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The Age-Productivity Gradient: Evidence from a Sample of F1 Drivers

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The Age-Productivity Gradient: Evidence from a Sample of F1 Drivers

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Abstract
Aging is a global phenomenon. If older individuals are less productive, an aging working population can lower aggregate productivity, economic growth and fiscal sustainability. Therefore, understanding the age-productivity gradient is key in a aging society. However, estimating the effect of aging on productivity is a daunting task. First, it requires clean measures of productivity. Wages are not such measures to the extent that they reward other workers attributes than their productivity. Second, unobserved heterogeneity at workers, firms and workers/firms level challenges the identification of the age-productivity gradient in cross-sectional data. Longitudinal data attenuate some identification issues, but give rise to the problem of partialling out the effect of aging from the pure effect of time. Third, the study of the age-productivity link requires investigating the role of experience and of seniority. We tackle these issues by focussing on a sample of Gran Prix Formula One drivers and show that the age-productivity link has an inverted U-shape profile, with a peak at around the age of 30-32.

JEL Classification: J24,C23, L83.

Keywords: Aging, individual effects, firm effects, match effects, Formula One.

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1 Introduction

Aging is a global phenomenon. If older individuals are less productive, an aging working population can lower aggregate productivity, economic growth and fiscal sustainability. Therefore, understanding the age-productivity gradient is key in a aging society. However, estimating the effect of aging on productivity is a daunting task. First, it requires clean measures of productivity. Second, unobserved heterogeneity at workers, firms and workers/firms level challenges the identification of the age-productivity gradient in cross-sectional data. Longitudinal data attenuate some identification issues, but gives rise to the problem of partialling out the effect of aging from the pure effect of time. Third, the study of the age-productivity link requires investigating the role of experience and of seniority. Fourth, jobs differ with respect to the skills they require and different skills may evolve very differently over different working careers.

The literature on micro data has tackled some of these issues, but some remain unresolved. The available evidence seems to indicate that the elderly do suffer a drop in productivity. Medoff and Abraham (1980, 1981), and Waldman and Avolio (1986) use supervisors' rating to measure productivity and show that older workers are less productive than younger ones. These early studies have been important attempts to tackle the above mentioned issues, but still suffer from severe shortcomings. First, being most of these studies based on cross-sectional data, they are unable to disentangle the effect of age from the effect of tenure, and are unable to control for the fact that workers may self-select into firms according to their productivity. Second, supervisors may tend to over-reward senior workers for loyalty and past achievements and therefore supervisors' rating might be only an imperfect proxy for individual productivity.

These shortcomings are later addressed in the literature. Stephan and Levin (1998) study researchers in the fields of Physics, Geology, Physiology and Biochemistry. The number of publications and the standard of the journals they appear in are found to be negatively associated with the researchers' age. Similar evidence is found in the field of economics where Oster and Hamermesh (1998) conclude that older economists publish less than younger ones in leading journals, and that the rate of decline is the same among top researchers as among others.[1] The productivity of individuals doing "creative" jobs, such as authors and artists, is measured by the quantity and sometimes the quality of their output. The evidence seems to indicate that the elderly are less productive. 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 and painters. These papers share a common feature, the use of piece-rate samples, which provide a clean measure of productivity. However, they cannot easily separate the workers' ability from firm effect and control accordingly for workers selection into firms.

To overcome these problems a number of studies use employer-employee matched data-set. The evidence based on such data-sets, where individual productivity is

[1] The same pattern applies to Nobel economists (Dalen, 1999)

measured as the workers' marginal impact on the company's value-added, finds an inverted U-shaped work performance profile (Andersson et al. (2002), Crépon et al. (2002), Ilmakunnas et al. (2004), Haltiwanger et al. (1999), Hægeland and Klette (1999)).

Individuals in their 30s and 40s have the highest productivity levels. Employees above the age of 50 are found to have lower productivity than younger individuals, in spite of their higher wage levels. These papers basically estimate the effect of aging on productivity by comparing output (or value added) per worker in plants (or firms) with a different age composition of the workforce. A problem with the fact that most studies on age-productivity differences are based on cross-sectional evidence (with the notable exception of Dostie (2006)) is that reverse causality may be at work: for example, successful firms generally increase the number of new employees and this mechanically leads to a younger age structure. Thus, a younger workforce could be the effect rather than the cause of firms good performances.

In order to overcome this problem, this paper casts the age-productivity test in its correct setting: within the worker-firm pair. We rely on a unique data-set, that records the race performances for all Gran Prix Formula One (F1) drivers from 1991 to 1999. The data provide a clean measure of productivity and have enough information to identify the age-productivity profile after controlling for a host of workers and firms characteristics. In particular, we are able to account for tenure and experience – on top of drivers, firms and match effects – and still identify the age-productivity gradient. We find that productivity peaks at the age of 30-32 and then decreases. Moreover, in accordance with the findings of Abowd et al. (1999), we show that workers effects are more important than firms and match effects in determining productivity, as they account respectively for 25, 12, and 2 percent of the explained variability. Consistently, we find that omitting either firms or match effects (or both) in a model with workers effects does not alter the age-productivity gradient.

This paper complements the available results on the age-productivity gradient and provides new insights on the determinants of individual productivity focusing on an admittedly special sample. However, the usefulness of professional sports as a labor market laboratory has long been recognized (Kahn, 2000) and many labor-related questions (e.g. racial discrimination; the relationship between managerial quality and performance) have been tackled using professional sports data (Kahn, 1991, 1993, 2006). Of course, it would be unwise to readily generalize our results to the general population. Yet, the neat identification strategy obtained in this setting makes our results a useful supplement to those obtained in more standard contexts with – perhaps – less clean identification procedures.

The rest of the paper is organized as follows. Section 2 describes the F1 industry and data. Identification is discussed in Section 3. Section 4 presents the results and Section 5 concludes.

2 The Formula One Industry

With its 350 Millions TV viewers per race, F1 racing is considered today the most popular sport worldwide. The Auto Club de France held the first Grand Prix race in 1906, but it was not until 1950 that the first World Championship series was held, linking national races in the UK, Monaco, the US, Switzerland, Belgium, France, and Italy. In that year, the form of racing previously called Formula A came to be known as Formula One and became the pinnacle of automotive technology. We believe that there are several grounds on which to focus on F1 to investigate the age-productivity relationship.

First, there are few contexts that provide cleaner measures of performance differences than that of F1 racing. In F1 racing, there are a limited number of racing teams and a limited number of races; in a given year, all of the teams participate in all the races on the circuit.[2] Since all teams are racing on the same racetracks and have cars that must adhere to the same rules, performance differences are easy to measure. Second, although performance is clear after either a race or a racing season is completed, there is a certain degree of uncertainty on how a team is going to perform in either the next race or next season. In particular, given the inherent complexity of F1 cars and given that cars are usually entirely redesigned between seasons, it is uncertain how a new car will stand against competition.

