Life cycle patterns of cognitive performance over the long run

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Little is known about how the age pattern in individual performance in cognitively demanding tasks changed over the past century. The main difficulty for measuring such life cycle performance patterns and their dynamics over time is related to the construction of a reliable measure that is comparable across individuals and over time and not affected by changes in technology or other environmental factors. This study presents evidence for the dynamics of life cycle patterns of cognitive performance over the past 125 y based on an analysis of data from professional chess tournaments. Individual move-by-move performance in more than 24,000 games is evaluated relative to an objective benchmark that is based on the respective optimal move suggested by a chess engine. This provides a precise and comparable measurement of individual performance for the same individual at different ages over long periods of time, exploiting the advantage of a strictly comparable task and a comparison with an identical performance benchmark. Repeated observations for the same individuals allow disentangling age patterns from idiosyncratic variation and analyzing how age patterns change over time and across birth cohorts. The findings document a hump-shaped performance profile over the life cycle and a long-run shift in the profile toward younger ages that is associated with cohort effects rather than period effects. This shift can be rationalized by greater experience, which is potentially a consequence of changes in education and training facilities related to digitization.

cognitive performance | lifetime | artificial intelligence | age–period–cohort decomposition | digitization

Aging represents a key challenge for labor markets in many countries. While capital deepening and rising education levels tend to increase labor productivity on the aggregate (1, 2), the work environment changes rapidly with cognitively demanding tasks becoming more prevalent and important due to technological change and digitization (3–5). Existing evidence suggests that cognitive skills are formed early in life (6, 7), but surprisingly little is known about how individual performance in cognitively demanding tasks varies over the life cycle and about how these life cycle performance patterns have changed over the past century.

The main difficulty of measuring life cycle patterns of cognitive performance and their long-run dynamics is related to the construction of a reliable performance measure that is comparable across the life cycle for individuals of different cohorts and over time. Empirical work in economics has traditionally focused on work-related information about labor productivity at the level of individuals (8, 9), at the team level (10), or at the firm level (11, 12). The evidence from this literature suggests that life cycle productivity profiles are hump shaped, although the evidence for a productivity decline at older ages is rather mixed, which might depend on the specific context (13–15). Likewise, studies based on aggregate data have typically found hump-shaped life cycle productivity profiles (16–18). Work-related measures of productivity are not ideal for measuring performance in cognitively demanding tasks, however, and are limited in terms of comparability, technological work environment, labor market institutions, and demand factors, which all exhibit variation over time and across skill groups (1, 19). Investigations that account for changes in skill demand have found evidence for a peak in performance potential around ages of 35 to 44 y (20) but are limited to short observation periods that prevent an analysis of the dynamics of the age–performance profile over time and across cohorts. An additional problem is related to measuring productivity or performance in the presence of self-selection and variation in job-related tasks (21, 22). Related work on scientific creativity has documented substantial shifts in life cycle performance over time due to changes in technology (23, 24), which has precluded analyzing the long-run evolution of age–performance profiles in this context (25).

Existing work in cognitive psychology has measured cognitive performance in various dimensions. The results of cross-sectional studies have shown that performance in tasks that are primarily related to speed, memory, visualization, or reasoning in information processing (related to fluid intelligence) exhibits a decline with age, whereas performance in tasks that rely on experience and accumulated knowledge (related to crystallized intelligence) increases until age 50 or above (26, 27). Research on expert performance has emphasized the role of practice (28), and recent work has shown that intelligence and practice interact in determining performance (29), thereby jointly affecting lifetime performance profiles (30, 31). Neurological evidence

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Significance

Despite evidence for an increasing importance of cognitively demanding tasks in the workplace, little is known about the life cycle performance in such tasks, particularly over the long run. We estimate the life cycle patterns of cognitive performance over the past 125 y using a methodology that is based on the comparison of individual move-by-move performance of professional chess players relative to the best move suggested by a chess engine in a given configuration. The findings document a hump-shaped profile of performance over the life cycle and an increase in individual performance, particularly at younger ages, that is associated with dynamics across birth cohorts rather than over time.

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suggests that learning and adaptability are related to biological changes over the life cycle (32, 33). However, measures of cognitive performance often involve abstract tasks that are unfamiliar to subjects and unrelated to their professional activity. Moreover, they are typically only available at one point in life (e.g., for military conscripts), which has prevented their use for studying age-related variability and period–cohort decompositions (34). Due to the lack of direct measures of cognitive performance that exhibit within-person variation over a sufficiently large age spectrum and that are comparable across individuals and over time, longitudinal studies for cognitive performance profiles over the life span, in particular over long horizons, are missing.

