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Marco Bertoni
Giorgio Brunello
Lorenzo Rocco

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Forschungsinstitut
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of Labor

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Marco Bertoni
University of Padova
and LSE

Giorgio Brunello
University of Padova,
CESifo, IZA and ROA

Lorenzo Rocco
University of Padova

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

Does Mental Productivity Decline with Age? Evidence from Chess Players*

We use data on international chess tournaments to study the relationship between age and mental productivity in a brain-intensive profession. We show that less talented players tend to leave the game in the earliest phases of their career. When the effects of age on productivity vary with unobserved ability, commonly used fixed effects estimators applied to raw data do not guarantee consistent estimates of age-productivity profiles. In our data, this method strongly over-estimates the productivity of older players. We apply fixed effects to first-differenced data and show that productivity peaks in the early forties and smoothly declines thereafter. Because of this, players aged 60 are 11 percent less productive than players in their early forties.

JEL Classification: D83, J14, J24

Keywords: aging, productivity, mental ability

Corresponding author:

Lorenzo Rocco
Department of Economics and Management, M. Fanno
University of Padova
Via del Santo, 33
35123 Padova
Italy
E-mail: lorenzo.rocco@unipd.it

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Introduction

There is a broad perception that mental ability declines with age, and not just for humans[1]. Unless experience and knowledge can fully compensate the decline in ability, productivity is also bound to decline. In many developed countries, population is ageing. If individual productivity declines with age, overall productivity will also decline, with important macroeconomic implications.

In spite of the important implications for modern economies, surprisingly little is known about the relationship between age and productivity, and the little we know is not pointing unambiguously in the same direction. On the one hand, Skirbekk, 2003, reviews the empirical literature and concludes that productivity follows an inverted U-shaped profile, with significant decreases taking place from around age 50[2]. Van Ours, 2009, on the other hand, finds that while physical productivity does decline after age 40, mental productivity – measured by publishing in economics journals – does not decline even after age 50. Borsch-Supan and Weiss, 2007, use data on production workers of a large German car manufacturer and conclude that productivity does not decline at least up to age 60.[3]

Measuring the effects of age on productivity is difficult. First, it is hard to find reliable measures of individual productivity. Second, in many jobs individual productivity should include also the effects on the productivity of others, either because of knowledge spillovers or because some jobs involve a relevant team component. Third, the relationship between age and productivity in observed samples is affected by selection. If more productive workers are more likely to stay longer in their jobs, selection may induce a spurious positive correlation between age and productivity.

In this paper, we address some of these difficulties by studying the relationship between age and mental productivity for professional chess players. Focusing on chess players has important advantages. First, we can compute a quality - adjusted measure of individual productivity by looking at wins and ties in international tournaments, weighting each result with the measured strength of the opponent. Second, chess is a purely individual activity, differently from most

[1] See The Economist, 2004 and Bloom and Sousa-Poza, 2013.

[2] Recent contributions in this area that use individual productivity data include Weinberg and Galenson, 2005, and Castellucci, Pica and Padula, 2010.

[3] Pekkarinen and Uusitalo, 2012, look at the population of Finnish blue-collar employees and use piece-rate wages as proxies for output: their findings confirm that labour productivity stays roughly constant after age 40.

professional activities where team work and spillovers among agents influence individual productivity. Because of this, our measure of productivity is accurate.

We show that endogenous selection implies that older players are positively selected on ability. We then argue that, if the marginal effect of age on productivity depends on unobserved ability, for instance because productivity is not separable in terms of age and ability, commonly used fixed effects methods produce consistent estimates only when applied to first - differenced rather than to raw data. We compare the age-productivity profiles generated by fixed effects applied to raw and first-differenced data, and find that they are monotonously increasing in age in the former and hump - shaped in the latter case. We conclude that the failure to recognize that ability and age interact in determining observed productivity leads to substantially over-estimating the productivity of senior players.

When we allow for this interaction, we find that productivity at chess increases by close to 20 percent from age 15 to its peak at age 42, and smoothly declines by 11 percent until age 60. Several studies (see Skirbekk, 2003) have shown that the decline of mental abilities from early adulthood is a universal phenomenon. Unless the acquisition of skills and experience on the job outweighs this decline, productivity in cognitive tasks is likely to fall with age. Our evidence from professional chess, a brain – intensive activity, shows that better skills and longer experience cannot completely offset the decline in numerical and reasoning abilities.

