Age, Technology and Labour Costs

Francesco Daveri
Università di Parma, and IGIER
francesco.daveri@unipr.it

Mika Maliranta
ETLA, Helsinki
mika.maliranta@etla.fi

This draft: March 24, 2006

Is the process of workforce aging a burden or a blessing for the firm? Our paper seeks to answer this question by providing evidence on the age-productivity and age-earnings profiles for a sample of plants in three manufacturing industries ("forest", "industrial machinery" and "electronics") in Finland. Our main result is that exposure to rapid technological and managerial changes does make a difference for plant productivity, less so for wages. In electronics, the Finnish industry undergoing a major technological and managerial shock in the 1990s, the response of productivity to age-related variables is first sizably positive and then becomes sizably negative as one looks at plants with higher average seniority and experience. This declining part of the curve is not there either for the forest industry or for industrial machinery. It is not there either for wages in electronics. These conclusions survive when a host of other plausible productivity determinants (notably, education and plant vintage) are included in the analysis. We conclude that workforce aging may be a burden for firms in high-tech industries and less so in other industries.

(*) Preliminary version of a paper prepared for the 43rd Economic Policy Panel Meeting in Vienna, April 20-21, 2006. We are grateful to Paul Seabright and two referees for their comments on a previous draft, which greatly helped us sharpen our argument and improve the focus of our paper. We are also indebted to seminar participants at the Government Institute of Economic Research (Helsinki), Bocconi (Milan), Humboldt (Berlin), Parma and to conference participants at the 5th "Economics of ICT Conference" in Mannheim, the 2005 ONS Conference on the "Analysis of Enterprise Micro-Data" in Cardiff, and, in particular, to Gilbert Cette, Pekka Ilmakunnas, Olmo Silva and Alexandra Spitz for their useful comments on previous drafts. Maliranta gratefully acknowledges financial support provided by Tekes within the Research Programme for Advanced Technology Policy (ProAct).

1. INTRODUCTION

Since the mid 1990s, the first wave of baby-boomers - the bulky generation born between 1946 and 1964 – has entered the age group of the population classified as “old workers” (those aged between 50 and 64). This marshals the completion stage of a long phase of workforce aging, initiated in the mid ‘60s, which will go hand in hand with the “greying” of the baby-boom generation for another twenty-five years or so. Then, as the baby boomers gradually leave the workforce, the process of workforce aging - though not that of population aging - will be stopped and workforce demographics will probably move to a steady state situation. By 2030, in the absence of major changes in labour force participation, we (the rich countries) will be left with a workforce with a stable structure but on average older (due to increased longevity) than in 1970.

While population aging is known to entail significant adjustment costs which urge social security and health care reform,[1] whether the process of workforce aging is a burden or a blessing for society - and for the firm in particular - is a less explored though by no means less contentious issue.

1.1 The controversy

Workforce aging may be a *blessing* for the firm. Aging, thanks to the secular improvements in health care, has the potential to raise workers’ productivity by enhancing ability and attitude to work, also increasing and lengthening labour force participation. Moreover, an older labour force is a more experienced, and therefore more productive, labour force.

At the same time, though, the studies of psychologists and medical scientists have often shown that cognitive abilities tend to deteriorate with age. While this decline is not uniform across abilities, there is little doubt that, after a certain age threshold, further advancements in age are seemingly associated to lower productivity at work. And this occurs right at the time when people have usually reached top positions in their career paths, which makes it particularly hard for firms to detach age from seniority and wages. The two things together (declining ability above an age threshold and wages higher than ever in career) concur to make an old worker a potential *burden* for the firm.

This productivity-wage race during the individual career paths and its counterpart for the company costs is affected by many interacting variables. An educated workforce may succeed postponing or outright cancelling the age-related skill deterioration, therefore making the increase in labour costs less marked. Labour market institutions associated to the presence of collective agreements also tend to make the age-linked part of the wage a particularly large fraction of workers' wages. This implies that wages may continue to go up with age irrespective of what happens to productivity, thereby preventing companies from keeping wages aligned to the declining productivity levels of the elderly. Last, technology - whose rapid diffusion may accelerate the process of individual skill obsolescence naturally occurring with age - also affects the race between earnings and productivity. Holding other things constant, fast technical change, usually embodied in new machines and methods of work, makes it more likely that older workers become a burden for the firm.

1.2 Policy relevance

The "blessing vs. burden" aspects of workforce aging are very relevant for policy-makers.

Confirming that an older labour force gives a useful contribution to the life of a company, the looming retirement of the baby-boomers generation is often seen as a significant threat for companies at risk of losing valuable knowledge management[2] and expertise.[3] And some companies have already started adapting their workplaces to their aging labour force, at times swiftly changing their hiring and firing strategies and personnel policies at large, so as to turn the "greying tide" into an advantage for the company. Near the top of the list of the best employers for its members, the AARP, an American association that monitors how firms treat older workers, puts Deere & Company, an Illinois-based industrial-equipment manufacturer, with a disproportionately high share of old workers (about 35% of its 46.000 are in their 50s or above). Deere has simply kept recruiting people who would stay with the company for their whole careers, and – as a result - a number of its employees have more than 40 years of service.[4] Similar attitudes are apparently shared by Toyota, the world's most advanced car manufacturer, and BMW, which has recently set up a factory in Leipzig that expressly set out to employ people over the age of 45.

But then, if companies are such a cosy environment for old workers, where's the policy issue? Well, the examples above are still very unusual, in America and worldwide. Available OECD data

---

[1] In the past, *Economic Policy* has devoted considerable space (and a special issue) to the discussion of population aging *per se*.

[2] As a recent survey of human-resources directors by IBM concluded: "When the baby-boomer generation retires, many companies will find out too late that a career's worth of experience has walked out the door, leaving insufficient talent to fill the void."

[3] As recently reported by *the Economist*, in the aerospace and defence industries, as much as 40% of the workforce in some companies will be eligible to retire within the next five years while, in parallel, the number of engineering graduates in developed countries is in steep decline.

[4] This has been carried out through means such as flexible working and telecommuting but also spending money on the ergonomics of its factories – all factors that also incidentally help older workers extend their working lives.

indeed show that older workers typically fare worse than younger workers in the labour market. Although their unemployment rates are not much different from those of younger age groups, this is often simply the result of their lower labour market participation. Labour market transition data also indicate that they are less likely to be hired and less likely to re-enter the labour market when they happen to lose a job. Not by chance, only few of the almost 1000 global companies questioned by Deloitte in 2005 - while expecting a shortage of salaried staff over the following three to five years - is looking to older workers to fill that shortage.

All in all, the obstacles for the elderly to stay over in the labour market are many, which makes workforce aging a clearly relevant policy issue. Some of these obstacles have seemingly become particularly relevant in the last few years. The rapid diffusion of outright new and "globalised" methods of production and work in those countries and industries most heavily affected by the IT revolution have probably contributed to the skill deterioration of older workers and hence to the worsening of their labour market position. This is the slice of the problem we will take up in this paper.

1.3 Our contribution

Our paper seeks to illuminate the debate on the implications of workforce aging for companies by providing evidence on the age-productivity and age-earnings profiles for a sample of plants in three manufacturing industries ("forest", "industrial machinery" and "electronics") in Finland.

We implemented our empirical exercise by analyzing aging-productivity and aging-earnings profiles at the plant level. 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 does Finland provide the scope but also the means for properly analyzing such issues as the relation between seniority, market experience and plant productivity. Accordingly, the three industries have been picked so as to include the most traditional Finnish industry one can think of (the forest industry) 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 two industries), one of which technologically dissimilar and another not too dissimilar from electronics. Insofar the use of ICT technologies will spread to other industries in the years to come, it can also be expected that the productivity pattern seen in the Electronics industry today will emerge in other industries later. So, the findings for Electronics may be seen as foretelling developments in the Finnish economy – and possibly other economies - more broadly.

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 an index of total factor productivity (TFP).

Then we analyzed the statistical relation between the computed productivity index and age and age-related variables (seniority, potential experience) – our main object of analysis. In doing so, we also look at the correlation between productivity and wages, on the one hand, and an array of their other determinants to account for their remaining plant heterogeneity of productivity and wages through a variety of specifications and estimation methods. Some of these determinants – workers' education, vintage, foreign ownership, size of the plant - are observed; some others are not, but there are statistical methods to implicitly account for their effect.

Altogether, our statistical analysis provides a reasonably coherent picture of the empirical relation between age-related variables, plant productivity and wages in Finland in the years of the IT revolution.

Preliminarily, we find that age as such is not the right variable to look at when thinking about the determinants of plant productivity. Distinguishing between seniority and general experience is important in this respect.

Our main result, though, is that exposure to rapid technological and managerial changes makes a difference for plant productivity and wages. While productivity and wage responses to age-related variables are not too dissimilar in industries not undergoing major shocks, things are different for the electronics industry. In electronics, the response of productivity to age-related variable (seniority, in particular) is first sizably positive and then becomes sizably negative as one looks at plants with higher average seniority and experience. This declining part of the curve is not there either for the forest industry or for industrial machinery. These effects are most precisely measured along the cross-sectional dimension. Similar, though less precisely determined, conclusions hold, though, when one looks at the time variation of plant productivity. These conclusions survive when other plausible productivity determinants are included in the analysis, the most important of which are education (particularly strongly related to productivity in electronics) and plant vintage. As to plant wages, their response to age-related variables in electronics is similar to the one observed for the other industries – a likely symptom of the prevailing Finnish wage bargaining institutions which tend to make seniority an important element in wage determination.

These latter findings indicate that, in high tech-industries (the most dynamic industries of the economy), the productivity advances of experience are exhausted sooner than can be inferred from wages. This is the most apparent indication of the main message of our paper that we can bring to bear: workforce aging is likely to constitute a burden in high-tech firms and industries and less so in other industries.

1.4 Organization of the paper

The paper's structure is as follows. In Section 2, we describe the main stylized facts and trends on workforce aging and the firm. In section 3, we discuss the main ideas to structure our thinking about the relation between aging, productivity and wages. In Section 4, our empirical strategy and results, in their various facets, are presented and discussed. Section 5 concludes. The paper also includes a Data Appendix, where a description of our data set and the main summary statistics are presented, together with additional tables that complete the results in the main text.

2. WORKFORCE AGING AND THE LABOUR MARKET: MAIN TRENDS AND FACTS

2.1 Workforce aging: basic trends

All OECD countries are in the midst of a process of population aging. As a result of the increase in longevity, life expectancy at birth has gone up from 64 to 77 years in the fifty years between 1950 and 2000, with a further projected increase to 83.5 in 2050. Over the same period of time, as a result of declining births, fertility rates have gone down from 3.2 in 1950 to 1.8 in 2000, with a projected rough constancy for 2050 (see OECD, 2006). These trends may well imply a rough doubling of the share of OECD population aged 65 and over by 2050. For many countries, this increase will be concentrated in the last three decades to 2050 (so after 2020), as the baby-boom generation moves above the 65+ age group.[5]

In parallel with population at large, the workforce is also aging. As recently reported by *The Economist*, within the EU, the number of workers aged between 50 and 64 is projected to increase by 25% over the next two decades, while those aged 20-29 will decrease by 20%. This is due to the influence of the baby-boom on demographics. Even in the United States the number of workers aged 55-64 will have increased by more than half in this decade, at the same time as the 35-to-44-year-olds will decline by 10%.

[5] Why this may be a burden to society is witnessed by the sharp rise in the ratio of the inactive population aged 50 and over per each member of the labour force. At unchanged participation rates, this ratio is projected to almost double from 0.38 in 2000 to over 0.70 in 2050. In the EU25, this ratio is projected to be even more unfavourable, with almost one retiree per worker, this being partly the result of lower labour force participation ratios. These trends are predicted to pose increasing strain on public finances, given their adverse implications for the sustainability of pension schemes, health care and other expenditure programmes tied to old age dependency.

Underlying these projected net changes in the size of the labour force, there will be – much larger - gross flows of workers entering and leaving the labour force. Therefore employers will face even greater adjustments to their workforce than is indicated by the projected declines in overall labour force growth. Once the baby-boom generation approaches retirement age, increasingly large cohort of workers will be retiring relative to the number of new labour market entrants available to replace them. Assuming unchanged participation behaviour by age and gender across the OECD as a whole, the number of labour market exits among older people (aged 50 and over) could rise from around 8.5 million per year during 2000-05 to around 12 million per year during 2025-30. Over the same period, the annual number of new labour market entrants (younger than 30) could decline from around 12.9 to 11.9 million. For the EU25, the number of retirees projected to exceed the number of younger entrants by the year 2015 and by almost one million persons annually around the year 2030.

These imbalances could result in large adjustment costs for employers in terms of managing an increased number of workers retiring while trying to recruit from a shrinking pool of labour. It could lead to labour shortages in certain areas, especially in the provision of health care and long-term care. In between, however, it will also entail a definite, though gradual, increase of the average age of the workers.

