ソシオネットワーク戦略ディスカッションペーパーシリーズ ISSN 1884-9946
第27号　2012年8月
RISS Discussion Paper Series
No.27　August, 2012

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Technological Progress and the Wage Growth of Older Japanese Workers[*]

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Abstract.

Declining birth and mortality rates are leading to population aging throughout the OECD countries. This paper examines one possible consequence for national productivity – we ask: Are older workers able to take advantage of new technologies as effectively as their younger counterparts? Using Japanese data for 1973-2000, we find that if we ignore job tenure, workers beyond the age of 50 do not seem as able to benefit from total factor productivity growth as their younger colleagues. However, Japanese workers past age 50 move to lesser paying positions more frequently than is common elsewhere, and we believe that the complete answer to our question depends upon whether an inability to keep up with new technologies induces late-in-career job changes or whether the changes follow, in practice, from other factors.

Keywords: Aging population; technological progress; age-based wage rates; earnings dynamics; secondary jobs

JEL Classification Codes: J31, J14, O49

[*] This work was supported by "a Promotion Project for Distinctive Joint Research" from the Ministry of Education, Culture, Sports, Science and Technology (MEXT), Japan, April 2012 - March 2013.

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1 Introduction.

A combination of falling birth rates and declining mortality is leading to aging populations around the OECD countries. As the fraction of people who are working diminishes, government budgets will come under stress — the demand for government services will remain high, or even grow, but the tax base will shrink. The fraction of GDP devoted to medical services will almost surely rise. To the extent that public and private pension plans are unfunded (i.e., designed as pay-as-you-go systems) or underfunded, solvency problems will grow. As the fraction of the population below traditional retirement ages shrinks, pressures may rise for healthy individuals to remain at work longer. In fact, the effects of global aging may be mitigated — perhaps considerably — if older workers can remain productive until retirement, and even until extended retirement ages, and the purpose of this paper is to explore that possibility.[1]

Specifically, it is sometimes suggested that older workers may be less adept at utilizing new technologies, so that older labor forces may lead to less vibrant and progressive economies. For example, Nyce and Schieber [2005] write

> "There appears to be a fairly strong inverse relationship between entrepreneurial activities and aged dependency [ratios] ... This suggests that aging societies may be less likely to engage in creative destructive activities that accelerate the adoption of technological innovations and can ameliorate the effects of capital deepening on rates of return." [p. 255]

To take a second example, discussing the work force in Germany, Borsch-Supan [2004] writes,

> "This fundamental change in the age structure of the working population will have profound effects on the microeconomics and the sociology of the labor market. The most important — and most controversial — aspect is the potential effect on labor productivity. If labor productivity is age dependent, a shift in the age structure will also bring about a change in aggregate productivity, even if age–specific productivity were to remain constant." [p. 16]

This paper examines evidence from Japan on the ability of older workers to participate fully in technological progress. We attempt to measure this by tracking their wage growth — asking whether their wages follow improvements in technology as closely as do those of the

[1] For proposals to adjust government policy to encourage later retirement, see, for example, Laitner and Silverman [2012], Goda et al [2009], and Burtless and Quinn [2002].

young. If the productivity of older workers benefits from technological progress as much as younger workers, global aging may be less threatening — and longer careers may be attractive in the future.

We base our analysis on an "earnings dynamics model." Such a model regresses year-by-year changes in worker earnings (typically log earnings or log wage rates) on factors directly reflecting age — such as work experience — and on measures of the overall rate of technological change. Since the rate of technological progress is uneven over time, we can hope to identify its effects. We consider different education groups separately. In contrast to previous studies, we interact the rate of technological change with age. As stated, we want to ask whether technological progress tends to cause younger workers' wages to rise more rapidly than older workers'. In other words, can the young take better advantage of new technologies than the old?

In earlier work with US data, Laitner and Stolyarov [2005] found little evidence that older workers absorbed the benefits of technological change less effectively. That work was hindered by data limitations, however. Technological progress proceeded more rapidly prior to the 1970s in the US than after, yet wage and earnings data is most readily available only from the latter 1960s onward.[2]

The present paper uses Japanese data from 1973-2000. Although the time series are even shorter than for the US, TFP growth in Japan was rapid from 1973-1990, but then it abruptly stalled. (See Figure 1 in page 8.) This pattern potentially provides a basis for analysis despite the short time frame of the data.

Our first results for Japan seem more pessimistic than the preliminary evidence for the US in the sense that wage rates for older Japanese workers seem noticeably less responsive to technological progress than is the case for younger workers.

Looking in more detail, however, it seems apparent that institutional structures differ in the two countries. In Japan, job changes in the years leading up to retirement are much more common. Job changes associated with outside offers that reflect competition among employers tend to generate wage increases; job changes forced upon workers, on the other hand, presumably lead to wage decreases. Japanese late-in-career job changes have the second character.

If we add job tenure to our regression, the Japanese results resemble the Laitner-Stolyarov

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[2] See also, however, the ongoing project of Laitner, Stolyarov, Gorodnichenko and Song at UM12-01, "Technological Progress and the Earnings of Older Workers," <http://www.mrrc.isr.umich.edu/>.

[2005] US outcomes more closely. Late-in-career job changes in Japan are associated with reductions in earnings. Whatever the merits of the Japanese system, late-in-work-life job changes fall exactly in the age range in which we are most anxious to monitor the effects of technological progress. Multicollinearity may be at work — the Japanese job transfer system may have moderated over recent decades exactly as TFP growth was diminishing.

We end up concluding that negative effects of aging on absorption of new technology appear after age 50, if at all. The effects disappear if we treat same-job-tenure as an exogenous variable in our regressions. Future work with more disaggregated data may help to establish the validity of doing so.

The organization of this paper is as follows. Section 2 outlines a range of possible connections between the wage growth of older workers and an economy's rate of technological progress. Section 3 lays out a specific model. Section 4 presents preliminary regression results. Section 5 concludes.

2 Possible Outcomes.

A number of different outcomes are conceivable. Consider the following range of possibilities:

P1: As individuals age, they become less adaptable at accepting new ways of doing things. This is a physiological consequence of aging.

P2: Workers allocate part of their workday to learning and acquiring knowledge and part to actual production. At the beginning of their careers, their allocation to acquiring new skills is large — because the payoff period is long. Near retirement, their optimal time allocation for skill acquisition is shorter.

