Aging, Technology and Productivity

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The possibly negative productivity counterpart of an aging workforce at times of fast technical change is often seen as an important policy issue. We use Finnish plant data constructed by linking various registers of firms, plants and individuals to test whether plants employing an older labor force have suffered productivity shortfalls compared to other plants during the 1990s through the early 2000s – the new economy period - while controlling for other plant productivity determinants, such as plant age, size and turnover rates. Our estimates indicate that this has not been equally the case in all industries. In the electronics industry, the seniority-productivity profile at the plant level reaches a peak in the sixth year of tenure, but then productivity dramatically falls by a cumulative 40% in the following five years. The declining part of the curve is instead either absent or more delayed in time, and definitely less steep for the other manufacturing industries. The age-earnings relation is instead usually concave but stays upward sloping. The discrepancy of results for productivity and wages is consistent with Lazear's theory of deferred payments. It also suggests that the practice of exploring the relation between plant or worker characteristics and wages as if an age-productivity relation were investigated may be misleading.

Keywords: Aging, Technology, Productivity, High-tech Industries, Total Factor Productivity, Wages, Finland

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1. Introduction

The possibly negative productivity counterpart of an aging workforce at times of fast technical change is often seen as an important policy issue.

Declining fertility and increasing life expectancy - almost ubiquitous phenomena in the OECD - raise the share of the elderly in the overall population and labor force. As such, this is not a particularly worrisome phenomenon for productivity. Aging, after all, may imply enhanced ability and attitude to work, due to improvements in health, and, as a result, potentially increased labor force participation. Moreover, an older labor force is a more experienced, and therefore more effective, labor force (Becker, 1962). At the same time, however, it is also widely accepted that cognitive abilities deteriorate with age (see Skirbekk, 2003). While this decline is not uniform across abilities, there is no doubt that, after a certain age threshold, growing older is seemingly associated to lower, not higher, productivity.

This issue may have become more serious in the last few years, because the rapid diffusion of information technology has brought about outright new modes of production and working. This acceleration of technical change may have also possibly accelerated the process of individual skill obsolescence naturally occurring with age. This is why Governments are worried and, on our side, this is why we thought of writing this paper.

To properly address the question of whether technical change is biased against age, one would ideally like to investigate the determinants of individual ability, searching for discontinuities before and after the introduction of a major invention or innovation. This is not feasible, however, because individual ability is unfortunately unobserved. The bulk of the studies exploring these issues have then analyzed these issues employing *earnings* data, at the individual, plant or company level. A typical result of such studies is that, in accordance with the main tenets of the theory of human capital, the relation between aging and productivity (namely: earnings) follows an inverted U or an increasing, but concave, function.[1]

[1] Aubert and Crépon (2004) estimated average earnings relations and found that the age-productivity profile (as captured by such earnings functions) does not differ much across industries. Aubert, Caroli and Roger (2004) estimated labor demand curves by using wage bill shares conditioned on value added as well as old and new economy capital; they did find significant evidence that innovative firms and work-practices present lower wage bill shares. The same result seemingly applies within occupational groups. Neuman and Weiss (1995) also found that earnings peaks are located earlier in age in the high-tech sector. Abowd, Kramartz and Margolis (1999) and Hellerstein, Neumark and Troske (1999) also found evidence of heterogeneous response of earnings to tenure across industries.. Other studies have found that the relation has changed over time. According to the findings of Eriksson and Jäntti (1997), the peak of the wage profile seems to have moved towards older workers in Finland. The seniority-

Yet earnings are not necessarily a good proxy of productivity. As surveyed, for instance, by Hutchens (1989), labor economists have provided two alternative explanations for why productivity and wage may not go hand in hand. Models of firm-specific human capital imply that wage *exceeds* marginal productivity early on in people's career. This is because, with firm-specific skills, the firm pays the cost of training. Later on, however, this initial investment must be repaid by wage moderation later on: the productivity profile is then *steeper* than the wage profile and productivity ends up exceeding wage in the last part of people's career, which also provides a good reason not to lay-off experienced workers. The alternative view – due to Lazear (1981) - suggests that, to keep effort incentives alive until retirement age, wages are set *below* marginal productivity early on and then go up *above* marginal productivity at later stages. In any case, irrespective of which theory is borne out by the data, they both provide reasons not to expect wage profiles to closely mirror productivity profiles, neither over time nor at a given point in time.

This is why we took a different route and investigated whether a direct measure of plant productivity may be related to an array of worker characteristics, including seniority, experience and schooling, all averaged at the plant level, as well as other inherently plant-specific characteristics (such as plant age and size, and turnover rates), as well as other period and regional controls. This is different from most previous studies that have extrapolated their conclusions abut aging and productivity from the estimation of plant or individual earnings equations.

We implemented our empirical exercise by analyzing the relation between aging and productivity at the plant level in four Finnish manufacturing industries. Under two respects, Finland represents a potentially ideal laboratory to study such issues: it was hit by a technological revolution in the 1990s and it has good data to study it. So not only Finland provides the scope but also the means for properly analyzing such issues as the relation between seniority, labor market experience and plant productivity. Accordingly, the four industries have been picked so as to include the two most traditional Finnish industries one can think of (the forest industry and basic metals) and two industries producing capital goods, one (production of electronics equipment) playing a crucial role and another one (production of machinery and equipment) less involved in the IT revolution. In this way, we may be able to study the plant age-productivity relation in "treated" industries (electronics) and "control" industries (the other three industries), two of which technologically dissimilar and one not too dissimilar from electronics.

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wage profile has seemingly become steeper and its peak moved forwards in Denmark (Bingley and Westergaard-

To carry out our econometric exercise, we first computed a plant productivity index by growth accounting methods, netting out the contribution from capital deepening from the log of value added per hour worked and thereby constructing a TFP index. Then we regressed the computed TFP on an array of plant-averaged worker characteristics, plant characteristics and other controls separately for each industry (four panels for about 2200, 400, 2700 and 800 observations overall) through a variety of specifications and estimation methods, starting from the simplest OLS, with seniority and experience entered through linear terms only, and a rich set of controls to account for the remaining plant heterogeneity of TFP. To deal with the potential endogeneity of some regressors (including our main variables of interest, *i.e.* seniority and experience), we also estimated the same relations by system GMM, with a somewhat narrower set of controls. Although drawing general lessons for the four industries is hard, one might tentatively conclude that the linear specifications do not provide very robust statistical results on the relation between aging and productivity. It should be kept in mind, however, that the consensus theoretical view on the relation between aging and productivity leads one to expect a non-linear relation between the variables of interest.

This is why our preferred set of results stems from the estimates obtained from a polynomial representation of the relation between our variables of interest (seniority and experience) and productivity, estimated through OLS and whose quantitative implications have been explored through Monte Carlo simulation. The results from this last batch of regressions in fact indicate that, in the electronics industry, the seniority-productivity profile at the plant level reaches a peak in the sixth year of seniority. Beyond that point, productivity dramatically falls by a cumulative 40% in the following five years. The declining part of the curve is instead either absent or more delayed in time, and definitely less steep for the other manufacturing industries. The peak in the "Basic Metals" industry is reached after ten years and in the Forest industry after sixteen years, with productivity declines since then for cumulative -18% and -11%, respectively. We colud not detect any such peak for the Machinery and equipment industry, instead.

Hence, having controlled for the potential selectivity effects induced by the between-plant movement of workers by appending lagged turnover rates and for the other potential cause of the negative relation between aging and productivity (namely, the fact that old workers are more

Nielsen (2003)) as a result of the decentralization of wage determination.

likely employed in old plants) by appending plant age controls, we interpret our results as evidence of the presence of age-biased technical change in Finland throughout the 1990s.

Finally, we also ran the same type of regressions having plant wages as a dependent variable. Interestingly, the age-earnings relation turns out to be usually concave but always upward sloping in all industries. Hence, in addition to be consistent with Lazear's theory of deferred payments and with the findings of Ilmakunnas and Maliranta (2004, 2005) for Finland and of a number of authors for other countries, our TFP and wage results are also suggestive that the practice of exploring the relation between plant or worker characteristics and wages *as if* an age-productivity relation were instead investigated may be misleading.

The paper's structure is as follows. In Section 2, the main predictions about the relation between aging and productivity are surveyed and briefly discussed. In Section 3, the main features of our data set are described, including an short introductory discussion of why we think that Finland is good case in point. In Section 4, our empirical strategy is presented, emphasizing the methodological difficulties of our task and our proposed solutions. Section 5 describes the main results. Section 6 concludes.

2. Aging (of workers and plants) and plant productivity: testable predictions

Two distinct strands of literature have investigated the relation between aging and individual productivity, on the one hand, and the relation between firm (or plant) age and its productivity, on the other. Our study draws on both.

2.1 Aging and individual productivity

The study of the relation between aging and individual productivity is a special case of the study of the relation between individual characteristics and various individual labor market outcomes.

Human capital theory suggests that an older labor force is a more experienced - and therefore more effective - labor force. This is for three reasons.

First, aging often brings about higher worker seniority within a given firm. As long as some on-the-job training is undertaken at an early stage in career, higher seniority is associated to higher worker's productivity and, eventually, into higher wages.[2] Second, aging is also typically

[2] The extent to which higher productivity results in higher wages depends on whether training is of a general or a firm-specific type. If on-the-job training is general, the worker will be able to fully appropriate the productivity

associated to longer generic experience in the labor market over and above the increased seniority within a given firm. If generic experience buys enhanced flexibility and adaptability to the worker, this is again likely associated to higher productivity (and wages). Third, as long as the prospect of a longer working life is appreciated in advance, this may also induce individuals to invest more in their human capital, which in turn will feed into higher productivity of labor through the standard educational and training channels.