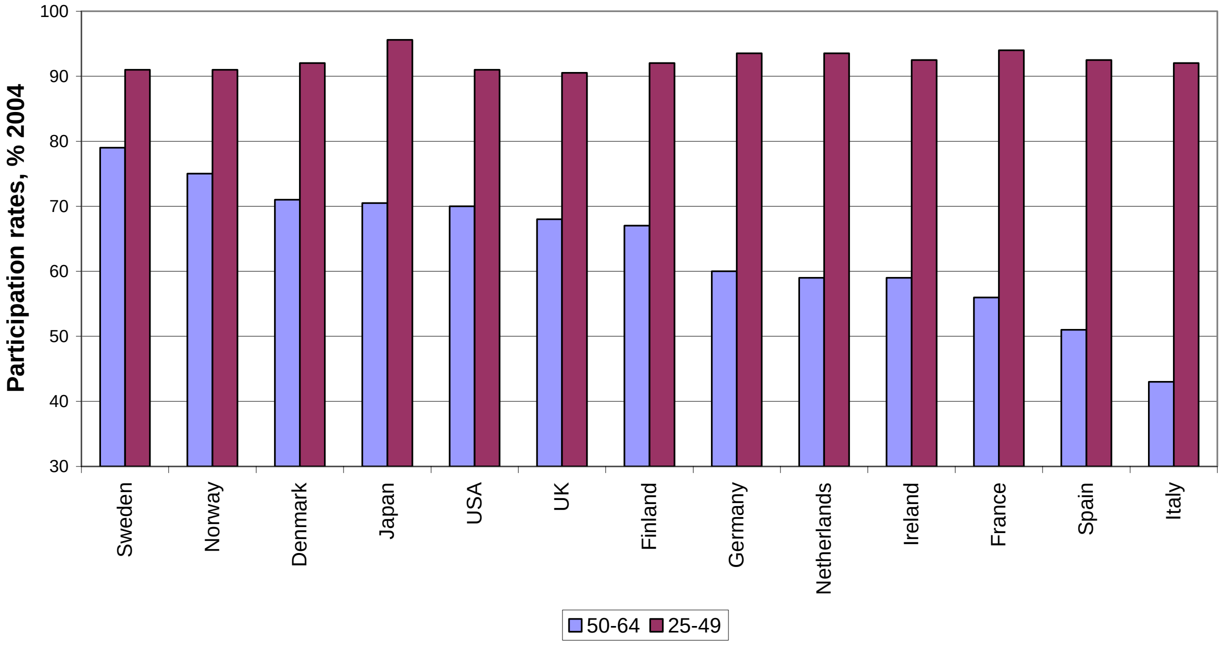
2.2 How older workers fare in the labour market

The aging of the workforce is socially relevant phenomenon for older workers do not fare as brilliantly as younger age groups in the labour market. This may be seen along various dimensions. [6]

Figure 1 shows that, in the rich OECD countries, older workers (those in the 50-64 age group) tend to participate much less in the labour market than the workers in the 25-49 age group. While labour market participation (the ratio between the labour force and the total population in working age) was between 90% and 95% in all OECD countries in 2004, the variability of the same ratio was instead substantial for older workers (from a high of some 80% in Sweden to a low of about 45% in Italy).

[6] In this sub-section we heavily draw on OECD (2006), an invaluable source of information for our purposes.

Figure 1 - Older workers participate less in the labour market than prime-aged workers



As indicated in Table 1, labour force participation among older people (50-64) in the OECD has gone up in the last ten years or so, substantially reversing the declining trend started some time in the 1970s. But this reflects two opposite trends: the declining trend between 1970 and 1994 used to reflect the prevailing trends towards early retirement, which mostly hit older male workers. The subsequent reversal in participation rates between 1994 and 2004 is instead largely driven by the increased labour market participation of older females, which in turn closely mirrors the secular trends towards overall higher female participation. If female data are taken out of the picture, the declining tendency of males to participate less in the labour market has only partially been reversed. Not by chance, OECD data indeed indicate that the effective age of retirement (the average effective age, at which older workers retire from the labour force) is still often well below the official age for receiving a full-age pension in most countries in Continental Europe and Finland. This is instead not the case in Japan, the US and the Scandinavian countries.

Table 1: Long run trends in labour force participation of the old workers

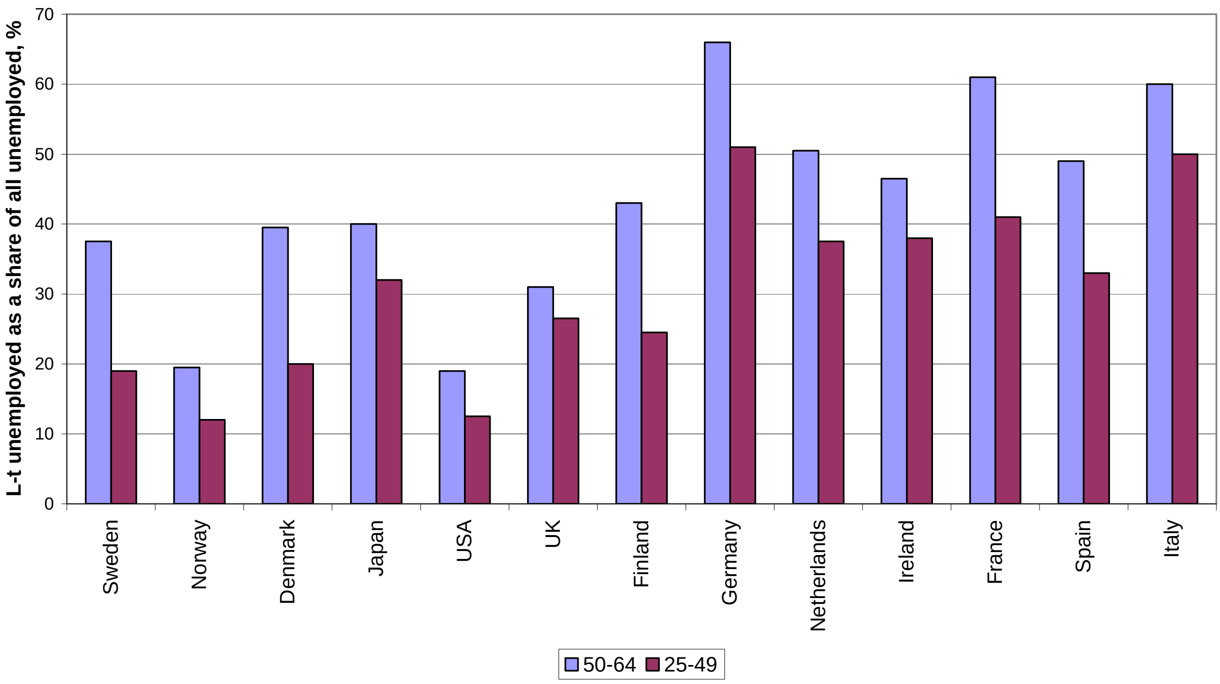
	Swe	Nor	Den	Jap	USA	UK	Fin	Ger	Net	Ire	Fra	Spa	Ita
1970	70.0	63.0	62.0	69.0	68.0	69.0	59.0	52.0	49.0	58.5	59.0	51.0	43.0
1994	76.5	71.0	64.5	71.0	65.8	63.8	57.9	55.0	44.0	50.0	46.0	42.6	39.0
2004	79.0	75.0	71.0	70.5	70.0	68.0	67.0	60.0	59.0	59.0	56.0	51.0	43.0

Notes: Labour participation is defined as the ratio between labour force and working age population.
This table shows that labour participation declined between 1970 and 1994 and then rose in 1994-2004 for most European countries.
Source: own calculations from OECD (2006)

Similar trends show up when considering the employment situation of older workers, *i.e.* the share of the old workers actually employed divided by the working age population. Irrespective of the specific employment rate considered (one might use the headcounts-based or the one corrected for the average number of hours worked to adjust it to a full-time-equivalent basis), the so called "intensive" dimension of labour market participation reveals the same thing: older workers are less frequently employed than prim-aged workers.

The close correlation between participation and employment rates has a partially less unpleasant counterpart: in most OECD countries, if anything, older people generally face lower unemployment rates than younger people. If unemployed, though, they are often long-term unemployed (see Figure 2). And if left on the dole, they simply leave the battlefield (leave the labour force) rather than strolling around unemployed in search of a better opportunity. This also applies to countries with higher employment rates such as Sweden, Norway and Denmark, as well as – more mildly - in the US and Japan.

Figure 2 - When unemployed, the older remain longer on the dole



The relatively low unemployment rates of the old cannot be interpreted as implying a lower risk of job loss on the part of older workers vis-à-vis younger workers, but simply that, when losing their job, older workers are more likely to drop out of the labour market altogether. Likewise, a relatively high incidence of long-term unemployment may be the result of barriers to entry (or re-entry) as well as weaker incentives to look for a job when the eligibility requirements for benefits are less stringent for the older unemployed.

Very similar indications also show up from the OECD data on labour market transitions. Five additional main facts emerge:

(i) the hiring rate of older workers is much lower (between one third and one half) than for younger workers

(ii) job-to-job shifts account for the bulk (between one half and two thirds) of all hires of older workers

(iii) very few of the older unemployed find a job (with the exceptions of the UK and Norway) and very few of those who left the labour force come back to work (no exceptions in the OECD countries)

(iv) older workers are more likely to quit their jobs than younger workers, while the risk of job loss is not significantly different

(v) once they stop working, only a minority of them moves into unemployment, while more than half retire early and a significant proportion does not work because of reported disability; for women, family and other personal reasons are crucially important

Altogether, there is plenty of evidence that aging is typically associated to a weakening of the individual labour market situation.

2.3 Workforce aging and the Finnish IT revolution in the 1990s: basic trends and facts

As documented above, Finland is an interesting case in point when it comes to the labour market situation of old workers.

Nowadays, old workers in Finland are somehow in between workers of the same age group in other Nordic countries and those in Continental Europe. They tend to achieve lower labour market participation and employment rates, and suffer from higher unemployment rates than workers in the same age group in other Nordic countries (Denmark, Norway, Sweden, and Iceland). At the same time, if one compares Finland to countries in Continental Europe, one comes to opposite conclusions: higher participation and employment and lower unemployment for the older workers. These relatively disappointing labour market outcomes compared to the other Nordic countries may be for many reasons, one of which is the difficulty for older workers to re-enter the labour market after the big recession of early 1990s.

For the purpose of this paper, however, another big shock of opposite sign that hit the Finnish economy in the 1990s plays a more important role than the recession of the early 1990s: the incredibly fast restructuring of the economy away from traditional industries into the production of cellular phones. This is perhaps the most popular world manifestation of the IT revolution in a small country.

The boom in the world demand for cellular phones, fed by the worldwide trend of declining prices labelled Moore's law and by Nokia's ability to gain a leadership position in the world market, has driven markedly up the share of the electronics industry 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.[7]

Such sizable figures imply 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. In parallel - 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 "Industrial machinery and equipment" (NACE 29-31) slightly fell from 5.7% in 1995 to 5.4% in 2000 and then to 5% in 2003.

The Nokia-driven shock has been unique in an international landscape. As reported in Table 2, the share of IT goods production over total manufacturing went up by 13.4 percentage points in Finland between 1995 and 2001. This is remarkable because the potential beneficial effects of Moore's law were out there for everybody. The other OECD countries, however, have seemingly not taken this opportunity (or have exploited it differently, on the IT services side). In the same OECD report, Canada and Mexico come next with increases in the IT manufacturing share of 3 percentage points and then Ireland, Korea, Japan and the US with increases of about 2 percentage points. The rest of the OECD countries showed more modest changes, below half a percentage point or even negative.

Table 2 – The exceptional increase in the share of IT manufacturing goods in total manufacturing in Finland in the second half of the 1990s (1995-01, % points)

Swe	Nor	Den	Jap	USA	UK	Fin	Ger	Net	Ire	Fra	Spa	Ita
-1.4	+.4	+.1	+2.0	+2.0	+.6	***+13.4***	+1.0	-.3	+2.3	+.8	-.4	-.8

Source: OECD (see 2003)

[7] This increase was also the result of the rapid development of a myriad of ancillary manufacturing and high-tech consultancy activities around Nokia. As reported by Ali-Yrkko, Paija, Reilly and Yla-Anttila (2000), about 4000 firms (mostly small and medium-sized) and 200 electronics manufacturing services companies make up the so-called "IT cluster". About 350 of them are first-tier suppliers to Nokia. Some others provide such electronic manufacturing services as component sourcing, equipment renting, production design and testing, and thus bridge the gap between equipment manufacturers and component suppliers. The input-output evidence supplied by Daveri and Silva (2004) is suggestive that, however, no major inter-industry links between electronics and the production of other machinery and equipment outside the IT cluster was present in the Finnish economy. Nokia is, really, a big company in a small country.