This paper develops an empirical strategy to estimate the age profile of performance in cognitively demanding tasks and its dynamics over the past 125 y, based on the performance of professionals in high-stakes environments related to their profession. Concretely, the empirical strategy is based on the analysis of data from professional chess tournaments involving world champions and their opponents. These data have several features that make them ideal for measuring age–performance profiles and their long-run dynamics. First, chess has been used in psychology and neuroscience as a paradigmatic cognitive task that combines processes related to perception, memory, and problem solving (35, 36). Chess has a complex neural basis of automated processes related to identifying the configuration of pieces and their relations on the board, which involve circuits of different brain regions (37, 38). Mounting evidence from psychology suggests that becoming an expert in chess and other cognitively demanding tasks is not just related to higher innate cognitive abilities but also to training and the accumulation of experience (35, 39–42). The quality of a particular move thus reflects an ideal measure of performance in a demanding cognitive task of the sort that is gaining importance in the labor market. Second, chess data are of exceptionally high quality and allow for measuring individual performance with extreme accuracy, at the level of individual moves during a chess game. In particular, performance in chess can be measured against an objective benchmark, the move that a chess engine suggests as the best-possible move when facing the exact same decision problem. This allows for constructing a measure of performance by comparing actual individual moves with the optimal move for a given configuration. Third, the exact same benchmark can be applied to each configuration, and the benchmark does not change over time. In contrast to the use of ratings that change over time and with the performance of others (43), the use of move-level performance has the advantage of measuring performance in a fully comparable way across individuals and regardless of the temporal or environmental context. This implies that performance can be compared directly within individuals and across individuals, as well as over long periods of time, providing a unique possibility to investigate the consequences of technological change and digitization across cohorts and over time: for instance, in the context of the emergence of chess engines that changed education and preparation facilities. Fourth, the analysis of performance in a task that is observed repeatedly for the same individuals allows for decomposing age patterns based on within-individual variation from variation across different cohorts and over time. Fifth, in terms of external validity, performance estimates based on professional chess players are likely to constitute an upper bound of cognitive performance over the life cycle. The resulting measure thus provides a unique opportunity to isolate age–performance patterns and analyze their dynamics over time and across cohorts.

We use data from more than 24,000 chess games between 1890 and 2014 for the best players in the world, with more than 1.6 million move-by-move observations. The data are based on all games played by world champions in history throughout their entire lives and contain performance information for world champions and their respective opponents. The high stakes related to financial rewards and reputation rule out incentive problems. At the same time, the analysis delivers an estimate of the life cycle patterns of cognitive performance and its dynamics over time and across cohorts.

The empirical strategy is based on the comparison of individual performance against an objective benchmark—the optimal move for a given configuration suggested by a chess engine—as a measure of cognitive performance that is fully comparable over long time ranges. Longitudinal data for the same individuals over the life cycle allow disentangling age patterns from cohort and period effects in a nonlinear specification. This enables an exploration of the long-run dynamics of the age–performance profile across periods and cohorts. In particular, the analysis applies flexible panel regression models to estimate the age profile of cognitive performance and its changes across groups of birth cohorts and periods (*Materials and Methods*).

Previous work on the variation of cognitive performance in the context of chess either has been based on behavioral experiments with a cross-section of chess players of various ages and strength, focusing on measures of decision speed and working memory (44), or has been based on variation between individuals using rating information as a proxy for performance in the relation between age and mental performance among amateur chess players (29, 30, 43, 45). In contrast, the analysis here uses within-individual variation over a long range of time and many cohorts and measures cognitive performance using a comparable and objective measure based on move quality. This allows for exploring the dynamics of the age–performance profile over a long time horizon.

The Dynamics of the Age–Performance Profile

The estimation results reveal several insights about the life cycle profile of cognitive performance and its dynamics over the past 125 y. Fig. 1*A* shows the life cycle pattern of performance by plotting the results of nonparametric estimates of the age profile using a local linear regression without conditioning on additional control variables and using data for the pooled sample of world champions and their opponents. Performance reveals a hump-shaped pattern over the life cycle. Individual performance increases sharply until the early 20s and then reaches a plateau, with a peak around 35 y and a sustained decline at higher ages. The emerging life cycle performance pattern corresponds to several findings in the previous literature that have estimated the age profile on the basis of variation between individuals or using work-related measures.

To rule out that the estimate of the life cycle performance pattern is driven by third factors, we estimated richer specifications of a multivariate regression model that controls for the color of chess pieces, the number of moves per player in a game (to account for fatigue), and the player-specific average complexity of a game, as well as birth cohort, calendar period, and player dummies. These estimates deliver similar results in terms of a hump-shaped age pattern, with performance increasing during young ages and decreasing during older ages. Fig. 1*B* illustrates the estimated age profile for the cubic specification of age (estimates are presented in *SI Appendix*, Table S1). Paralleling the previous findings, the performance peak obtained with a cubic specification for age and an extensive set of control variables is at an age of around 35 y. The subsequent decline is much less pronounced in the multivariate regressions. Similar results are obtained for a specification with age bins instead of a quadratic specification for age (*SI Appendix*, Fig. S1 and Table S1).