This is not all, however. It is also widely accepted that cognitive abilities deteriorate with age. While this decline is not uniform across abilities (see below on the distinction between fluid and crystallized abilities), nobody denies that, after a certain age threshold, growing older is seemingly associated to lower, not higher, productivity. As surveyed by Skirbekk (2003), for most jobs, the age-productivity relation is thought of as reversing its sign some time in between the age of 50 and 60. Beyond this threshold, the depreciation of past human capital investment more than offsets the net addition to human capital formation possibly coming from education or training, therefore depressing productivity. Verhaegen and Salthouse (1997) present a meta-analysis of 91 studies, which investigate how mental abilities develop over the individual life span. Based on these studies, they conclude that the cognitive abilities (reasoning, speed and episodic memory) decline significantly before 50 years of age and more thereafter. Maximum levels are instead achieved in the 20s and the 30s. This is a universal phenomenon, independent of country and sex (this same phenomenon appears to hold even among non-human species - from fruit flies to primates).

To sum up, the age-productivity profile for an individual is expected to be concave and possibly non-monotonic, with an upward sloping part possibly changing its slope into negative beyond a certain threshold.

Particularly relevant to our paper, the deterioration of individual ability may be a more serious shortcoming at times of - and in companies and industries subject to - fast technological change. This has been seemingly the case in a large part of the Finnish economy since the early 1990s, when information technology started changing radically modes of production and work over a relatively short period of time. If this is true, one expects to observe an age-productivity profile with an earlier turnaround point and/or a steeper decline in high-tech industries (such as those

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increase enabled by training at a later stage in his/her career. If training is firm-specific, instead, worker and firm will share in the quasi-rents generated by training. Moreover, as discussed by Acemoglu and Pischke (1999, 2001), producing electronics equipment) than in traditional, technologically mature, industries (such as forest and basic metals) as well as relatively less IT-intensive but still capital-good-producing industries, such as machinery and equipment. These cross-sectional implications are the main working hypotheses brought to the data in this paper.

In putting together our pieces of evidence, we will leave aside a few important aspects, which are likely to make the picture more complicated than this. First, a distinction must be drawn between fluid abilities and crystallized abilities. Fluid abilities concern the performance and speed of solving tasks related to new material, and they include perceptual speed and reasoning. They are strongly reduced at older ages. Crystallized abilities, such as verbal meaning and word fluency, even improve with accumulated knowledge and remain at a high functional level until a late age in life (Horn and Cattell (1966, 1967)). The distinction between fluid and crystallized abilities is supported by empirical findings, where the psychometric test results of young and old men are analyzed. It is found that verbal abilities remain virtually unchanged, while reasoning and speed abilities decline with age. Hence, one should not expect to see the declining part of the age-productivity profile to set in equally for all tasks and jobs.

Second, the relative demand for work tasks that involve certain cognitive abilities may have shifted asymmetrically over recent decades. As argued and empirically documented by Autor, Levy and Murnane (2003), the demand for interactive skills (hence for abilities that stay relatively stable over the life cycle) has likely increased more than the demand for mathematical aptitude (which instead declines substantially with age). This suggests that older workers may become relatively more productive in value terms over time. Whether such countervailing factors are relevant for Finland remains to be seen, being presumably particularly important for IT users rather than for the workers involved in the production of IT goods.[3]

Third, in spite of the seemingly unavoidable reductions in cognitive abilities, targeted training programs seem effective in softening, or halting altogether, the age-related decline in abilities and productivity. Schaie and Willis (1986a, 1986b) conclude that such programs can stabilize or even reverse age-specific declines in inductive reasoning and spatial orientation among many individuals. Ball et al. (2002) find that exercising speed, reasoning and memory abilities enhances the functional level of those who undergo training relative to those who do not.

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another relevant aspect determining the degree of shifting of productivity developments onto wages is the structure of labour markets.

Our plant-level data set does not give us much leeway to exploit such additional interesting implications, and we leave them aside.

2.2 Firm (or plant) age and productivity

While the study of the relation between individual characteristics and the labor market is much investigated, much less is known about the relationship between firm characteristics and the labor market. Among this more limited set of studies, firm size, unionization and industry has been pointed out as important determinants of wages and, possibly, productivity.

Only a handful of studies have analyzed the relation between firm size and wages. With US data, Dunne and Roberts (1990) and Davis and Haltiwanger (1991) reported a positive correlation between firm age and wages, after controlling for size, industry and region, with and without controlling for the probability that the plant will close (usually lower for older firms). As to Europe, Blanchflower and Oswald (1988) found no such relation with UK data, while Winder-Ebmer found a positive relation with Austrian data. The very careful study by Koelling, Schnabel and Wagner (2005) shows that, in Germany, older firms pay on average higher wages for workers with the same broadly defined degree of formal qualification. These results are in line with the findings in Brown and Medoff (2001) for the US economy.

The evidence on the relation between firm age and wages is often seen as implying that, as predicted by the standard competitive model of the labor market, the wages paid by firms reflect the quality (and thus the higher productivity) of the workers they hire (see Brown and Medoff (2001)), as well as the working conditions they offer. This need not be the case, though: Older firms may pay higher wages to grant fringe benefits, such as pensions or health insurance, to their most faithful workers or, more subtly, because they cannot deny pay raises to people who have developed a good knowledge of the company's ability to pay throughout the years.

No such study presents direct evidence for productivity, however. In our plant-level data, we will take into account the potential relation between firm (plant) age and productivity by controlling for plant age. We do to make sure that the potentially negative relation between age and productivity is not simply due to the fact that older workers use old machines, and has instead to do with something else (such as declining ability). If after controlling for plant age, the relation

[3] The micro data employed by Maliranta and Rouvinen (2004) indicate that the use of ICT has had a particularly significant effect on productivity in ICT producing and using manufacturing industries.

between average seniority of the workforce and plant productivity is still there, this should not be attributed to any of the mechanisms linking firm size and wages in the survey by Brown and Medoff (2001).

3. Data

3.1 Why Finland

Finland is an ideal laboratory for investigating issues such as the potential age bias of new technologies for two reasons.

From a substantive point of view, the emergence of Nokia as a world-class cellular producer is a good example of a swift change in the industrial structure of a country, in this case from “old-economy” to “new-economy” industries. This occurred during the 1990s, after the end of the sharp recession that severely hit the Finnish economy in 1990-91.

A few figures concerning the changes in the composition of value added at current prices will suffice. The boom in the world demand for cellular phones, partly fed by the worldwide trend of declining prices, has made the share of the electronics industry go up from about 3.5% of nominal GDP in 1995, to 8.2% in 2000 and then down, as a result of the sharp 2001 recession, to 6.5% in 2003. This amounts to a major reallocation of resources away from other industries. Throughout the same period of time, the value added of the forest industry (and notably of the industry named “Pulp, paper and wood products”, NACE 20-21) fell from 7.5% in 1995 to 6% in 2000 and 5% in 2003. Also the share of basic metals gently fell from some 3% in 1995 to 2.6% in 2000 and 2.3% in 2003. Finally, in parallel, as an example of how not all of the so called high-tech industries have gained throughout this period of time, the value added share of “Machinery and equipment” (NACE 29-31) slightly fell from 5.7% in 1995 to 5.4% in 2000 and then to 5% in 2003. This is why we picked such four industries paradigmatic of the sudden changes that have swept the Finnish economy over the last ten years.

3.2 The data set

A second reason for choosing Finland as a case-study has to do with data availability.

In fact, similarly to the other Nordic countries, Finland is endowed rich register data of companies, plants and individuals (Statistics Denmark et al., 2003). The unique identification codes for persons, companies and plants used in the different registers forms the backbone of the

Finnish administrative register network and the Finnish statistical system, whereby different sources of information can be integrated conveniently for various statistical purposes.[4]

By using this system, Statistics Finland has constructed the Finnish Longitudinal Employer-Employee Database (FLEED), which is tailored for various needs of economic research. Its most comprehensive and detailed version is maintained in Statistics Finland. It contains information of companies, plants and individuals. Plants are linked to their companies, and individuals to their employer plants and companies. Data are collected from Business Register (plants and companies in the business sector), Manufacturing Census (manufacturing plants), Financial Statements Statistics (companies in the business sector), R&D survey and ICT survey (companies in the business sector), and Employment Statistics (individuals aging between 16 and 69 years).

These data include a variety of detailed information on these units. A large proportion of variables are available from 1990 to 2002. These data cover essential the whole target population of companies, plants and individuals.[5] Due to confidentiality concerns, outside researchers do not have a direct access to it. For the outside researchers, Statistics Finland has constructed a separate version of it. The variable set is more limited and some of the categorical variables are broader (many industries are combined, for example).[6] Within this smaller data set, one third of individuals in 1990 are randomly selected to the sample of individuals. These individuals picked up from the register until the year 2002, unless their have died or moved abroad. Every year since 1991, one third of individuals aged 16 years are therefore included in the sample for the remaining years. Data include encrypted identifiers that enable to follow companies, plants and individuals over time.

This paper employs plant level information for plants and workforce. Productivity measures, plant age, plant size originate from the Census of Manufacturing. We do not have information of the levels of value added, hours worked or capital stock as such , but we do have the ratio of value added to the number of hours worked (by which we identify labor productivity) and the capital

[4] Data sources and linking of them is described in greater detail in (Ilmakunnas et al., 2001) and (Maliranta, 2003)

[5] Information content varies between different kinds of units. The cut-off limits are different in the different sources. The number of variables for the very small businesses, for example, is very limited.