In a nutshell, no doubt, the intensity of the technological shock hitting Finland was incomparable to the entity of the technological shocks simultaneously hitting other European and Nordic countries. This is why we think that the plant data from different Finnish industries in the second half of the 1990s may be an appropriate testing ground for investigating in detail whether workforce aging is good or bad for companies and their plants.

Our main question for investigation will thus be whether, given the recognized weakness in the labour market position of older workers (and the observed declining trends in labour market participation of old males) in Finland, evidence can be brought about that the older workers actually faced a worsening of their labour market situation as a result of the Nokia-driven shock.

3. AGE, PRODUCTIVITY AND WAGES: EMPIRICAL PREDICTIONS

In the previous section, we learned that that workforce aging is a fact that all OECD countries will confront for many years to come. In parallel, the available evidence indicates that older workers tend to confront an unfavourable labour market situation compared to other age groups.

This is for many reasons. On the employer side, in addition to the employers' negative perceptions about the adaptability and productivity of older workers[8] and to strict employment protection legislation that often raises labour costs in a lumpy fashion, the labour market outcomes of the older workers may be undermined in case aging of the workforce affects the marginal benefits and costs of labour for the company, *i.e.* when aging drives a negative wedge between the worker's productivity and its wage. This raises the question of which relation between aging, productivity and wages one expects to see in the data.

3.1 Age, productivity and wages: theories

The obvious starting point here is a well-known tenet of the human capital model (1962, p.119): an older labour force is a more experienced and therefore more productive labour force for two reasons. First, aging often brings about higher worker seniority within a given firm. As long as

[8] The various country reviews undertaken within the series on *Ageing and Employment Policies* by the OECD indeed reveal that employers hold rather stereotypical views about the labour market strengths and weaknesses of older workers. This also holds in those countries where the employment rates of the elderly are high. In a 2001 survey conducted in Sweden, 50% of all employers reportedly considered older workers to be endowed with less relevant skills than younger workers and to be more rigid and inflexible with respect to changes in the workplace. In the US, a survey conducted in 1998 revealed that, although older workers were deemed more loyal and committed than younger workers, they were also seen as less flexible less willing to participate in training and less likely to have up-to-date skills. Very similar results to those found in Sweden and the US are reported in the other Review countries, with the notable exception of Denmark.

some on-the-job training is undertaken at an early stage in career, higher seniority should be associated to higher worker's productivity and, eventually, higher wages. The extent to which higher productivity results in higher wages depends on whether training is of a general or a firm-specific type. If training is general, the worker will fully appropriate the productivity 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. In other words, models of firm-specific human capital imply that, early on in career, wage exceeds marginal productivity, but the productivity profile is steeper than the wage profile so that later on in career productivity eventually exceeds wage.[9]

Second, aging is also typically associated to the acquisition of generic experience in the labour 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 market wages. Hence, aging affects productivity both through seniority and general experience, the effects of each of which may not coincide empirically.

This is not all, however. The returns from experience alone (without further educational or training inputs) do not stay constant with age. As also widely accepted by medical scientists, (see Skirbekk, 2003), cognitive abilities tend to deteriorate with age. As further discussed in Box 1, common wisdom based on psychometric analysis says that, after a certain age threshold, growing older is seemingly associated to lower, not higher, productivity.

BOX 1: Age and individual 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). Kanazawa (2003) shows that age-genius curve of scientists bends down around between 20 and 30 years. Similar curves are also found for jazz musicians, painters and authors. Given that the decline seems to apply mainly to married men, Kanazawa ventures the idea that changed levels of testosterone provide the psychological micro-foundation for this productivity decline.

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

[9] As discussed by Acemoglu and Pischke (1999b; 1999a) another relevant aspect determining the degree of shifting of productivity developments onto wages is the structure of labour markets.

in life. 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. 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. That study also provided evidence that the use of ICT has a stronger positive effect on productivity in younger organisations.

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. Previous studies have concluded that such programs can stabilize or even reverse age-specific declines in inductive reasoning and spatial orientation among many individuals and that exercising speed, reasoning and memory abilities enhances the functional level of those who undergo training relative to those who do not.

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

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 also possibly been the case in 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 these rapid changes had an impact, one would expect to observe an age-productivity profile with an earlier turnaround point and/or a steeper decline in high-tech industries (such as those today 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.

To sum up, based on the theory of human capital, individual age-productivity profiles are expected to be concave and possibly non-monotonic, with an upward sloping part possibly changing its slope into negative beyond a certain threshold.

A major problem in the research on the connections between age and productivity at the micro level has been the difficulty of measuring the marginal productivity of individuals, although their earnings can be measured with reasonable precision (see Box 2).

Box 2: Measures of individual productivity

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. Bosses are often senior workers and many older workers have been familiar to them from a distant past. This may be positively reflected in the wage levels of older workers.

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 in this paper, 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. How to deal with these issues is discussed in the main text.

One way out is to use data on wages. If wages were directly related to productivity, the age-earnings profile would also measure the productivity profile. Indeed, as reported by the OECD (2006, p.66), earnings profiles are often hump-shaped, especially for men, which may result from the value of individual productivity declining with age.

Yet age-earnings profiles do not always follow the path implied by age-productivity profiles. The same available OECD evidence also shows that seniority-based wages are commonplace in many countries. Explicit or implicit seniority-based rules lead earnings to rise even more steeply with age than early on in career in Austria, France, Japan, South Korea, Luxembourg, and Switzerland. In Finland and the US, the non-wage components of labour costs (for health insurance purposes) rise steeply with age.

Altogether, earnings appear to continue to grow well beyond the moment when the age-productivity profile would be predicted to flatten or change its sign into negative: human capital theory does not correctly predict the outcome of the wage-productivity race.

This raises the question of why firms accept to pay above-productivity wages. One possibility (see Lazear (1981)) is that firms must motivate workers whose performance is hard to monitor to exert their work effort until late in career. Related to this, the institution of mandatory retirement would be an effective and cheap way to put older workers out of the labour force and resolve the potential un-sustainability of such a pay system. The seniority-based wage systems observed in

Korea and Japan are broadly consistent with this model. A complementary possibility – plausibly more relevant for European countries - is the presence of collective agreements or social norms that often make seniority a firmly embedded feature of the wage setting process.

In turn, other models imply upward sloping seniority-wage profiles in the absence of productivity effects. Search models also lead to the result that high wages and older age are associated with more time spent in the labour market and higher chances of finding a good match (Manning, 2000). In the extreme, there are only search effects on wage without any genuine productivity-based experience effects. The search argument implies that when age is controlled for, firm-specific seniority has little impact on wage. But a positive effect of tenure on wage may also be related to the bargaining power of insiders, who can appropriate steady wage increases not directly related to productivity, especially in high wage industries.

3.2 Age, productivity and wages: theoretical predictions to contrast with the data

In the end, we plan to contrast the different predictions of the various models asking our Finnish data set three main questions on the relation between workforce aging and labour costs

1) Is age related to productivity and wages at all?
2) Is the seniority effect of age on productivity and wages different from the effect of age through the general experience channel?
3) Are the effects of age on productivity and wages significantly different across industries, and in particular between industries subject to fast technical change and the other industries?

4. AGE, PRODUCTIVITY ANS WAGES: THE EVIDENCE FROM FINNISH PLANTS

4.1 Empirical strategy

To learn about the relation between aging and productivity, one would ideally estimate regressions where individual productivity is related to individual, firm and other "environmental" characteristics. Yet, as discussed above in Box 2, individual productivity is typically unobserved.

Given the unavailability of individual productivity measures, a possible way to approach this issue is to study whether theories concerning the relation between age and productivity for the individual workers hold for worker averages at the plant level. In this vein, register-based data sets that match information on individual employees and their employers provide a way of measuring and comparing the wage and productivity profiles of the workers.

We use data from a data set made available by Statistics Finland (described at length in the Data Appendix) for a sample of Finnish manufacturing plants from three industries ("forest", "industrial machinery" and "electronics"). The three industries have been selected - as discussed in section 2 - for being representative, respectively, of an "average" pre-technological-boom manufacturing industry ("forest"), of a non-booming capital-intensive industry ("industrial machinery") and a booming high-tech industry ("electronics"). One such industry (forest) is a traditional Finnish industry, 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) 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 2002 - our period of analysis.

Hence, in our empirical analysis we exploit three industry panels along the cross-plant and time series dimensions. As reported in the summary statistics in Table A2., we have data for 365 plants for the forest industry, 567 plants for "industrial machinery and equipment" and 172 plants for "electronics". For each of these plants, we have a maximum of eight observations (concerning the years 1995-2002). The unbalanced nature of our panel is such that, when using the variation of the data over time, we are able to employ at most respectively 1523, 1717 and 496 observations (hence about 52%, 38% and 36% of the total potential observations). A fraction of these missing observations is due to plant "death" in 1996-2002, which represents about 12% of the forest industry, 20% of machinery and 22% of electronics.

To evaluate the relation between aging and plant productivity, we first relate the plant productivity index (computed as indicated in Box 3) to our main variables of interest: age, potential experience and seniority of the workforce, and to a number of other relevant variables whose statistical significance is of secondary importance for our main purpose in this paper.

Box 3: Two methods to calculate age-productivity profiles at the plant level

Hellerstein and Neumark (1995), Hellerstein, Neumark and Troske (1999), Hægeland and Klette (1999) and Ilmakunnas, Maliranta and Vainiomaki (2005) have used information on the shares of workers in different groups (such as to education, age and the like) to model the quality of the labour input of a plant in a production function estimated from plant level data. By directly estimating this production function jointly with an equation for average wage, they were able to quantify and compare the productivity and wage profiles.

At least with our Finnish data set (but this is known to be a more general problem), this method often tends to produce implausibly low estimates for the capital input coefficients, which may bias the estimated coefficients for age-productivity profiles. Thus, following Griliches and Rinstad (1971) and, more recently, Ilmakunnas and Maliranta (2004, p.16), we take a two-step procedure.

First, we numerically compute a TFP (total factor productivity) index - an index of disembodied technical knowledge under constant returns to scale and perfect competition in factor markets, from the standard growth accounting formula in natural logarithms:

$$Ln(TFP)_{pit}=ln(Y/L)_{pit}-(1-\bar{a}_i)*ln(K/L)_{pit}$$

With $\bar{a}_i$ denoting the average industry specific labour share during the period. The average is calculated from the annual labour shares in the industry that first are smoothed by a nonlinear filter. Thus we allow the output elasticity of capital and labour to vary between different industries. While constructed in this manner, our TFP index is suitable both for using cross-sectional and time dimension of our data.

In the second step of our empirical analysis, we relate the computed TFP index to the plant characteristics indicated in the main text. In the end, our two-step specification, partly based on growth accounting techniques, comes at the cost of accepting the - possibly plausible but essentially untested – constant returns to scale and perfect competition assumptions mentioned above. Maliranta (1997) found that the assumption of constant returns to scale in the Finnish manufacturing sector is approximately correct. For further robustness checks, see Box 7 where the result sensitivity to alternative values for the value added shares is discussed.

To test whether age is important as such or if instead the productivity-wage implications of aging within the firm are different from those of aging outside the firm (as predicted by the theories discussed in the previous section), we will also check whether the effects of seniority and general experience are different from each other. Moreover, to understand whether the intuition underlying human capital theories is borne by the data, we will check whether aging has a declining effect on productivity and wages for older people and whether all these effects are different between productivity and wages.

In addition to that, the cross-industry variation in our data gives us the possibility of testing whether the industry (and, more ambitiously, the technological content of industrial production) makes a difference for age-productivity profiles. If new technologies significantly affect the wage-productivity race, we expect to find an industry-specific patterns of partial correlation, with differences showing up in particular between electronics and the other industries.

Finally, productivity and wages do not depend on age-related variables only, but also on education, measured as the number of years of schooling, as well as a few additional other observed and unobserved factors varying across plants but more or less constant over time (such as plant size, foreign ownership and outright time-invariant plant vintage, discussed right below), as well as those factors varying over time but equally for all plants (such as unobserved year-specific effects).[10] Hence, the influence of all these variables together with the effects of aging is jointly tested in our statistical analysis. In each table, notes report the list of the explanatory variables employed in the different specifications.

[10] Such period effects are appended to the list of the explanatory variables when the time variation of the data is considered, and not when cross-sectional plant data are used.

4.2 Statistical tools

A second methodological issue concerns the statistical tools we employ to derive conclusions from the empirical evidence we bring to bear.

If the theoretical predictions of the various models were to imply that the effect of age on productivity is always the same irrespective of individual age, one might easily compute the effect of aging on productivity. The estimated coefficient would tell us by how many percentage points productivity varies as a result of a unit change in the age of a given person (or the average age of a typical worker in a given plant).

Unfortunately, the psychometric studies mentioned above indicate that the world is more complicated and that the effect of age on productivity changes its sign from positive into negative starting from some threshold age onwards. This is moreover consistent with Becker's human capital theory. This is why, in our preferred empirical specification, we employ statistical simulation – a quantitative technique that allows one to describe complicated phenomena in a flexible way (how is described in the top part of Box 4).

