimation Methods

To test our hypotheses, we use TFP growth rates in 24 industries for 21 countries during the 20-year period between 1985 and 2005. Annual TFP growth rates are averaged over four quinquennial periods between 1985 and 2005, and, thus, we have four observations on each industry in the country where they are available. We use value-added TFPs from the EU KLEMS Database, March 2008 (Timmer et al., 2007).[3] The 24 industries that we examine are listed in Table 1.[4]

<Insert Table 1 here>

The key concept for this paper is the low-age labor intensity of an industry. The EU KLEMS database reports the shares of three age groups in total hours worked in 24 industries from a few countries. The age of the three groups of workers are between 15 and 29, between 30 and 49, and greater than 50. For convenience, we will call the first group, "young workers," the second, "prime-age workers," and the third "old workers." Thus, we can measure the low-age labor intensity of each industry by young worker share or prime-age worker share, though our preferred measure is prime-age worker share as most workers seem to reach the peak of their innovative capacity during prime age. In most of the regressions below, we include both as proxies for low-age labor intensity and evaluate their effectiveness. The hours worked by three age groups in all 24 industries are available only for six countries. In Table 1, we report the young worker shares and prime-age worker shares observed in US industries. We will use these figures as low-age worker shares in 24 industries, presuming that they reflect the technological industry characteristics shared by all countries in the sample.[5]

[3] The 21 countries are Austria, Belgium, Czech Republic, Denmark, Spain, Finland, France, Germany, Hungary, Ireland, Italy, Luxembourg, Netherlands, Portugal, Slovenia, Sweden, UK, USA, Japan, Korea, and Australia. For Czech Republic, Hungary, Ireland, Luxembourg, Portugal, Slovenia, and Sweden, TFP growth rates are available only for the last two quinquennial periods. For the other 14 countries, TFP growth rates are available for all four periods.

[4] The database reports TFPs for 28 non-overlapping industries. We drop three nonmarket services (public administration and defense, education, and health and social work) and real estate industry, as Timmer et al. (2007) do in their analysis of TFPs. Output in real estate mainly reflects imputed housing rents.

[5] Following Rajan and Zingales (1998), the use of US observations as proxies for technological industry characteristics became popular in industry-level studies. The presumption here is that the US has industries least influenced by regulations and labor unions; and, hence, observations in the US best reflect the inherent technological characteristics of industries. We will check the robustness of our results to this practice.

<Insert Tables 2 and Table 3 here>

One may criticize the presumption by arguing that the worker age profiles of industries are largely determined by demography and labor market institutions that greatly vary across countries, not by technological industry characteristics. To get an idea on the issue, we examine correlations between the US shares and those of other countries in Table 2. The first row shows correlations between US young worker shares and those of five other countries across 24 industries. All of them are significantly positive, averaging 0.55, but do not seem to be impressively high. The second row reports the correlations of prime-age worker shares. They are generally higher, averaging 0.66. The last two rows show correlations between the US and the other countries for skilled worker shares and capital shares—both are widely used to measure the skill and capital intensities of industries. The average correlation between the US and the other countries for skilled worker share is quite high at 0.77, and that for capital share is 0.63. Thus, using prime-age worker shares as technological industry characteristics for industry-level studies seems to make roughly as much sense as using skilled worker shares or capital shares, though the case for using young worker shares seems weaker.

In Table 3, we show the correlations of young and prime-age worker shares with skilled worker shares and capital shares across US industries to check if our measures of low-age labor intensity are not really picking up skill or capital intensities. We can see that young worker shares are negatively correlated, and prime-age worker shares are positively correlated with skill and capital intensities. However, these correlations are insignificant except for the one between prime-age worker shares and capital shares. In contrast, young worker shares and prime-age worker shares have a highly negative correlation, suggesting that it may not be a good idea to use both variables as regressors.