Our contribution goes beyond the specific environment that characterizes international chess, because it emphasizes the importance of correctly modelling the interaction between age and ability when studying the relationship between productivity and age. In a similar vein, Heckman, Lochner and Todd, 2008, have criticized the Mincerian earnings function, which relies on the assumption that earnings are separable in terms of experience and schooling. This assumption is convenient but not supported by the empirical evidence, which shows that wage experience profiles are not parallel with respect to education.

The paper is organized as follows. In Section 1 we introduce our measure of productivity for chess players. Section 2 presents the data and Section 3 shows some evidence on selection patterns. The estimation strategy is discussed in Section 4, results and sensitivities are presented in Sections 5 and 6. Conclusions follow.

1. **Measures of Ability and Productivity for Professional Chess Players**

Ranking players has been a critical issue in chess until the 1960s, when the ELO rating system was introduced by FIDE, the International Chess Federation. This system was developed by the

Hungarian mathematician Arpad Elo and is based on a Thurstonian model for paired comparisons (see Thurstone, 1927). In this section, we argue that ELO is not a measure of individual productivity but rather an indicator of individual (relative) ability in the game of chess.

In the ELO system, the latent ability of player i, α_i, is assumed to be normally distributed with mean s_i and standard deviation arbitrarily set at 200[4]. Let the outcome of a match between players *i* and *j* be the random variable $z_{ij} = \alpha_i - \alpha_j$. Player *i* wins if $z_{ij} > 0$. With independent abilities, the probability of winning is $p_{ij} = \Phi\left(\frac{s_i - s_j}{\sigma}\right)$, where Φ is the cumulative distribution function of a standard normal random variable and $\sigma = 200\sqrt{2}$[5].

The expected ability s_i of player *i* is estimated by using the outcomes of the games she plays. Players are initially classified as unrated[6]. Starting from their first official ELO score, s_{i0}, the score after game *g* is obtained as $s_{ig+1} = s_{ig} + K(w_{ij} - p_{ij})$, where w_{ij} is equal to one if player *i* wins, to 0.5 if she draws and to zero if she loses the match, p_{ij} is the expected winning probability of player *i* against player *j*, and *K* is a scale factor which weights the importance of a single game with respect to her entire previous career. This weight declines with the number of games played and with the ELO score[7].

The updating rule adjusts the ELO score when actual performance in the game differs from expected performance. When the current ELO perfectly predicts p_{ij}, no further update occurs. Since only unexpected wins and losses matter in the updating mechanism, ELO cannot be considered a measure of productivity at chess, which depends on total rather than unexpected wins and losses. To illustrate, a player can be very productive in terms of having a high winning rate and yet experience

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[4] The normality assumption is based on observational data collected by Arpad Elo on the distribution of individual chess performance (see Gransmark and Gërdes, 2010). Currently, FIDE prefers to use a logistic distribution.

[5] For example, consider two players with $s_i - s_j = 200$. In this case, the likelihoods that players *i* and *j* win are $\Phi(200/200\sqrt{2}) = 0.76$ and 0.24 respectively.

[6] The results of their first games and the ELO score of their opponents determine a provisional rating. The following conditions are required to obtain such rating: (see FIDE, 2012): 1) having played in at least one official FIDE tournament; 2) having completed a minimum of nine games against rated players and having scored at least one point against them (i.e., having won a match or having drawn two); 3) the initial score ought to be above a minimum rating floor – equivalent to 1400 ELO points for players in our sample, who obtained their first rating before 2009.

[7] In practice, K = 30 for a player who has completed less than 30 games, K = 15 for players with a score lower than 2400 and K = 10 once a player's rating reaches 2400 and she has completed at least 30 games (see Glickman, 1995, for details). Using the example in footnote 2, if player *i* wins, her ELO score increases by 0.24*K, while if she loses her ELO decreases by -0.76*K.

no change in ELO if these wins are expected.[8] Rather than a measure of productivity, ELO is a measure of relative ability at chess at a given point in time.[9]