The simulation results are then translated out of the jargon using CLARIFY, a software developed by Harvard political scientists Gary King, Michael Tomz and Jason Wittenberg expressly for delivering the results of the application of even complicated quantitative techniques to a wider audience not necessarily trained in statistics but still interested in achieving a rather precise knowledge of the quantitative aspects of economic and social issues (see the bottom part of Box 4).

Box 4: Numerical simulations

a. The issue

The starting point may be a standard multivariate regression exercise where the statistical relation between a dependent variable (say, productivity) and a host of potential explanatory variables (say: age, education and so on) is investigated. The result of a regression exercise usually consists of quantitative information ("estimated coefficients") on the sensitivity of the dependent variable to each of the explanatory variables, while holding the other explanatory variables constant. This piece of information is, however, subject to various sources of uncertainty (the statistical model may be wrong or incomplete; the available information on the explanatory variables may be incomplete as well; some variables of interest may be outright unobserved). Hence, this "partial correlation" may thus be more or less precisely estimated. If the researcher obtains a precise estimate, the quantitative implication of his-her research may be trusted; otherwise not.

b. Simulation-based approach to interpreting statistical results

Among other things, numerical (so called "Montecarlo") simulation essentially applies survey sampling techniques to proxy complicated (but presumably more realistic) mathematical relations and eventually determines how trustworthy the results of a given regression are. In surveys, random sampling from the population of interest is commonly used to estimate key features (such as mean and variance) of such population, with the precision of the estimate increasing in sample size. Simulation essentially follows the same logic to learn about probability distributions of estimated coefficients, not populations. In the same fashion as with real samples, approximations can be computed to any desired level of precision by varying the number of simulations.

c. How statistical simulation works in practice through the software CLARIFY

Start from a set of point-wise estimated coefficients of age, education and the other variables set out to explain productivity. Each of these coefficients has a sampling distribution. The central limit theorem guarantees that, for a large enough sample, one can randomly draw ("simulate") coefficient ("parameter") values from a multivariate normal distribution, with mean equal to the point estimates of the coefficients and variances equal to the estimated variance and covariance matrix of the point-wise estimates. By random drawing, one can obtain a realization of the estimated coefficients on average consistent with their point-wise estimates. This is the result of one simulation round. This experiment can be repeated many times at will (clearly, if the coefficient were precisely known, each draw would be identical) and many values for the estimated coefficient of interest computed. Each coefficient can then be multiplied by the value of its corresponding explanatory variable (age). The variability in the values of the simulated coefficients translates in variability (randomness) of the expected value of productivity (the dependent variable), while the effects of the other variables on productivity are held constant at their means.

As a result, we can compute (and graph) the average partial effect of age on productivity and also confidence intervals that delimit the degree of trustworthiness of such an average.

To sum up, in our case, the true relation between age and productivity is likely complicated, for the effect of age on productivity may be positive or negative depending on age. If this is the case, describing the results of statistical analysis becomes rapidly cumbersome and only imperfectly related to the question at hand. King, Tomz and Wittenberg (2000) have developed a software program (CLARIFY) that, without changing any underlying data or statistical assumption, provides interpretation-friendly and graphical answers to the questions of interest.

4.3 Cross-sectional results

A very common problem with short panels such as the one at hand is that the plant variation over time may be very volatile and thus add very little to the knowledge of the phenomenon at hand, while subtracting statistical precision.

Using plant data averaged over all available years (irrespective of the number of the years available for each cross-sectional unit) may allow one to get rid of this unnecessary noise and, hopefully, concentrate on the underlying production relation (with some caveats to be discussed below). Hence, instead of relying on both times series and cross-sectional variation, we start presenting statistical results from the three cross-sections of industries. In sub-section 4.5, we will study how sensitive our results are the within-plant time variation is allowed for.

First, we look at whether age *as such* is statistically related to plant productivity and wages. The results in Table 3 and 4 explain 50% of the total variability of productivity and wages in the three industries. They also show that workforce age *per se* is unrelated to productivity while it is positively related to wages in all three industries, with some evidence of declining effects of age in the industrial machinery industry only.

Among the other variables which do not represent the main focus of this paper but are, however, possibly important determinants of productivity and earnings, it is worth mentioning education and plant vintage. Education turns out always positively related to wages in the three industries, while being positively related to productivity in the modern industries (industrial machinery, electronics) only. Instead, no relation is there in the forest industry. Plausibly, the effect of education on productivity and wages is more pronounced in electronics than in industrial machinery. As to the effects of plant vintage, we find evidence that older plants tend to be less productive than newer plants. This effect is consistently present for the three industries. The evidence for wages is – somehow at odds with the findings in the literature briefly surveyed in Box 5 - present for industrial machinery only, and not for forest and electronics. The effects of plant vintage will be analyzed more extensively further below.

Box 5: Old plants, old workers, productivity and wages

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). This may partly explain why older workers tend to stick with these less productive but financially sound firms.

On the other hand, it has often been found that older firms pay higher wages, even after controlling for other relevant firm characteristics. This is often taken to reflect the quality (and thus the higher productivity) of the workers they hire, as well as the working conditions they offer. Yet, as discussed in the main text, this need not be the case. Older firms may pay higher wages to extend 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.

Davis and Haltiwanger (1991) find that older manufacturing plants indeed pay higher wages, and age remains a statistically significant determinant of wages once industry, region and size differences are accounted for, with and without controlling for the probability that the plant will close (usually lower for older firms). Troske (1999, 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, while Winter-Ebmer (1994) 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. More recently, Brown and Medoff (2003) have analyzed the relationship between how long an employer has been in business (firm age) and wages. According to their analysis, 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.
Finally, regarding evidence with Finnish data, Nurmi (2004) finds that old and large firms are less likely to fail and less sensitive to exogenous shocks than young and small firms.

Altogether, the results from simple cross-section analysis confirm the importance of looking at the effects of aging on both productivity and wages: assuming that the two go hand in hand - as many previous studies have done - may thus be misleading. But they also indicate that aging *per se* may not be the right variable to look at to explain what happens to productivity.

INSERT TABLE 3 AND 4 ABOUT HERE (SEE THE VERY END OF THIS DRAFT)

Indeed, our theory discussion motivates us to be more specific than in the formulation underlying the results in Table 3 and 4: the correlation of aging with productivity and wages is expected to differ depending on whether aging takes place within the walls of the same plant (seniority) or if it goes through the acquisition of general experience in the labour market at large.

Checking whether this is the case requires use more complicated models so as to allow the age-related variables, productivity and earnings to change its sign at some age threshold. While keeping our empirical specification as flexible as possible, we also try and make the presentation of our results less cumbersome by relying on the simulation techniques embodied in CLARIFY, the user-friendly software developed by King, Tomz and Wittenberg (2000) and Tomz, Wittenberg and King (2003) (see Box 4 above).

Graphs 1, 2 and 3 are the outputs of CLARIFY and concern, respectively, the seniority, experience and education profiles of productivity and wages. The statistical simulations underlying each of them (ten thousands repetitions of random drawing of coefficients of the variable of interest) revolve around the multivariate statistical analysis whose point-wise results and significance are reported in Table A3 in the Appendix. This analysis is in turn a generalization of the statistical analysis in Table 3 and 4, and has thus the goal of evaluating the effects of age-related variables and other determinants on productivity and wages.

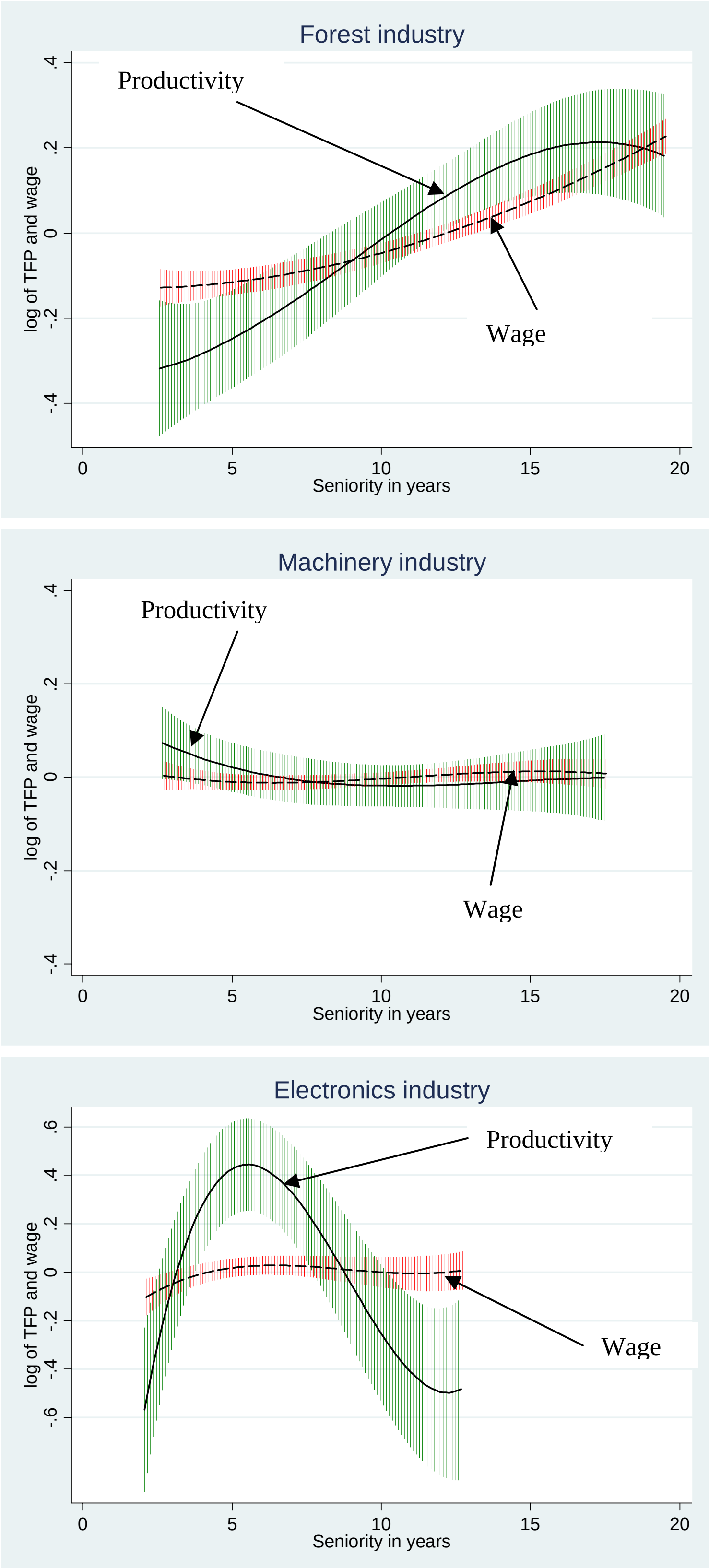
In each Graph, along the vertical axis, one reads the marginal response of the dependent variables (logarithms of TFP and wages) to changes in seniority, experience and education years, measured along the horizontal axis. Such responses are defined over the interval of values taken by each explanatory variable in the industry at hand. The thick and dotted lines indicate, respectively, the average marginal response of TFP and wages (with the average taken over the very many potential values of the coefficients of interest). The dot-shaded and line-shaded intervals around such estimated average responses represent confidence intervals, which provide an indication of the degree of precision of the simulated estimates. To more precisely fix ideas, some of the numerical counterparts of Graphs 1, 2 and 3 are also reported in Table 5 below. Our results are as follows.

Seniority profiles (graph 1) Productivity and wage responses to the cross-section variability in the number of seniority years are very similar to each other in the forest industry (both growing fast) and in industrial machinery (both essentially flat, once confidence intervals are taken into account). From the figures reported in the upper part of Table 5, one learns that, moving from a plant with a seniority of 7 for the average worker to a plant with seniority equal to 17, having set the other determinants of productivity to their means results in a productivity increase of 38% in the forest industry. In electronics, the seniority-productivity profile follows a well-defined inverted-U shape, while the wage is mildly increasing. These trends correspond to a swift positive productivity response of cumulated 107% as one shift from plants with an average worker seniority of 2 to plants with worker seniority equal to 6 years (with wages going up more moderately). If one moves further by another four years from plants with seniority equal to 6 to plants with seniority equal to 10, productivity undergoes a (relative) shortfall of cumulative 68%, with roughly unchanged wages.