The absolute values of worker shares by age groups would no doubt be strongly influenced by demographic and institutional country characteristics, and, hence, only the approximate rankings of industries on these shares would reflect pure technological characteristics. Thus, in most regressions below, we use tercile dummies for young and prime-age worker shares instead of continuous measures. In Table 1, top tercile industries in terms of young worker shares are hotels and restaurants, retail trade, construction, business services, post and telecommunications, motor vehicle sales, finance, and wood manufacturing. In terms of prime-age worker shares, electricity, mining and quarrying, transport equipment, chemicals, transport and storage, non-metallic mineral, electrical equipment, and general machinery belong to the top tercile. An additional concern might be that technological industry characteristics may change over time, especially around a general technology shock, such as information technology innovations in the late 1990s, which correspond to the middle of our sample period. Thus, we use separate worker shares for the period between 1985 and 1995 and the period between 1995 and 2005. However, the correlation between the worker shares of the two periods is higher than 0.9, and our results are not sensitive to whether we allow them to change.

Finally, for the growth rates of young and prime-age workforce for each country, we can use employment by age from OECD labor force statistics. However, we should address problems that may arise from the endogeneity of industry-level worker shares and country-level workforce growth. The worker age profile of an industry can be influenced by its TFP growth rate. For instance, young workers may move from industries with low TFP growth to those with a higher growth. Because we are using worker shares observed in US industries, we drop US observations from our regressions to eliminate the problem. Regarding workforce growth, it is not very likely that TFP growth in a single industry affects country-level workforce growth. However, some of our 24 industries can be big enough so that their TFP growth influences the national level of employment through changes in participation rates or migration. To address the issue, we instrument young workforce (15–29 years) on the population in the 0–14 age group 15 years ago. Likewise, prime-age workforce (between 30 and 49 years) is instrumented on the population in the 15–34 age group 15 years ago. Old workforce (aged between 50 and 69) is instrumented in the same way. Thus, as instruments for workforce growth rates by age group, we use the past growth rates of corresponding population.[6] In Figure 1, we show average annual growth rates of prime-age population in sample countries for 20 quinquennial periods between 1950 and 2050. Data after 2015 are projected values taken from the United

[6] Feyrer (2007) and Aiyar et al. (2016) use similar methods. According to our prediction equations, 60.4 percent of the population between 0 and 14, 80.5 percent between 15 and 34, and 53.5 percent between 35 and 54 years enters young workforce, prime-age workforce, and old workforce, respectively, in fifteen years. The R-squared of the prediction equation is 0.981, 0.997, and 0.965 for young workforce, prime-age workforce, and old workforce, respectively.

Nations (2017). We can see that the growth rate of prime-age population was on average rising until 1990, and, then, began to fall. It is expected to maintain a downward trend until 2030. Thus, our sample period lies on the declining phase of prime-age population growth, though the experience of individual countries varies greatly, as the red dots representing Japan show. Figure 2 plots average annual growth rates of the ratio of the prime-age to working-age population (defined as the population between 15 and 69); it displays a pattern similar to Figure 2, but the movements of growth rates across periods and countries are somewhat muted.

Summarizing, our benchmark regression for testing the first hypothesis is an extension of (8). We include both young and prime-age worker shares as proxies for low-age labor intensity. Because we use panel data, the values of variables change over time and, thus, we add time subscripts.

$$\begin{aligned} TFP\ Growth_{ikt} = \gamma_0 + \gamma_1\ (&young\ worker\ share_{it} \times young\ workforce\ growth_{kt}) \\ &+ \gamma_2\ (prime\text{-}age\ worker\ share_{it} \times prime\text{-}age\ workforce\ growth_{kt}) \\ &+ \delta_{it} + \delta_{jt} + \varepsilon_{ikt}. \end{aligned} \tag{19}$$

All growth rates in this paper are calculated as log differences. They are annualized and expressed in percentage.

To test the second hypothesis, we replace young and prime-age workforce growth in the above equation by the difference between young and old workforce growth and between prime-age and old workforce growth, respectively. By addressing them as relative young workforce growth and relative prime-age workforce growth, our estimation equation for testing the second hypothesis becomes:

$$\begin{aligned} &TFP\ Growth_{ikt} = \gamma_0 \\ &+ \gamma_1\ (young\ worker\ share_{it} \times relative\ young\ workforce\ growth_{kt}) \\ &+ \gamma_2\ (prime\text{-}age\ worker\ share_{it} \times relative\ prime\text{-}age\ workforce\ growth_{kt}) \\ &+ \delta_{it} + \delta_{jt} + \varepsilon_{ikt}. \end{aligned} \tag{20}$$