P3: Different people have different interest in, and ability for, absorbing new information and adopting new procedures for doing jobs. Age is not the major determinant of these differences.

The quotations in the introduction seem consistent with P1. It is, perhaps, the most pessimistic possibility in the list. If older people are inherently less flexible, aging societies may not be able to benefit from new technologies as readily as economies in the recent past.

P2 is consistent with the human capital model of Ben-Porath [1967]. According to that model, workers' absorption of new ideas and procedures is an endogenous process. As under P1, we may expect to see older workers not benefiting as much as their younger colleagues from overall technological progress. However, under P2, if in the future workers plan to retire later, the age at which their productivity peaks will advance as well. In other words, given P2, future workers can adjust their human capital acquisition. If they need, or want, to work longer, they can continue investing in human capital until later ages.

Under P3, age may be far less important that other personality traits in determining ability to profit from new technologies. We would then expect companies to assign workers who have a comparative advantage in learning and evaluating new technologies into the role of facilitating progress. Provided learning to incorporate new technologies is one of many tasks that need doing, the age composition of the overall labor force may make little difference.

3 Model.

Let w_{it} be the time t constant-dollar earnings per hour — i.e., wage rate — of individual i, who has education $e = e_i$, sex $s = s_i$, career start (i.e., "career birth") date $b = b_i$, and tenure on current job $x = x_{it}$. We model w_{it} with an "earnings dynamics equation" (e.g., Lillard and Willis [1978], Lillard and Weiss [1979], Hause [1980], and MaCurdy [1882], as well as more recent work by Baker [1997], Haider [2001], Baker and Solon [2003], Guvenen [2007], and Altonji et al [2009]). An unusual feature of our setup is that we allow economywide technological progress to affect w_{it} differently at different ages. In particular, our focus is the possibility that the link between general technological progress and the growth of an individual's earnings deteriorates with an individual's age.

Consider an agent with wage w_{it}. His/her career age is $a_{it} = t - b_i$. Let MPL_t be the time-t economywide marginal product of labor. Our earnings dynamics specification is[3]

$$w_{it} = MPL_t \cdot e^{\phi(e_i, s_i, a_{it}, x_{it})} . \tag{1}$$

Taking logs,

$$\ln(w_{it}) = \phi(e_i, s_i, a_{it}, x_{it}) + \ln(MPL_t) . \tag{2}$$

[3] We assume pay based upon marginal productivity — as opposed to, say, seniority-based pay (e.g., Lazear [1979, 1981]). A full dynamic analysis of seniority pay is beyond the scope of this paper.

We next examine the right-hand side terms of (2) in detail.

i) $\phi(.)$. A conventional treatment approximates $\phi(e,s,a,x)$ with a polynomial in a and x, the coefficients being functions of (e,s).

Suppose career age a runs from $a=0$, when the individual in question first begins his/her career, to $a=R$, when the individual retires.[4] We expect $\partial\phi(e,s,a,x)/\partial a>0$ for low a and $\partial^2\phi(e,s,a,x)/\partial a^2<0$ all a. The idea is that earnings rise with experience and on-the-job training, but that human capital from experience and training yields diminishing returns. On the other hand, at ages near retirement $\phi(e,s,a,x)$ may reach a peak and then begin to fall, with the declining segment perhaps due to failing health.

Data limitations lead us to adopt a linear model of the role of tenure on current job, x. The existing literature (e.g., Altonji and Williams [1998], Farber [1999], Kambourov and Manoviskii [2009], and others) often finds $\partial\phi(e,s,a,x)/\partial x>0$.

A simple specification is

$$\phi(e,s,a,x)=\beta_0(e,s)+\beta_1(e,s)\cdot a+\beta_2(e,s)\cdot\frac{a^2}{2}+\beta_3(e,s)\cdot x, \tag{3}$$

for which we expect

$$\beta_1(e,s)>0, \quad \beta_2(e,x)<0, \quad \beta_3(e,s)>0. \tag{4}$$

ii) $\ln(MPL_t)$. A standard treatment replaces $\ln(MPL_t)$ with a set of time dummies, the coefficients on the latter being taken to reflect the economy's rate of technological progress. To save degrees of freedom, and to provide a basis for identifying the effect of technological progress on agents' earnings at different ages, we eschew time dummies, basing our analysis on aggregative measures of productivity growth instead.

If GDP is Y_t, the aggregate physical capital stock is K_t, aggregate employment (measured in units correcting for differences in education, sex, and experience (i.e., career age)) is L_t, and the level of "total factor productivity" is T_t, assume an aggregate production function

$$Y_t=A\cdot T_t\cdot[K_t]^{\alpha}\cdot[L_t]^{1-\alpha}, \quad \alpha\in(0,1). \tag{5}$$

[4] This paper's analysis assumes an exogenous age of retirement.

Letting APL_t be the average product of labor,

$$MPL_t = \frac{\partial A \cdot T_t \cdot [K_t]^{\alpha} \cdot [L_t]^{1-\alpha}}{\partial L_t} = \frac{(1-\alpha) \cdot Y_t}{L_t} = (1-\alpha) \cdot APL_t . \quad (6)$$

We replace $\ln(MPL_t)$ in (2) with $\ln(APL_t)$, for which aggregative data is available. For future reference, note that (5) also implies

$$\ln(APL_t) = \ln(Y_t / L_t) = \ln(A) + \ln(T_t) + \alpha \cdot \ln(K_t) - \alpha \cdot \ln(L_t). \quad (7)$$

iii) Measurements of APL_t and T_t. Economists since Solow [1956, 1957] have worked to develop aggregative measures of T_t. Essentially, these begin from (5), using