We therefore distinguish between ELO and productivity Y: the former is an estimate of relative ability, which is refined whenever the player performs better or worse than expected. The latter is the weighted sum of wins and ties divided by the number of games played

$$Y_{it} = \frac{\sum_{j=1}^{G_{it}} [I(win_{it}) * ELO_j + \frac{1}{2} I(draw_{ij}) * ELO_j]}{G_{it}} \qquad [1]$$

where G_{it} is the number of games played in international tournaments by player i in year t and $I(win_{it})$ and $I(draw_{it})$ are dummies equal to 1 when either a win or a tie occurs. Each win has weight equal to 1, each draw is weighted 0.5 and each loss has zero weight. This measure of productivity is quality adjusted because each win or draw is weighted with the relative quality of the opponent. Since the weighted sum of wins and losses is divided by the number of games played, Y_{it} is the productivity per match.[10]

2. The Data

We use data on all official FIDE (World Chess Federation) tournaments played worldwide between 2008 and 2011. These data are downloaded from the FIDE online archive.[11] Each tournament record reports the results of all games played by every participant (wins, losses or draws), their ELO score at the beginning and at the date of the tournament. We merge these data with the official FIDE lists of rated players, which include quarterly information on the ELO scores of active players, their national federation, date of birth and gender. These lists are available since the early 2000.

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[8] Furthermore, two players with the same initial ELO but different K factors (i.e. different experience) have different ELO adjustments even if their game results are the same, making the use of ELO as a measure of productivity even more problematic.

[9] ELO raises faster at younger ages, because the updating mechanism generates larger variations when the initial ELO is lower and because younger players try to fill their ability gap with more experienced players by learning, training and accumulating experience in tournaments. Since ELO tends to increase with age, it is an informative but imperfect measure of innate talent at chess.

[10] Our weighting system implies that playing two games against players of a given strength and winning both is equivalent to playing two games against opponents twice as strong and winning only one game. It also implies that winning one game against a player with ELO score x yields more in terms of productivity than drawing one game against a player with ELO equal to 2*(x-ε).

[11] As of December 2012, the web address of this archive is http://ratings.fide.com.

Our initial sample consists of all male FIDE rated players born between 1948 and 1993 who were listed by 2008 and have played in at least one FIDE tournament between 2008 and 2011. From this sample, we drop players who obtained an official rating for the first time in 2008 and have played only in 2008, as we want to avoid considering "casual" players. For the remaining players, we only consider the outcomes of games played against rated players, both because we do not have a measure of ability for unrated opponents and because games against these opponents do not count for rating.[12] We also drop those players belonging to national federations with less than 30 affiliates. Our final sample consists of 40,545 players aged between 15 and 60 who are listed in 2008 and remain in the FIDE list from a minimum of 1 to a maximum of 3 years[13], and of 140,074 observations.

Table 1 presents descriptive statistics on productivity, age and number of games played. Age ranges from 15 to 60 and has an average of 38.09. The annual number of games of active players range from 1 to 289 and averages at 17.45, and measured annual productivity ranges from 0 (no wins or draws in a year) to 2,551, with an average of 972. Figure 1 shows the distribution of annual productivity: there is a peak at zero (3.6% of observations), due to players who have never won or drawn a game in a single year, and an upper tail with few players having very high productivity. Our dataset also includes two variables at the federation-by-year level: the GDP per capita in real PPP 2005 (thousand) dollars and the number of internet users per 100 inhabitants. Both variables are drawn from the World Bank World Development Indicators.

3. Selection

Since professional players enter and exit the FIDE lists every year, our raw data are affected by endogenous selection. In this section, we describe this selection process by using the longitudinal information contained in the FIDE lists. We consider the pool of active players who were present in the lists in 2001 and track their activity and ELO until 2011. By so doing, we are able to follow each cohort for a maximum of ten years and to document selection over this relatively long time span. We distinguish between "stayers", who were included in the FIDE list in 2001 and were active players between 2009 and 2011, and "dropouts", who were not in the list between 2009 and 2011.

[12] In the few cases where annual productivity is missing in either 2009 or 2010 but not in 2008 and 2011, we estimate missing values by interpolation.

[13] The number of players enrolled in the lists in 2008 is 40,545, 37,396 of whom are still present in 2009, 33,475 in 2010 and 28,658 in 2011.

We use regression analysis to show that selection depends on talent and age, with weak players leaving chess at the early stages of their career. Table 2 reports the estimates of a linear probability model where the dependent variable is a dummy equal to one if the individual drops out of professional chess and to zero otherwise, and the controls include the log of the 2001 ELO score as a proxy for talent, age in 2001 and the interaction between age and log ELO. We also control for country (chess federation) dummies and use robust standard errors. The estimates in column (1) show that less talented and younger players are more likely to drop out. The interaction term is positive and statistically significant, meaning that selection on ability weakens with age. When we split the sample between players aged up to 25 and more than 25 years in 2001 in columns (2) and (3), respectively, we see that the negative effect of age on the probability of dropping out is driven mainly by younger players, for whom selection based on ability is stronger.