Experience profiles (graph 2) Productivity and wage responses to the cross-section variability in the years of potential experience are much less precisely estimated, particularly for productivity. This may be the result of multi-collinearity between experience and seniority, which may be at the origin of the initially downward sloping response of productivity to experience in the forest industry and in electronics. In industrial machinery, one finds instead plausible results with positive wage and productivity responses to experience (with wages and productivity by 15% and 12% respectively over seven years; see Table 5). A possible way out is to compute the implied productivity response of both higher experience and seniority (after all, if a worker stays with the same plant, he/she acquires both experience and seniority at once). When this is done (see the results in the lower panel of Table 5, “Seniority and experience combined”), one finds an essentially flat productivity response to the combination of seniority and experience and a moderately positive wage response for a cumulated 15% over seven years of time. The combination of seniority and experience leaves the results for electronics qualitatively unchanged, instead. When the number of seniority and experience years is relatively low, moving from low-seniority and low-experience plants to high-seniority and high-experience plants corresponds to a cumulated productivity increase of about 60%. When this is done moving from intermediate to high levels of seniority and experience, the productivity shortfall is of about 70%. Wages do not follow suit, instead, but keep going up.

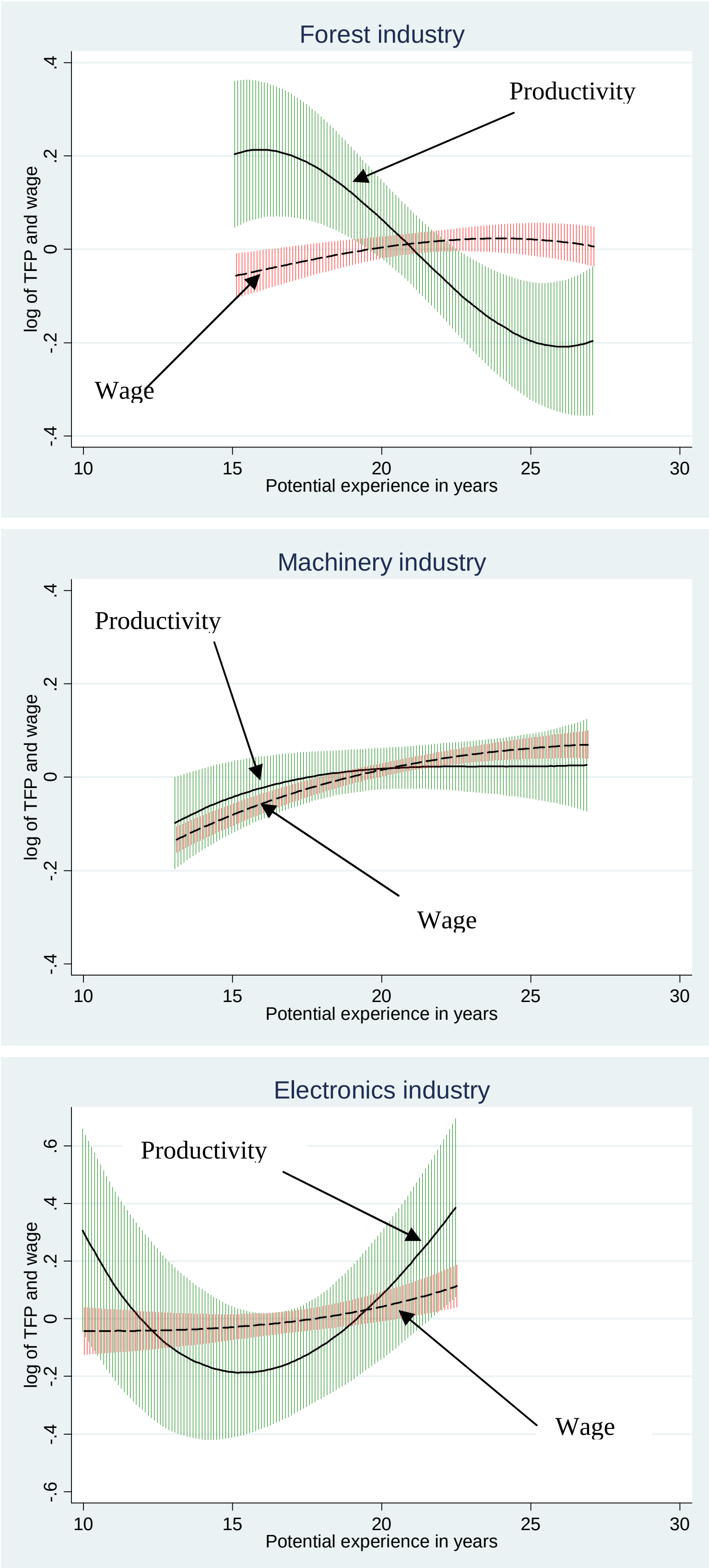
Schooling profiles (graph 3) Productivity and wage responses to the cross-section variability in the years of schooling reveal the presence of an educational premium for wages in all industries and for productivity in the more advanced industries (industrial equipment and, more markedly, electronics – a largely expected result). This positive association with productivity is essentially not there when it comes to measuring the productivity response to education in the forest industry.

Graph 1 – Productivity and wage responses to seniority. Simulation analysis from estimates in Table A3



Notes: See box 4 for a detailed explanation of how such profiles are constructed.

Graph 2 - Productivity and wage responses to potential experience. Simulation analysis from estimates in Table A3



Notes. See box 4 for a detailed explanation of how such profiles are constructed.

Graph 3 - Productivity and wage responses to schooling. Simulation analysis from estimates in Table A3

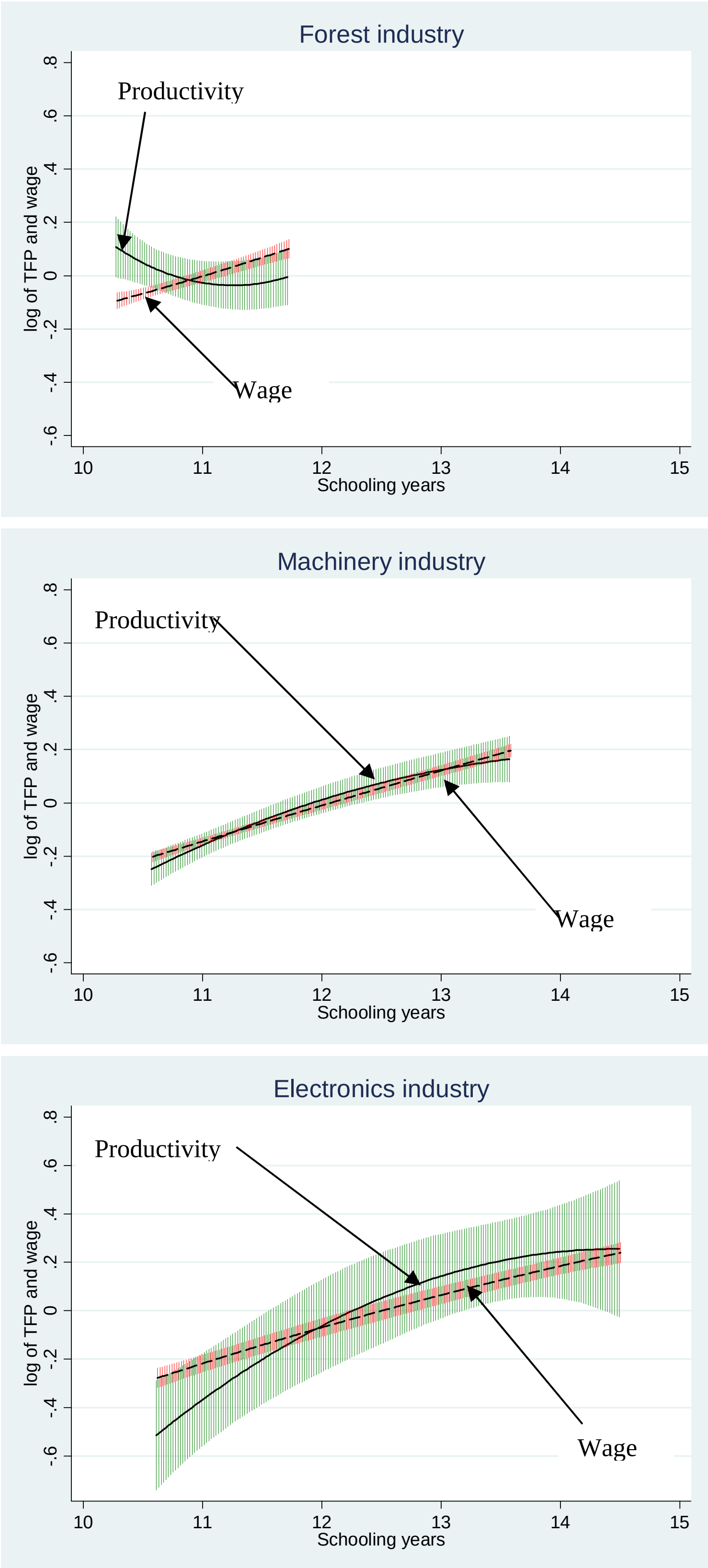


Table 5: Simulations of cumulated productivity and wage responses under various settings

	Difference…		… in log of TFP			…in log of monthly wage		
Seniority	**from …**	**to …**						
Forest			Mean	Std. err.	t-value	Mean	Std. err.	t-value
Seniority in years	7	17	0.38	0.15	2.60	0.23	0.04	5.81
and other variables	at their means	at their means						
Machinery								
Seniority in years	7	17	0.00	0.08	0.01	0.02	0.03	0.73
and other variables	at their means	at their means						
Electronics								
Seniority in years	2	6	1.07	0.32	3.31	0.13	0.07	1.83
and other variables	at their means	at their means						
Seniority in years	6	10	-0.68	0.20	-3.34	-0.03	0.05	-0.61
and other variables	at their means	at their means						
Potential Experience								
Forest								
Experience in years	15	25	-0.40	0.17	-2.33	0.08	0.05	1.69
and other variables	at their means	at their means						
Machinery								
Experience in years	13	20	0.12	0.07	1.77	0.15	0.02	7.76
and other variables	at their means	at their means						
Electronics								
Experience in years	10	16	-0.48	0.22	-2.22	0.02	0.05	0.46
and other variables	at their means	at their means						
Experience in years	16	22	0.49	0.25	1.95	0.12	0.06	2.13
Other variables	at their means	at their means						
Seniority and experience combined								
Forest								
Seniority in years	7	17	-0.02	0.12	-0.16	0.31	0.04	8.22
and experience in years	15	25						
and other variables	at their means	at their means						
Machinery								
Seniority in years	3	10	0.04	0.07	0.53	0.15	0.02	6.62
and experience in years	13	20						
and other variables	at their means	at their means						
Electronics								
Seniority in years	2	6	0.61	0.29	2.11	0.14	0.05	2.71
and experience in years	10	14						
and other variables	at their means	at their means						
Seniority in years	6	12	-0.69	0.25	-2.77	0.05	0.05	1.06
and experience in years	14	20						
and other variables	at their means	at their means						

Notes: Simulations are based on the same regression models (results in Table A3) used for drawing Graphs 1-3. "Mean" indicates the log difference of productivity (or wage) levels. Multiplying the number by 100 provides an approximation of percentage difference in productivity (or wage) levels in the different hypothetical situations. For more details on how these figures are computed see Box 4.

4.4 Implementation difficulties

Sensitivity to errors in the measurement of value added shares Being aware that we may be measuring the value added shares of labour and capital with error, we re-computed our productivity index (whose method of calculation is described in Box 3) with somewhat higher and somewhat lower value added shares. Our results do not change at all. Box 7 reports more details on these experiments.

Box 7 - What if value added shares were higher or lower?

As discussed in Section 4.1 (and as made clear by the formula reported in Box 3), our statistical analysis is carried out by computing a productivity index from value added data by imputing industry-wide value added shares of labour and capital. The resulting residual is legitimately interpreted as "productivity" as long as the assumptions of constant returns to scale and perfect competition are accepted. This may be hard to swallow.

In this section, while not providing a full-fledged test for such assumptions, we provide some robustness checks of our results by running again our regressions after imputing, respectively, 10% higher and 10% lower value added shares of labour (and therefore lower and higher value added shares of capital) when calculating productivity.

For brevity, we do not report the results here. The crucial result that the productivity response of seniority in electronics is, anyway, first positive and then negative withstands this test, irrespective of the higher or lower imputed values for the labour and capital shares of value added. Hence the thrust of the quantitative results obtained above carries over to this experiment as well.

Reverse causation To be able to interpret our results as capturing the relation between workforce aging and plant productivity, we confront at least one big empirical hurdle, reverse causation.