These results do not account for changes in the performance of chess players over the past 125 y. Unconditional estimates depicted in Fig. 2*A* show that the average performance was substantially higher for later-born birth cohorts. The increase

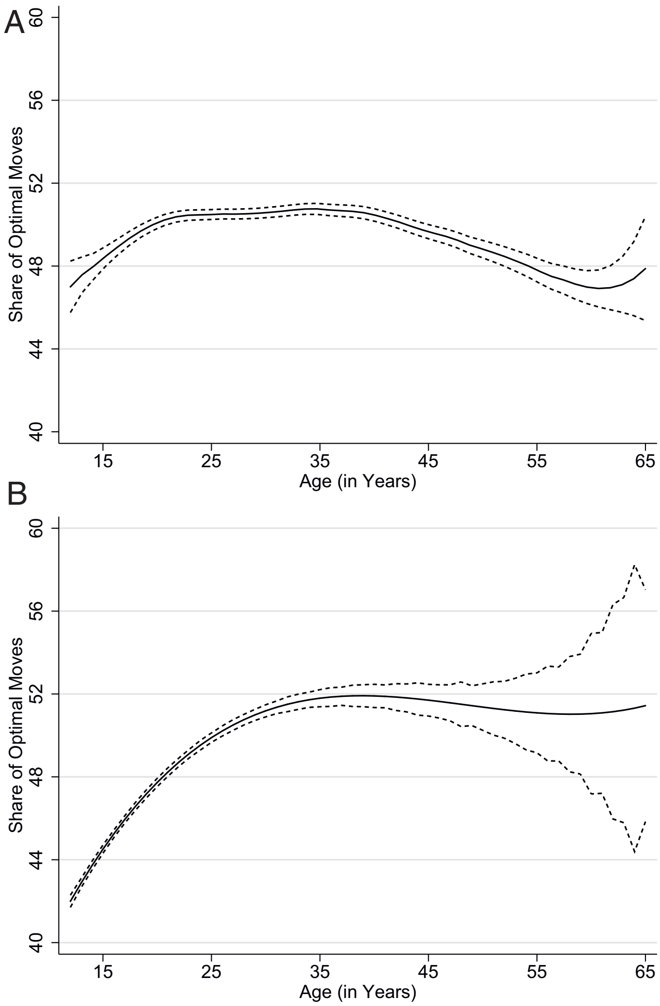

Fig. 1. Performance over the life cycle. (*A*) Local linear regression using an Epanechnikov kernel for age. No other controls were added. The bandwidth of 2.6 y is specified with Silverman's rule of thumb. (*B*) Implied age pattern from a multivariate estimation of the parametric specification of age using a third-order polynomial, as in *SI Appendix*, Table S1, column (1). Dashed lines report the 95% CIs (both panels).

in performance among players of the cohorts born after the 1970s compared with players born around the 1870s corresponds to approximately eight percentage points (from 44% optimal moves to approximately 52% optimal moves). For more recent birth cohorts, the life cycle performance profile has increased more rapidly at younger ages than for older cohorts. A similar acceleration is visible in Fig. 2*B* for performance patterns by calendar year. Performance increased steadily over the course of the twentieth century, but the data also reveal a steepening of the performance increase during the 1990s. This coincides with a phase when new information technology and the availability of powerful and affordable chess engines on home computers made chess-specific knowledge widely available and dramatically changed players' preparation possibilities. The availability of these new technologies may have improved the performance of players in more recent cohorts by providing them with the possibility to gain more practice early in their careers but might have equally benefited players of older cohorts by providing them with better training facilities. The results are qualitatively and quantitatively very similar for world champions, for whom there is considerably more within-person variation, and for opponents, suggesting that the findings regarding the age profile and the variation across time and cohorts are not driven by a particular subsample (*SI Appendix*, Figs. S2–S4).

In order to disentangle whether and how these dynamics affected the age–performance profile, Fig. 3 plots the age profile for different birth cohorts and calendar periods. The resulting pattern for birth cohorts in Fig. 3*A* confirms the finding that performance increased for later birth cohorts. However, while the increase was rather uniform across all age groups for the earlier-born cohorts, the increase in performance is more pronounced among younger ages for the later-born cohorts. Performance did not increase equally across the entire age spectrum, but younger cohorts experienced a faster increase early in life. The age profile for different calendar periods shown in Fig. 3*B* reveals that the increase in performance over time was associated with an upward shift of the entire age profile during more recent periods. Similar to the cohort patterns, the age gradient has become steeper, particularly for ages below 20. For the remaining age spectrum, performance increased fairly uniformly over time.