There is a third reason for using F1 racing data, which has to do with the teams seeking constantly to enhance performance by developing their products in collaboration with their suppliers and their drivers. Most of the teams are owned by the world's major automobile manufacturers whose motivation is, at least in part, the exposure to "cutting-edge" technological advances in car design. Unlike other forms of motor-sport, such as Champ Car or IRL where all competitors race in almost identical cars built using standard components, F1 racing teams must design, construct and race their own chassis (for this reason F1 teams are officially called Constructors and a special championship, the World Constructors Championship, is held every year and awarded to the team that scores the most championship points during a racing season). As F1 teams can, and often do, buy the remaining parts of a racing car from external suppliers, a coordination problem for F1 teams emerges both in design and racing of the car. Each F1 team seeks to design a car that it regards as the best compromise of aerodynamic performance, maneuverability, structural rigidity, and engine power within the rules imposed by the governing body of F1, the Fédération Internationale de l'Automobile (FIA). By imposing strict constraints on dimensions, weight, and safety, these rules limit the degrees of freedom in designing a car by taking the interrelations among the various design dimensions to the extreme. For instance, to increase the horsepower of an engine, designers have to consider that the increased heat needs to be dissipated by a redesigned cooling system with bigger radiators and, consequently, an increased weight. Given the constraints in size and

[2] We refer to F1 racing teams as "team" as customarily called in the industry. However, these "teams" are in reality middle-sized firms averaging 164 employees and $34.5 million dollars in assets in 1997. Besides the racing department in charge of running the cars during the race, these firms have R&D, Marketing, Production, and Testing departments.

weight, other parts of the car need to be redesigned, making sure that the final outcome - a racing car - not only produces the desired performance consistently in every race, but also passes compulsory safety tests.

A fourth reason for focussing on F1 has to do with the role of drivers. Although they are believed to be less important for the final performance than in the past, drivers also play a relevant role in the success of a F1 car. Not only do drivers need to skillfully drive the car during the race itself, but they also need to be involved in the development of a specific car design. Despite the heavy use of telemetry to obtain detailed information on a car's behavior on the track, the driver is still the ultimate provider of feedback to the car's engineers and mechanics. Providing feedback on a F1 car is different than providing feedback on any other racing car. Even drivers considered talented in other racing series need time to acquire this skill. Ultimately, a car's performance is determined not only by a driver's sheer talent, but also by her/his ability to provide feedback. For this reason, every time a team wants to hire a new driver, it tries to find somebody who, in the words of one team owner, "is immediately operational". That is, the team seeks someone who has proven in the past s/he can help the team extract the highest performance from the car.

The identification of the age-productivity gradient requires reliable and repeated measures of productivity over time. Moreover, to partial out individual from firm effects, one has to focus on high turnover industries, where employee change often employers. F1 is the case of an industry where transitions between employers and employee are frequently observed. This provides a further reason to focus on F1. Abowd et al. (2002) discuss the group-connectedness in employer-employee match data and highlight its role in disentangling the firm from the individual effect. Table 1 provides an example of the degree of connectedness provided by the F1 data.

Data are drawn from `http://www.formula1.com` and `http://www.4mula1.ro`, which provide information on races, drivers and teams. We sample all races that took place between the 1991 and the 1999 seasons. In each race, performance is measured on the basis of the final position of the car. In our time window, points are awarded to those cars that finish in the first six places. 10 points are awarded for first; 6 points are awarded for second, 4 for third, 3 for fourth, 2 for fifth, 1 for sixth, and 0 for the other placements. Therefore, the sum of points awarded does not grow from race to race and is fixed to 26. This means that in measuring productivity with the points awarded to each driver at the end of the race, one does not need to allow for aggregate effects to capture growth from race to race (or from season to season) in aggregate productivity. This is quite an advantage over measures of productivity based on wages and value added, since both increase (or decrease) over time because of aggregate time effects, not related to aging.[3] Beyond the final position of each car, we also know the time to complete the race. This an equally valid measure of car performance, but contrary to points it is affected by the aggregate effect on cars' speed of technological evolution.

[3]The problem of identifying time from age effects is common to many settings, such as the evaluation of the age-consumption and saving profile, the age-income profile, and the estimation of depreciation of capital goods (or durable goods) from price data.

Each record in our data-set provide car-race level information. Therefore, our data-set contains 3,180 observations including all races from 1991 to 1999. For each observation, we have the car, the chassis and the engine numbers; the name, nationality, team, the tenure with the team and the year of birth of the driver; the date of the race, the weather conditions in the day of the race, the country where the race is held, and the track length; the nationality, the assets, the number of employees and the age of the team, the name, nationality and the age of the technical director. Overall, we have data on 89 drivers, 22 teams, 8 seasons, and 16 races per season. Table 2 collects the drivers' names, Table 3 the teams names, and Table 4 a sample of the variables available for each race in the 1994 season.

Selected summary statistics are provided in Table 5. The across races mean of drivers scores is just above 1, which hides substantial variability between drivers (1.19) and races (1.99). The age of drivers is on average 29.43 and drivers start driving F1 cars at the age of 25.16. The age of entry in F1 varies across drivers. Esteban Tuero enters at the age of 20, Toshio Suzuki at the age of 38. We observe the entire career of 36 out of 89 drivers, for 30 drivers the career is left truncated, for 17 right truncated and for 6 both left and right truncated. During their careers, drivers change often team: 58 percent of the drivers change team at least once, 36 percent twice, 16 percent three times, 4.5 percent four times, and 2.2 five times. Moreover, Andrea De Cesaris, Eric Van De Poele, J. J. Lehto, Jarno Trulli, Johnny Herbert, Mika Salo change team once in a season, Philippe Alliot twice.

Table 5 also contains information on teams and their technical directors. F1 teams count on average 146.8 employees, the average age of technical directors is 44.5 and the age of drivers' entrance in F1 is just below 30. These variables will be used in the estimation exercise, as we clarify in the next section.

3 Identification

To identify the effect of age on drivers performance we provide three alternative models. In the baseline model, which we call Model I, we just allow for drivers fixed effects.[4] The estimation of such model would just require panel data on drivers performance and does not exploit any information on teams. To disentangle teams from drivers effect we estimate our Model II, which uses the matched employer-employee structure of the data. Finally, Model III recognizes that drivers mobility between teams might depend on match specific effects. Comparing the three models allows to understand the importance of drivers, teams and match effects in the estimation of the age-productivity link.

[4] An alternative identification strategy is to assume random drivers effects. This approach has obvious computational advantages over ours in the context of large-scale employer-employee data-sets (see Woodcock (2006) for an application to wage data). However, it requires assuming that drivers ability is uncorrelated with all regressors including age. In our setting this assumption is not likely to hold, as also confirmed by the Hausman test that compares the fixed and the random effect models and reveals the presence of systematic differences in the estimated coefficients.