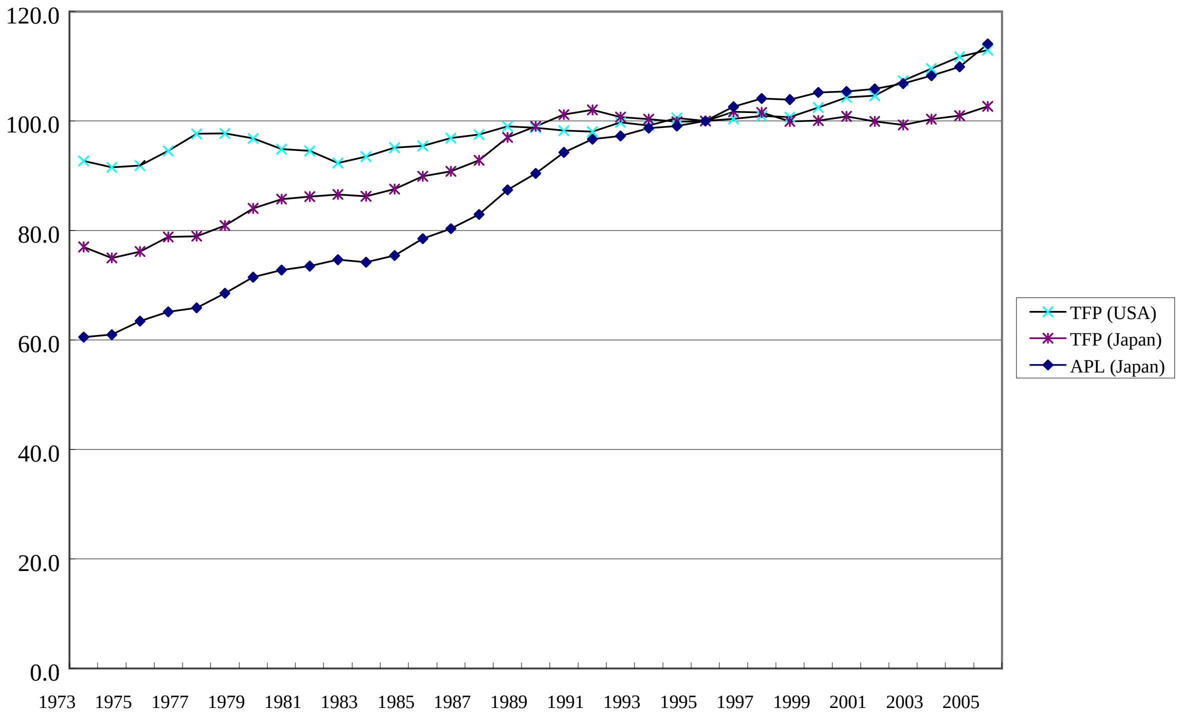
$$\ln(T_t) = \ln(Y_t) - \ln(A) - \alpha \cdot \ln(K_t) - (1-\alpha) \cdot \ln(L_t).$$

TFP calculations typically adjust L_t for quality (i.e., taking into account the education and experience of the current labor force). Standard sources tend to derive APL_t without quality adjustments. Thus, we develop our own APL_t variable below.

We use the EU KLEMS Growth and Productivity Accounts for both T_t and APL_t.[5] In particular, we construct our APL_t variable from real Japanese value added divided by the product of total hours worked by employees and a labor services quality index (i.e., LABQI in the KLEMS data). Figure 1 graphs our APL_t measure.

[5] See <http://www.euklems.net/>.

Figure 1 Productivity Indices, TFP (USA and Japan) and Adjusted Averege Productivcity of Labor (Japan)



iv) The Impact of Technology at Different Ages. We enhance (2) to study the possibility that technological progress affects workers differently at different ages.

Econometric issues induce us to want to estimate (2) in first differences.[6] Let

$$\chi_j(a) = \begin{cases} 1, & \text{if } a = j, \\ 0, & \text{otherwise.} \end{cases}$$

Then the specification that we use for our detailed analysis is

$$\begin{aligned} &\ln(w_{i,t+1}) - \ln(w_{i,t}) \\ &= \phi(e_i, s_i, t+1-b_i, x_{i,t+1}) - \phi(e_i, s_i, t-b_i, x_{it}) \\ &+ \beta_4 \cdot [\ln(APL_{t+1}) - \ln(APL_t)] \\ &+ \sum_{j=0,\ldots R} \gamma_j \cdot \chi_j(t-b_i) \cdot [\ln(T_{t+1}) - \ln(T_t)] \\ &+ \epsilon_{it}. \end{aligned} \qquad (8)$$

[6] Earlier versions of this work checked the principal variables for stochastic trends. We could not reject the hypothesis that both $\ln(w_t)$ and $\ln(APL_t)$ are $I(1)$, for example.

In (8), the $\ln(APL)$ terms replace $\ln(MPL)$ from (2) — see (6).[7] In accordance with the analysis above, we may impose

$$\beta_4 = 1. \tag{9}$$

The second-from-the-last line in (8) is

$$[\sum_{j=0,\ldots R} \gamma_j \cdot \chi_j(t-b_i)] \cdot [\ln(T_{t+1}) - \ln(T_t)]. \tag{10}$$

In other words, for each age (i.e., experience level) j we have a regression term $\gamma_j \cdot [\ln(T_{t+1}) - \ln(T_t)]$. If workers of all ages benefit fully from the current technology, we expect

$$\gamma_j = 0 \quad \text{all} \quad j. \tag{11}$$

In that case, technological progress affects wages through the $\beta_4 \cdot [\ln(APL_{t+1}) - \ln(APL_t)]$ term of (8) alone and no corrections are required.

In Solow [1960], new machines "embody" the current technology, but they cannot subsequently be upgraded. If workers were the same — in the sense that they finished school embodying knowledge of the best technology at that moment, but they could not upgrade their knowledge thereafter — we would expect

$$\gamma_0 = 0 \quad \text{and} \quad \gamma_j = -1 \quad \text{all} \quad j \neq 0. \tag{12}$$

More generally, if younger workers, of, say, ages $j = 0, \ldots, J$, can upgrade their skills to take advantage of new technologies, but older workers cannot, we expect to find

$$\gamma_j = 0 \quad \text{all} \quad j = 0, \ldots, J, \quad \text{and} \quad \gamma_k < 0 \quad \text{all} \quad k > J. \tag{13}$$

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[7] The $(1-\alpha)$ term in (6) disappears as we take differences in logs.

When older workers cannot absorb new technologies at all in (13), then

$$\gamma_k = -1 \quad \text{for} \quad k > J . \tag{14}$$

If the absorption difficulties of older workers apply only to technological progress, the last term in (10) should be $[\ln(T_{t+1}) - \ln(T_t)]$, as above. If the difficulties apply to taking advantage of capital deepening as well, that term should use $[\ln(APL_{t+1}) - \ln(APL_t)]$ instead. We assume the former.

Our null hypothesis is

$$H_0: \quad \gamma_j = 0 \quad \text{all} \quad j = 0, ..., R . \tag{15}$$

Under the null, T_t, through its role in APL_t, affects workers' earnings symmetrically at all ages.