IV. Estimation Results

<Insert Table 4 here>

We report our first set of results in Table 4. T3 young worker share is a dummy variable that takes the value 1 when an industry belongs to the top tercile industries in terms of young worker share. T2 young worker share is a dummy for the second tercile. T3 and T2 prime-age worker shares are similarly defined. In all regressions in the table, numbers in parentheses are robust standard errors clustered by country-industry pairs. In principle, we should include in the regressions both industry-period and country-period dummies because industry fixed effects and country fixed effects can change over time. However, doing so creates multicollinearity, and, thus, we could allow for either time-varying industry effects or time-varying country effects. In regression (1), our benchmark regression, time-varying industry fixed effects, and time-invariant country fixed effects are included. We find that the estimated coefficients of all interaction terms are positive, but they are insignificant except for the interaction of T3 prime-age worker share and prime-age workforce growth, which is significant at 5 percent level. The result indicates that the TFP growth rates of the top tercile industries in terms of prime-age worker share tend to increase compared to those of the bottom tercile industries when the growth rate of prime-age workforce increases. In other words, a relative fall in the TFP growth rates of industries that are highly dependent upon prime-age workers is likely when the growth rate of prime-age workforce falls with workforce aging. The estimated coefficient of 0.487 implies that the difference in TFP growth rates between the top and bottom tercile industries increases by about 0.5 percentage point when the growth rate of prime-age workforce increases by 1 percentage point. The differential effects of workforce aging on industry-level productivities seem to be quantitatively large.

The other regressions on Table 4 are robustness checks for the benchmark results. In regression (2), we control for time-invariant industry fixed effects and time-varying country fixed effects. Again, only the interaction of T3 prime-age worker share and prime-age workforce growth is significant, although there is a slight decline in its coefficient. In regression (3), we separately introduce industry, country, and period dummies. Now, the interaction of T3 prime-age worker share and prime-age workforce growth becomes significant at 1 percent level, but the coefficient changes little from that in the benchmark case. Though we do not report the results, we also checked how significance levels are affected when clustering methods for estimating standard errors are altered. When standard errors are clustered by industry-period pairs or by country-period pairs, the interaction of T3 prime-age worker share and prime-age workforce growth remains significant at 5 percent level, while the other interaction terms remain insignificant. When we do not cluster standard errors, the interaction term becomes significant at 1 percent level.

In regression (4), we drop the interaction terms for young worker share because it has a highly negative correlation with prime-age worker share, as shown in Table 3. There is little change in the size and the significance of T3 prime-age worker share × prime-age workforce growth. Regression (5) adds several more controls. We add the old dependency ratio because population aging, independently of workforce aging, may influence industry-level productivity, perhaps from the demand side. We also add the interaction of skilled worker share and human capital growth, as well as that of capital share and physical capital per worker growth. As we saw in Table 3, prime-age worker share is weakly correlated with skilled worker share and capital share; thus, our results might be picking up the differential effects of human and physical capital accumulation on industry productivity levels instead of those of workforce aging.[7] However, we find that our benchmark results do not change with the inclusion of these variables.

<Insert Table 5 here>

In Table 5, we show the results of some more robustness checks. In regression (6), we divide industries into quartile groups instead of the tercile grouping earlier. In this case, we find that the interaction of the dummy for the top quartile of prime-age worker shares and prime-age workforce growth has the estimated coefficient of 0.71, which is significant at 1 percent level. Interestingly, we also find that the interaction of the dummy for second quartile young worker

[7] Data on human capital and physical capital per worker are obtained from the Penn World Table 9.0. (Feenstra et al., 2015) Human capital is estimated from average years of schooling of workers and returns to education.

shares and young workforce growth is highly significant. All the other interaction terms are insignificant. In regression (7), we drop quantile dummies and use continuous measures for worker shares. We find that the interaction of young worker share and young workforce growth and the interaction of prime-age worker share and prime-age workforce growth are both highly significant. Thus, our basic results do not depend upon the classification of industries, though the TFPs of industries do seem to be differentially affected by young workforce growth when there is a finer classification.