The unconditional estimates in Fig. 3 do not account for systematic variation across players and games. To account for this, an extended version of the multivariate regression model with the same controls as before was estimated that also allows for

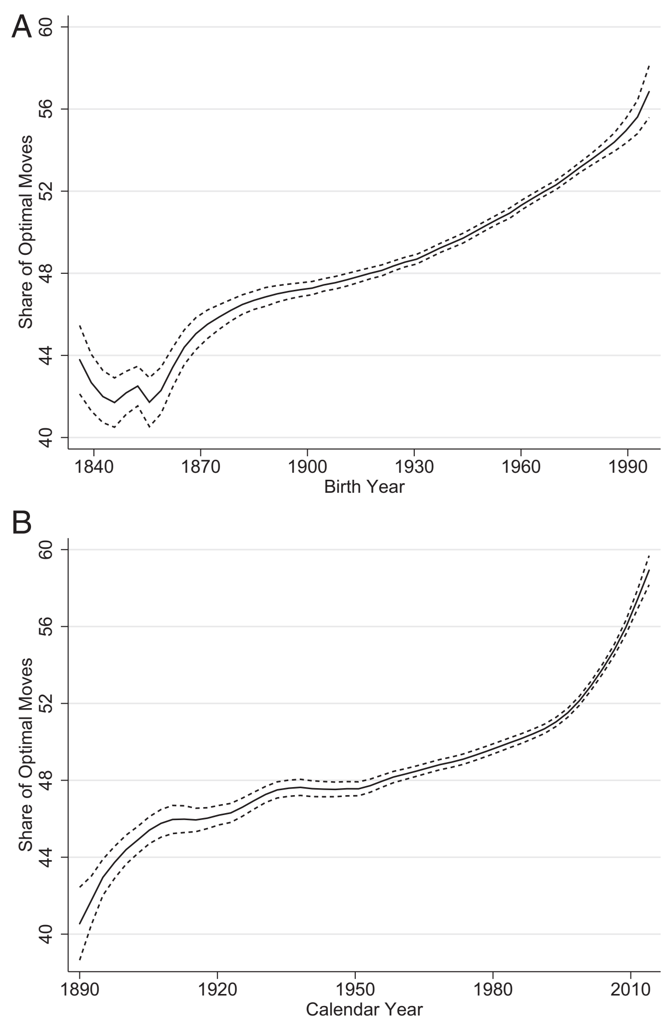

Fig. 2. Changes in performance over the past 125 y. Local linear regressions using an Epanechnikov kernel for age. No other controls were added. (*A*) The bandwidth of 9.2 y is specified with Silverman's rule of thumb. (*B*) The bandwidth of 5.9 y is specified with Silverman's rule of thumb. Dashed lines report the 95% CIs (both panels).