[6] The stripped-down version of the data is such that outside researchers may be given an off-site access to. The idea is that researchers may begin the economic analysis with these data. If the data are not detailed enough for accurate or reliable results, Statistics Finland may carry out the final estimations with the complete data by the codes provided by the researcher.

stock per hour worked (a measure of the capital-labor ratio). [7] We can thus measure the productivity of plant *p* in industry *i* in year *t* as a TFP-index:

$$TFP(pit)=\exp(\ln(Y/L)-(1-a(it)*\ln(K/L))$$

where a(it) denotes the year-industry specific labor share. This is a way of smoothing value added shares.

Up to the year 1994 the main criterion to include plants was that the plant employed at least five persons. Since 1995, though, all plants owned by firms that employ no less than 20 persons are basically included. Therefore, since 1995 the data also include the very small plants of multi-unit firms, but, on the other hand, the plants of small single-unit firms are left outside. In this analysis we have focused on plants employing at least 20 persons. At the level of total manufacturing, these plants cover roughly 90% of total nominal value added (Maliranta, 2003). In addition, some plants are dropped from the sample because of failure of linking some plants in Manufacture Census to other sources of information. An important link is the one between Manufacture Census and Employment Statistics.

Thanks to this link, we have information about the labor characteristics of the plants. This includes the average potential experience (years after the last completed degree), seniority (the number of years spent working in the current company) and the number of schooling years (usually needed for the degree). Moreover, we have variables measuring the dispersion of these characteristics between individuals within plants, occasionally used as control variables in our analysis. The labor characteristics of the plants are computed in Statistics Finland by using the comprehensive version of the database. About 80-90% of individuals can be linked to their plants so that our variables should be measured with a reasonable accuracy. In the analysis, we have also dropped some outliers that may distort results, especially as it comes to productivity. [8] By making use of the sample of individuals that can be linked to our plant observations, we can estimate what the proportion of total employment our plant sample covers.

All in all, while the number of observations actually employed varies depending on the specification and the method of estimation, the data set endows us with a maximum of 6140

[7] The capital stock measure is calculated through the perpetual inventory method. For more details, see (Maliranta, 2003).

[8] In the estimation, some extreme outliers are removed from the regression analysis. Identification has been carried out by using the method by Hadi (1992, 1994). The variables used in this procedure are the log of labor productivity, the log of monthly wage and the log of capital intensity.

observations for the four industries in 1994-2002 (2200 from the forest industry, more than 420 from basic metals, about 2700 for machinery and equipment and 820 for electronics. The total number of observations falls by about 20% when GMM is used (see the extensions section).[9]

3.3 Summary statistics

Before delving into the multivariate statistical analysis of the next sections, we spend a few words describing the summary statistics of the main variables of interest, TFP and wages on the one hand, and experience, seniority and education on the other. **Table 1** presents data relevant for this purpose.

A preliminary point to make is that, by its very method of calculation, our plant TFP does not lend itself to be meaningfully aggregated into an “industry TFP” (this is because time-varying industry value added shares are employed to compute it at the plant level). This problem does not arise for the other variables.

While we will provide evidence of the meaningfulness of our TFP figures later on in Section 5 by showing that it is tightly related to schooling, we still want to provide some figures for the growth rate of industry TFP. Hence, to compute it, we rely on national accounting statistics (under the same assumptions of constant returns to scale and perfect competition employed at the plant level). Even plant wages as such cannot be compared over time, for they are not adjusted for inflation. To gain some hints about their behavior over time and make this comparison possible, we deflated wages by industry-specific value added deflators from the National Accounts.

The results are shown in **Table 1**. The most striking result for TFP and wages is that in most cases the industries where TFP grew faster are also those where wages have gone up the most (with the only exception of basic metals, where the growth of wages has clearly outpaced TFP. This is interesting to keep in mind because it shows how aggregate correlation may not necessarily stem from microeconomic correlation. As shown in the results sections, plant TFP and wages cannot really be said to go hand in hand.

[9] Missing plant-specific information about plant employment levels, we are unfortunately unable to evaluate the proportion of the total employment covered for each industry in our sample. We can estimate provide a rough estimate of this coverage by using the sample of individuals that can be linked to our sample plants and the number of employees in each industry reported in the National Accounts by Statistics Finland. It turns out that our sample, after taking out the outliers and the very small plants, covers about 67% of total forest employment, 80% of basic metals, 53% of machinery and equipment and 66% of electronics.

It may be worthwhile pointing out, however, that, in our regressions, we do not use deflated values for TFP and wages (say, through the officially published price indices), but rather, following Caselli and Coleman (2001), append yearly dummies as regressors, each allowed to take different coefficients in the four industries. In this way, we expect to be able to lessen the problems caused by the potential mis-measurement of the quality-unadjusted price deflators.

The other (rough) indication from **Table 1** is that the cross-industry variability of workers' characteristics has been much more limited than the wild variability observed for productivity and wages. Experience, tenure and schooling have gone up the most in the industry (Forest) where productivity and wages have gone up the least. They have gone up the least in the industry with the fastest growth rate of TFP.

Although not graphically shown, it is also remarkable that schooling is highest and experience & seniority lowest in Electronics. This was there already in 1994, but has become more apparent in 2002. This may be taken to indicate that schooling is a more important determinant of productivity and wages in high-tech industries than elsewhere in the economy. This result will be validated in the results section.

4. Empirical strategy

To learn about the relation between aging and productivity, one would ideally like to estimate regressions where individual productivity is related to individual, firm and other "environmental" characteristics. Yet individual productivity is typically unobserved.

To gauge indirect information about individual productivity, three main approaches have been followed: supervisors' ratings, piece-rate samples and the study of age-earnings data within matched employer-employee data sets.

Studies based on supervisors' ratings tend not to find any clear systematic relation between the employee's age and his/her productivity. At most, a slightly negative relation is found, anyway small. A problem with these studies is that managers often wish to reward loyalty rather than productivity. Hence supervisory evaluations may be inflated and results biased.

Work-samples provide evidence from task-quality/speed tests. Here it is typically found a negative relation between age and productivity. The slope of the decline is not steep for blue-collar workers and leads to cumulative declines of around 15-20% compared to peak levels, while the productivity decline of older workers in creative jobs is probably more pronounced. Moreover, even these studies suffer from selectivity and truncations, which may give rise to biased results.

Employer-employee linked data sets, such as the one we are using, are less prone to subjectivity issues than the studies based on supervisors' ratings and to selectivity issues than work-samples. The problem here is to isolate the genuine contribution of the age of the marginal worker to the company's value added from other intervening factors.

Here two options would be in principle available. The one we follow here is to estimate productivity regressions at the plant level, where plant-averaged TFP – a proxy for plant productivity – is computed first and then regressed over a set of plant-wide (including average workers') characteristics. The other option, taken by previous studies, is to estimate individual age-earnings profiles to rule out unwanted aggregation effects. Yet, clearly, the sensitivity of wages to individual characteristics may differ from the sensitivity of productivity to the same characteristics for a number of reasons.

In what follows, we first describe our basic specification, and then provide a discussion of the main issues involved and our proposed solutions.

4.1 Basic specification

To evaluate the relation between aging and productivity at the plant level, we relate the plant TFP index - computed numerically as indicated in the previous section - to potential experience (EXP), seniority (TEN) and schooling (SCHOOL), as well as to a number of additional controls (CONTROLS), both plant and time varying, as well as period fixed effects:

$$(1) \quad \ln(TFP)^{i}_{pt} = \beta_E \, EXP^{i}_{pt} + \beta_S \, SEN^{i}_{pt} + \beta_S \, SCHOOL^{i}_{pt} + \beta \, CONTROLS^{i}_{pt} + \beta_Y \, YEAR^{i}_{t} + e^{i}_{pt}$$

$p=1,2,..,N^i$, i=forest, basic metals, machinery and equipment, electronics

$t= 1994, .., 2002$

where *p* is for plant, *i* for industry and *t* for time periods. The list of appended CONTROLS may include size and regional dummies, but also (and crucially) some other variables such as plant age and turnover rates.

Productivity (total factor productivity; TFP) is computed for each plant under the assumption of constant returns to scale and perfect competition in the factor markets, using industry-year specific income shares.[10] TFP (in logs) is computed as the difference between the log value added per hour worked and the product of the current and lagged value added share of capital (for the industry) times the log of capital per hour worked. Under the assumptions of constant returns to scale and perfect competition, this is TFP, the disembodied component of technical change.

Maliranta (1997) indeed found that the assumption of constant returns to scale in the Finnish manufacturing sector is not a bad assumption, given that the estimated (α+β-1) parameter conventionally estimated in the econometric exercises where the constant returns to scale assumption is dropped has turned out indeed statistically significant but with a point-wise estimate of about -0.01, thus a very small number.

This is different from (and less sophisticated than) the econometric approach to the production function, which would instead obtain an estimate of plant productivity as a residual, *i.e.* an unobserved plant-specific time-varying effect, as suggested by Olley and Pakes (1996) and Levinsohn and Petrin (2001). Such semi-parametric estimation approaches are aimed at producing consistent parameter estimates - a necessary ingredient to carry out the second step of the analysis (*e.g.* analyzing the productivity counterpart of aging), while escaping the risk of simultaneity. Within this framework, the error term e_{it} should be further decomposed into two plant-time varying components, one measuring the level of efficiency - known to the plant manager but not to the econometrician, and therefore potentially responsible for the inconsistency of the estimates - and a genuinely residual component. Selectivity issues are also likely to be important as long as only the plants that continue to produce are observed. Unless a correction for self-selection is allowed for, the estimated coefficients of the inputs of production will be biased as well (downwards, if expected profits are the key variable driving exit decisions and capital is positively correlated to profits).