In regression (8), we restrict our sample to the observations from the 13 countries for which we can observe industry-level TFP growth rates for all four periods. Thus, Czech Republic, Hungary, Ireland, Luxembourg, Portugal, Slovenia, and Sweden are excluded. The size and the significance of the coefficient for T3 prime-age worker share × prime-age workforce growth are not affected much. In regression (9), we restrict our sample to the 11 manufacturing industries listed in Table 1. We divide manufacturing industries into tercile groups in terms of young worker share and prime-age worker share and apply the same methods as before. Again, we find that only the interaction of the dummy for top tercile prime-age worker shares and prime-age workforce growth is significant. The top four manufacturing industries in terms of prime-age worker share are transport equipment, chemical, other non-metallic mineral, and electrical and optical equipment.

As our final robustness check, we change the way we rank industries. Instead of using the US observations, we use the world averages of young and prime-age worker shares to divide industries into tercile groups. Because young and prime-age worker shares are observable for all 24 industries only in the US and six other countries of Table 2, we take the average of the worker shares of these seven countries. Again, the interaction of the dummy for top tercile prime-age worker shares and prime-age workforce growth is significant at 5 percent level.[8] The interaction of the dummy for top tercile young worker shares and young workforce growth rate is also marginally significant.

[8] The top tercile industries in terms of prime-age worker share are almost identical, whether we use US observations or world averages. The difference arises in financial intermediation, which belongs to the bottom tercile in US observations, while it belongs to the top tercile in terms of world averages. The case of the US seems peculiar in regard to the worker age profile of the financial industry.

<Insert Table 6 here>

Now we test our second hypothesis: the TFP growth of young-labor-intensive industries relatively increases when the growth rate of the ratio of young to old workforce rises. To test this hypothesis, we replace the growth rates of young and prime-age workforce in the previous regressions by the relative growth rates of workforces: the difference in the growth rates of the young and old workforce, as well as the difference in the growth rates of the prime-age and old workforce. In regression (11) in Table 6, we find the interaction of T3 prime-age worker share and relative prime-age workforce growth significant at 10 percent level; this partially supports the second hypothesis. However, the result is not robust. In regression (12), when we restrict the sample to the 13 countries where TFPs are observable for all periods, the significance vanishes. Though we do not report it here, the loss of significance also arises in other specification changes that we experimented on Tables 4 and 5 to check for robustness. In regression (13), we measure the relative growth rates of young and prime-age work workforce by subtracting the growth rate of total workforce from the growth rates of young and prime-age workforce, as many other studies on workforce aging have done. Again, the interaction term is not significant. We conclude that our dataset does not support the second hypothesis.

V. Conclusion

The possible negative effects of workforce aging on long-term productivity growth have become one of the primary concerns in countries experiencing rapid increases in the proportion of old workers. Workforce aging is projected to intensify in most advanced countries in the coming years, and can be a further drag on productivity growth, which has been low since the Great Financial Crisis.

This study derives testable hypotheses regarding the relationship between workforce aging and industry-level productivity growth from simple general equilibrium models. One of the hypothesis is based on a simple intuition that knowledge spillovers among firms producing related products, if any, would come mostly from the activities of younger workers, who are more mobile and in a more innovative stage of their life. This, in turn, implies that TFP growth would be more adversely affected in industries where younger workers are more intensively used when the growth rate of younger workforce declines. We find that this hypothesis has some empirical support. The effect also seems quantitatively large. TFP growth rates in industries that are heavily dependent on prime-age workers falls by 0.5 percentage point more than other industries, when the growth rate of prime-age workforce declines by 1 percentage point.

Our approach has several advantages over previous studies on workforce aging. Because our estimation equation is explicitly derived from a model, it allows a sharper interpretation of empirical results. Additionally, we use industry-level panel data, which allow us to add more controls to reduce endogeneity biases. However, the prediction of our model may be compatible with an entirely different theory. Because we employ a difference-in-differences approach, our study does not address the absolute magnitude of the effect that workforce aging has on productivity growth. The correlations that are reported may hold true only for the specific periods that our dataset covers. Through these advantages and limitations, we hope to complement the growing literature on workforce aging and productivity.