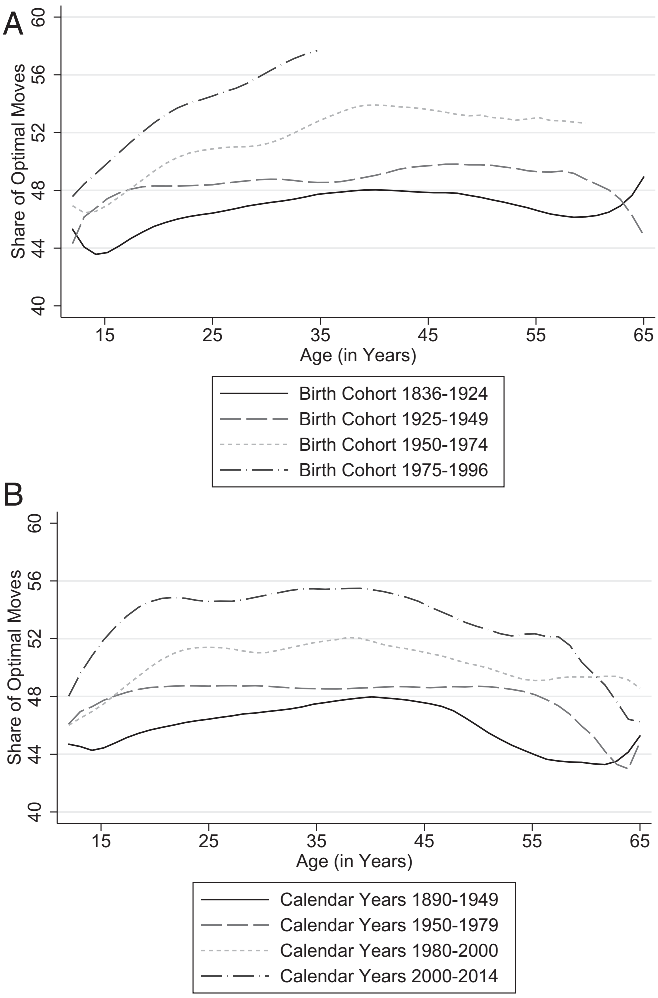

Fig. 3. Unconditional age–performance patterns by birth cohorts and calendar periods. (*A* and *B*) Local linear regression using an Epanechnikov kernel for age. No other controls were added. The bandwidth of 2.6 y is specified with Silverman's rule of thumb.

systematic variation in the age profile for different birth cohorts and for different calendar periods. The corresponding estimates are visualized in Fig. 4 (results for the specification with age groups are shown in *SI Appendix*, Fig. S5). Similar to the unconditional estimates, the results reveal evidence for a hump-shaped age profile. The combined estimates for changes in performance across birth cohort bins and calendar period bins reveal that the age profile exhibits substantial variation across birth cohorts. In particular, for later-born cohorts, the performance profile is higher and the increase in performance is considerably steeper during younger ages. Considering calendar period, there is much less discernible variation in the levels of the age profile, although the age profile is mildly steeper at young ages in more recent periods. Taken together, this suggests that the age profile exhibits more variation across cohorts and that the unconditional results for variation across calendar periods may partly pick up this variation across cohorts.

Discussion

The finding of a hump-shaped pattern in cognitive performance is robust to alternative performance measures, model specifications, and time periods. Very similar results were obtained when using as a performance measure the average (logarithmic) distance between actual moves and best moves in terms of pawn units (*SI Appendix*, Table S2). The results of the cubic specifications reveal a hump-shaped age pattern with a peak at an age of around 40 y for the specification with controls, which is comparable with the baseline results for the share of optimal moves as dependent variable. The results for the specification with age bins deliver a significant increase in performance with age for younger chess players below 35 y (*SI Appendix*, Table S1). Performance decreases above the age of 45 y, although the decline is not statistically significant. Qualitatively similar results are obtained for the propensity to make important mistakes as a dependent variable. Here, the results reveal a u-shaped age pattern (*SI Appendix*, Figs. S6 and S7), although older players do not appear to make more important mistakes (ref. 15 also has a similar finding).

A possible concern about the external validity of these results is related to the sample of games played by chess world champions and their opponents and the potential problem of positive selection into a professional activity based on playing strength (21, 46, 47). Conceptually, positive selection of players into the sample would imply that measured cognitive performance and in particular, the performance beyond the peak age of 35 to 45 y constitute an upper bound when interpreting the implications of the results for the general population. In fact, there is little evidence for selection of top chess players on the basis of other factors than performance. Over the entire sample period, becoming

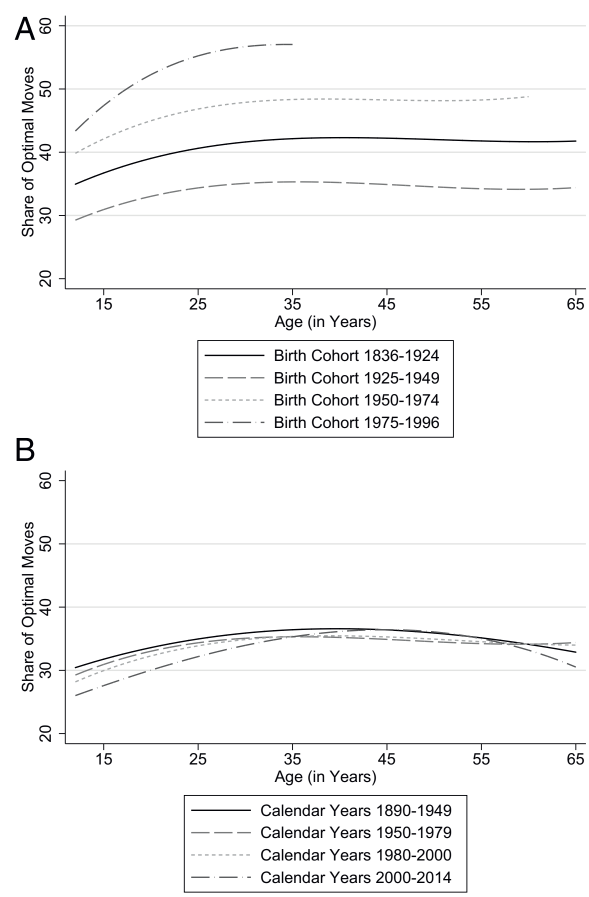

Fig. 4. Conditional age–performance patterns by birth cohorts and calendar periods. Implied age pattern from a multivariate estimation of the parametric specification of age using a third-order polynomial and additional control variables. The empirical model underlying *A* and *B* is equivalent to the results in *SI Appendix*, Table S1, column (1) extended for interactions between the cubic age profile with the dummies for cohort and calendar period categories, respectively.