The alternative hypothesis that we consider is

$$H_1: \quad \gamma_j < 0 \quad \text{for high } j . \tag{16}$$

Under H_1, although increases in the marginal product of labor stemming from capital deepening or reductions in L_t have identical effects at all ages, older employees are less able than the young to take advantage of improvements in the MPL_t coming from T_t.

The last term in (8) is a regression error ϵ_{it}. If there is measurement error, say, η_{it} in $\ln(w_{i,t+1})$, perhaps we should use[8]

$$\epsilon_{it} + \eta_{i,t+1} - \eta_{it} \tag{17}$$

We begin, however, with (8).

[8] If business cycles lead to longer-term deviations between $\ln(w_{it})$ and our model, we might need to consider autocorrelated regression errors. On the other hand, inclusion of, for example, unemployment rates, in the regressions below seems to make little difference.

4 Regressions.

This section presents regression analysis of equation (8). When we difference the function $\phi(.)$ for the regression specification, only two terms remain beyond a constant — recall (3). One is the quadratic term for age, for which we expect a negative coefficient — recall (4). The expected sign for this term always appears in our results. The other is the linear term for same-job-tenure, x. We expect a positive coefficient on this term — recall (4). Again, that sign always arises in practice.

Our theory implies a coefficient of 1 on $\ln(APL_{t+1}) - \ln(APL_t)$. We impose in our regressions.[9]

Our attention focuses on the terms $\ln(T_{t+1}) - \ln(T_t)$ interacted with age. We omit ages below 30, in effect imposing a coefficient of 0 for them. Coefficients for other age groups should be interpreted as measurements relative to the youngest ages.

Some of our specifications include the unemployment rate while others do not. There is little difference in the results.

We have data for five-year age groups. We designate our differences from the lowest age. $\ln(w_{i,t+1}) - \ln(w_{it})$, i = 20, t = 1981, for example, refers to

$$\ln(\sum_{a=25}^{29} \omega_{a,1986} \cdot w_{a,1986}) - \ln(\sum_{a=20}^{24} \omega_{a,1981} \cdot w_{a,1981}),$$

where ω_{at} are weights. We drop ages below 20. In columns 1-4 of the tables below, we use age groups for 20, 25, 30, 35, 40, 45, and 50; in columns 5-8, we add the age 55 as well.[10] We have differences for years 1973-2000. Thus, columns 1-4 have $7 \times 28 = 196$ observations; columns 5-8 have 224.

Tables 1A-D present results for 4 separate education groups. Our remarks focus on the second and fourth groups, high school and college/above. We also focus on columns 5-8, which cover the longest age range.

Notice that our dependent variable, the average wage rate, includes bonus payments and benefit packages.

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[9] Earlier versions of this work verified that $\beta_4 = 1$ was an acceptable hypothesis.

[10] Note that our observations apply to full-time work. Hence, individuals still in school do not appear in the analysis.

Table 1A. Male Earnings Profile for Junior High School Graduates:
Dependent Variable = Change Log Real Total Wage Earnings
Less Change Log Average Product of Labor

	R001	R002	R003	R004	R005	R006	R007	R008
Intercept	0.32786	0.29798	0.30516	0.28458	0.43571	0.25286	0.28265	0.24499
	(19.56)	(15.16)	(14.25)	(12.55)	(18.34)	(12.50)	(10.64)	(11.29)
dAge								
dAge2	-0.00062	-0.00062	-0.00055	-0.00057	-0.00095	-0.00065	-0.00048	-0.00061
	(14.62)	(14.92)	(9.22)	(9.62)	(16.84)	(14.74)	(6.66)	(10.25)
dYrJob		0.01157		0.01057		0.03166		0.02981
		(2.78)		(2.50)		(15.43)		(10.77)
dUnempR			-0.00859	-0.00605			-0.03513	-0.00426
			(1.69)	(1.18)			(8.95)	(1.00)
dln(TFP)*a25	-0.19644	-0.20655	-0.22887	-0.22851	-0.27164	-0.22297	-0.35665	-0.23614
	(1.36)	(1.46)	(1.58)	(1.60)	(1.20)	(1.43)	(1.84)	(1.51)
dln(TFP)*a30	-0.25354	-0.29224	-0.29720	-0.31964	-0.15363	-0.34635	-0.38149	-0.36272
	(1.81)	(2.11)	(2.09)	(2.28)	(0.70)	(2.28)	(2.01)	(2.37)
dln(TFP)*a35	-0.11380	-0.16960	-0.20005	-0.22551	0.16149	-0.24142	-0.33758	-0.27839
	(0.81)	(1.22)	(1.35)	(1.54)	(0.74)	(1.58)	(1.74)	(1.78)
dln(TFP)*a40	-0.04670	-0.06772	-0.14802	-0.13724	0.39818	-0.06755	-0.25641	-0.11971
	(0.33)	(0.48)	(0.96)	(0.90)	(1.82)	(0.44)	(1.27)	(0.74)
dln(TFP)*a45	-0.00022	0.03961	-0.12145	-0.04917	0.61423	0.15705	-0.21562	0.08312
	(0.00)	(0.27)	(0.74)	(0.30)	(2.73)	(1.00)	(1.01)	(0.48)
dln(TFP)*a50	-1.16031	-0.72283	-1.20456	-0.79171	-0.40830	0.09456	-0.99959	-0.00665
	(7.46)	(3.30)	(7.68)	(3.50)	(1.76)	(0.58)	(4.79)	(0.03)
dln(TFP)*a55					-1.45374	-0.21657	-2.02792	-0.35872
					(6.02)	(1.17)	(9.38)	(1.54)
R Square	0.723	0.734	0.728	0.736	0.734	0.874	0.806	0.874
Adjusted R2	0.713	0.723	0.716	0.724	0.724	0.869	0.798	0.869
Observations	196	196	196	196	224	224	224	224

Note: absolute t-statistic in parentheses

Table 1B. Male Earnings Profile for Senior High School Graduates:
Dependent Variable = Change Log Real Total Wage Earnings
Less Change Log Average Product of Labor