3.1 Drivers effects

Productivity, as measured the points at the end of the race, of driver i at time t is:

$$y_{it} = \mu + \theta_i + \alpha \times age_{it} + \varepsilon_{it}$$

where θ_i is driver i ability and age_{it} is driver's i age at time t measured in years. We assume that:

$$E(y_{it}|age_{it}) = \mu + \theta_i + \alpha \times age_{it}$$

It is immediate to verify that α is identified if:

$$E(y_{it+1}|age_{it+1}) - E(y_{it}|age_{it}) = \alpha \tag{1}$$

which requires that $E(\varepsilon_{it} - \varepsilon_{it-1}|\theta_i, age_{it}, age_{it-1}) = 0$. This leads to our first model for drivers performance. Model I can be estimated by regressing y_{it} on a set of drivers dummies and age. Notice that drivers can sort into teams according to unobserved individual characteristics. Adding workers fixed effects allows to control for the sorting due to drivers time-invariant characteristics. However, for the estimates of Model I to be unbiased, one does require that mobility is exogenous, conditional on age and drivers effect.[5]

Differently, if drivers mobility between teams depends on omitted characteristics (e.g. the quality of the team) that are correlated with age, α cannot be consistently estimated in Model I. To understand how this can happen consider the case where young drivers move to higher quality teams while old drivers do the opposite. The omitted teams characteristics would then be captured by age, possibly generating a spurious inverse U-shaped relationship between ageing and productivity. More formally, $E(\varepsilon_{it} - \varepsilon_{it-1}|\theta_i, age_{it}, age_{it-1})$ cannot be equal to zero if the performance varies systematically between teams and mobility is related to age. To account for the effect of teams characteristics on drivers performance we turn to our second model.

3.2 Drivers and teams effects

Model II assumes that the drivers performance depends also on team characteristics that are fixed over time:

$$y_{ijt} = \mu + \theta_i + \psi_{j(it)} + \alpha \times age_{it} + \varepsilon_{ijt}$$

where $j(it)$ is the team to which driver i belongs at time t. It easy to verify that the team effect is not identified if no driver changes team from one year to the other. For driver s, who does not change team between years t and $t+1$, the analogue of (1) is:

$$E(y_{sjt+1}|age_{st+1}) - E(y_{sjt}|age_{st}) = \alpha \tag{2}$$

[5]We also estimate a baseline model without drivers effect. The results, not reported for brevity, show that the exogenous mobility assumption, in a model with age effects only, is rejected.

while for driver m who changes from team j to team k, it is:

$$E(y_{mkt+1}|age_{mt+1}) - E(y_{mjt}|age_{mt}) = \alpha + \psi_{k(mt+1)} - \psi_{j(mt)} \tag{3}$$

Equations (2) and (3) identify the team from the age effects. Model II can be estimated by regressing y_{ijt} on a set of drivers and team dummies and age. Model II provides consistent estimates of the age effects, unless drivers mobility between teams depends on a match specific team effect. If that is the case, the estimates of α are not consistent and therefore one needs to add match effects to the model.[6] This leads us to specify and estimate our third model, which accounts for match effects.

3.3 Match effects

Allowing for match specific effects on the top of team and drivers effect poses a fundamental identification problem. Since the match effects results from the interaction of the driver and team effects, the model with match, team and driver effects is over-parametrized. Suppose for the sake of exposition that α is equal to zero and that the model is:

$$y_{ijt} = \mu + \theta_i + \psi_{j(it)} + \phi_{ij} + \varepsilon_{ijt} \tag{4}$$

where ϕ_{ij} is the match effect. If $E(\varepsilon_{ijt}|\theta_i, \psi_{j(it)}, \phi_{ij}) = 0$, the sample analog of the expected value (4) is:

$$\frac{1}{T_{ij}} \sum_{t=1}^{T_{ij}} y_{ijt} \tag{5}$$

where it is assumed that driver i stays with team j for T_{ij} years. If the number of matches is equal to M, there are M sample moments like (5). With N drivers and J teams, identification of driver, team and match effects requires recovering from M sample moments, $N + J + M + 1$ parameters, which is an impossible task. Identification thus requires additional assumptions. There are many alternative identification assumptions. One possibility is to give up on identifying driver from team and match effects. Assuming that drivers performance changes with age, the model can be written as:

$$y_{ijt} = \mu + \theta_i + \psi_{j(it)} + \phi_{ij} + \alpha \times age_{it} + \varepsilon_{ijt} \tag{6}$$

The linearity of the right-hand side of (6) ensures that α can be consistently estimated if one can find a sufficient statistic for the sum of driver, team and match effects. This leads to the following model:

$$y_{it} - \overline{y}_{ij} = \alpha(age_{it} - \overline{age}_{ij}) + \eta_{it} \tag{7}$$

[6]Of course, the estimates of α are still consistent if age and match effects are uncorrelated, given the drivers and teams effects.

where:

$$\overline{y}_{ij} = \frac{1}{T_{ij}} \sum_{t=1}^{T_{ij}} y_{ijt} \tag{8}$$

$$\overline{age}_{ij} = \frac{1}{T_{ij}} \sum_{t=1}^{T_{ij}} age_{ijt} \tag{9}$$

where T_{ij} is the number of years driver i stays with team j.

This approach allows to identify the age effect, but is silent about the driver, the team and the match effect.[7] We therefore consider an alternative possibility. Namely, we exploit the richness of our data to model the match effects. In particular, we allow for match effects to depend on drivers age and assume that they are related to the distance between the age of the driver and the age of the team, and that between the age of the driver and the age of technical director. Furthermore, we assume that the match effects also depend on whether the team and the driver have the same nationality, and whether the technical director and the driver have the same nationality.

Section 4.1 shows results from the three above-described models, extended so as to include a host of time-varying factors that may affect the age-productivity profile. Section 4.2 presents results from specifications that control for a number of additional confounding factors that may lie behind our findings. Among other things, we will control for the changing quality of the opponents and will be able to separately identify the effect of age from the effect of tenure and experience.

4 The age-productivity gradient

4.1 Results from baseline specifications

We estimate our three models in turn: model I, featuring drivers effect only, model II featuring drivers and teams effects, and model III, where we add match effects. For each of them we consider two specifications. A baseline specification with no additional controls and an extended specification which allows for a list of additional covariates including years dummies for 1995-1997, number of entrants in each race, a dummy for rainy weather at the day of the race, the track-length, the number of race-laps, a dummy for whether the race takes place at the drivers home.

The results are reported in Table 6 and show that the coefficient on the linear term of age is positive while the coefficient on the quadratic term is negative in both the baseline and the extended specification.