a successful world class chess player was exclusively meritocratic, and it required no particular parental, cultural, geographic, or socioeconomic background and involved no restrictions by social class or birth (48).*

As a consequence of the sampling, which is based on all games played by world champions throughout their lives, the group of world champions should exhibit less selection than the group of opponents. Nevertheless, the results about the age–performance pattern and its shift across cohorts rather than over time are robustly found for both groups (*SI Appendix*, Figs. S2, S8, and S9). To investigate the influence of selection on the results obtained with the baseline sample in more detail, we focus on the opponents of the world champions for whom the performance information over the life cycle is more sparse and collected data of all games played by these opponents in the base sample over their entire life. This allows replicating the results with data from an alternative sample and exploring the role of positive selection in games against world champions during particular stages of their life. The results reveal qualitatively similar age–performance patterns, including when considering the extended sample for opponents that is less prone to such selection (*SI Appendix*, Fig. S10), and corroborate the finding that shifts are related to variation across cohorts rather than periods. In addition, the results from these data do not deliver strong evidence for selection in terms of level differences in performance.

An exploration of selection related to the observation of players over shorter or longer age ranges using the baseline data (for world champions) or the alternative data (for opponents) delivers evidence for positive selection, particularly during younger ages (*SI Appendix*, Figs. S11 and S12), but the main results about the age–performance profile and its dynamics remain unaffected. This analysis also suggests that the results should be seen as an upper bound of the estimate of the cognitive performance patterns in the overall population, particularly at higher ages. The implications of unobservable selection are not entirely clear, however.

Possible channels that could cause the observed changes in the age profile include variation in fatigue related to physical and cognitive demands, variation in the style of play reflected in the average complexity of a game, or variation in experience. Accounting for fatigue, complexity, or experience in the estimation of the age–performance profile by ways of interaction terms reveals that the shape of the age profile is largely unaffected (*SI Appendix*, Tables S3 and S4).

Systematic variation in the length of games might influence performance through fatigue, which might vary differentially by age. Using the number of moves played during a game as a proxy measure for fatigue documents no clear relation between the age pattern and the length of games (*SI Appendix*, Fig. S13). However, among more recent cohorts and games, younger players seem to play somewhat longer games, although the effects are not very pronounced. Nevertheless, this might be an indication of an emerging advantage. At the same time, the average number of moves per game increased considerably during the most recent decades, potentially reflecting improvements in preparation related to the availability of microcomputers and chess engines. Regression results again reveal a hump-shaped age profile for all levels of fatigue, with the lowest performance among the younger and older players. Perhaps surprisingly, performance increases with the number of moves played per game, but fatigue leaves the findings for the age profile of performance essentially unaffected (*SI Appendix*, Fig. S14).

Likewise, changes in complexity might affect the age pattern. Using the average search depth of the chess engine in the respective configuration for a given time budget as an inverse measure of complexity reveals that complexity has decreased (the search depth measured by the nodes evaluated by the engine has increased) across cohorts and over time (*SI Appendix*, Fig. S15). If complexity affects performance negatively, this might explain the higher performance of more recent birth cohorts and potentially, the variation in age patterns. Regression results indeed reveal a significantly positive effect of search depth on performance (*SI Appendix*, Tables S3 and S4). However, we also find that changes in the age profile are not affected by systematic variation in the complexity of games. In particular, the age–performance pattern is essentially identical and only moderately shifted in parallel by the complexity on the board (*SI Appendix*, Fig. S16). This suggests that dynamics in cognitive demand or complexity do not explain the dynamics in the hump-shaped age cycle.

Finally, using the number of previously played professional chess games as a proxy for experience reveals that experience increases with age. Moreover, the dynamics of experience suggest that younger cohorts are more experienced for a given age, and experience is higher in more recent periods, which might explain the observed increase in performance at younger ages (*SI Appendix*, Fig. S17). The results of the multivariate regressions indeed reveal that, similar to age, the effect of experience on performance is hump shaped. In light of evidence from psychology that has shown that performance is a combination of ability and practice (29, 30, 49), this suggests that the more rapid spread of chess knowledge and the emergence of chess engines and online playing opportunities led to a faster increase in performance at younger ages. When allowing the age profile to vary by experience, we continue to find a hump-shaped age profile, but higher experience also accounts for some of the age profile (*SI Appendix*, Fig. S18). In particular, for players with low experience, the performance increases with age sharply until about 37 y of age. In contrast, for players with high experience, the increase is much less pronounced and positive until only about 30 y of age. Hence, variation in experience partly captures the dynamics in the age profile over time. Taken together, technical change in terms of the availability of chess engines could have accelerated the accumulation of knowledge and experience and thereby, led to a higher performance of players at younger ages.