	R001	R002	R003	R004	R005	R006	R007	R008
Intercept	0.43496	0.36548	0.45146	0.38480	0.55377	0.28220	0.41590	0.28878
	(24.17)	(13.45)	(19.43)	(13.32)	(21.98)	(12.37)	(13.88)	(12.35)
dAge								
dAge2	-0.00086	-0.00077	-0.00091	-0.00084	-0.00123	-0.00067	-0.00080	-0.00071
	(18.87)	(14.79)	(14.06)	(12.92)	(20.43)	(13.20)	(9.81)	(12.01)
dYrJob		0.01337		0.01491		0.03047		0.03226
		(3.35)		(3.68)		(17.13)		(14.12)
dUnempR			0.00626	0.01037			-0.03191	0.00522
			(1.12)	(1.88)			(7.07)	(1.25)
dln(TFP)*a25	0.02149	0.01703	0.04568	0.05657	-0.06468	0.01106	-0.14571	0.02875
	(0.14)	(0.11)	(0.29)	(0.37)	(0.27)	(0.07)	(0.67)	(0.18)
dln(TFP)*a30	0.00741	-0.06116	0.03983	-0.01538	0.11367	-0.13951	-0.09585	-0.12014
	(0.05)	(0.41)	(0.26)	(0.10)	(0.48)	(0.90)	(0.45)	(0.78)
dln(TFP)*a35	0.13725	0.02746	0.20040	0.11939	0.43372	-0.09410	-0.01797	-0.05128
	(0.90)	(0.18)	(1.24)	(0.76)	(1.86)	(0.61)	(0.08)	(0.32)
dln(TFP)*a40	0.22693	0.12952	0.30069	0.24044	0.70678	0.03291	0.11853	0.08948
	(1.47)	(0.84)	(1.79)	(1.47)	(3.00)	(0.21)	(0.52)	(0.54)
dln(TFP)*a45	0.18956	0.17234	0.27954	0.31936	0.86762	0.18812	0.10757	0.27245
	(1.17)	(1.10)	(1.55)	(1.83)	(3.59)	(1.16)	(0.44)	(1.55)
dln(TFP)*a50	-1.25308	-0.67447	-1.21580	-0.54608	-0.39995	0.11170	-0.97017	0.23499
	(7.36)	(2.82)	(7.01)	(2.21)	(1.60)	(0.67)	(4.05)	(1.22)
dln(TFP)*a55					-1.23478	-0.39408	-1.65726	-0.27561
					(4.78)	(2.25)	(6.88)	(1.38)
R Square	0.802	0.814	0.804	0.817	0.788	0.911	0.828	0.911
Adjusted R2	0.795	0.806	0.795	0.808	0.781	0.907	0.821	0.907
Observations	196	196	196	196	224	224	224	224

Note: absolute t-statistic in parentheses

Table 1C. Male Earnings Profile for Junior College Graduates:
Dependent Variable = Change Log Real Total Wage Earnings
Less Change Log Average Product of Labor

	R001	R002	R003	R004	R005	R006	R007	R008
Intercept	0.55088	0.51736	0.53665	0.51437	0.65186	0.45721	0.49739	0.44049
	(31.35)	(21.71)	(23.59)	(20.03)	(27.54)	(18.32)	(19.26)	(17.61)
dAge								
dAge2	-0.00109	-0.00104	-0.00104	-0.00103	-0.00141	-0.00100	-0.00092	-0.00090
	(24.26)	(20.93)	(16.19)	(15.98)	(24.79)	(17.80)	(12.94)	(13.92)
dYrJob		0.00615		0.00581		0.02168		0.01647
		(2.06)		(1.83)		(11.67)		(6.69)
dUnempR			-0.00568	-0.00193			-0.03823	-0.01572
			(0.99)	(0.32)			(9.42)	(3.14)
dln(TFP)*a25	0.09296	0.08120	0.06946	0.07386	0.04008	0.04650	-0.08370	-0.00594
	(0.58)	(0.51)	(0.43)	(0.46)	(0.17)	(0.25)	(0.42)	(0.03)
dln(TFP)*a30	-0.03473	-0.07423	-0.06567	-0.08257	0.08639	-0.13537	-0.18790	-0.19484
	(0.22)	(0.48)	(0.41)	(0.52)	(0.38)	(0.75)	(0.96)	(1.09)
dln(TFP)*a35	0.18989	0.14021	0.13403	0.12396	0.46219	0.09127	-0.06710	-0.03718
	(1.22)	(0.90)	(0.81)	(0.76)	(2.03)	(0.50)	(0.33)	(0.20)
dln(TFP)*a40	0.40405	0.36314	0.33542	0.34206	0.86471	0.38361	0.14072	0.20160
	(2.55)	(2.29)	(1.94)	(1.99)	(3.76)	(2.07)	(0.67)	(1.06)
dln(TFP)*a45	0.48870	0.48942	0.40759	0.46180	1.11291	0.65611	0.21052	0.39490
	(2.96)	(2.99)	(2.21)	(2.49)	(4.72)	(3.48)	(0.95)	(1.95)
dln(TFP)*a50	-1.21664	-0.88801	-1.24744	-0.91661	-0.45188	0.14251	-1.09671	-0.26550
	(7.05)	(3.80)	(7.12)	(3.65)	(1.86)	(0.72)	(5.08)	(1.14)
dln(TFP)*a55					-1.66426	-0.53256	-2.17784	-1.01577
					(6.57)	(2.41)	(9.89)	(3.83)
R Square	0.853	0.856	0.854	0.856	0.849	0.908	0.893	0.912
Adjusted R2	0.848	0.850	0.848	0.849	0.844	0.904	0.889	0.908
Observations	196	196	196	196	224	224	224	224

Note: absolute t-statistic in parentheses

Table 1D. Male Earnings Profile for University Graduates:
Dependent Variable = Change Log Real Total Wage Earnings
Less Change Log Average Product of Labor