Figure 1 displays the age and productivity profile for the three models respectively with drivers, drivers and teams, and drivers, teams and match effects for the baseline specification. The profiles are obtained by projecting the estimated quadratic polynomial on age. The figure shows that productivity increases with

[7] We also estimate (7) and get very similar results to those obtained estimating Models I and II.

age, until the age of 30 and decreases afterward. The maximum is reached between age 30-32. Our estimates also imply that productivity increases by just below half point (0.46) between the age of 20 and 21 in models I and II, and by just above half point (0.52) in model III; and decreases by just below 1/5 of point (0.18) between the age of 34 and 35 in models I and II, and 0.123 in model III.

Overall, our estimates imply that age accounts for as much as 4.5 percent of explained variance of productivity, while drivers effects explain as much as 25 percent, and teams and match effect account respectively for 12 and 2 percent. Results are consistent with Abowd et al. (1999) who find that firm effects are not as important as individual effects in explaining individual wage variation in France.

Even though we are able to reject the null that drivers and teams effects are equal to zero, the differences across models and specifications are not sizeable.[8] As models with teams and match effects are meant to account for the endogeneity of mobility decisions, the finding that the age-productivity gradient does not differ much across models suggest that the endogeneity bias is small. This is a notable finding in a high-turnover industry such as the F1 industry (see section 2) which may suggest that the bias induced by endogenous mobility decisions may be even smaller in industries characterized by lower rates of job mobility.[9]

Summing up, this first set of results shows that GP drivers have an age-productivity profile consistent with that predicted by the theory of human capital. Whether or not this is an artifact of our data is the concern to which we devote the rest of this section.

4.2 Results from additional specifications

Interactions between drivers effects and race characteristics

The list of factors that might lie behind our results is potentially large, even if our estimates allow for drivers, teams and match effects. At the top of the list, factors that change across drivers and between races (and seasons). For instance, some drivers can be better at racing on wet ground, or on long tracks. Therefore, the change in their performance from race to race might depend on the weather conditions at the day of the race, or on the tracks characteristics, which might confound the effect of age.

We therefore add to our extended specification interaction terms between drivers effects and tracks length, driver effects and number of race-laps, and driver effect and a dummy for rainy weather at the race day. The results are reported in Table 7 and are very similar to those reported in Table 6. Productivity increases by 0.45-0.50 between the age 20 and 21 in all models, and decreases by 0.15-0.21 between the age of 34 and 35.

[8] We do not reject at the standard level the null that the age coefficients are equal across models I and II, while we do reject the null that they are equal across models II and III.

[9] Booth et al. (1999) examine job mobility and job tenure in the UK over the period 1915-90. They find that British men and women held an average of five jobs over the course of their work lives. In our data we observe the entire career for 36 out of 89 drivers. Those drivers change team almost once a year during their career.

Controlling for all the interactions between drivers effects and race characteristics in the same regressions does not alter the picture. The results are provided in Table 8, and Figure 2 shows the age-productivity profile. Productivity peaks between the age 30 and 32, and has a concave shape in accordance with human capital theory.

Changing rules

Changes in the rules between seasons might also affect differently different drivers. This is another potential factor that might confound the age effects. For instance, major innovations were introduced in 1994. Refuelling was permitted again with the use of a standardized refuelling rig, the active/reactive suspension systems was banned, and so were the electronic driver aids, such as the traction control, launch control. Moreover, after San Marino accident in 1994, where drivers Roland Ratzenberger and Ayrton Senna died, restrictions imposed on the front and rear wings, the size and shape of the rear diffuser, and a wooden “plank” introduced on the underside of the car to raise the ride height. We therefore add to our specification the interaction of dummies for years after 1994 with the drivers effects. The results are reported in Table 9 and are again quite similar to those reported in the Tables 6-8. The age-productivity profile is concave and peaks at the age of 30-32, as shown in Figure 3.

Quality of opponents

Another source of bias that might affect the estimates of the relationship between aging and productivity may derive from the absence of a proper correction for the quality of the opponents. If, for example, the average quality of opponents decays over time one may underestimate the effects of aging on productivity. Changes in the average quality of the opponents may be due either to the changing quality of incumbent drivers or to compositional changes in the pool of drivers. To address the first problem Table 10 presents results controlling for the quality of the opponents, as measured by the cumulative number of points of the rivals since the start of the season. While the table shows that the quality of opponents does have a negative influence on drivers performances, the coefficients of age and age square are hardly affected. Next, to address the potential effect of compositional changes in the pool of drivers due to the fact that low productivity drivers may sort themselves out of the profession in younger ages, we control for non-random attrition using propensity score weights. Predicted probabilities of staying in the sample are obtained running a probit on a dummy equal to one if the driver is present in the following year (and zero otherwise) on the cumulative number of points in the season and a quadratic in age. The propensity score weights are then computed on the basis of these predicted probabilities and used in the estimation of the age-productivity gradient. Table 11 presents the results that confirm the findings of the previous tables.

Experience and tenure

The shape of the age productivity gradient is likely to depend on drivers experience and possibly tenure. Drivers’ performance might improve with experience, and also longer driver-team relationship might have a positive effect of performance, allowing the driver to learn better about his car.

Disentangling the effect of experience and tenure on productivity from that of age is often hard. Experience and tenure coincide for those worker who do not move between jobs, and both change hand-in-hand with age. The high turnover among GP drivers allows to distinguish experience from tenure. We measure the former with the age of entry in F1, and the latter with the duration of team-driver relationship for each driver. However, the age of entry in F1 is fixed for each driver and therefore it is absorbed into the driver fixed effect. To understand if experience and tenure matter for the estimated age-productivity profile, we thus exploit the fact that sum of scores at the end of each race is fixed. This allows adding the normalization equation that the sum of driver effect is zero, and therefore estimating models that account for the effect of experience and tenure on productivity and separate that from the effect of age and the individual effect. The results for experience are reported in Table 12 and those for tenure in Table 13. The Tables reveal that both experience and tenure matter, but leave the overall picture unaffected.

Past performances

Aging is not the only and possibly the main driver of performance changes over time. Productivity changes across races (and seasons) might reflect past performances. State dependence in the productivity process come from the good performances in the past having a positive or a negative effect on current performances. The former case might arise when past bad performances make drivers less confident and then drive less aggressively. The latter, when bad past performances increase the incentives to drive better in future races. While we cannot identify the precise channel from which state-dependency in performances arises, we can control for past performance. This is done in Table 14, where we add to the set of regressors the scores in the previous race. The results suggest that past has a positive effect on current performance, and that the shape of the age productivity gradient is not very much affected.

Non-parametric specification

So far we have restricted the age effect to enter the productivity equation in a quadratic fashion. Such assumption is made for convenience. To model more flexibly the effect of age on productivity, we replace the linear and quadratic age terms with a set of age dummies. The results are reported in Table 15. The baseline category is age between 20 and 22: productivity increases with age until age 32-34 and then starts decreasing. Therefore, allowing for a more flexible specification moves the peaks by around 1 year, but leaves the concavity unchanged. Moreover, as one can see from Figure 4, productivity increases relatively little at the beginning of the career, and more from the age of 28 until the peak, and it decreases quite dramatically at the very end of the career.