To explore the link between experience and higher performance at younger ages among more recent birth cohorts, we conducted an additional robustness check considering performance during a game. If improved preparation and knowledge accumulation early in life in the context of new technologies were to play a role, this could show in terms of differences in performance during the different phases of a game. Performance in the early phase of a game is influenced by the opening, which typically follows moves that are studied and memorized before the game, whereas the endgame exhibits more positional variability but lower complexity. The advantage of improved computer-based training and preparation might thus manifest itself in different ways during different phases of the game. To explore this possibility, the analysis was replicated by considering separately the performance before move 30 and from move 30 onward. The results show that the performance increase during young ages is more pronounced during later phases of the game (*SI Appendix*, Figs. S19 and S20). Alternative robustness checks were conducted when restricting to the first out-of-book moves (moves 10 to 15) or to the last 10 moves of a game, with similar results (*SI Appendix*, Figs. S21 and S22). Together, these results confirm that changes in the age profile mostly refer to variation among cohorts, not over time.

*This has been suggested as an explanation for the historically large proportion of chess grandmasters and world champions with a nonexceptional socioeconomic background. For example, Wilhelm Steinitz (1836 to 1900) was the youngest of 13 children born to a tailor, Emmanuel Lasker (1868 to 1941) was the son of a cantor, and José Raúl Capablanca (1888 to 1942) was the son of an army officer. The current world champion, Magnus Carlsen (born 1990), is the son of an information technology consultant and a chemical engineer (sources: Wikipedia [https://simple.wikipedia.org/wiki/List_of_World_Chess_Champions] accessed on 18 March 2020).

In sum, we presented an analysis of the long-run changes in life cycle profiles of cognitive performance based on panel data with repeated observations of the same individuals over their life cycle using an identical task, chess, and a fully comparable performance evaluation across individuals and over time. The evidence reveals a hump-shaped performance pattern over the life cycle. Performance increased for more recent cohorts and over time. The age profile mainly changed across cohorts rather than over time, with the performance increasing faster at younger ages.

Materials and Methods

Performance in Chess. Modern chess rules originated during the fifteenth century in Italy and Spain and have essentially not changed since the early nineteenth century. Chess is a two-person zero-sum game with perfect information and alternating moves. For this class of games, the optimal strategy is strictly determined and may be found by backward induction (50–52). For each configuration, chess engines compute an evaluation that represents a proxy of the winning odds and is measured in so-called pawn units, where one unit approximates the advantage of being up one pawn. Based on a game tree for all possible moves by white/black of a given prespecified length of n moves ahead (the so-called search depth), engines determine the best next move, applying a best-response logic (*SI Appendix*, Fig. S23 shows an illustration). As a measure of performance, we compute the difference in the evaluation before a move (conditional on following the computed continuation path of best responses) and right after (when the engine has recalculated the evaluation of the configuration). This procedure is equivalent to comparing the player's positional evaluation right after the actual move with the player's evaluation had the player conducted the move suggested by the engine.

The central advantage of this setup for addressing the research question on performance over the life cycle and its long-run dynamics is that each move played in the dataset can be evaluated using the exact same objective benchmark, regardless of period, age, or birth cohort of the player. Alternative measures such as conventional Elo-ratings (43) are not comparable over time.

Data. The data are a collection of all games played at regular time controls (usually 40 moves within 2 h) by all chess world champions since the first generally accepted world champion Wilhelm Steinitz (lived 1836 to 1900) to Magnus Carlsen (born in 1990, world champion since 2013). The data were assembled originally in ref. 53 and are based on the commercially available chess database Chessbase and other online sources commonly used in the chess community (the data are available at http://www.alliot.fr/CHESS/ficga.html.en). The main dataset comprises 25,072 games with more than 1.6 million configurations, which were played by (or against) the world champions of chess since 1859.[†] The data contain nearly the entire lifetime history of games played in chess competitions by world champions (including games before and after their acting as world champion). The dataset contains detailed information about the date of the game, color of chess pieces, scored points, and chessboard configurations before and after each move (of the world champions and their opponents). To rule out memorized moves and economize on computing costs, only moves between moves 10 and 100 (so-called "out-of-book moves") are considered (the first moves of a chess game, "book moves," are studied intensively during the preparation of a game and usually correspond to routine openings that have been memorized by players).