4. The Empirical Strategy

A natural starting point is to assume that productivity *Y* is a function of age *A* and mental ability μ. Let this function be non separable in terms of age and ability

$$Y_{it} = Y(A_{it}, \mu_{it}) = \pi_0 + \pi_1 A_{it} + \pi_2 \mu_{it} + \pi_3 A_{it} \mu_{it} \qquad [2]$$

where we expect π_3 to be positive if individuals with higher ability are better capable of accumulating skills as they age.

Mental ability μ_{it} consists of time invariant innate talent α and a component that declines with age

$$\mu_{it} = \alpha_i - \rho A_{it} \qquad [3]$$

Using [3] into [2], we obtain that productivity is a function of an age polynomial, innate talent, and the interaction of talent with age. Age affects productivity both directly, by changing effort, motivation and skills, and indirectly, by affecting mental ability. Moreover, the marginal effect of age on productivity is heterogeneous with respect to innate talent.

We describe the empirical relationship between productivity, age, talent and other covariates as follows

$$Y_{it} = \beta_0 + \sum_{d=1}^{D} \beta_d A_{it}{}^{d} + \beta_x X_{it} + \gamma \alpha_i + \delta \alpha_i A_{it} + \varepsilon_{it} \qquad [4]$$

where X is a vector of exogenous covariates and ε is a random error. Innate talent has unconditional zero mean and is orthogonal to age in the population. Productivity depends on an age polynomial of order d.

The orthogonality of talent and age implies that the conditional mean of [4] in the population is given by

$$E[Y_{it} \mid A_{it}, X_{it}] = \beta_0 + \sum_{d=1}^{D} \beta_d A_{it}{}^{d} + \beta_x X_{it} \qquad [5]$$

If we had population data, we could estimate the relationship between age and productivity by ordinary least squares. The conditional mean in the population and in the observed sample do not coincide, however, when individual players select in and out of the sample in a non-random way. In the case of professional chess players, the decision to stay or leave the FIDE lists depends both on individual talent and on age. Therefore, in the selected sample $E(\alpha_i \mid A_{it}, X_{it})$ is different from zero and

$$E[Y_{it} \mid A_{it}, X_{it}] = \beta_0 + \sum_{d=1}^{D} \beta_d A_{it}{}^{d} + \beta_x X_{it} + E(\alpha_i \mid A_{it}, X_{it})(\gamma + \delta A_{it}) \qquad [6]$$

The conditional expectation of productivity depends both on the (nonzero) conditional mean of innate talent and on the interaction of this mean with age. Failure to control for talent imparts a bias to the ordinary least squares estimates of the relationship between productivity and age. This bias cannot be removed by applying the fixed effects estimator to the raw data – as done by Castellucci et al (2010) – because the within-transformation only removes the linear component of talent. To fully remove the bias due to selection and the presence of heterogeneous age effects, it is necessary to apply the within-player transformation to first-differenced data, as done for instance by Pischke (2001) in his paper on the returns to training in Germany.

5. Results

Equation [4] suggests that productivity depends on a polynomial in age. We allow the data to establish the degree of the polynomial and find that a fifth and a second order polynomial are adequate when we apply fixed effects to levels and first-differences of productivity. We capture country specific time effects with real GDP per capita and the percentage of individuals with an internet connection. GDP per capita is a proxy for the economic conditions in the federation of the player, which are likely to affect participation to international tournaments and access to resources to improve game specific skills. Since chess training is often done on the internet, access to the web can affect training and performance.

Table 3 reports the estimates of Equation [4] when we use fixed effects on levels (column (1)) and first differences (column (2)). In both cases, standard errors are clustered at the level of the individual player. Figure 2 plots the predicted age-productivity profiles associated to each estimate, using a continuous line for fixed effects applied to raw data and a dotted line for fixed effects applied to first differenced data. Both the continuous and the dotted line show productivity at age j relative to productivity at age 15, which we normalize at 1. When we apply fixed effects to the raw data, and thereby ignore that innate ability and age interact in affecting productivity, estimated productivity increases monotonously with age, albeit at a slower pace from close to age 30 onwards.