Our specification, being based on growth accounting techniques, insulates us from the endogeneity and selectivity biases pinpointed above. But this comes at the cost of accepting the - possibly plausible but untested - CRS and perfect competition assumptions mentioned above. Moreover, in order to be able to interpret our results as capturing the intended relation between workforce aging and plant productivity, we have to confront two other empirical hurdles, discussed in the next section.

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[10] As mentioned in the previous section, this method of calculating value added shares smoothens the otherwise erratic behavior of income shares but, at the same time, also make aggregation of our TFP figures unfeasible. To make aggregation possible, one should go for time-invariant income shares, at the cost of biasing plant TFP in case

4.2 Discussion

4.2.1 Simultaneity

In addition to the difficulties emphasized above, our estimated equations may suffer from additional simultaneity problems, *i.e.* the possibly negative relation between old age and productivity may be due to reverse causation. Old-aged firms are typically less productive and may typically disproportionately hire old-age workers. The evidence on the relation between firm age and productivity is not abundant, though. Dunne, Roberts, and Samuelson (1989) report that manufacturing plants that have been in business longer are less likely to close, and Brock and Evans (1986) show that older firms are less likely to fail (controlling for plant and firm size, respectively). On the other hand, it has often been found that older firms pay higher wages, even after controlling for other relevant firm characteristics. Davis and Haltiwanger (1991) find that older manufacturing plants pay higher wages, and age remains a statistically significant determinant of wages once industry and size are held constant. Troske (1998, Table 11.11) reports similar results: controlling for employer size and location, workers in plants that are less than five years old earn nearly 20 percent less than workers in plants that have been in business 15 years or more. Blanchflower and Oswald (1988) find no significant relationship between wages and years in operation in British data. More recently, Brown and Medoff (2001) have analyzed the relationship between how long an employer has been in business (firm age) and wages. According to their analysis, which also controls for workers' characteristics, firms that have been in business longer pay higher wages (as previous studies have found), but pay if anything lower wages after controlling for worker characteristics. There is some evidence that the relationship is not monotonic, with wages falling and then rising with years in business.

Altogether, these previous studies point to the importance of controlling for plant age (as well as for workers' characteristics) - something we are about to do in our regressions.

4.2.2 Selectivity

The estimation of (1) is also confronted with another problem. It might also be that the - supposedly estimated - negative relation between aging and productivity arises as a result of selectivity. Longitudinal studies typically suffer from non-random attrition, *i.e.* the loss of respondents over time tends to generate an upward bias in the age-productivity estimate, given that those remaining in the sample are usually positively selected. Those who choose to stay and continue to work in a given form instead of engaging in job shopping to improve the existing match may be the least productive workers. Plant productivity may thus decline as a result of the process of job turnover that “may leave behind” older workers, rather than being the sheer consequence of declining ability. In other words, regression results may not indicate a true negative relation between aging and productivity, but simply that the most able workers are more likely to leave an inefficient firm.

4.2.3 Our proposed solutions

To tackle the issues described in the previous sub-sections, we append plant age and past turnover rates to the list of our controls. This is meant to reduce both the risk of simultaneity and selectivity.

The inclusion of plant age is expected to capture the potentially harmful effects on plant productivity of the presence of older machines, inherently thought of as less efficient than modern ones. In the data set, we have information about plant age, namely a categorical variable indicating the year of establishment of the plant classified in eight categories (before 1976, 1977-80, 1981-85, 1986-90, 1991-95, 1996-98, 1999-2000, 2001-02). We use this as an additional control. If the relation between seniority or experience and TFP is a spurious one essentially due to the fact that still very productive workers are simply trapped working with older machines, the statistical significance of workers’ seniority and experience should disappear.

In turn, the inclusion of past hiring and separation rates in the list of controls is meant to capture the selectivity bias. If the possibly negative effect of seniority on productivity is due to the reallocation of workers across plants and industries, appending such variables to the list of regressors may weaken the statistical significance of workforce aging.

If instead the statistical significance of workforce aging survives the inclusion of such variables, then the interpretation of the significance and sign of the coefficients of EXP and SEN will be reinforced.

Moreover, it should not be forgotten that we are estimating (1) for four manufacturing industries (forest, basic metals, machinery and equipment, and electronics). Two such industries (forest and basic metals) are industries where a large chunk of the Finnish economic activities used to take place in the past (say, before the fall of the Berlin Wall). The two other industries in our sample (machinery and electronics) may be labeled high-tech industries, for both produce capital goods. With one difference: only one of them (electronics) has been blessed by the presence of Nokia, which became a world-class leader in cellular phone production over the 1990s through today – our period of analysis.[11] This gives us the possibility of testing whether industry (and, slightly more ambitiously, the technological content of industrial production) made a difference for age-productivity profiles, as theory would predict.

In the end, we start by assuming that all of our variables of interest and controls are related to TFP through linear terms only, as in (1). Having done our best to control for simultaneity and selectivity, we start estimating such linear relation through OLS techniques.[12]

If there is an age-bias of new technologies, we expect to find a different pattern of partial correlation across industries, and in particular between electronics and the other three industries. This should materialize in different significance, sign and size of the estimated coefficients of the three variables of interest and TFP. To allow for generic experience (in short, experience) and specific experience (tenure) to bear possibly different correlation with TFP, different specifications respectively constraining and not constraining the coefficients on the two variables to be the same are estimated.

Irrespective of whether they enter such regressions with the same or different coefficients, we interpret a lower estimated coefficient for any of these variables in the electronics industry than in the other industries (or, *a fortiori*, a negative coefficient, where a positive coefficient is estimated elsewhere) as a first-hand indication that there is age-bias content of new technologies.

At the same time, we are aware that approximating the "true" relation between aging and productivity only through linear terms in a static model cannot but be a first attempt. More sensibly, the true relation between experience, seniority and either TFP or wages is likely to involve higher order terms in the same variable, so as to allow the aging-productivity relation to change its sign. Moreover, although most of the variability in our sample comes from its cross-sectional component, one could also estimate the relation between plant productivity and the variables of interest using the system GMM estimator proposed by Blundell and Bond (1998).

[11] The input-output evidence supplied by Daveri and Silva (2004) is suggestive that no major inter-industry links between electronics and the production of other machinery and equipment was instead present in the Finnish economy.

[12] In the extensions section, we also discuss the results obtained using system GMM.

To capture such more complicated influences, we also ran the same regressions as above with quadratic and cubic terms appended as well as using system GMM, both with predetermined and endogenous average worker characteristics.

So as not to make the presentation of the non-linear results cumbersome, we rely on CLARIFY, the user-friendly software developed by King, Tomz and Wittenberg (2000) and Tomz, Wittenberg and King (2003). This allows us to show the results of Montecarlo simulations from such "flexible" OLS regressions. Among other things, this also enables us to construct confidence intervals to evaluate the reliability of the estimated marginal impact of any variable of interest and productivity, holding the other explanatory variables at their means.

Finally, given that all of the previous studies employed wages as a dependent variable, we re-ran all of our regressions, using wages as an alternative dependent variable. This is to show that choosing one or the other dependent variable may make a big difference for the results.

5. Results

The presentation of our results follows our strategy detailed in the previous section. The OLS-with-linear-terms-only and GMM results for TFP and wages are organized in four main Tables (**Table 2, 3, 4** and **5**), one for each industry. The presentation of results from regressions involving higher order polynomials takes advantage of the nice graphical devices offered by CLARIFY and is carried out through **Figure 2** through **6**, where the implied marginal relation between any variable of interest and the dependent variable obtained from Monte Carlo simulations is plotted (with confidence intervals appended). The full-fledged results from such regressions are not reported in a detailed way, with the relevant exception of the numerical implications of the estimated seniority-productivity marginal profile, which - being the *summa* of the paper - is singled out in **Table 6**.

5.1 Linear OLS and GMM

Table 2-5 shares the same structure. In column [1], it is assumed that experience is the only way in which aging matters for productivity. In addition to schooling, the other controls in this regression are plant size, plant age, hiring and separation rates, and year dummies. In column [2], in addition, tenure is appended. In column [3], the results of the same regression as in column [2] but leaving out the plant age controls are reported. Finally, column [4] and [5] reports the results of GMM regressions, with a lagged dependent variable on the right-hand side, as well as plant age, plant size, hiring and separation rates, and year dummies as genuinely exogenous instruments. In column [4], then, worker characteristics are considered predetermined variables (hence instrumenting themselves), while they are treated as endogenous variables (and therefore instrumented by the genuinely exogenous instruments) in column [5]. So much is for those regressions having TFP as a dependent variable. The same sequence of regressions and specifications is then replicated in the rightmost part of each Table, where the log of TFP is replaced by the log of wages as a left-hand side variable. These ten columns are shown in each of the four tables.

A general remark that applies to the bulk of the TFP regressions is that age-related variables (such as potential experience and seniority) do not appear to be either important or robustly statistically significant determinants of productivity, at least in the specifications experimented in these Tables. Three only exceptions exist to this general pattern: experience is positively related to productivity in the Forest industry and negatively related to productivity in Electronics with OLS estimation, while seniority is negatively related to productivity in the industry producing Machinery and equipment with system GMM.

What accounts for the variability of plant productivity, then? Essentially, three main things (plus the period dummies): schooling, plant age and turnover rates.