	R001	R002	R003	R004	R005	R006	R007	R008
Intercept	0.58240	0.50181	0.59349	0.52224	0.65910	0.49578	0.55928	0.50685
	(38.97)	(27.63)	(30.82)	(26.21)	(34.99)	(31.47)	(25.73)	(31.27)
dAge								
dAge2	-0.00108	-0.00102	-0.00112	-0.00110	-0.00134	-0.00101	-0.00100	-0.00108
	(27.85)	(28.13)	(19.76)	(21.85)	(29.37)	(28.07)	(16.24)	(23.88)
dYrJob		0.01951		0.02086		0.02036		0.02321
		(6.63)		(7.03)		(16.80)		(13.92)
dUnempR			0.00522	0.01222			-0.02909	0.00990
			(0.91)	(2.36)			(7.30)	(2.46)
dln(TFP)*a25	0.33021	0.18856	0.35999	0.24853	0.33320	0.18402	0.16789	0.21937
	(2.15)	(1.35)	(2.30)	(1.77)	(1.58)	(1.32)	(0.88)	(1.59)
dln(TFP)*a30	0.25765	0.07882	0.29145	0.14563	0.39587	0.06846	0.14161	0.10909
	(1.71)	(0.57)	(1.87)	(1.04)	(1.91)	(0.50)	(0.75)	(0.79)
dln(TFP)*a35	0.45167	0.21252	0.50806	0.32806	0.72211	0.19543	0.27684	0.27313
	(2.98)	(1.50)	(3.11)	(2.22)	(3.50)	(1.40)	(1.42)	(1.93)
dln(TFP)*a40	0.57477	0.33290	0.63796	0.46418	0.97864	0.31154	0.42978	0.40480
	(3.72)	(2.31)	(3.77)	(3.04)	(4.70)	(2.18)	(2.14)	(2.77)
dln(TFP)*a45	0.42785	0.33513	0.50024	0.49819	0.96138	0.31616	0.29748	0.45166
	(2.68)	(2.32)	(2.81)	(3.14)	(4.53)	(2.18)	(1.41)	(2.94)
dln(TFP)*a50	-1.04374	-0.14543	-1.01662	-0.02009	-0.37858	-0.12573	-0.85505	0.07195
	(6.25)	(0.72)	(5.99)	(0.10)	(1.73)	(0.87)	(4.13)	(0.44)
dln(TFP)*a55					-0.99075	-0.04704	-1.37872	0.21743
					(4.34)	(0.29)	(6.52)	(1.13)
R Square	0.876	0.900	0.877	0.903	0.875	0.946	0.900	0.948
Adjusted R2	0.872	0.896	0.872	0.898	0.870	0.944	0.896	0.945
Observations	196	196	196	196	224	224	224	224

Note: absolute t-statistic in parentheses

i) Results. We find that whether we include years of same-job-tenure in the list of independent variables makes a large difference. Consider column 7 of tables 1B and 1D. In both, the interaction terms $dln(TFP)*a30$, etc., have small coefficients until the two highest age groups. For ages 50 and above, however, the coefficients are large and negative — larger than 1 in absolute value for ages 55+.

Column 7 then seems to imply that Japanese employees of age 50 and above benefit little, or not at all, from technological progress.

Consider column 8, however, where we add same-job-tenure as an independent variable. Again, look at tables 1B and 1D. The coefficient on the new variable is positive, as expected. But the coefficients on the technology interaction variables drop to near zero.

From the regressions of column 8, we would tend to conclude that older workers benefit just as much from technological progress as younger workers do.

Figures 2-3 graph the $dYrJob$ variable for different age groups. What we find is that job tenure rises with age prior to age 50. In contrast, it is negative or zero for the oldest workers. The graphs are especially dramatic for years before 1990, when large, negative values emerge.

In Figures 2-3, almost all of the variation occurs for ages above 50. The variation after age 50, on the other hand, closely matches the changes in the average product of labor that we see in Figure 1. We seem to have a substantial multicollinearity problem.

ii) Interpretations. Columns 7-8 in the regression tables point to opposite result: in column 7, the oldest workers do not benefit from TFP growth; in column 8, they do benefit as much as the young. At least two interpretations are possible.

Japanese workers, the data show, frequently change jobs after age 50. These changes appear to lead to substantial reductions in earnings. In recent decades, the job changes have become somewhat less common (though they remain quite prevalent). Perhaps the moderation has occurred because of improvements in the health and stamina of older workers, or because of diminishing age discrimination. Then column 8 regression results may be the most valid. They imply that older workers benefit as much from technological progress as the young.

Figure 2 dYrJob by 5 Year Age Group (Male Senior High)