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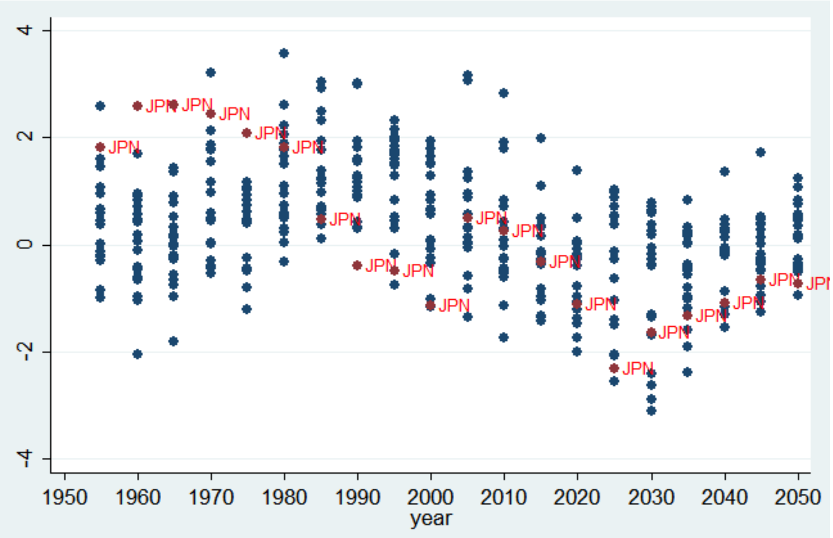
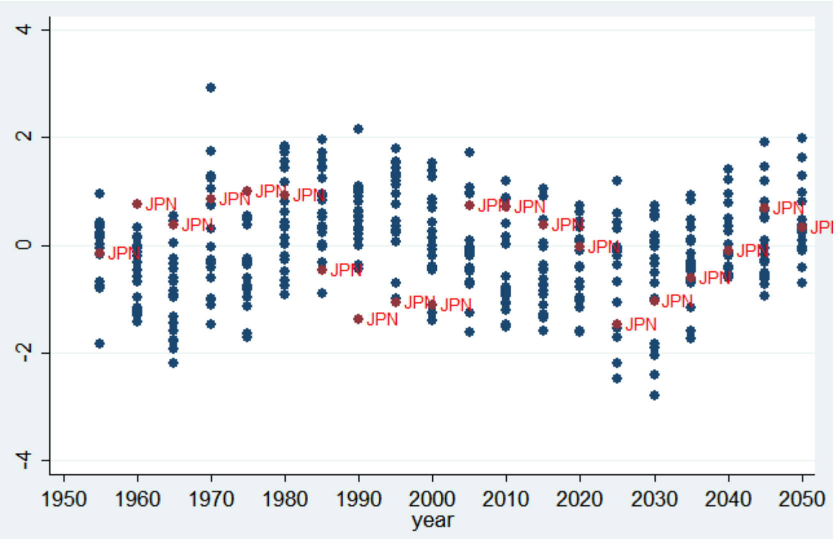
Figure 1 Annual growth rates of prime-age population (30–49 years), in %



Source: United Nations (2017)

Figure 2 Annual growth rates of the share of prime-aged in working age population (15–69 years), in %



Source: United Nations (2017)

Table 1. Worker age profile of US industries

NACE code	Industry name	Young worker share	Prime-age worker share
AtB	Agriculture, hunting, forestry, and fishing	0.305	0.477
C	Mining and quarrying	0.266	0.624
15t16	Food, beverages, and tobacco	0.344	0.541
17t19	Textiles, textile products, leather, and footwear	0.323	0.526
20	Wood and of wood and cork	0.370	0.514
21t22	Pulp, paper, paper products, printing, and publishing	0.328	0.537
23t25	Chemical, rubber, plastics, and fuel	0.314	0.573
26	Other non-metallic mineral	0.309	0.565
27t28	Basic metals and fabricated metal	0.319	0.548
29	Machinery, nec	0.303	0.558
30t33	Electrical and optical equipment	0.313	0.563
34t35	Transport equipment	0.283	0.587
36t37	Manufacturing, nec; recycling	0.351	0.524
E	Electricity, gas, and water supply	0.224	0.662
F	Construction	0.382	0.519
50	Sale, maintenance, and repair of motor vehicles; retail sale of fuel	0.379	0.497
51	Wholesale trade, except of motor vehicles	0.341	0.531
52	Retail trade, except of motor vehicles; repair of household goods	0.419	0.444
H	Hotels and restaurants	0.539	0.374
60t63	Transport and storage	0.302	0.565
64	Post and telecommunications	0.380	0.539
J	Financial intermediation	0.370	0.509
71t74	Renting of m&eq and other business activities	0.380	0.493
O	Other community, social, and personal services	0.348	0.485