Schooling is often statistically significant, but more so in the high-tech industries and notably in the electronics industry, with its point-wise estimate usually smaller and less precisely measured with GMM. This is an important result: learning that the constructed TFP variable correlates positively, therefore with the expected sign, with schooling is reassuring. And even the fact that, consistently with expectations, correlation is higher in the electronics industry than in any other industry also conforms to commonsense.

As depicted in **Figure 1**, plant age is also often a statistically significant determinant of productivity and with the negative sign. More recent plants are more productive and bigger plants are more productive, irrespective of the industry. This is important, because it signals that the endogeneity bias mentioned in the previous discussion is something to worry about.

Finally, hiring and separation rates are always statistically significant with the expected signs (negative for separation and positive for hiring rates). If turnover rates were left out, the statistical performance of age-related variable would substantially improve. This suggests that the selectivity mechanism envisaged above also plays an important role in explaining the correlation between aging and plant productivity.

It is then finally instructive to compare such results with the results obtained from wage regressions. As mentioned above, these are reported in the rightmost part of each panel. Interestingly, if one were to draw a conclusion about the relation between aging and productivity from such regressions, he or she would be driven to conclude that there is not much evidence of an anti-age bias of new technologies. In all Tables, the estimated coefficients for experience is often significant when entered alone while it stops being significant when seniority is also entered as a regressor (except for Machinery and Equipment). This is perhaps more apparently so, however, for the traditional industries, where the statistical significance holds irrespective of the estimation method, and less robust for Electronics, where significance outright disappears with GMM estimation.

Based on this initial set of estimates, there would seem to be not too much scope for asserting the existence of an anti-old-age bias of new technologies. Before jumping to such a conclusion, it is useful, however, to consider that an estimated zero coefficient may simply be the result of the omission of a relevant quadratic term. As seen below, this seems to be the case, at least for seniority in the electronics industry.

5.2 Monte Carlo simulations

Figure 2, 3, 4, 5 and **5** graphically presents the results from regressions inclusive of quadratic (and even cubic) terms in the same variables of interest used as regressors in the baseline regressions, as well as with an additional set of controls aimed at controlling for intra-plant heterogeneity, such as the standard deviations of experience, seniority and schooling. Such additional controls serve the purpose of controlling for intra-plant heterogeneity possibly averaged out in our plant-wide regressions.

Once again, each figure has the same structure. Figure 2 concerns schooling; Figure 6 concerns potential experience, while Figure 3-5 concern seniority (for a reason). Each of them depicts the effect of marginally changing a variable of interest (whose values are reported along the x-axis), while holding the values of the other variables at their sample means, onto the dependent variables, TFP and wages - both plotted in the same graph on the y-axis (TFP with a solid line and wage with a dashed line). Each figure includes four panels, one for each industry (Forest in the North-West panel; Basic metals in the North-East panel; Machinery and equipment in the South West panel; Electronics in the South-East panel).

The lines (and the confidence intervals around them) are obtained by drawing one thousand values of the OLS estimates of the main and ancillary parameters from a multivariate normal distribution and computing the implied predicted values of the dependent variable. This is a practical way (devised by King, Tomz and Wittenberg at Harvard) to present the results from a regression with many linear, quadratic and cubic terms, whose quantitative implications would otherwise be very cumbersome to read and therefore hard to gauge.

Such comprehensive experiments give sometimes outright different results from the linear baseline regressions presented above.

As visible in **Figure 2**, schooling is indeed the variable most closely connected with productivity. Except for Basic metals, in the other three industries the relation between schooling and productivity is a tight one and not too far from a linear one. Moreover, the estimated line is definitely steeper for Electronics than for the other industries. These results are quite in line with the results seen above.

Figure 3-5 indicates that the relation between seniority and productivity exhibit some non-marginal non-linearity. This is so irrespective of the inclusion of both turnover and plant age or just one of these variables, whose inclusion among the regressors seemingly proved damaging for the statistical significance of seniority in the linear regressions. Instead, particularly for Basic metals and for Electronics, an inverted-U shape is clearly visible for the marginal seniority-productivity profile in all the Figures. Table 6, moreover, allows one to investigate more precisely the quantitative implications of these Figures. In the electronics industry, the peak in the seniority-productivity profile is reached at the sixth year of work in a given company. This is long before than in Basic Metals and the Forest industry, whose peaks are respectively at the tenth and sixteenth year of work. Moreover, the decline in productivity beyond the peak seniority sets in much faster in the electronics industry than in the forest and basic metals industries (no peak can be estimated for machinery and equipment).

Taken at face value, these results imply that, over a five-year period of time, workers in electronics undergo a productivity shortfall close to minus 40%, while, for basic metals and forest workers, the decline is milder and stabilizes to an upper level of productivity than for workers in electronics.

The same pattern is not visible instead for potential experience, for which the quality of the estimates is not as good as for seniority. However, the productivity decline is very mild for the workers employed in the forest and the machinery and equipment industries, and imprecisely measured for electronics workers. Instead it seems to be particularly significant and sharp after twenty-three years of work experience for those employed in basic metals. The first part of the profile is very imprecisely measured as well, which suggests further investigation before drawing conclusions.

Finally, again in accordance with the results from baseline regressions, wages appear to follow a rather diverse path with respect to productivity. Where productivity may go eventually downwards, wages rarely do so and often go up until very late in career. This reinforces our initial presumption that studying the behavior of productivity as such would be the right thing to do, rather than inferring its behavior from wage data. It also indicates that Lazear's theory of deferred payments may be a sensible starting point to try and understand wage and productivity dynamics in the Finnish manufacturing plants.

6. Conclusions

In this paper, we have investigated the relation between aging, technology and productivity from a rather novel angle. Instead of looking at the sensitivity of earnings to worker characteristics, we constructed a productivity indicator at the plant level and checked whether it correlates with experience, seniority and schooling, in addition to a number of other firm characteristics and controls that may possibly explain why there is a relation between aging and plant productivity. Having controlled for the potential selectivity effects induced by the between-plant movement of workers by appending lagged turnover rates and for the other potential cause of a negative relation between aging and productivity by appending plant age controls, we interpret our results for a sample of Finnish firms as indicating that the "old-age bias" hypothesis deserves being taken seriously. Our data show that the productivity shortfall coming about as a result of aging may be substantial and as high as 40% over a five-year period of time. This same result would simply not be there in case wage data were used instead, as most previous studies have done.

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To be completed

Table 1: Cumulated growth of the main variables of interest

Summary statistics

	Forest	**Basic metals**	**Machinery & equipment**	**Electronics**
TFP (% points)	+27.9	+26.2	+44.5	+139.5
Wages (% points)	+28.9	+61.2	+33.9	+121.3
Experience (# of years)	+1.2	+0.9	+1.4	+1.5
Seniority (# of years)	+1.1	+0.1	+0.4	+0.5
Schooling (# of years)	+0.8	+0.3	+0.3	+0.3

Table 2 – Productivity and wages, Forest industry (NACE 20-21)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Equation features	OLS, plant controls	OLS, plant controls	OLS, plant controls	GMM, plant controls, predetermined characteristics	GMM, plant controls, endogenous characteristics	OLS, plant controls	OLS, plant controls	OLS, plant controls	GMM, plant controls, predetermined characteristics	GMM, plant controls, endogenous characteristics
Dep. Variable	TFP	TFP	TFP	TFP	TFP	Wages	Wages	Wages	Wages	Wages
Industry	Forest	Forest	Forest	Forest	Forest	Forest	Forest	Forest	Forest	Forest
Experience	-.006 (.004)	-.013 (.011)	-.014 (.011)	.013 (.013)	.007 (.016)	.033*** (.001)	-.007** (.0035)	-.0061* (.0035)	.003 (.003)	.007* (.004)
Tenure	-	.008 (.007)	.008 (.007)	-.000 (.011)	.004 (.012)	-	.029*** (.003)	.029*** (.003)	.0051* (.0029)	.002 (.003)
Schooling	.040 (.033)	.050 (.037)	.036 (.037)	.054 (.055)	.021 (.070)	.198*** (.011)	.138*** (.015)	.140*** (.016)	.046*** (.015)	.042** (.020)
Plant age	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Plant size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hiring rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Separation rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dep.	-	-	-	.40*** (.03)	.39*** (.03)	-	-	-	.73*** (.06)	.77*** (.07)
R-squared	.13	.18	.17			.49	.68	.67		
# obs.	2214	2214	2214	1840	1840	2214	2214	2214	1840	1840
P-values for:										
Hansen test over-id restr's				.37	.15				.19	.08
Arellano-Bond AR(1)				.00	.00				.00	.00
Arellano-Bond AR(2)				.32	.33				.60	.64