5 Conclusions

Measuring the age-productivity gradient has both positive and normative implications. The shape of the age-productivity profile has implications for aggregate productivity, economic growth, the sustainability of pension systems and the design of tax systems. Moreover, the optimality of wage schemes based on seniority depends on the extent to which productivity decreases at old ages.

The empirical evaluation of the age-productivity link is, however, problematic, in that it requires repeated measures of productivity and possibly employer-employee match data. Data with such features are seldom available. Good proxies of productivity are provided by piece-rate samples, such as those on scientist or criminals. However, such data do not allow to disentangle the firm and the individual effects on productivity. This issue can be addressed by employer-employee match data, which, however, often lack of convincing measures of productivity. Here, we use very special data, which share the advantages of both the piece-rate and the employer-employer match data: data on GP drivers.

GP drivers change often employer in their careers, which makes identification of firm and individual effects possible. Moreover, it is easy to observe their productivity, which we measure as the points awarded to each driver at the end of each race. This is an objective measure of productivity and is not affected by aggregate growth, since the sum of points awarded in each race is constant over time.

We find that the age-productivity profile is concave and reaches the maximum between the age of 30 and 32. Our result is robust to a number of checks, which control for the fact that there might be factors changing across races (or seasons) which affect drivers differently. Moreover, we show that the productivity increases by around 2.6 points between the age of 20 and 30, and decreases by 2.4 points between the age of 30 and 40. We also show that drivers, teams and match effect matters, as they account respectively for 25, 12, and 2 percent of the explained variance of productivity. However, omitting team and match effects from the driver effect model does not alter the overall picture on the age-productivity. Since it is very likely that in a population of GP drivers mobility depends on team and match characteristics, we see this result as indicating that the endogeneity of mobility does not affect how productivity evolves with age. While the result pertain to a peculiar population, we might expect the effect of endogenous mobility to be even smaller in those populations where the role of employer and match specific human capital is less important.

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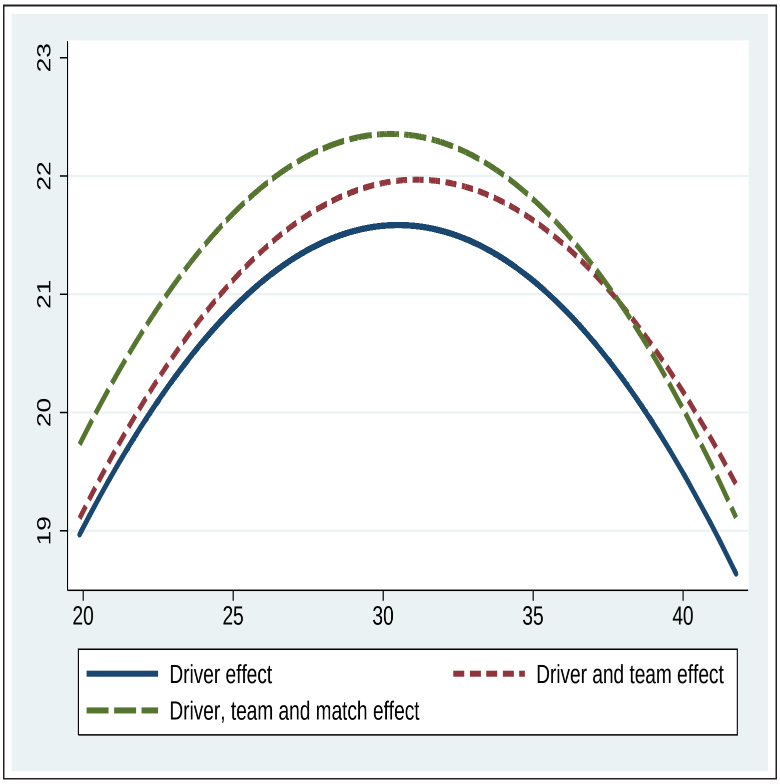
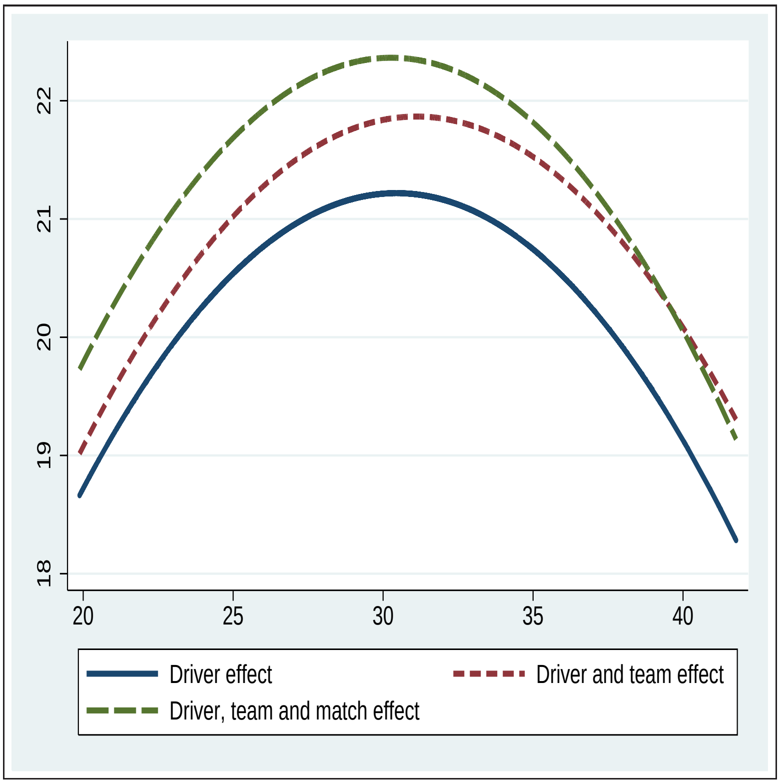
Figure 1. Age-productivity profile