Source: EU KLEMS, March 2008
Young worker share refers to the share of hours worked by 15-29-year-old workers in total hours worked. Prime-age worker share refers to the share of hours worked by 30-49-year-old workers. The numbers are averages for the period between 1995 and 2005.

Table 2. Correlation between shares in the US and those in other countries

	Belgium	Denmark	Italy	Japan	Netherland	Average
Young worker share	0.47	0.83	0.37	0.54	0.54	0.55
Prime-age worker share	0.49	0.75	0.71	0.80	0.66	0.66
Skilled worker share	0.69	0.85	0.81	0.74	0.77	0.77
Capital share	0.72	0.62	0.57	0.56	0.67	0.63

Source: EU KLEMS, March 2008
Young worker share is the share of 15-29-year-old workers in total work hours. Prime-age worker share is the share of 30-49-year-old workers. Skilled worker share is measured as the share of college graduates in total work hours. Capital share is the share of physical capital in total costs. For each country, shares are averaged over the period 1985–2005. Numbers in the table are the correlation coefficients between US shares and the corresponding shares in other countries across 24 industries.

Table 3. Correlation between measures of technological industry characteristics

	Young worker share	Prime-age worker share	Skilled worker share	Capital share
Young worker share	1.00			
Prime-age worker share	-0.86	1.00		
Skilled worker share	-0.16	0.25	1.00	
Capital share	-0.26	0.36	0.00	1.00

Source: EU KLEMS, March 2008
Young worker share is the share of 15-29-year-old workers in total work hours. Prime-age worker share is the share of 30-49-year-old workers. Skilled worker share is measured as the share of college graduates in total work hours. Capital share is the share of physical capital in total costs. All observations are from US industries and taken on average over the period between 1985 and 2005. Numbers on the table are the correlation coefficients between measures across 24 industries.

Table 4. Industry TFP growth, young labor intensity, and young workforce growth

Dependent variable: Industry TFP growth rate (%)	(1)	(2)	(3)	(4)	(5)
T3 young worker share	0.082	-0.126	0.056		0.014
× young workforce growth	(0.149)	(0.158)	(0.128)		(0.148)
T2 young worker share	0.177	0.006	0.167		0.109
× young workforce growth	(0.148)	(0.148)	(0.128)		(0.147)
T3 prime-age worker share	0.487**	0.424**	0.480***	0.462**	0.483**
× prime-age workforce growth	(0.202)	(0.213)	(0.183)	(0.203)	(0.199)
T2 prime-age worker share	0.197	0.059	0.130	0.149	0.183
× prime-age workforce growth	(0.186)	(0.186)	(0.156)	(0.180)	(0.184)
Old dependency ratio growth					-0.594***
					(0.189)
Skilled worker share					1.095
× human capital growth					(1.724)
Capital share					-0.072
× physical capital growth					(0.187)
Fixed effects	Industry-period Country	Industry Country-period	Industry Country Period	Industry-period Country	Industry-period Country
Obs.	1,584	1,584	1,584	1,584	1,584
R^2	0.281	0.277	0.240	0.280	0.286

Young worker share is the share of 15-29-year-old workers in total work hours. Prime-age worker share is the share of 30-49-year-old workers. Tn young worker share (n = 2, 3) is a dummy that takes the value of 1 when an industry belongs to the nth tercile in terms of young worker share. Tn prime-age worker share (n = 2, 3) are similarly defined. Workforce growth rates are measured in percentage. Human capital is measured as average schooling years of workers, and physical capital is measured by physical capital per worker. Both of them are from Penn World Table 9.0. Numbers in parentheses are robust standard errors clustered by country-industry pairs.