Table 3 – Productivity and wages, Basic metals (NACE 27)										
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Equation features	OLS, plant controls	OLS, plant controls	OLS, plant controls	GMM, plant controls, predetermined characteristics	GMM, plant controls, endogenous characteristics	OLS, plant controls	OLS, plant controls	OLS, plant controls	GMM, plant controls, predetermined characteristics	GMM, plant controls, endogenous characteristics
Dep. Variable	TFP	TFP	TFP	TFP	TFP	Wages	Wages	Wages	Wages	Wages
Industry	Basic metals	Basic metals	Basic metals	Basic metals	Basic metals	Basic metals	Basic metals	Basic metals	Basic metals	Basic metals
Experience	.010*** (.002)	-.015 (.016)	-.011 (.017)	.002 (.011)	.006 (.012)	.010*** (.002)	-.003 (.007)	-.001 (.008)	-.001 (.002)	-.002 (.002)
Tenure	-	-.018 (.014)	-.015 (.014)	-.015* (.009)	-.019* (.010)	-	.011** (.005)	012** (.006)	.0041** (.0016)	.004** (.002)
Schooling	.126*** (.014)	.008 (.076)	-.020 (.081)	.059 (.048)	.010** (.046)	.126*** (.014)	.110*** (.026)	.111*** (.028)	.036*** (.011)	.039*** (.011)
Plant age	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Plant size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hiring rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Separation rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dep.	-	-	-	.56*** (.06)	.56*** (.06)	-	-	-	.76*** (.04)	.74*** (.04)
R-squared	.56	.40	.20			.57	.65	.62		
# obs.	420	420	420	349	349	420	420	420	349	349
P-values for:										
Hansen test over-id restr’s				1.00	1.00				1.00	1.00
Arellano-Bond AR(1)				.00	.00				.00	.00
Arellano-Bond AR(2)				.47	.47				.11	.11

Table 4 – Productivity and wages, Machinery & equipment (NACE 29-31)										
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Equation features	OLS, plant controls	OLS, plant controls	OLS, plant controls	GMM, plant controls, predetermined characteristics	GMM, plant controls, endogenous characteristics	OLS, plant controls	OLS, plant controls	OLS, plant controls	GMM, plant controls, predetermined characteristics	GMM, plant controls, endogenous characteristics
Dep. Variable	TFP	TFP	TFP	TFP	TFP	Wages	Wages	Wages	Wages	Wages
Industry	Mach. equipm.	Mach. & equipm.	Mach. equipm.	Mach. & equipm.	Mach. & equipm.	Mach. equipm.	Mach. & equipm.	Mach. equipm.	Mach. & equipm.	Mach. & equipm.
Experience	.0027 (.0024)	-.004 (.003)	-.003 (.006)	-.008 (.010)	.011 (.012)	.016*** (.001)	.010*** (.002)	.011*** (.002)	.008*** (.003)	.007* (.004)
Tenure	-	.006 (.005)	.007 (.005)	-.003 (.009)	-.012 (.010)	-	.0034* (.0019)	.0033* (.0019)	-.002 (.003)	-.003 (.003)
Schooling	.120*** (.011)	.112*** (.018)	.124*** (.019)	.038 (.039)	-.015 (.041)	.135*** (.004)	.128*** (.007)	.131*** (.007)	.052*** (.010)	.044*** (.010)
Plant age	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Plant size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hiring rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Separ'n rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dep.	-	-	-	.43*** (.05)	.40*** (.05)	-	-	-	.59*** (.04)	.62*** (.05)
R-squared	.30	.33	.31			.53	.59	.58		
# obs.	2713	2713	2713	2190	2190	2713	2713	2713	2190	2190
P-values for:										
Hansen test over-id restr's				.40	.41				.26	.21
Arellano-Bond AR(1)				.00	.00				.00	.00
Arellano-Bond AR(2)				.13	.14				.62	.69

Table 5 – Productivity and wages, Electronics (NACE 32-33)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Equation features	OLS, plant controls	OLS, plant controls	OLS	GMM, plant controls, predet'd character's	GMM, plant controls, endogenous character's	OLS, plant controls	OLS, plant controls	OLS	GMM, plant controls, predetermined characteristics	GMM, plant controls, endogenous characteristics
Dep. Variable	TFP	TFP	TFP	TFP	TFP	Wages	Wages	Wages	Wages	Wages
Industry	Electronics	Electronics	Electronics	Electronics	Electronics	Electronics	Electronics	Electronics	Electronics	Electronics
Experience	-.018** (.008)	.016 (.023)	.011 (.023)	-.007 (.016)	-.006 (.019)	.015 (.010)	.005 (.005)	.007 (.005)	.006 (.006)	.0083 (.0055)
Tenure	-	-.033 (.024)	-.045* (.025)	-.010 (.023)	-.014 (.028)	-	.010** (.005)	.012** (.005)	.007 (.007)	.010 (.009)
Schooling	.164*** (.024)	.207*** (.041)	.178*** (.026)	.115*** (.043)	.114*** (.041)	.123*** (.026)	.133* (.009)	.133*** (.008)	.083*** (.018)	.087*** (.018)
Plant age	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Plant size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hiring rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Separ'n rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dep.	-	-	-	.63*** (.05)	.66*** (.05)	-	-	-	.56*** (.09)	.55*** (.10)
R-squared	.17	.24	.21			.56	.67	.67		
# obs.	809	809	809	634	634	809	809	809	634	634
P-values for:										
Hansen test over-id restr's				1.00	1.00				1.00	1.00
Arellano-Bond AR(1)				.00	.00				.00	.00
Arellano-Bond AR(2)				.78	.82				.55	.58