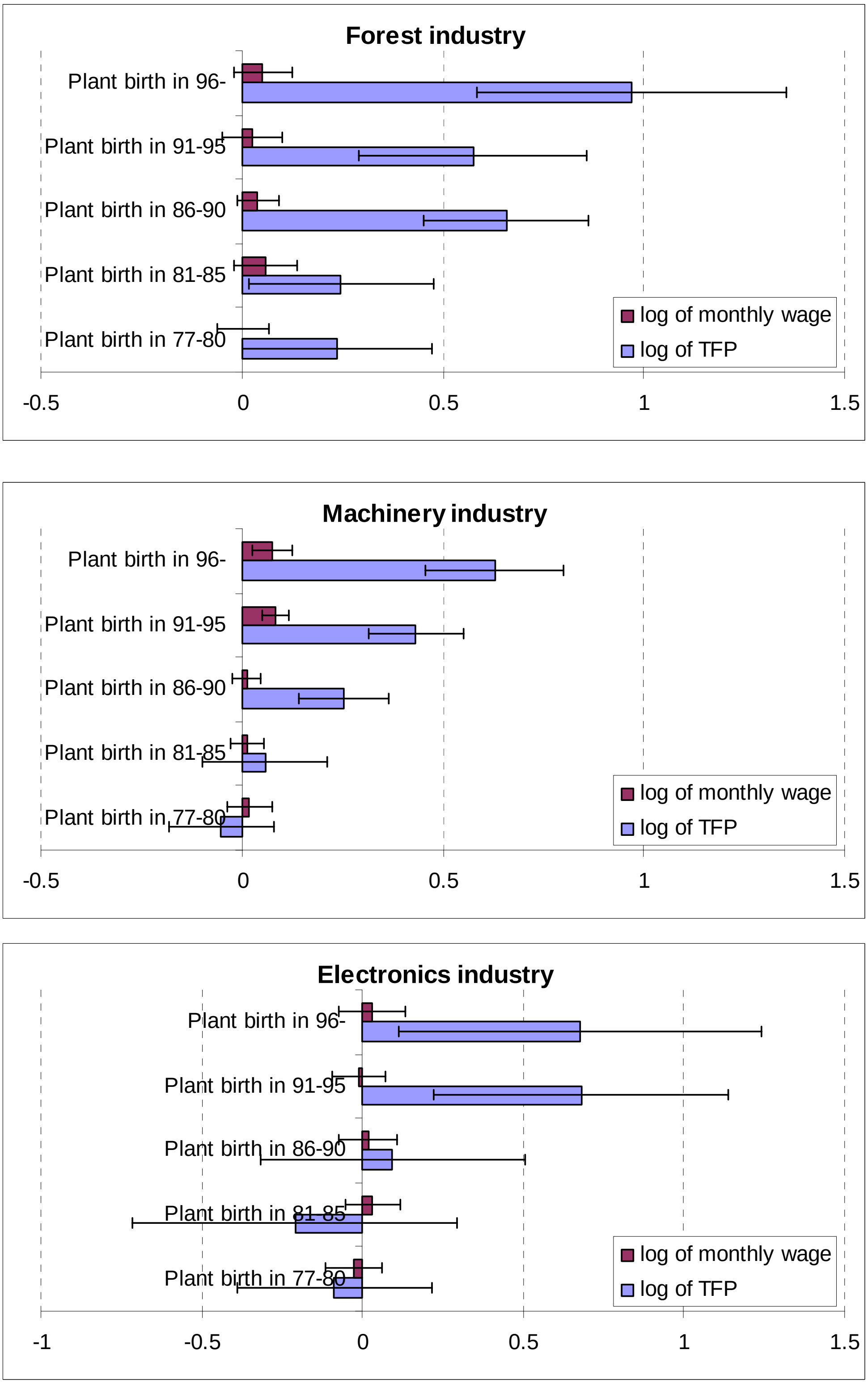
The statistical relations we intend to analyze posit that aging is the independent variable and productivity the dependent variable. But data as such (in particular when observed at a given point in time, as implied when a cross-section of plants is studied) only indicate correlation, not causation. If a negative coefficient linking age and productivity (say, after a certain age threshold) is observed, this may not signal that old age causes low productivity, but rather that less productive plants – perhaps employing old and outdated machines and methods of production - tend to disproportionately hire old workers, while new, innovative and high-productivity plants are more often matched to young workers. In the econometrics jargon, this is a simultaneity problem.

Altogether, these previous studies point to the importance of controlling for plant age (as well as for workers' characteristics). The inclusion of plant vintage in the list of the other variables potentially affecting productivity and wages serves the purpose of capturing the potentially harmful effects of older machines, inherently thought of as less efficient than modern ones, on plant productivity. In the data set, we have information about plant age, namely a categorical variable indicating the year of establishment of the plant classified in six categories (before 1976, 1977-80, 1981-85, 1986-90, 1991-95, after 1996). We have consistently used this as an additional control. If the correlation between seniority or experience and productivity hides a causal correlation from low-productivity old machines onto old (potentially high-productivity) workers, the statistical effect of workers' seniority and experience on plant productivity should disappear once the effect of plant age is accounted for.

Graph 4 shows a graphical illustration of productivity and wage effects of plant vintage, whereas the horizontal bars indicate the average effects of plant vintage on productivity (printed light grey) and wages (printed dark grey), with 95% confidence intervals appended. The Graph points to the relevance of such effects. Younger plants are indeed definitely more productive in all industries and, less strongly, also present higher wages (the evidence for wages is particularly weak in electronics).[11]

[11] Maliranta (1999) experimented with alternative capital stock measures (perpetual inventory method vs. fire insurance value of capital stock). They yielded quite similar results for the plant vintage effects. More recent Finnish evidence of the plant vintage effects include Ilmakunnas, Maliranta and Vainiomäki (2004) and Ilmakunnas and Maliranta (2005).

GRAPH 4 - An illustration of productivity and wage effects of plant vintage (source: Table A3)



Notes: Bars indicate the log difference of total factor productivity and monthly wage with respect to the reference group (plants established in 1976 or earlier). Error bars around the mean bars indicate 95% confidence intervals.

However, this correction for the effect of plant vintages and other productivity determinants may not be enough. Surely, a lot of unobserved heterogeneity is still there in the data even once we have appended the other explanatory variables listed above. The problem with the statistical analysis exploiting cross-sectional estimates only arises when there are unobserved (therefore unmeasured) plant variables correlated with the included explanatory variables. For example, an able plant manager may be particularly gifted in hiring young productive workers. If management ability is not observed, the effect of management ability may show up in the negative estimated relation between old workers and productivity: we would be wrongly attributing the effect of managerial ability to age. This is why, in addition to appending plant age controls, we further complement our baseline statistical analysis in the two ways discussed in the section 4.5 (instrumental variables and fixed-effects estimation).

Selectivity Our statistical analysis also confronts another problem. In addition to reverse causation, it might also be that the 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 (and senior) workers rather than being the sheer consequence of declining ability. In other words, the statistical results from our cross-section of plants 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.

A remedy for selectivity would entail splitting the statistical analysis into two steps, the first of which to estimate the probability of plants (and workers) to disappear from our sample and then, in the second step, to correct the estimated coefficients taking into account the bias induced by the omission of the disappeared plants. We do not go that far. More simply, in putting together our cross-sectional evidence we check the statistical significance of a variable taking value equal to zero for the plants continuing throughout the period and one for the plants exiting the sample between 1996 and 2002 (as Griliches and Regev (1995) did in their Israeli study). This variable is not significantly related to productivity or wages in our sample and therefore does not affect our results.

4.5 Dealing with reverse causation

To try and establish whether age is at least temporally predetermined with respect to productivity and wages, we first experiment the statistical significance of the lagged (1990-94) values of aging and the other variables of interest, interacted with the current values of those same variables (the so called “Instrumental Variables” (IV) approach, for the lagged values are employed as instruments).

We do so retaining our cross-sectional framework of analysis, while also appending some pre-determined variables to the list of the explanatory variables to weaken the potential simultaneity link between current explanatory variables (seniority and experience among others) and the dependent variable (productivity).

A problem with the IV approach is that it is very hard to implement for flexible formulation such as the one underlying graphs 1, 2 and 3 (and the related statistical results in Table A3). A flexible formulation implies many coefficients to estimate whose individual effects may be very hard to disentangle. Hence, we implement a feasible IV approach by experimenting among many less flexible (*i.e.* with a smaller number of included coefficients) alternative statistical models for each industry. We pick the one that, while giving a reasonable good fit of the data, most closely replicates our cross-sectional specification. As a result, however, our IV approach is implemented using slightly different formulations across industries.

The IV results are reported in Table 6. In spite of the decrease in the number of observations (some of the values for the explanatory variables are missing for 1990-94), they tend to reproduce the thrust of the results reported previously.

Namely, in the forest industry, productivity does not depend on education while the relation between seniority and productivity is constant and does not depend on the number of years of seniority. In electronics, education matters a lot for productivity (and the relation does not depend on the outstanding levels of education) while the relation between seniority and productivity is an inverted U, although less precisely measured than above. In industrial machinery and equipment, education is related to productivity with a smaller effect than in electronics and potential experience matters, not seniority. All these features reproduce the overall features present in previous results. A twist of novelty of the IV estimates is that the estimated statistical relation between experience and productivity does now change its sign into negative for higher levels of experience (pretty much as seniority does in electronics).

Altogether, the results from IV estimation do substantially confirm the pattern of statistical correlations brought to bear in previous sections.

Table 6 – Statistical results from the Instrumental Variable (IV) approach to explain plant productivity

	Forest	Machinery	Electronics
Schooling years		0.093***	0.188*
		(0.026)	(0.079)
Potential experience	-0.046+	0.130*	
	(0.024)	(0.059)	
Potential experience squared		-0.033*	
		(0.014)	
Seniority	0.039*		0.276
	(0.018)		(0.198)
Seniority squared			-0.168
			(0.119)
R-squared	0.192	0.277	0.165
Observations	279	348	98
P-value of overident. test	0.352	0.594	0.214
P-value of relevance test	0.000	0.000	0.000

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Notes: Dependent variable: logarithm of plant productivity. Other control variables (included instruments) include dummies for plant vintage groups and size groups. Schooling years, potential experience, potential experience squared, seniority and seniority squared are instrumented when they are included in the model. Excluded instruments are regional dummies (6 regions) and lagged (the average in the period 1990-94) schooling years, potential experience, potential experience squared, seniority and seniority squared. Schooling, experience squared and seniority squared were dropped in forest industry, seniority variables were dropped in machinery industry and experience variables were dropped in electronics industry because their estimates were close to zero, they were statistically insignificant and their removal improved statistical properties of the model. High P-values (> 10%) for the over-identification test (Hansen J statistics) indicate that the validity of the instruments cannot be rejected and low P-values (<0.1%) of relevance test (Anderson canonical correspondence Likelihood Ratio statistic) gives indication that the instruments are relevant.

To verify the importance of the possible residual influence of unobserved plant-specific heterogeneity, we also consider the time dimension of our data. We do so appending plant-specific variables constant over time, thereby carrying out the so called “fixed-effects” estimation of the determinants of plant productivity. By including the time variation of our data, we can significantly extend sample size (which goes up to 1523 observations for the forest industry, 1717 observations for industrial machinery and 496 observations for electronics).

Clearly, however, the additional observations cannot be taken as independently distributed over time, being repeated observations of the same plant. Thus in our statistical analysis, we allow for the error term (the residual unobserved components not captured by the explanatory variable included in our statistical analysis) to be auto-correlated, *i.e.* to be time-dependent. This serves the purpose of not being misled by the potentially increased gain of precision achieved in capturing the phenomena at hand, thanks to the increased sample size. Accounting for auto-correlation is instead important to correctly appreciate the explanatory power of our model along the time dimension.

When adopting the fixed-effects statistical model, however, one effectively relinquish information contained in the cross-sectional framework and concentrate on the so called "within-plant" variation in the panel data set. This may be a good thing if the goal is to answer some questions which – by construction - could not be addressed in the cross-sectional framework, the main of which is whether the relation between the age-related variables, education, productivity and wages is a simultaneous one or whether it operates with some delay.

The results in Table 7, 8 and 9 give useful information in this respect. In general, as expected, the estimated statistical model is less precise than the model estimated using the cross-sectional data only. The total time series variability accounted for by the explanatory variables dramatically falls from the approximate 50% of the cross-sectional estimates to less than 10%. As expected, our statistical model does a better job in predicting plant productivity along the cross sectional dimension. The explanatory power of the variables employed to explain the behaviour of productivity in the forest industry is drastically reduced. But the pattern of correlations seen above for the other industries is still somewhat there, once the lagged values of the variables are considered. Potential experience and education, not seniority, matter for productivity in industrial equipment, while seniority and, mostly, education matter for productivity in electronics.

Yet, along the time series dimension, these effects are present only when the delayed values of the explanatory variables are considered instead of the current ones. Education is indeed positively associated to productivity with a delay of about two years (the lagged value of education is almost significantly related to productivity, though with a small coefficient, even for the forest industry).

Table 7 - Statistical analysis based on the variation within plants over time (fixed effect models), forest industry

	(1)	(2)	(3)
Schooling years	0.084+	0.072	
	(0.046)	(0.056)	
Schooling years (t-1)		-0.016	
		(0.056)	
Schooling years (t-2)		0.042	0.069
		(0.051)	(0.043)
Potential experience	0.019	0.019	
	(0.013)	(0.013)	
Seniority years	-0.018	-0.019	
	(0.014)	(0.014)	
Potential experience (t-2)			0.020+
			(0.011)
Seniority years (t-2)			0.004
			(0.011)
Observations	1523	1523	1523
R-squared (within)	0.088	0.088	0.090
Autocorrelation	0.252	0.251	0.253

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Notes: Other controls include dummies for fixed year effects. Autocorrelation of the error terms is allowed.