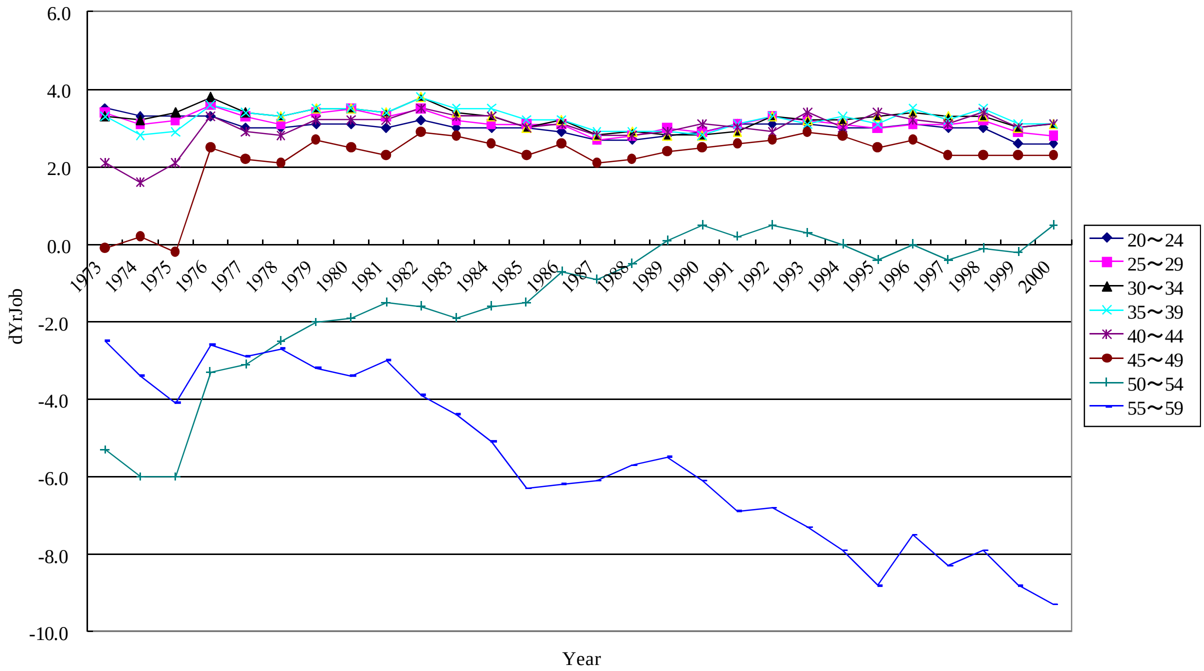
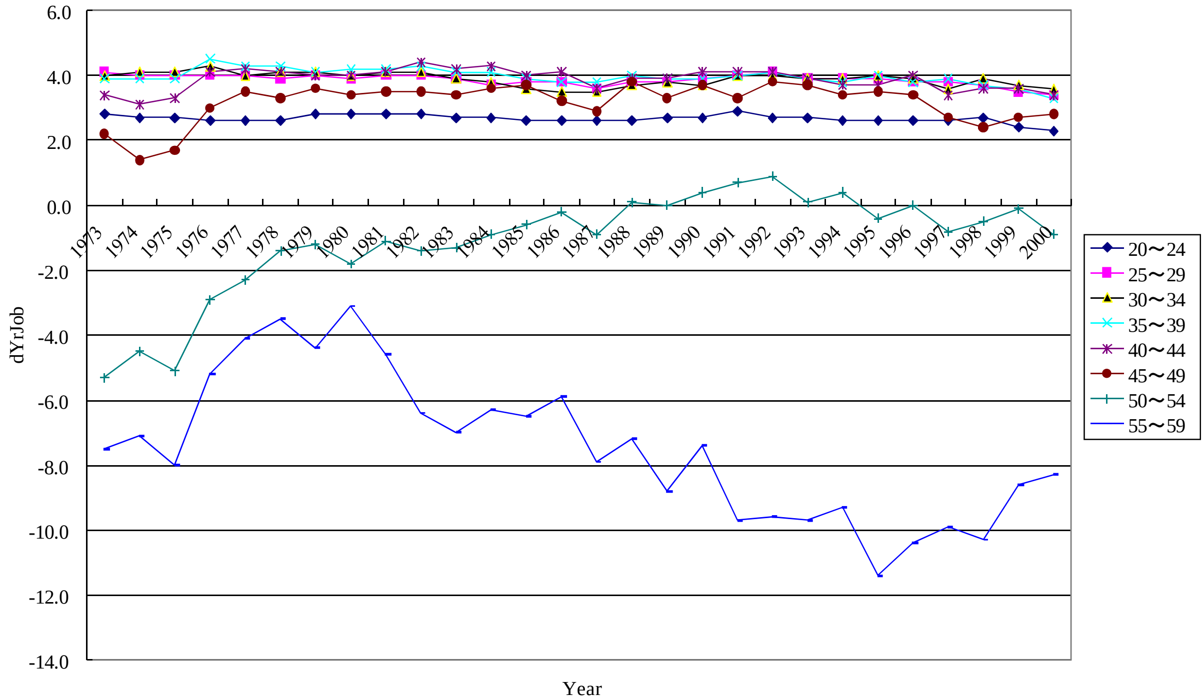


Figure 3 dYrJob by 5 Year Age Group (Male University)



Alternatively, late-in-career job changes may occur because older workers are unable to cope with the most modern technologies. In other words, technological progress may cause late-in-career job changes, with the latter, in turn, leading to reduced earnings. The slowdown in technological progress in Japan after 1990 may have reduced employers' impetus to move older workers to new jobs. Then the column 7 regression results are valid, implying that the oldest workers do not benefit from technological progress at all.

At this stage, we draw two conclusions. First, even if column-7 results are correct — so that older workers are unable to benefit at all from technological progress — the age at which this phenomenon emerges appears to be 50-55. Figure 1 shows that recent TFP growth in Japan has, at best, averaged about 1 percent per year. The loss in earning power by age 65, for example, might then average 10-15 percent in a growth environment resembling the 1970s or 80s, and much less in more recent decades. Although this may create disincentives to continue working at older ages, it is perhaps not an overwhelming factor given its late emergence in workers' life cycles.

Second, the effects above tend to disappear if we include in our analysis a same-job-tenure variable and view it as exogenous.

It seems possible that we can make further progress in the future on evaluating the tenure variable's exogeneity by disaggregating our results across industries. If the changes in Figures 2-3 are sociological in nature, or health related, they may apply to all industries. Evidence suggests that TFP growth may, on the other hand, be more uneven — see, for example, Baily and Solow [2001].

5 Conclusion.

We present earnings dynamics regression results for Japanese males 1973-2000. Our formulation enables us to distinguish the effects of total factor productivity growth on wage-rate changes at different ages.

Evidence emerges that suggests that older workers, perhaps workers aged 50-55 and above, do not benefit as much from TFP growth as their younger colleagues. If this is true, it could be the consequence of physiological factors related to age — or it could be the consequence of optimal patterns of human capital accumulation, with workers choosing to stop accumulation as retirement approaches.

We also find that data on same-job-tenure can affect our results substantially. A question arises as to whether job changes late in career tend to be caused by worker obsolescence in the face of continuous technological progress or whether the job changes arise for other reasons. If we can view the job changes as exogenous, our results about older workers' problems in absorbing new technologies disappear.

Future work with more disaggregated data may shed light on the nature and causes of late-in-career job changes.

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Appendix (Explanation of Data)

The average value of the total wage earnings and the total hours of work are tabulated by educational category (ED), sex (MF) and age group (a) in *Basic Survey on Wage Structure*, Ministry of Health, Labour and Welfare, Japan. The educational categories are given by employees' completion of Junior High School (JH, 9 years), Senior High School (SH, 12 years), Junior College (JC, 14 years) and University (U, 16 years or more). The 5 year age group between 20 and 64 is available for all educational categories in the survey. We exclude Under 17 and 18-19 for Junior High School Graduates, 18-19 for High School Graduates, 60 and over in 1975, 1976 and 1977, and 65 and over for other years (selection bias).

The total wage earnings (12×regular wage earnings ＋ bonus and other pay) are deflated by the price indices of the gross value added. The price indices are given in EU-KLEMS data base. The average real wage rate, WR(ED, MF, a), is obtained as a ratio of the total real wage earnings and the total hours of work. Wage Income and Employees' Benefits are shown in *Annual Report on National Accounts*, Cabinet Office, and the benefit wage ratio is used to adjust the Total Wage Earnings as follows:

$$\text{Real Total Wage Earnings} = \frac{\dfrac{\text{(Total Wage Earnings)(1+Benefit Wage Ratio)}}{\text{(Gross Value Added Price Index)}}}{\text{(Total Hours of Work)}}$$

The value added based total factor productivity growth (1995=100) is given by EU-KLEMS database. (See Figure A1 and, for comparison, Figure A2.) The average productivity of labor is obtained by dividing the value added deflated by price indices by quality adjusted hours of work by employees (see text). Length of service which may be considered as job experience, or a proxy for the level of human capital, corresponding to the age-sex-education cell is given in *Basic Survey on Wage Structure*, Statistics Bureau of Japan. Finally, unemployment rates by sex and 5 year age group are given in *Labour Force Survey*, Statistics Bureau of Japan.