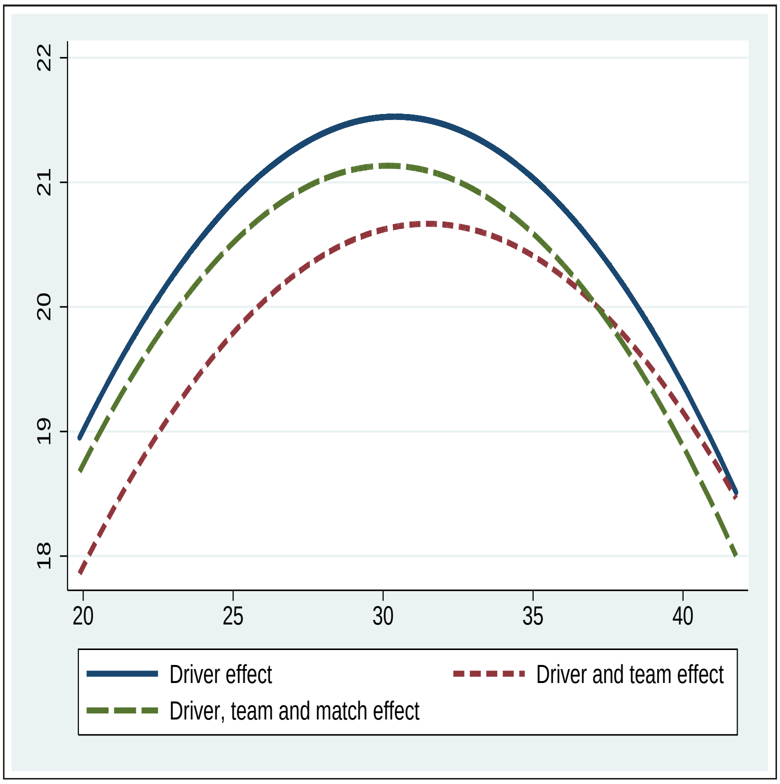
Note. The figure shows the relation between age and productivity. Age is recorded on the horizontal axis, and $\alpha_1 \times age_{it} + \alpha_2 \times age_{it}^2$ on the vertical axis.

Figure 2. Age-productivity profile, interactions



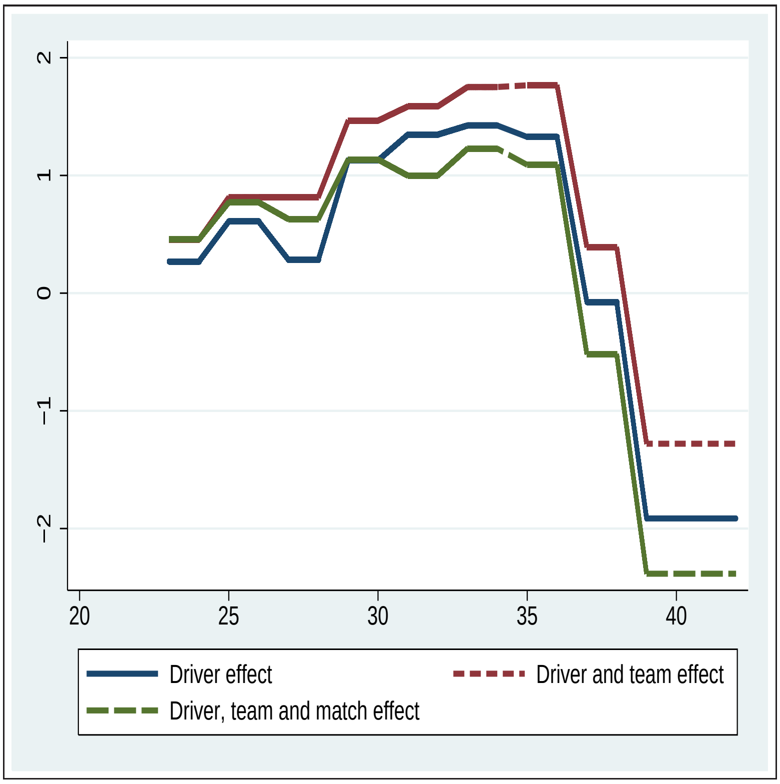
Note. The figure shows the relation between age and productivity, accounting for a full set of interactions between drivers effects and track length, number of race-laps, and a dummy for rainy weather. Age is recorded on the horizontal axis, and $\alpha_1 \times age_{it} + \alpha_2 \times age_{it}^2$ on the vertical axis.

Figure 3. Age-productivity profile, changes in the rules



Note. The figure shows the relation between age and productivity, accounting for a full set of interactions between drivers effects and track length, number of race-laps, a dummy for rainy weather, and a dummy for season 1994. Age is recorded on the horizontal axis, and $\alpha_1 \times age_{it} + \alpha_2 \times age_{it}^2$ on the vertical axis.

Figure 4. Age-productivity profile, age dummies

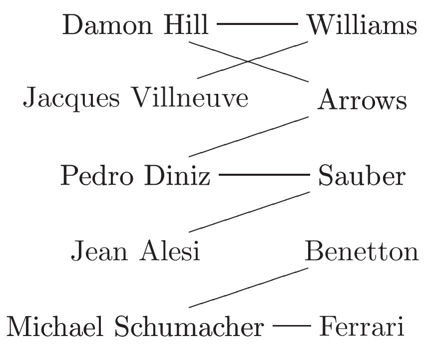


Note. The figure shows the relation between age and productivity, accounting for a full set of interactions between drivers effects and track length, number of race-laps, a dummy for rainy weather, and a dummy for season 1994, and modeling the age effect with a piece-wise function. Age is recorded on the horizontal axis, and the age dummies coefficients on the vertical axis.

TABLE 1. Connectedness between teams and drivers

Driver	Team
Damon Hill	Williams
Jacques Villeneuve	Williams
Damon Hill	Arrows
Pedro Diniz	Arrows
Pedro Diniz	Sauber
Jean Alesi	Sauber
Michael Schumacher	Benetton
Michael Schumacher	Ferrari

Connectedness



Note. The table shows an example of the degree of connectedness among teams and drivers.

TABLE 2. The drivers

Aguri Suzuki	Alain Prost	Alessandro Zanardi	Alex Caffi	Alexander Wurz
Andrea Chiesa	Andrea De Cesaris	Andrea Montermini	Ayrton Senna	Bertrand Gachot
Christian Fittipaldi	Damon Hill	David Brabham	David Coulthard	Derek Warwick
Domenico Schiattarella	Eddie Irvine	Emanuele Naspetti	Enrico Bertaggia	Eric Bernard
Eric Van De Poele	Erik Comas	Esteban Tuero	Fabrizio Barbazza	Franck Lagorce
Gabriele Tarquini	Gerhard Berger	Giancarlo Fisichella	Gianni Morbidelli	Giovanna Amati
Giovanni Lavaggi	Heinz-Harald Frentzen	Hideki Noda	Ivan Capelli	J. J. Lehto
Jacques Villeneuve	Jan Lammers	Jan Magnussen	Jarno Trulli	Jean Alesi
Jean Christophe Boullion	Jean Denis Deletraz	Jean Mark Gounon	Johnny Herbert	Jos Verstappen
Karl Wendlinger	Luca Badoer	Marc Gene	Marco Apicella	Mark Blundell
Martin Brundle	Massimiliano Papis	Mauricio Gugelmin	Michael Andretti	Michael Schumacher
Michele Alboreto	Mika Hakkinen	Mika Salo	Nicola Larini	Nigel Mansell
Norberto Fontana	Olivier Beretta	Olivier Grouillard	Olivier Panis	Paul Belmondo
Pedro Diniz	Pedro Lamy	Pedro De La Rosa	Perry McCarthy	Philippe Alliot
Pierluigi Martini	Ralf Schumacher	Ricardo Rosset	Ricardo Zonta	Riccardo Patrese
Roberto Moreno	Roland Ratzenberger	Rubens Barrichello	Shinji Nakano	Stefano Modena
Stephane Sarrazin	Taki Inoue	Tarso Marques	Thierry Boutsen	Toranosuke Takagi
Toshio Suzuki	Ukyo Katayama	Vincenzo Sospiri	Yannick Dalmas	

Note. The table contains the names of all drivers contained in our sample.