Figure 1: The estimated effects of plant age on TFP and wages

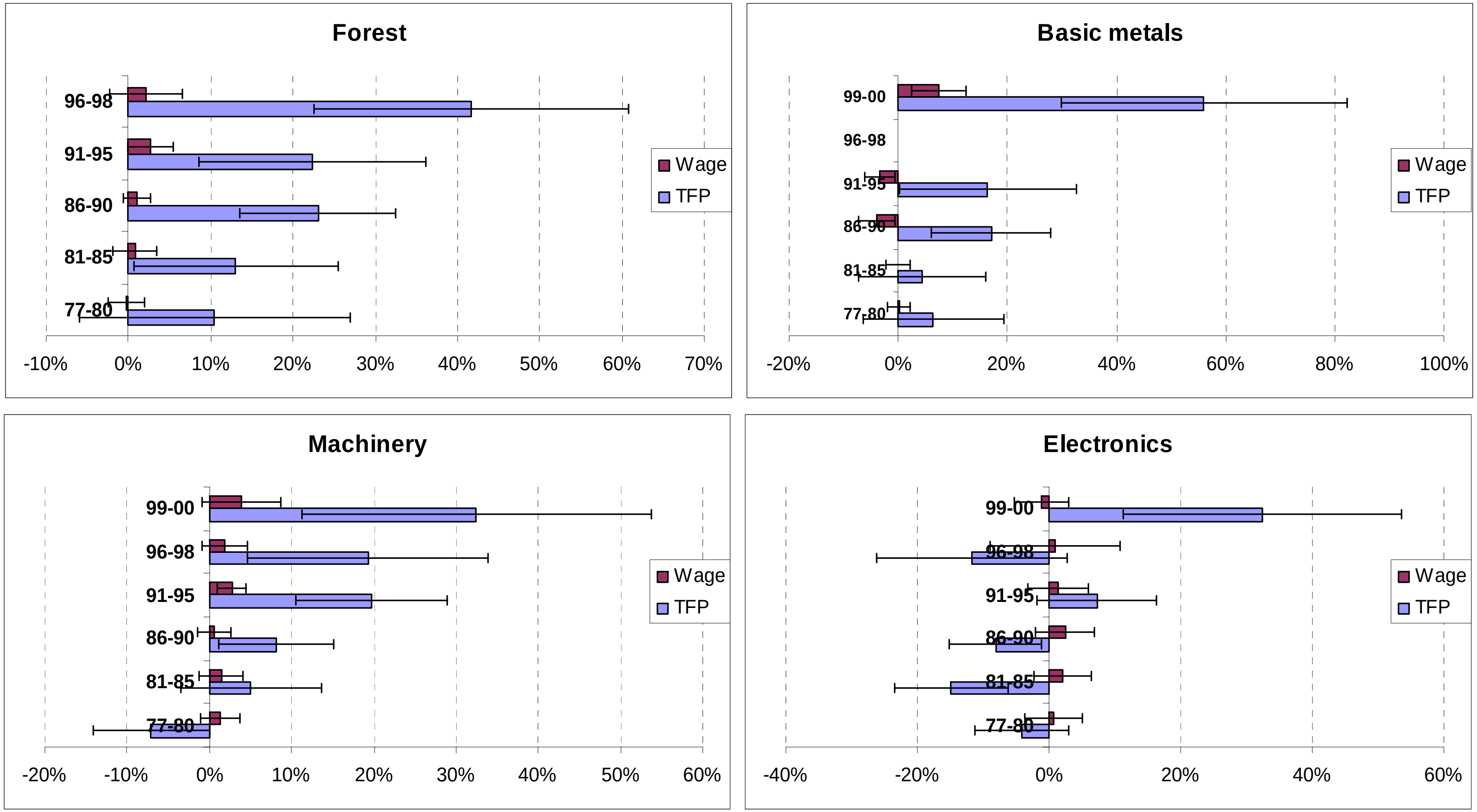

Figure 2: TFP, Wages and Schooling -- Plant age and turnover controls included

Montecarlo Simulations

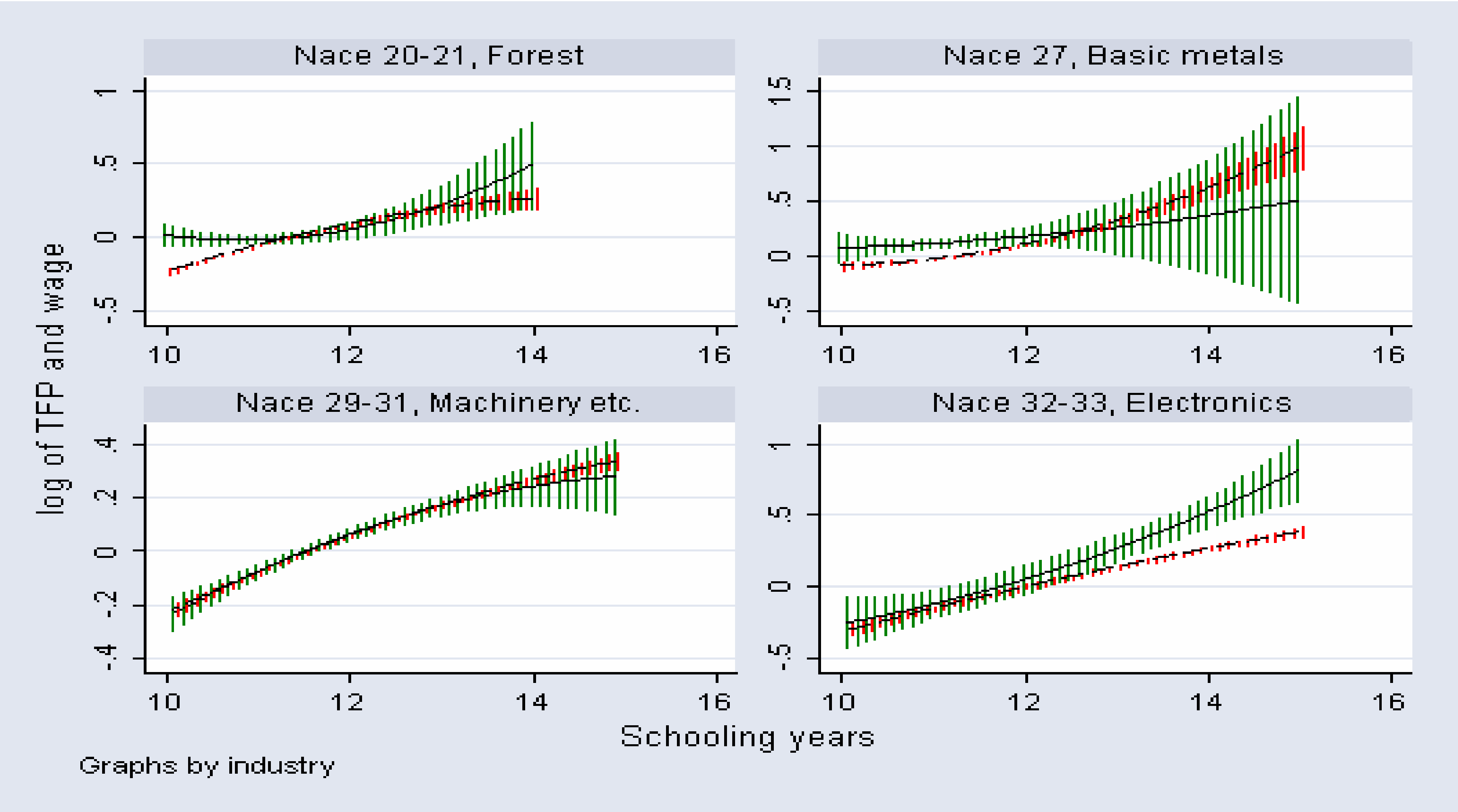

Figure 3: TFP, Wages and Seniority -- Plant age and turnover controls included

Montecarlo Simulations

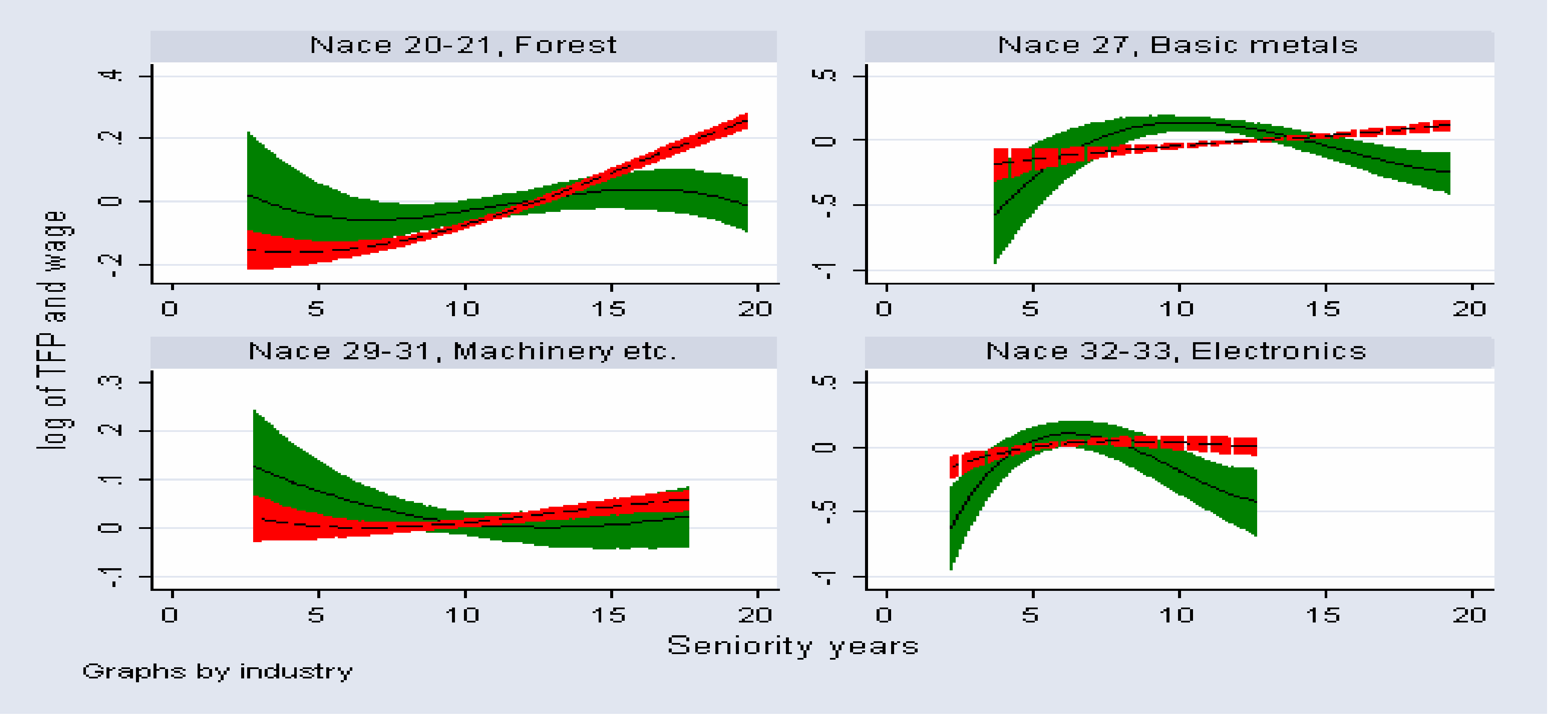

Figure 4: TFP, Wages and Seniority -- Plant age controls included

Montecarlo Simulations

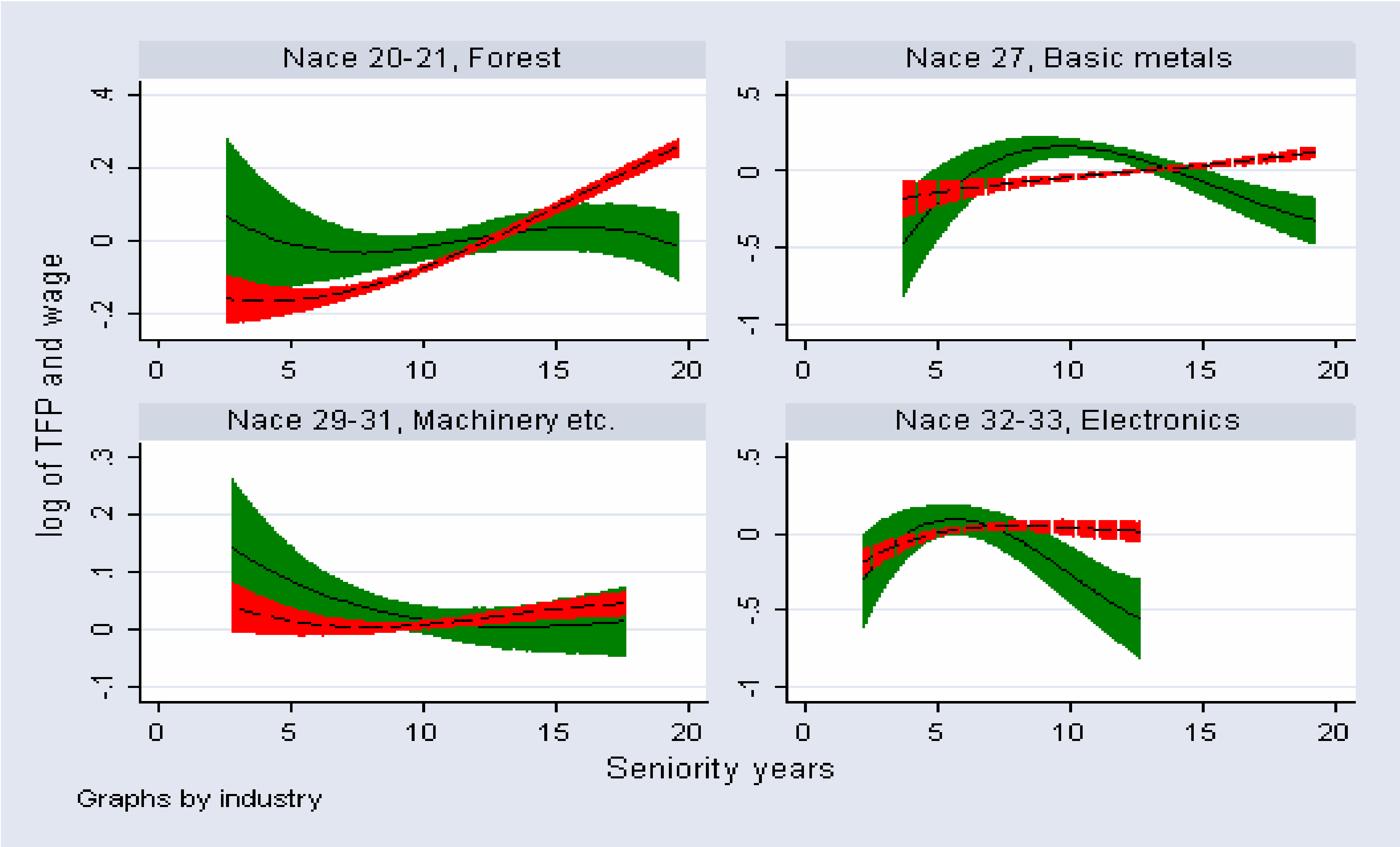

Figure 5: TFP, Wages and Seniority – Turnover rate controls included

Montecarlo Simulations

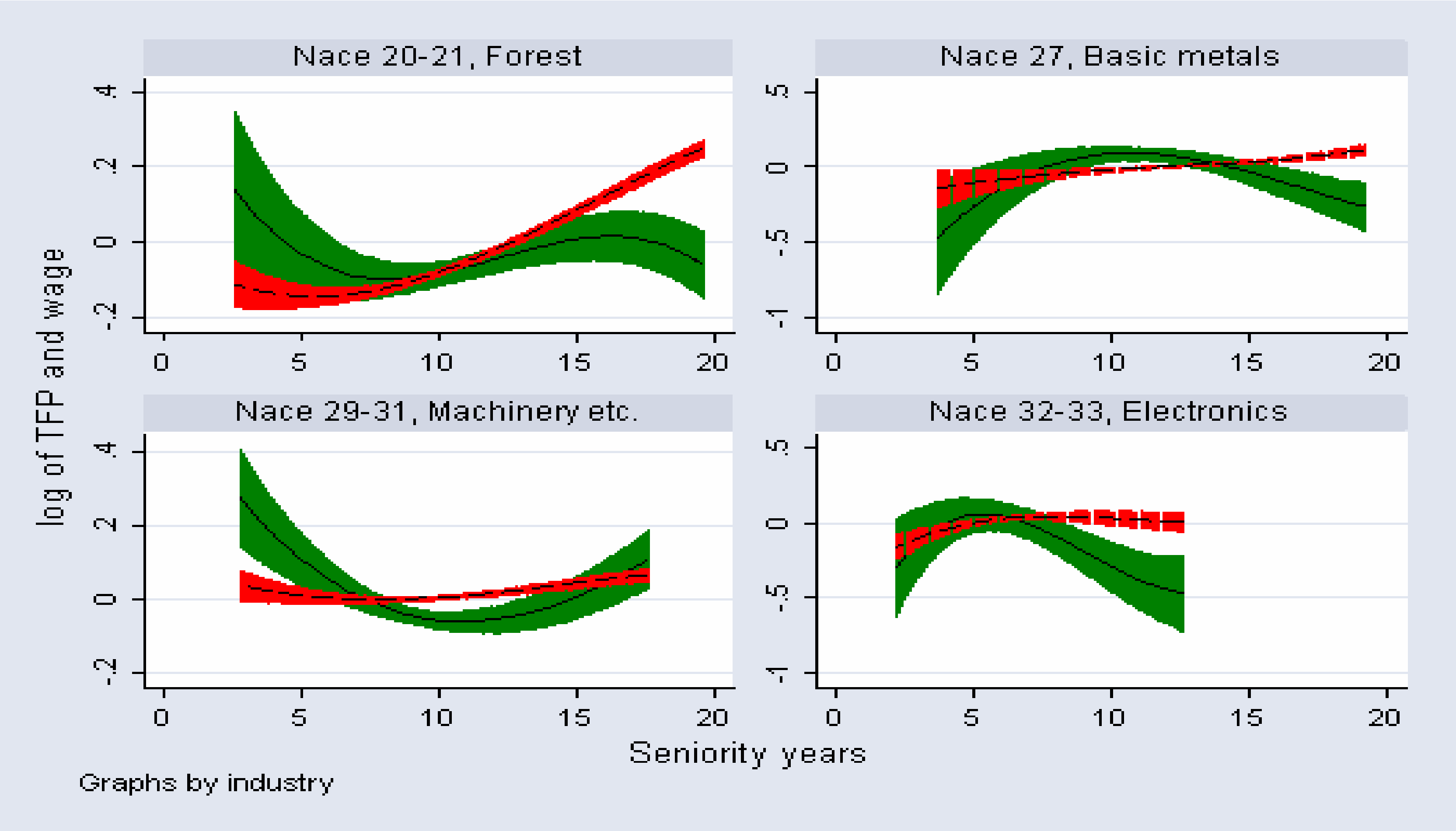