Table 8 – Statistical analysis based on the variation within plants over time (fixed effect models), machinery industry

	(1)	(2)	(3)
Schooling years	-0.049	0.040	
	(0.037)	(0.034)	
Schooling years (t-1)		0.001	
		(0.037)	
Schooling years (t-2)		0.103**	0.089**
		(0.036)	(0.031)
Potential experience	-0.056	-0.009	
	(0.037)	(0.007)	
[Potential experience]^2	0.008		
	(0.008)		
Potential experience (t-2)			0.079*
			(0.031)
[Potential experience (t-2)]^2			-0.015+
			(0.008)
Observations	1717	1717	1717
R-squared (within)	0.064	0.048	0.055
Autocorrelation	0.229	0.229	0.227

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Notes: Other controls include dummies for fixed year effects. Autocorrelation of the error terms is allowed.

Table 9 – Statistical analysis based on the variation within plants over time (fixed effect models), electronics industry

	(1)	(2)	(3)
Schooling years	-0.022	-0.030	
	(0.088)	(0.080)	
Schooling years (t-1)		-0.003	
		(0.089)	
Schooling years (t-2)		0.188*	0.217*
		(0.079)	(0.093)
Seniority years	0.042	0.050	0.059
	(0.072)	(0.070)	(0.072)
[Seniority years]^2	-0.069+	-0.072+	-0.076+
	(0.040)	(0.039)	(0.040)
Observations	496	496	496
R-squared (within)	0.081	0.093	0.094
Autocorrelation	0.335	0.319	0.325

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Notes: Other controls include dummies for fixed year effects. Autocorrelation of the error terms is allowed.

As to the age-related variables, lagged experience is related to productivity in the forest and the machinery industries. The inverted-U-shaped effect of seniority on productivity in electronics is instead no longer there: the only visible partial correlation between seniority and productivity is negative. Altogether, our main argument on the adverse effect of age on productivity is confirmed by such results.

4.6 Summing up our results

Our statistical analysis provides a reasonably coherent picture of the empirical relation between age-related variables, plant productivity and wages in Finland in the years of the IT revolution.

First, we find that age as such is not the right variable to look at when thinking about the determinants of plant productivity. Distinguishing between seniority and general experience is important in this respect.

More importantly, by looking at a period of fast technical change in the Finnish economy such as 1995-02, we were able to answer our main research question, namely whether being exposed to such rapid changes has made a difference for plant productivity and wages. It turns out it has. While productivity and wage responses to age-related variables are not too dissimilar in industries not undergoing a major technological and managerial shock, things change for the electronics industry.

In electronics, the response of productivity to age-related variable (seniority, in particular) is first positive and then becomes negative (sizably so) as one looks at plants with higher average seniority and experience. Similar, though less precisely determined, conclusions hold when one looks at the time variation of plant productivity. These conclusions are still there when other plausible productivity determinants are included in the analysis, the main of which are education (particularly strongly related to productivity in electronics) and plant vintage. As to plant wages, their response to age-related variables in electronics is similar to the one observed for the other industries. This is not too surprising: as recently discussed at length by Uusitalo and Vartiainen (2005), the combination of highly centralized collective agreements with relatively autonomous but still highly unionized industry wage setting has resulted in a very low weight (4.4%, on average) given to performance-related firm-level corrections of wages.

Finally, we are clearly not the first to try and single out the effects of age on productivity and wages with special emphasis on cross-industry differences (high-tech vs. other industries). Some of the results from previous studies are reported in Box 6.

Box 6: Previous statistical evidence on age, productivity and wages

Most studies concentrated on the analysis of whether productivity and wage profiles differ with not much regard to industry disaggregation. Hellerstein, Neumark, and Troske (1999) using US data, find that productivity and wage increase with age, except for the oldest age group in some specifications, and their patterns are fairly similar. Crépon et al. (2002) use French data and conclude that the relationship of productivity and age is inverse U-shaped, but wage is increasing in age. In manufacturing, wage increases with skill level, but productivity increases even more. In non-manufacturing, wage increases more than productivity as skill levels go up. Hægeland and Klette (1999) use Norwegian data and find that productivity and wage increase with education and the highly educated go hand in hand by productivity. Medium-level potential experience (age minus education years) gave higher productivity than short experience, but with long experience productivity declined although still stayed higher than with short experience. Medium-level experience was underpaid, but the wage premium for long experience corresponded to the productivity premium. They concluded that the wage-experience profile only partly reflected the productivity profile.

Only a few scholars have looked at cross-industry heterogeneity of productivity and wage responses. Crépon and Aubert (2004) estimated average earnings relations for France and found evidence of declining productivity after the age of 55, but they found that the age-productivity profile (as captured by such earnings functions) does not differ much across industries. In contrast, 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 for other countries. Similarly to our findings here, Neuman and Weiss (1995) found that earnings peaks are located earlier in age in the high-tech sector. Hellerstein and Neumark (1995), using Israeli data, find that earnings and productivity profiles are fairly similar for the relatively less skilled workers (the group that cover most of the workforce).
Other studies have in turn found that the relation has changed over time. The seniority-wage profile has seemingly become steeper and its peak moved forwards in Denmark as a result of the decentralization of wage determination (Bingley & Westergaard-Nielsen, 2003). Eriksson and Jäntti (Eriksson & Jäntti, 1997) found that in 1971 the peak of the wage profile was at the age group 35-39 years but has then moved forward being at the age group 45-49 years in 1990 in Finland.

5. Conclusions

Finland – with its comparatively older labour force than the European average - was indeed hit by a major technological and managerial shock in the mid 1990s. This made it the land of the IT revolution but also exposed the value of the abilities of the older part of its labour force to a major negative shock. The simultaneous presence of a relatively aged - and aging - workforce and a major external shock has provided us with a nice experiment to possibly evaluate the consequences of such a shock onto the labour costs of Finnish companies.

Our results are consistent with expectations and with some of the previous evidence on the relation between age, productivity and wages for other European countries. Being exposed to a rapid technological and managerial change does make a difference for plant productivity, less so for wages. In electronics, the response of productivity to age-related variables is first sizably positive and then becomes sizably negative as one looks at plants with higher average seniority and experience. This declining part of the curve is not there either for the forest industry or for industrial machinery or for wages in electronics. Based on these results, we conclude that workforce aging is more likely to be a burden for firms and their plants in high-tech industries than elsewhere in the Finnish economy.

At the same time, we do believe that our results, although derived from data on Finnish manufacturing plants, do not concern Finland only and are instead of broader policy interest. In a world where innovation forces, as opposed to catching up forces, have become the key engine of growth (see Acemoglu, Aghion and Zilibotti (2003) and the Sapir Report (2004)), companies and Governments will be more and more involved in such problems as the ones discussed in this paper.

The mega-trends of workforce aging will eventually stop to a plateau as the baby-boomers retire. But this will be in another twenty-five years and in the absence of major changes in labour force participation. In any case, we will have to live with aging workers and fast technical change at the same time. Whether this will pose a severe constraint to faster growth in the future remains to be seen. Some Governments are more aware of the problem than others. In the last few years, for instance, the Finnish Government has already embarked on a programme ("The National Programme on Ageing Workers"; see OECD (2004, p.119)) aimed at deferring retirement and, in parallel, improving the so called "employability" of older workers. It is however unclear whether grand-plans may be effective in counteracting the adverse labour market effects of workforce aging at times of technical change.

On the optimistic side, though, it should be recalled that older workers in the future will be likely more educated than they are today and therefore, as also implied by our results, they may be more apt to deal with the Next Big Things.

For sure, this will remain an exciting area of research.

References

ACEMOGLU, D., AGHION, P. and ZILIBOTTI, F. (2003). Vertical Integration and Distance to Frontier. *Journal of the European Economic Association, 1*(2/3), 630-638.

ACEMOGLU, D. and PISCHKE, J.-S. (1999a). Beyond Becker: Training in imperfect labour markets. *Economic Journal, 109*(453), F112-142.

___. (1999b). The structure of wages and investment in general training. *Journal of Political Economy, 107*(3), 539.

ALI-YRKKÖ, J., PAIJA, L., REILLY, C. and YLÄ-ANTTILA, P. (2000). *Nokia – A Big Company in a Small Country*. Helsinki: ETLA, The Research Institute of the Finnish Economy, Series B162.

AUBERT, P., CAROLI, E. and ROGER, M. (2004). *New Technologies, Workplace Organisation and the Age Structure of the Workforce: Firm-Level Evidence*. Paris: INSEE.

AUTOR, D. H., LEVY, F. and MURNANE, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics, 118*(4), 1279-1333.

BECKER, G. S. (1962). Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy, 70*(5, Part 2: Investment in Human Beings), 9-49.

BINGLEY, P. and WESTERGAARD-NIELSEN, N. (2003). Returns to Tenure, Firm-Specific Human Capital and Worker Heterogeneity. *International Journal of Manpower, 24*(7), 774-788.

BROWN, C. and MEDOFF, J. L. (2003). Firm Age and Wages. *Journal of Labor Economics, 21*(3), 677-697.

CASELLI, F. and COLEMAN II, W. J. (2001). Cross-Country Technology Diffusion: The Case of Computers. *American Economic Review, 91*(2), 328-335.

CRÉPON, B. and AUBERT, P. (2004). *Age salaire et productivité: la productivité des salariés décline-t-elle en fin de carrière*.Unpublished manuscript,

DAVERI, F. and SILVA, O. (2004). Not only Nokia: what Finland tells us about new economy growth. *Economic Policy, 19*(38), 117-163.

DAVIS, S. J. and HALTIWANGER, J. (1991). Wage Dispersion between and within U.S. Manufacturing Plants, 1963-86. *Brookings Papers on Economic Activity, Microeconomics 1991*, 115-180.

DUNNE, T., ROBERTS, M. J. and SAMUELSON, L. (1989). The Growth and Failure of U.S. Manufacturing Plants. *Quarterly Journal of Economics, 104*(4), 671-698.

ERIKSSON, T. and JÄNTTI, M. (1997). The Distribution of Earnings in Finland 1971-1990. *European Economic Review, 41*(9), 1763-1779.

HADI, A. S. (1992). Identifying Multiple Outliers in Multivariate Data. *Journal of the Royal Statistical Society, Series (B), 54*, 761-771.

___. (1994). A Modification of a Method for the Detection of Outliers in Multivariate Samples. *ournal of the Royal Statistical Society, Series (B), 56*, 393-396.

ILMAKUNNAS, P. and MALIRANTA, M. (2005). Technology, labour characteristics and wage-productivity gaps. *Oxford Bulletin of Economics and Statistics, 67*(5), 623-644.

ILMAKUNNAS, P., MALIRANTA, M. and VAINIOMÄKI, J. (2001). Linked employer-employee data on Finnish plants for the analysis of productivity, wages and turover. In T. Jensen & A. Holm (Eds.), *Nordic labour market research on register data* (pp. 205-246): TemaDord 2001:593.

___. (2004). The Roles of Employer and Employee Characteristics for Plant Productivity. *Journal of Productivity Analysis, 21*, 249-276.

KANAZAWA, S. (2003). Why productivity fades with age: The crime-genius connection. *Journal of Research in Personality, 37*(257-272).

KING, G., TOMZ, M. and WITTENBERG, J. (2000). Making the Most of Statistical Analyses: Improving Interpretation and Presentation. *American Journal of Political Science, 44*(2), 347-361.

LAZEAR, E. P. (1981). Agency, Earnings Profiles, Productivity, and Hours Restrictions. *American Economic Review, 71*(4), 606-620.

MALIRANTA, M. (1997). *Plant productivity in Finnish manufacturing - Characteristics of high productivity plants*. Helsinki: The Research Institute of the Finnish Economy (ETLA), Discussion papers No. 612.

___. (1999). Factors of Performance by Plant Generation: Some Findings from Finland. In S. Biffignandi (Ed.), *Micro- and macrodata of firms: Statistical analysis and international comparison* (pp. 391-424). Heidelberg: Physica.

___. (2003). *Micro level dynamics of productivity growth: An empirical analysis of the great leap in Finnish manufacturing productivity in 1975-2000*. Helsinki School of Economics, A-227, Helsinki.

MALIRANTA, M. and ROUVINEN, P. (2004). ICT and Business Productivity: Finnish Micro-Level Evidence. In *The Economic Impact of ICT; Measurement, Evidence and Implications* (pp. 213-240). Paris: OECD.