When we apply instead fixed effects to first differenced data, predicted productivity is hump-shaped and peaks at age 42. The two profiles are reasonably similar until the mid to late forties but diverge drastically at higher ages: while the continuous line in the figure suggests that productivity at 60 is more than 20 percent higher than at 15, the dotted line shows that the oldest chess players in our sample are only close to 5 percent more productive than the players in the youngest group. We conclude that the failure to recognize that ability and age interact in their effects on productivity may lead to erroneously infer from the data that productivity does not decline with age.

6. Robustness checks

Fixed effects applied to first differences increase the noise-to-signal ratio, thereby making it harder to obtain precise estimates and allowing for the possibility that relatively few observations drive the results. To check for this latter possibility, we have re-estimated the model after slightly perturbing the original sample, that is, after alternatively removing players: 1) aged between 15 and 18 in 2008; 2) aged between 55 and 60 in 2008; 3) endowed with an ELO score below 1800; 4) endowed with a ELO score above 2600. As shown in Table 4, columns (2) to (5), our results are remarkably robust to these perturbations.

We have also experimented with two slightly different measures of productivity, the raw winning rate[14] and the raw winning rate weighed by the average ELO score of the opponents met in a given year. Again, we report in columns (6) and (7) of Table 4 that our findings are remarkably robust and that productivity always peaks at around age 40.

Conclusions

We have used data on international chess tournaments to study the relationship between age and mental productivity in a brain-intensive profession. Using chess has the advantage that individual productivity can be measured with accuracy. We have shown that selective attrition is an important phenomenon, and that selection by ability is stronger at younger ages. We have argued that, when productivity is not separable in terms of ability and age, the fixed effects estimator produce consistent estimates of the age-productivity profiles only when applied to first-differenced data. Our key results are that mental productivity peaks in the early forties and smoothly declines afterwards, and that estimated productivity at age 60 is about 5 percent higher than at age 15 and about 11 percent lower than at age 42. These results are not in line with recent evidence presented by Van Ours on professional economists and by Borsch - Supan and Weiss on production workers, suggesting that productivity does not decline with age. Since we also find that productivity does not decline with age when we apply fixed effects to the raw data, we believe that a possible reconciliation of these different results is that we explicitly take into account the fact that productivity is not separable in terms of age and unobserved talent.

Our emphasis on the possibility that productivity is not separable in terms of age and ability is not only motivated by common sense – more talented individuals are better at learning skills as they age - but also by recent empirical evidence on age and experience earnings profiles. In the Mincerian tradition, it has been customary to assume that earnings (and productivity) are separable in age (experience) and education (ability), mainly because of lack of data on lifetime earnings. Recent work by Heckman, Lochner and Todd (2008) and Brunello, Weber and Weiss (2012) has shown that this assumption is convenient but not supported by empirical evidence, both in the US and in Europe.

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[14] This rate is defined as the number of wins plus number of draws weighted by 0.5 over the total number of games played in a given year.

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Tables and Figures

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Age	38.09	12.31	15	60
Games	17.45	19.20	1	289
Productivity	972.39	396.66	0	2551
GDP per capita (in thousand $ at constant prices)	24.29	11.39	1.35	73.34
Internet users (per 100 inhabitants)	61.29	19.78	2.50	96.62

Table 2. The effects of age and talent on the probability of dropping out from FIDE lists

	(1) All players	(2) Age<=25	(3) Age>25
log(ELO)	-2.555***	-6.198***	-1.525***
	(0.197)	(0.831)	(0.315)
Age	-0.266***	-1.506***	-0.0816
	(0.042)	(0.309)	(0.061)
log(ELO)* Age	0.0343***	0.196***	0.0104
	(0.005)	(0.040)	(0.007)
Observations	14,063	3,690	10,373
R-squared	0.119	0.162	0.096
Federation dummies	Yes	Yes	Yes

Note: Robust standard errors within parentheses. ELO stands for players' ELO score in 2001 and age for age in 2001. Three, two and one star for statistically significant coefficients at the 1, 5 and 10% level of confidence.

Table 3 – Estimates of Eq. [4] using fixed effects on raw data and first differences. Dependent variable: productivity.