Figure A3 shows our adjustment for benefits.

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EU-KLEMS Growth and Productivity Accounts, EU KLEMS, http://www.euklems.net/.
Annual Report on National Accounts, Cabinet Office, 1973-2005.
Labour Force Survey, Statistics Bureau of Japan, 1973-2005.

Figure A1. APL02Q(t+5) – APL02Q(t)

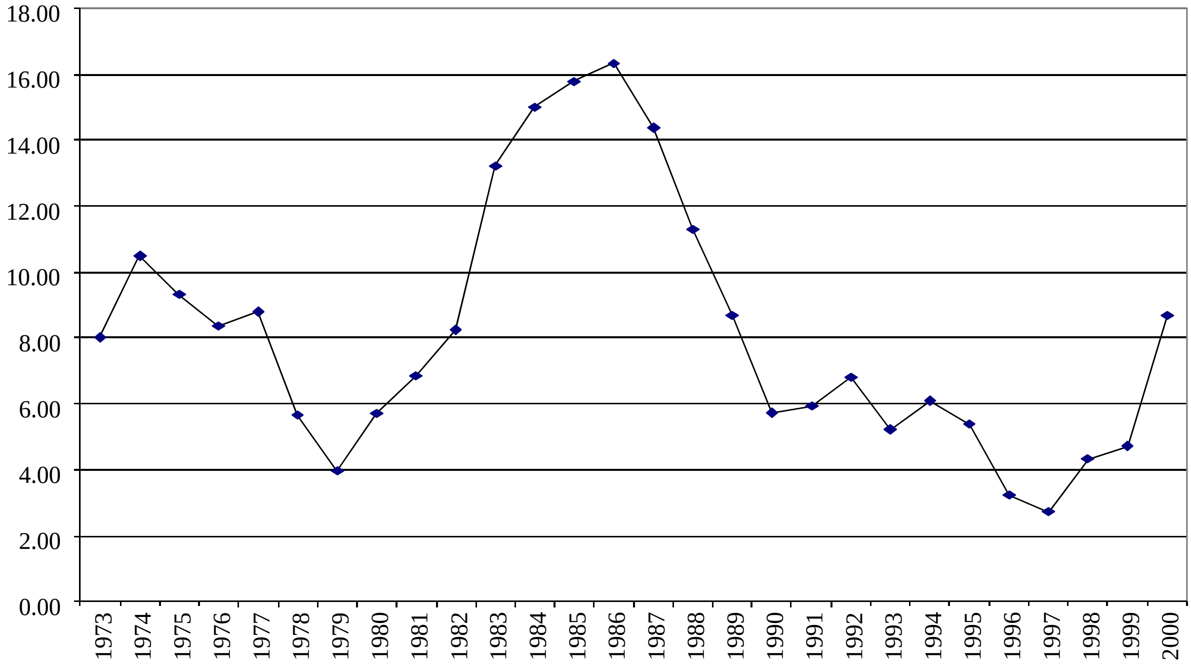

Figure A2. TFP(t+5) – TFP(t)

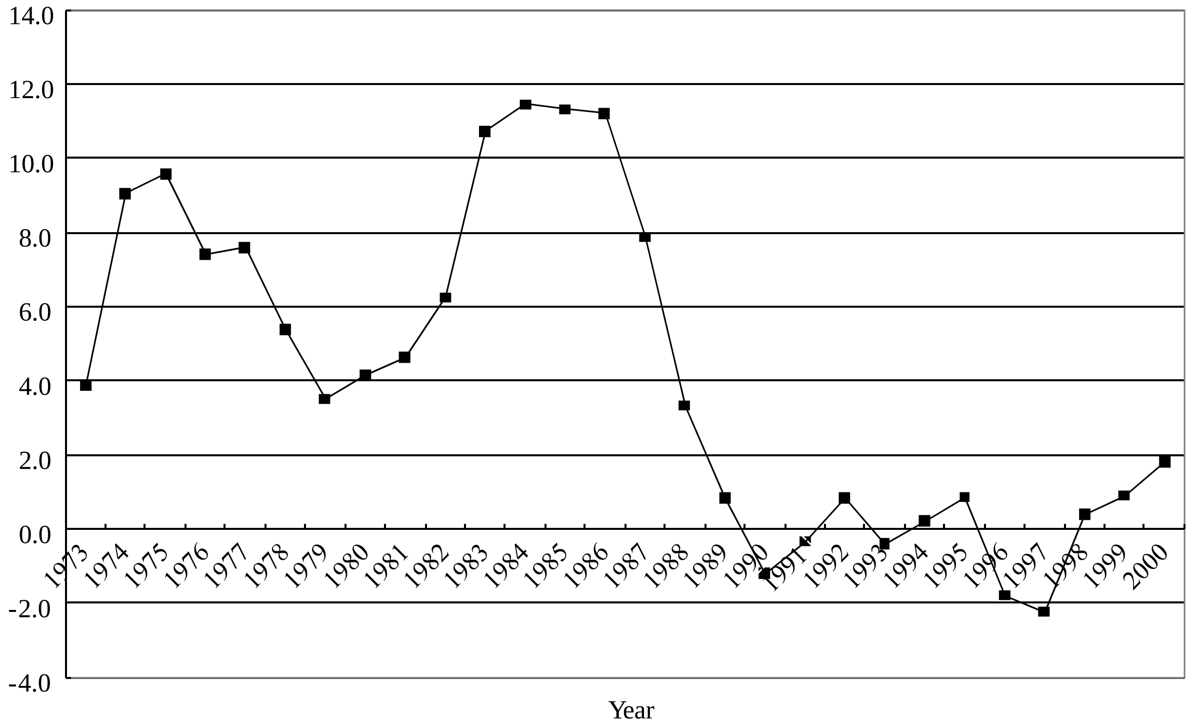

Figure A3. Benefits/Paid Wages