Table 3. The teams

Arrows	BAR/Supertec	Benetton	Brabham	Dallara-Judd
Ferrari	Fondmetal-Ford	Forti-Ford	Jordan	Larousse
March-Ilmor	Prost	Lola	Lotus	McLaren
Minardi	Moda-Judd	Pacific-Ilmor	Sauber	Simtek
Stewart	Williams			

Note. The table contains the names of all teams contained in our sample.

Table 4. The races

Grand Prix	Date	Winning Driver	Team	Laps	Time
Brazil	27/03/1994	Michael Schumacher	Benetton-Ford	71	1:35’38.759
Pacific	17/04/1994	Michael Schumacher	Benetton-Ford	83	1:46’01.693
San Marino	01/05/1994	Michael Schumacher	Benetton-Ford	58	1:28’28.642
Monaco	15/05/1994	Michael Schumacher	Benetton-Ford	78	1:49’55.372
Spain	29/05/1994	Damon Hill	Williams-Renault	65	1:36’14.374
Canada	12/06/1994	Michael Schumacher	Benetton-Ford	69	1:44’31.887
France	03/07/1994	Michael Schumacher	Benetton-Ford	72	1:38’35.704
Britain	10/07/1994	Damon Hill	Williams-Renault	60	1:30’03.640
Germany	31/07/1994	Gerhard Berger	Ferrari	45	1:22’37.272
Hungary	14/08/1994	Michael Schumacher	Benetton-Ford	77	1:48’00.185
Belgium	28/08/1994	Damon Hill	Williams-Renault	44	1:28’47.170
Italy	11/09/1994	Damon Hill	Williams-Renault	53	1:18’02.754
Portugal	25/09/1994	Damon Hill	Williams-Renault	71	1:45’10.165
Europe	16/10/1994	Michael Schumacher	Benetton-Ford	69	1:40’26.689
Japan	06/11/1994	Damon Hill	Williams-Renault	50	1:55’53.532
Australia	13/11/1994	Nigel Mansell	Williams-Renault	81	1:47’51.480

Note. The table contains the names of all races, the date, the winning drivers, the team, the number of laps, and the time to end of the winners for all races in the 1994 season.

Table 5. Summary statistics

	Mean	Standard deviation decomposition		
		Overall	Between	Within
Drivers' pts. scored	1.06	2.38	1.19	1.99
Drivers' age	29.43	4.45	4.43	1.52
Drivers' age of entrance	25.16	2.90	3.2	0
Teams' age	16.68	13.26	9.88	9.34
Size of team	146.8	54.11	36.99	38.94
Techn. dir. age	44.5	6.56	6.62	4.56
Techn. dir. age of entrance	29.94	8.53	6.50	6.33

Note. The table contains the mean, and the standard deviation decomposition between and within drivers for the variables used in the regressions.

TABLE 6. Age and productivity

	Model I		Model II		Model III	
	Baseline	Extended	Baseline	Extended	Baseline	Extended
Age	1.407	1.415	1.400	1.412	1.464	1.478
	(0.218)***	(0.219)***	(0.273)***	(0.276)***	(0.281)***	(0.286)***
Age square	-0.023	-0.023	-0.023	-0.023	-0.025	-0.024
	(0.004)***	(0.004)***	(0.005)***	(0.005)***	(0.005)***	(0.005)***
drivers effects	11.35	11.24	5.47	5.37	5.82	5.59
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Team effects			11.04	10.15	12.06	12.04
			(0.000)***	(0.000)***	(0.000)***	(0.000)***

Note. Robust standard errors are reported in parentheses. One star means 5 percent significant, two 1 percent, three 0.1 percent. The baseline specification contains a quadratic in age and drivers dummies in Model I, drivers and teams dummies in Model II, drivers and teams dummies, and the absolute difference between drivers age and technical directors' age, drivers age and teams age (measured as years from the foundation), a dummy for whether drivers and technical directors belong to the same nationality, and a dummy for whether drivers and teams belong to the same nationality. The extended specification adds years dummies for 1995-1997, number of participants to each race, a dummy for rainy weather at the day of the race, the track-length, the number of race-laps, a dummy for whether the race takes place at the drivers home. The bottom part of the table shows the F-statistics for the null that the drivers effects are zero and the team effects are zero.

Table 7. Age and productivity, interactions, one by one

	Track length			Race laps			Rain		
	Model I	Model II	Model III	Model I	Model II	Model III	Model I	Model II	Model III
Age	1.435	1.439	1.507	1.427	1.434	1.503	1.430	1.419	1.495
	(0.223)***	(0.282)***	(0.291)***	(0.224)***	(0.282)***	(0.291)***	(0.222)***	(0.280)***	(0.290)***
Age squared	-0.024	-0.023	-0.025	-0.023	-0.023	-0.025	-0.023	-0.023	-0.025
	(0.004)***	(0.005)***	(0.005)***	(0.004)***	(0.005)***	(0.005)***	(0.004)***	(0.005)***	(0.005)***

Note. Robust standard errors are reported in parentheses. One star means 5 percent significant, two 1 percent, three 0.1 percent. Model I has drivers effect, Model II drivers and teams effects, Model III drivers, teams and match effects. Each regression contains a quadratic on age, and years dummies for 1995-1997, number of participants to each race, a dummy for rainy weather at the day of the race, the track-length, the number of race-laps, a dummy for whether the race takes place at the drivers home. Columns headed by 'Track length' interact the driver effect with the length of tracks, columns headed by 'Race laps' interact the driver effect with the number of laps, by 'Rain' interact the driver effect with a dummy for rainy weather.

Table 8. Age and productivity, interactions, all

	Model I	Model II	Model III
Age	1.394	1.406	1.478
	(0.230)***	(0.291)***	(0.301)***
Age squared	-0.023	-0.023	-0.024
	(0.004)***	(0.005)***	(0.005)***

Note. Robust standard errors are reported in parentheses. One star means 5 percent significant, two 1 percent, three 0.1 percent. Model I has drivers effect, Model II drivers and teams effects, Model III drivers, teams and match effects. Each regression contains a quadratic on age, and years dummies for 1995-1997, number of participants to each race, a dummy for rainy weather at the day of the race, the track-length, the number of race-laps, a dummy for whether the race takes place at the drivers home, and interactions of the driver effect with the length of tracks, of the driver effect with the number of laps, and of the driver effect with a dummy for rainy weather.