	Fixed effects on raw data	Fixed effects on first differences
Age	332.50***	203.874**
	(68.178)	(94.369)
Age^2	-16.27***	-2.577**
	(4.238)	(1.232)
Age^3	0.402***	
	(0.124)	
Age^4	-0.005***	
	(0.002)	
$Age^5 *100$	0.002***	
	(0.000)	
N. obs	140,074	99,529
N. clusters	40,545	37,396

The regressions include real GDP per capita and the percentage of internet users per 100 inhabitants. Three, two and one star for statistically significant coefficients at the 1, 5 and 10% level of confidence. Robust standard errors clustered at the individual level.

Table 4 – Robustness checks. Estimates of Eq. [4] using first differences, different sub-samples and alternative measures of productivity. Dependent variable: productivity

	Original sample	ELO>1800	ELO<2600	Age 18-60	Age 15-55	Raw winning rate	Weighted winning rate
Age	203.874**	196.518**	205.445**	188.696*	197.979**	8.499*	223.243**
	(94.369)	(98.745)	(95.111)	(98.668)	(94.771)	(4.827)	(94.648)
Age^2	-2.577**	-2.516*	-2.593**	-2.358*	-2.643**	-0.102^{+}	-2.818**
	(1.232)	(1.294)	(1.240)	(1.269)	(1.309)	(0.063)	(1.236)
# obs.	99,529	91,017	98,874	97,004	89,462	99,529	99,529
#clusters	37,396	34,059	37,150	37,038	34,005	37,396	37,396
Peak age	39.56	39.05	39.62	40.02	37.45	41.55	39.61

Each regression includes real GDP per capita and the percentage of internet users per 100 inhabitants. Three, two and one star for statistically significant coefficients at the 1, 5 and 10% level of confidence. Symbol + indicates a p-value of 0.105. Robust standard errors clustered at the individual level.

Figure 1. The distribution of productivity in the sample

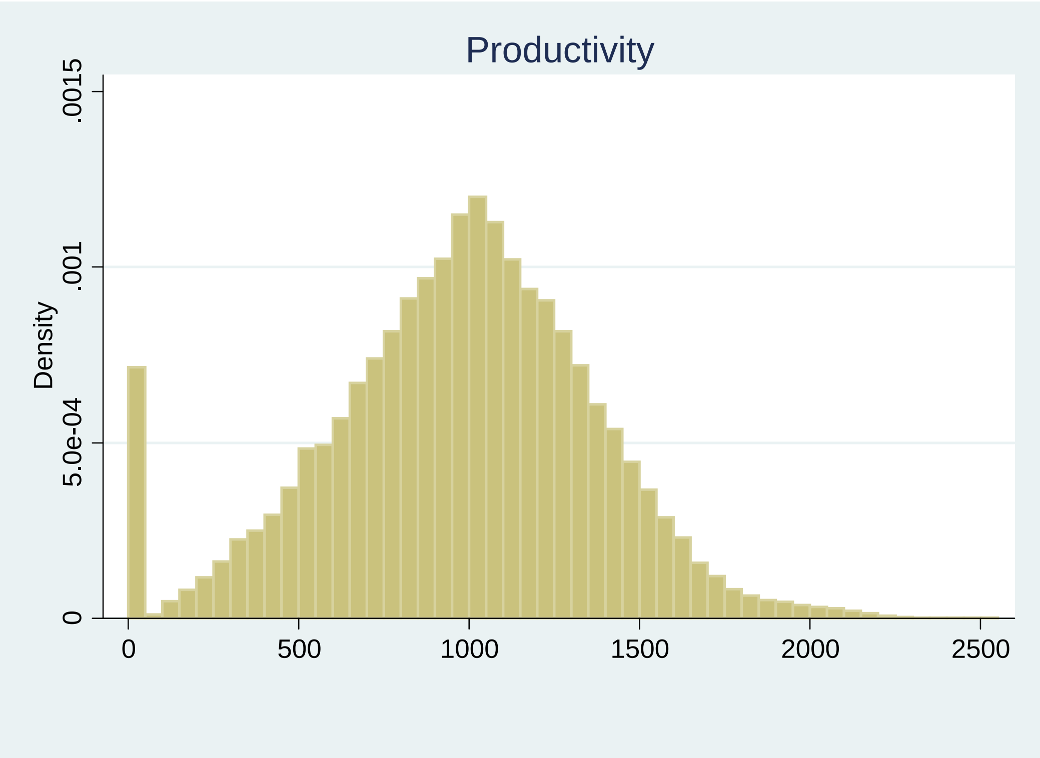

Figure 2. Estimated age productivity profiles. Fixed effects estimates on raw data and on differenced data, normalized at 1 at age 15.