MANNING, A. (2000). Movin' on up: Interpreting the Earnings-Experience Profile. *Bulletin of Economic Research, 52*, 261–295.
NEUMAN, S. and WEISS, A. (1995). On the Effects of Schooling Vintage on Experience-Earnings Profiles: Theory and Evidence. *European Economic Review, 39*(5), 943-955.
OECD. (2003). *OECD Science, Technology and Industry Scoreboard*. Paris: OECD.
___. (2004). *Ageing and Employment Policies: Finland*. Paris.
___. (2006). *Live Longer, Work Longer*. Paris: OECD.
SKIRBEKK, V. (2003). *Age and Individual Productivity: A Literature Survey* (No. 2003-028): MPIDR.
STATISTICS DENMARK, STATISTICS FINLAND, STATISTICS ICELAND, STATISTICS NORWAY and STATISTICS SWEDEN. (2003). *Access to microdata in the Nordic countries*. Örebro: Statistics Sweden.
TOMZ, M., WITTENBERG, J. and KING, G. (2003). CLARIFY: Software for Interpreting and Presenting Statistical Results. Version 2.1 (Version 2.1): Stanford University, University of Wisconsin, and Harvard University. January 5. Available at http://gking.harvard.edu/.
TROSKE, K. R. (1999). Evidence on the Employer Size-Wage Premium from Worker-Establishment Matched Data. *Review of Economics and Statistics, 81*(February), 15-26.
UUSITALO, R. and VARTIAINEN, J. (2005). *Finland: Firm Factors in Wages and Wage Changes*.Unpublished manuscript,June 9
VERHAEGEN, P. and SALTHOUSE, T. A. (1997). Meta-Analyses of Age-Cognition Relations in Adulthood. Estimates of Linear and Nonlinear Age Effects and Structural Models. *Psychological Bulletin, 122*(3), 231-249.
WINTER-EBMER, R. (1994). *Firm Size, Earnings, and Displacement Risk* (No. 9418): Institut fur Volkswirtschaftslehre, Johannes Kepler Universität Linz.

Data Appendix

A1. Data set and variable description

Similarly to the other Nordic countries, Finland is endowed with a rich register data of companies, plants and individuals (see 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.[12]

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), Census of Manufacturing (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 wide 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.[13] 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).[14]

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 labour productivity) and the capital

---

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

[13] 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.

[14] 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-labour ratio), with The capital stock measure is calculated through the perpetual inventory method (for more details, see Maliranta (2003)).

Up to 1994 the main criterion of plant inclusion for Statistics Finland was that the plant employed at least five persons. Since 1995 (our period of analysis), though, all plants owned by firms that employ no less than 20 persons are 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. 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 Census of Manufacturing and Employment Statistics.

Thanks to this link, we have information about the labour 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). The labour 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.[15]

A.2 Summary statistics for the industries

Table A1 presents 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.

A preliminary point to make is that, by its very method of calculation, our TFP index is not best possible for measuring the rate of TFP growth at the industry level. One of the reasons is that we have not used 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 three 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, as well as some other time-varying influence that affects TFP equally across plants.

[15] 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, the log of capital intensity, schooling years and potential experience. Overall, a couple of percentage of plants was dropped for being deemed outlier.

Therefore, in order to provide an aggregate picture of the development of TFP 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 behaviour 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 A1. 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.

The other (rough) indication from Table A1 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 useful to point out 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 is validated in the results reported in the main text.

Table A1: Cumulated growth of the main variables of interest, 1994-2002 Summary statistics for the industries			
	Forest	**Machinery & equipment**	**Electronics**
TFP (% points)	+27.9	+44.5	+139.5
Wages (% points)	+28.9	+33.9	+121.3
Experience (# of years)	+1.2	+1.4	+1.5
Seniority (# of years)	+1.1	+0.4	+0.5
Schooling (# of years)	+0.8	+0.3	+0.3

Notes: TFP and wage growth rates are computed from STAN national accounting data, experience, seniority and schooling from our data set

Table A2. Descriptive statistics of data on plants by industry, plant averages in 1995-2002

Variables	Forest industry					Machinery industry					Electronics industry				
	Mean	Sd	p5	Median	95p	Mean	Sd	p5	Median	95p	Mean	Sd	p5	Median	95p
Log of TFP index	1.80	0.74	0.88	1.66	3.28	2.83	0.59	2.08	2.72	4.00	2.27	1.04	0.99	2.05	4.58
Log of monthly wage (in euros)	7.61	0.24	7.23	7.59	8.02	7.69	0.19	7.36	7.69	8.00	7.65	0.23	7.27	7.67	8.03
Schooling years	11.0	0.4	10.3	11.0	11.7	11.6	0.9	10.6	11.4	13.6	12.2	1.2	10.6	11.9	14.5
Age in years	39.6	3.8	33.3	40.1	45.0	39.3	4.0	31.8	39.8	45.0	35.6	3.8	29.4	35.8	41.6
Potential experience in years	21.6	3.9	15.1	22.1	27.1	20.7	4.2	13.1	21.1	26.9	16.4	4.0	9.3	16.6	22.5
Seniority in years	10.9	5.6	2.6	10.8	19.5	9.2	4.8	2.7	8.9	17.5	6.3	3.3	2.1	5.3	12.69
	Proportion (%)					Proportion (%)					Proportion (%)				
Plant birth before 1977	57.0					34.57					27.91				
Plant birth 1977-1980	6.3					8.47					7.56				
Plant birth 1981-1985	5.5					6.88					4.07				
Plant birth 1986-1990	10.7					16.58					23.26				
Plant birth 1991-1995	9.9					18.87					19.77				
Plant birth 1996-	10.7					14.64					17.44				
Plant size 5-9 persons	1.8					3.14					3.17				
Plant size 10-19 persons	9.0					10.20					6.85				
Plant size 20-49 persons	30.9					41.08					33.51				
Plant size 50-99 persons	21.7					20.56					20.65				
Plant size 100- persons	36.7					25.02					35.81				
Foreign-owned plant	6.2					19.86					12.95				
Plant death during 1996-2002	11.8					19.22					22.09				
Number of plants	365					567					172				

Notes: The data are constructed in the Research Laboratory of Statistics Finland by linking the plants in the Finnish Manufacturing Census and individuals in the Employment Statistics with plant codes. Authors' calculations from the primary data of Statistics Finland

Table A3 – Statistical analysis behind the simulation graphs, between plants estimation

	Forest TFP	Forest Wage	Machinery TFP	Machinery Wage	Elect. TFP	Elect. Wage
Schooling years	-3.386	-0.073	0.826+	0.182	1.481	0.310
	(2.491)	(0.815)	(0.470)	(0.140)	(1.294)	(0.210)
[Schooling years]^2	1.503	0.095	-0.285	-0.020	-0.511	-0.070
	(1.113)	(0.368)	(0.194)	(0.057)	(0.524)	(0.084)
Potential experience	1.017**	-0.014	0.171	0.082+	-0.785	0.007
	(0.371)	(0.118)	(0.151)	(0.044)	(0.616)	(0.110)
[Potential experience]^2	-0.513**	0.021	-0.072	-0.024	0.364	-0.012
	(0.187)	(0.057)	(0.081)	(0.022)	(0.390)	(0.071)
[Potential experience]^3	0.081**	-0.005	0.010	0.002	-0.047	0.005
	(0.030)	(0.009)	(0.014)	(0.004)	(0.078)	(0.015)
Seniority in years	-0.013	-0.003	-0.045	-0.020	1.276***	0.131*
	(0.086)	(0.027)	(0.054)	(0.018)	(0.272)	(0.062)
[Seniority in years]^2	0.070	0.012	0.033	0.022	-1.665***	-0.161+
	(0.081)	(0.026)	(0.056)	(0.017)	(0.365)	(0.083)
[Seniority in years]^3	-0.025	-0.000	-0.008	-0.007	0.622***	0.061+
	(0.022)	(0.007)	(0.017)	(0.005)	(0.153)	(0.034)
Plant birth in 77-80	0.237*	0.003	-0.051	0.019	-0.088	-0.027
	(0.119)	(0.032)	(0.066)	(0.029)	(0.154)	(0.044)
Plant birth in 81-85	0.247*	0.059	0.057	0.014	-0.210	0.032
	(0.117)	(0.041)	(0.079)	(0.021)	(0.257)	(0.043)
Plant birth in 86-90	0.658***	0.040	0.255***	0.013	0.094	0.019
	(0.104)	(0.027)	(0.057)	(0.018)	(0.209)	(0.046)
Plant birth in 91-95	0.575***	0.026	0.432***	0.083***	0.680**	-0.012
	(0.144)	(0.037)	(0.060)	(0.017)	(0.232)	(0.042)
Plant birth in 96-	0.969***	0.052	0.629***	0.077**	0.677*	0.029
	(0.196)	(0.037)	(0.088)	(0.025)	(0.286)	(0.052)
R-squared	0.545	0.647	0.486	0.516	0.527	0.581
Adj. R-squared	0.510	0.620	0.461	0.493	0.442	0.505
Number of plants	365	365	567	567	172	172

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Notes: Other control variables include dummies for plant size (5 groups), foreign-ownership and death during 1996-2002. Robust standard errors are shown in parenthesis

Table 3 – Statistical analysis for the determinants of the log of productivity (TFP index; Ordinary Least Squares "between" estimates, plant averages in 1995-2002)

	Forest (1)	Forest (2)	Machinery (3)	Machinery (4)	Electronics (5)	Electronics (6)
Schooling years	-0.005	-0.001	0.119***	0.120***	0.206***	0.203***
	(0.074)	(0.074)	(0.025)	(0.025)	(0.061)	(0.060)
Age	0.142	0.005	0.083	0.005	-0.376	0.010
	(0.133)	(0.010)	(0.075)	(0.005)	(0.265)	(0.021)
Age squared	-0.018		-0.010		0.055	
	(0.017)		(0.010)		(0.039)	
Plant birth in 77-80	0.206+	0.204+	-0.045	-0.040	0.009	-0.006
	(0.119)	(0.117)	(0.064)	(0.064)	(0.162)	(0.156)
Plant birth in 81-85	0.223+	0.229+	0.068	0.070	-0.011	-0.069
	(0.129)	(0.129)	(0.076)	(0.076)	(0.230)	(0.222)
Plant birth in 86-90	0.641***	0.617***	0.269***	0.269***	0.226	0.223
	(0.112)	(0.107)	(0.053)	(0.054)	(0.197)	(0.199)
Plant birth in 91-95	0.512***	0.506***	0.444***	0.434***	0.622**	0.590**
	(0.136)	(0.136)	(0.055)	(0.054)	(0.213)	(0.210)
Plant birth in 96-	0.923***	0.911***	0.632***	0.622***	0.526+	0.491+
	(0.185)	(0.184)	(0.085)	(0.084)	(0.270)	(0.273)
Observations	365	365	567	567	172	172
R-squared	0.516	0.514	0.480	0.479	0.468	0.460
Adj. R-squared	0.486	0.486	0.460	0.460	0.394	0.388

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Notes: Other control variables include a dummy variable for foreign-owned plant, a dummy variable for plants that disappear in years 1996-2002 and 4 dummy variables to indicate size group (5 size groups). Robust (Huber/White/sandwich estimator of variance) standard errors are given in parenthesis

Table 4 – Statistical analysis for the determinants of the log of monthly wage (Ordinary Least Squares "between" estimates, plant averages in 1995-2002)

	Forest (1)	Forest (2)	Machinery (3)	Machinery (4)	Electronics (5)	Electronics (6)
Schooling years	0.151***	0.149***	0.117***	0.117***	0.120***	0.120***
	(0.023)	(0.023)	(0.007)	(0.007)	(0.010)	(0.009)
Age	-0.028	0.024***	0.104***	0.015***	-0.025	0.018***
	(0.042)	(0.003)	(0.022)	(0.002)	(0.062)	(0.004)
Age squared	0.007		-0.011***		0.006	
	(0.005)		(0.003)		(0.009)	
Plant birth in 77-80	-0.030	-0.029	0.016	0.023	-0.013	-0.015
	(0.033)	(0.034)	(0.029)	(0.029)	(0.044)	(0.043)
Plant birth in 81-85	0.041	0.039	0.009	0.012	0.045	0.038
	(0.045)	(0.046)	(0.021)	(0.022)	(0.040)	(0.037)
Plant birth in 86-90	0.007	0.016	0.011	0.011	0.020	0.019
	(0.028)	(0.027)	(0.018)	(0.018)	(0.042)	(0.042)
Plant birth in 91-95	-0.010	-0.007	0.083***	0.072***	-0.028	-0.031
	(0.036)	(0.036)	(0.017)	(0.017)	(0.042)	(0.041)
Plant birth in 96-	0.011	0.016	0.075***	0.064**	0.009	0.005
	(0.035)	(0.035)	(0.022)	(0.022)	(0.053)	(0.054)
Observations	365	365	567	567	172	172
R-squared	0.579	0.577	0.514	0.499	0.563	0.561
Adj. R-squared	0.553	0.552	0.495	0.480	0.502	0.503

+ $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Notes: Other control variables include a dummy variable for foreign-owned plant, a dummy variable for plants that disappear in years 1996-2002 and 4 dummy variables to indicate size group (5 size groups). Robust (Huber/White/sandwich estimator of variance) standard errors are given in parenthesis