Figure 6: TFP, Wages and General Experience -- Plant age and turnover controls included
Montecarlo Simulations

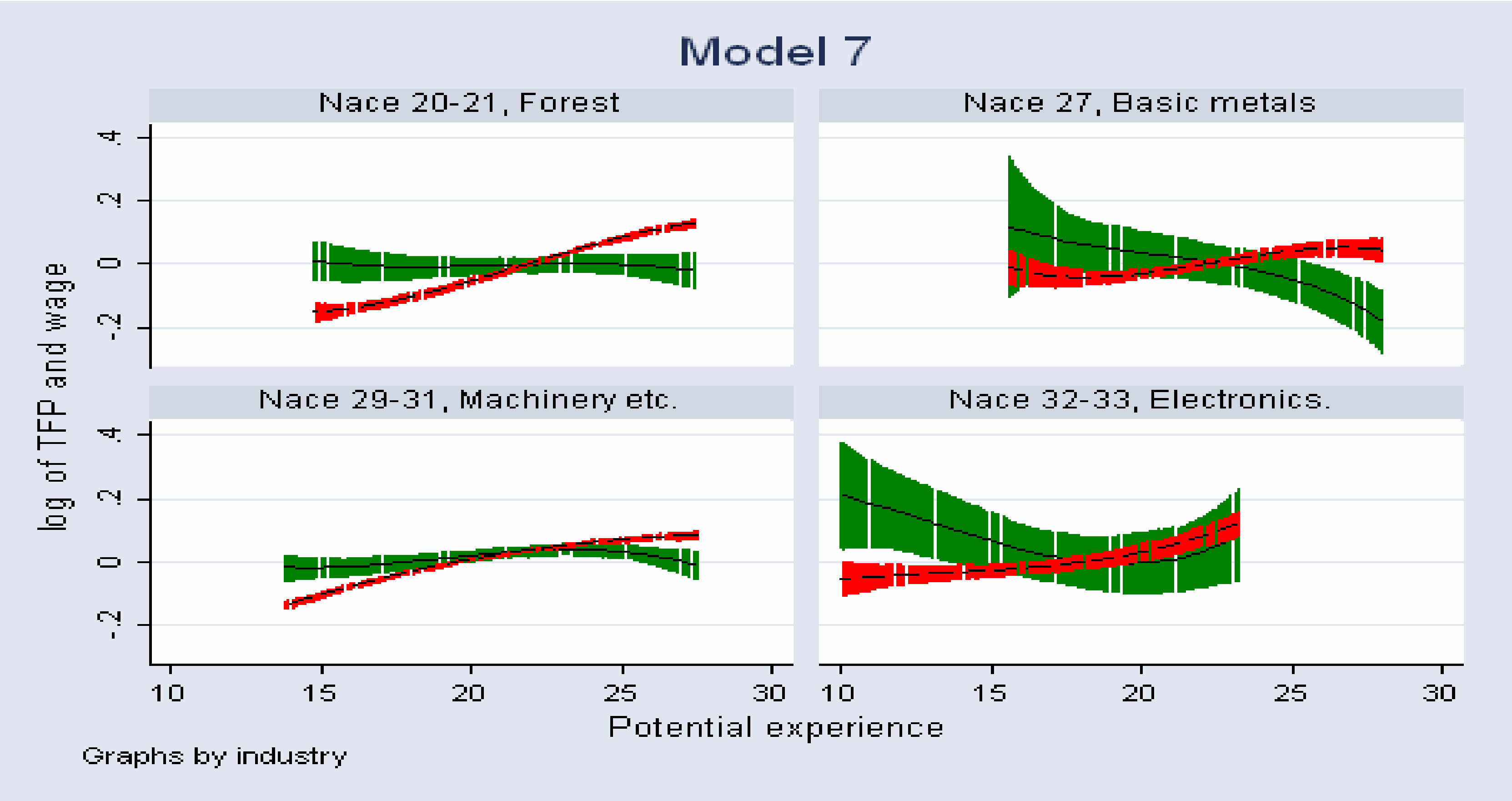

Table 6 - Numerical implications of Figure 3 (seniority and plant productivity)

		Productivity change (% points)			
		During the five years before the peak		During the five years after the peak	
Industry	**Peak in seniority-productivity profile at year**	**Mean**	**Standard error**	**Mean**	**Standard error**
Forest	16	5.2*	3.5	-10.7**	5.2
Basic Metals	10	41.8***	15.2	-18.00**	6.6
Machinery & equipment	No peak	-	-	-	-
Electronics	6	133.2***	33.7	-40.7***	12.1

Notes: Underlying data from Figure 2