Table 9. Age and productivity, changes in the rules

	Model I	Model II	Model III
Age	1.416	1.313	1.401
	(0.246)***	(0.321)***	(0.335)***
Age squared	-0.023	-0.021	-0.023
	(0.004)***	(0.005)***	(0.006)***

Note. Robust standard errors are reported in parentheses. One star means 5 percent significant, two 1 percent, three 0.1 percent. Model I has drivers effect, Model II drivers and teams effects, Model III drivers, teams and match effects. Each regression contains a quadratic on age, and years dummies for 1995-1997, number of participants to each race, a dummy for rainy weather at the day of the race, the track-length, the number of race-laps, a dummy for whether the race takes place at the drivers home, interactions of the driver effect with the length of tracks, with the number of laps, with a dummy for rainy weather, and with a dummies for years after 1994.

Table 10. Age and productivity, quality of opponents

	Model I	Model II	Model III
Age	1.419	1.417	1.482
	(0.219)***	(0.277)***	(0.286)***
Age squared	-0.023	-0.023	-0.024
	(0.004)***	(0.005)***	(0.005)***
Quality of opponents	-0.018	-0.015	-0.015
	(0.008)*	(0.008)	(0.008)*

Note. Robust standard errors are reported in parentheses. One star means 5 percent significant, two 1 percent, three 0.1 percent. Model I has drivers effect, Model II drivers and teams effects, Model III drivers, teams and match effects. Each regression contains a quadratic on age, and years dummies for 1995-1997, number of participants to each race, a dummy for rainy weather at the day of the race, the track-length, the number of race-laps, a dummy for whether the race takes place at the drivers home.

Table 11. Age and productivity, non-random attrition

	Model I	Model II	Model III
Age	1.534	1.386	1.431
	(0.239)***	(0.274)***	(0.287)***
Age squared	-0.025	-0.022	-0.024
	(0.004)***	(0.005)***	(0.005)***

Note. Robust standard errors are reported in parentheses. One star means 5 percent significant, two 1 percent, three 0.1 percent. Model I has drivers effect, Model II drivers and teams effects, Model III drivers, teams and match effects. Each regression contains a quadratic on age, and years dummies for 1995-1997, number of participants to each race, a dummy for rainy weather at the day of the race, the track-length, the number of race-laps, a dummy for whether the race takes place at the drivers home. We control for non-random attrition by using a propensity score matching estimator that predicts the probability of staying in the sample running a probit on a dummy equal to one if the driver is present in the following year (and zero otherwise) on the cumulative number of points in the season and a quadratic in age.

Table 12. Age and productivity, Experience

	Model I	Model II	Model III
Age	1.415	1.402	1.478
	(0.191)***	(0.234)***	(0.240)***
Age squared	-0.023	-0.022	-0.024
	(0.003)***	(0.004)***	(0.004)***
Age in F1	-0.423	-0.294	-0.442
	(0.157)**	(0.172)	(0.183)*

Note. Robust standard errors are reported in parentheses. One star means 5 percent significant, two 1 percent, three 0.1 percent. Model I has drivers effect, Model II drivers and teams effects, Model III drivers, teams and match effects. Each regression contains a quadratic on age, and years dummies for 1995-1997, number of participants to each race, a dummy for rainy weather at the day of the race, the track-length, the number of race-laps, a dummy for whether the race takes place at the drivers home, interactions of the driver effect with the length of tracks, with the number of laps, with a dummy for rainy weather, and with a dummies for years after 1994.

Table 13. Age and productivity, Tenure

	Model I	Model II	Model III
Age	1.188	1.340	1.402
	(0.221)***	(0.277)***	(0.285)***
Age square	-0.019	-0.021	-0.023
	(0.004)***	(0.005)***	(0.005)***
Tenure	0.015	0.013	0.014
	(0.004)***	(0.005)**	(0.004)**

Note. Robust standard errors are reported in parentheses. One star means 5 percent significant, two 1 percent, three 0.1 percent. Model I has drivers effect, Model II drivers and teams effects, Model III drivers, teams and match effects. Each regression contains a quadratic on age, and years dummies for 1995-1997, number of participants to each race, a dummy for rainy weather at the day of the race, the track-length, the number of race-laps, a dummy for whether the race takes place at the drivers home, interactions of the driver effect with the length of tracks, with the number of laps, with a dummy for rainy weather, and with a dummies for years after 1994.

Table 14. Age and productivity, Past Performance

	Model I	Model II	Model III
Age	1.200	1.267	1.340
	(0.190)***	(0.235)***	(0.240)***
Age squared	-0.020	-0.020	-0.022
	(0.003)***	(0.004)***	(0.004)***
Pts. in the prv. race	0.152	0.101	0.091
	(0.018)***	(0.018)***	(0.018)***

Note. Robust standard errors are reported in parentheses. One star means 5 percent significant, two 1 percent, three 0.1 percent. Model I has drivers effect, Model II drivers and teams effects, Model III drivers, teams and match effects. Each regression contains a quadratic on age, and years dummies for 1995-1997, number of participants to each race, a dummy for rainy weather at the day of the race, the track-length, the number of race-laps, a dummy for whether the race takes place at the drivers home, interactions of the driver effect with the length of tracks, with the number of laps, with a dummy for rainy weather, and with a dummies for years after 1994.

Table 15. Age and productivity, age dummies

	Model I	Model II	Model III
$22 < Age \leq 24$	0.269	0.454	0.456
	(0.186)	(0.248)	(0.259)
$24 < Age \leq 26$	0.609	0.813	0.771
	(0.214)**	(0.323)*	(0.348)*
$26 < Age \leq 28$	0.284	0.815	0.629
	(0.266)	(0.344)*	(0.365)
$28 < Age \leq 30$	1.127	1.465	1.135
	(0.363)**	(0.454)**	(0.473)*
$30 < Age \leq 32$	1.347	1.586	0.998
	(0.424)**	(0.518)**	(0.510)
$32 < Age \leq 34$	1.425	1.752	1.228
	(0.423)***	(0.529)***	(0.519)*
$34 < Age \leq 36$	1.327	1.766	1.090
	(0.518)*	(0.622)**	(0.616)
$36 < Age \leq 38$	-0.075	0.391	-0.519
	(0.638)	(0.670)	(0.670)
$Age > 38$	-1.914	-1.279	-2.384
	(0.761)*	(0.790)	(0.801)**

Note. Robust standard errors are reported in parentheses. One star means 5 percent significant, two 1 percent, three 0.1 percent. Model I has drivers effect, Model II drivers and teams effects, Model III drivers, teams and match effects. Each regression contains a quadratic on age, and years dummies for 1995-1997, number of participants to each race, a dummy for rainy weather at the day of the race, the track-length, the number of race-laps, a dummy for whether the race takes place at the drivers home, interactions of the driver effect with the length of tracks, with the number of laps, with a dummy for rainy weather, and with a dummies for years after 1994.