***: significant at 1 percent, **: significant at 5 percent

Table 5. Industry TFP growth, young labor intensity, and young workforce growth: more robustness checks

Dependent variable: Industry TFP growth rate (%)	(6)	(7)	(8)	(9)	(10)
			13 countries[a]	Manufact-uring	World worker shares
T3 young worker share			0.196	-0.031	0.238*
× young workforce growth			(0.131)	(0.195)	(0.135)
T2 young worker share			0.240	0.167	0.174
× young workforce growth			(0.162)	(0.128)	(0.158)
T3 prime-age worker share			0.423**	0.826***	0.506**
× prime-age workforce growth			(0.213)	(0.314)	(0.209)
T2 prime-age worker share			0.092	0.045	0.314
× prime-age workforce growth			(0.179)	(0.290)	(0.180)
Young worker share		0.659**			
× young workforce growth		(0.253)			
Prime-age worker share		0.934***			
× Prime-age workforce growth		(0.308)			
Q4 young worker share	0.167				
× young workforce growth	(0.173)				
Q3 young worker share	-0.004				
× young workforce growth	(0.153)				
Q2 young worker share	0.591***				
× young workforce growth	(0.162)				
Q4 prime-age worker share	0.712***				
× prime-age workforce growth	(0.218)				
Q3 prime-age worker share	0.219				
× prime-age workforce growth	(0.243)				
Q2 prime-age worker share	0.214				
× prime-age workforce growth	(0.191)				
Fixed effects	Industry-period	Industry-period	Industry-period	Industry-period	Industry-period
	Country	Country	Country	Country	Country
Obs.		1,584	1,248	726	1,584
R^2		0.282	0.305	0.310	0.282

Young worker share is the share of 15-29-year-old workers in total work hours. Prime-age worker share is the share of 30-49-year-old workers. Tn young worker share (n = 2, 3) is a dummy that takes the value of 1 when an industry belongs to the nth tercile in terms of young worker share. Tn prime-age worker share (n = 2, 3) is similarly defined. Qn (n = 2, 3, 4) are dummies for quartile classifications. Worker shares are measured in decimal, and workforce growth rates in percentage. Numbers in parentheses are robust standard errors clustered by country-industry pairs.

[a] 20 countries excluding the following, whose TFPs are observable from the third period: Czech Republic, Hungary, Ireland, Luxembourg, Portugal, Slovenia, and Sweden.
*** implies significant at 1 percent level and ** implies significant at 5 percent level.

Table 6. Industry TFP growth, young labor intensity, and relative young workforce growth

Dependent variable: Industry TFP growth rate (%)	(11)	(12)	(13)
		13 countries[a]	
T3 young worker share	-0.106	-0.018	0.018
× Relative young workforce growth	(0.128)	(0.126)	(0.183)
T2 young worker share	0.031	0.184	0.123
× Relative young workforce growth	(0.138)	(0.146)	(0.239)
T3 prime-age worker share	0.230*	0.069	0.297
× Relative prime-age workforce growth	(0.126)	(0.125)	(0.249)
T2 prime-age worker share	0.006	-0.064	0.067
× Relative prime-age workforce growth	(0.099)	(0.083)	(0.283)
Fixed effects	Industry -period	Industry -period	Industry-period
	Country	Country	Country,
Obs.	1,584	1,248	1,584
R^2	0.280	0.302	0.278

Young worker share is the share of 15-29-year-old workers in total work hours. Prime-age worker share is the share of 30-49-year-old workers. Tn young worker share (n = 2, 3) is a dummy that takes the value of 1 when an industry belongs to the nth tercile in terms of young worker share. Worker shares are measured in decimal, and workforce growth rates in percentage. In (13), relative young workforce growth is defined as young worker growth subtracted by entire workforce growth, not by old workforce growth as in (11) and (12). Relative prime-age workforce growth is defined similarly. Numbers in parentheses are robust standard errors clustered by country-industry pairs.

[a] 20 countries excluding the following, whose TFPs are observable only from the third period: Czech Republic, Hungary, Ireland, Luxembourg, Portugal, Slovenia, and Sweden.
*implies significant at 10 percent