After generating the move-by-move measure for performance, the data were aggregated on the player–game level.[‡] This implies two observations per game, one for each player. The aggregated data contain 50,143 game–player observations (for one game by Tigran Petrosian, we do not observe the moves of the opponent; we drop this game because it lasted for fewer than 20 moves); 329 observations are omitted because the respective game lasted for fewer than 20 moves. Furthermore, we restrict attention to games played since 1890, which implies that 757 observations of games that took place before 1890 are omitted.

In total, 4,294 players (20 world champions and 4,274 opponents) are observed. We omit 3,422 players (5,205 observations) because fewer than five games are observed for each of these players. The birth years of all players were collected from Wikipedia. For 98% of the remaining players, who represent 99% of all games in the data, we were able to obtain information about the birth year. We omit 284 observations because of missing player birth year. Furthermore, 34 observations are omitted because the birth year of the player is before 1836 (the birth year of the first world champion, Wilhelm Steinitz), and 898 observations are omitted because the player is aged below 12 or above 65 y. The final dataset contains 42,636 observations (24,379 games and 841 players). Descriptive statistics are reported in *SI Appendix*, Table S5.

For robustness checks regarding selection, we collected data on all games of the opponents of the world champions throughout their lives from the chess database Chessbase. In contrast to the baseline data, which contain all games played by world champions, the alternative data sample one random white game and one random black game for each year in which at least one game is observed in the database for a given opponent player in the baseline dataset. This sample contains the same set of players as the baseline sample but is not selected based on whether a world champion participated in a game. Performance evaluation for this dataset of 57,321 game–player observations over the period from 1890 to 2013 with 2.5 million configurations was conducted in a comparable way as in the baseline sample.

Measure of Performance. Evaluations of configurations and quality of moves were carried out with the use of Stockfish 8, an open-source program that computes, for a given configuration of the pieces on the chessboard, the best possible move (details are in ref. 53). With an estimated Elo-rating exceeding 3,200 points, this engine provides a relevant benchmark even for the best players in history (incumbent World Champion Magnus Carlsen had an Elo-number of 2,872 in January 2020; https://ratings.fide.com/toparc.phtml?cod=577; last accessed 17 March 2020).

In game g, the evaluation of player i's position according to the chess engine is $E_{igm'}$ pawn units before move m and E_{igm} pawn units after move m, so that the corresponding change of the evaluation as a result of move m is $\Delta_{igm} = E_{igm} - E_{igm'}$ pawn units. When computing $E_{igm'}$, the chess engine assumes that the player would play the move that the chess engine evaluates as optimal. This implies that $\Delta_{igm} = 0$ if a player plays the optimal move according to the chess engine and $\Delta_{igm} < 0$ if the player plays a move that the engine evaluates as suboptimal. Thus, Δ_{igm} is an increasing measure of performance of player i for move m in game g. This performance measure is comparable across different configurations, moves, games, and players because it is benchmarked against the objective computer-generated move. Players can achieve the performance of the computer-generated benchmark independent of endogenous factors, such as the initial evaluation of the configuration, the strength of the opponent, or the complexity of the configuration on the board.

As a baseline measure of performance, we use the share of optimal moves of a player in a given game. This measure reflects an overall composite of performance and is computed as

$$\bar{P}_{ig} = \frac{1}{\#(i,g)} \sum_{m=1}^{\#(i,g)} \left(1 - \mathbf{I}\left\{\Delta_{igm} < 0\right\}\right) \cdot 100\%,$$

with $\#(i,g)$ being the total number of moves of player i in game g and $\mathbf{I}\{\cdot\}$ being the indicator function. The resulting measure is distributed symmetrically between 0 and 100 and correlates positively with the probability of winning as reflected by scoring points (*SI Appendix*, Fig. S24). A greater share of optimal moves is associated with a higher winning probability, with more than 40% of optimal moves effectively implying a winning probability of more than 50%. As an alternative measure, we use the average (logarithmic) distance between actual moves and the computer-generated optimal benchmark in terms of pawn units (*SI Appendix*, Fig. S25).

In addition, the data contain information about the search depth in terms of nodes that the chess engine was able to evaluate within a prespecified time limit of 3 min. Since this search depth is directly related to the branching factor of the game tree that arises from a given chess configuration (as illustrated in *SI Appendix*, Fig. S23), lower search depth provides a useful measure of the complexity of each configuration. We aggregated this measure on the game level to obtain a measure of the average complexity of each game.

Empirical Strategy. The empirical analysis is based on the partial linear model,

[†]They are Wilhelm Steinitz, Emanuel Lasker, José Raúl Capablanca, Alexander Alekhine, Max Euwe, Mikhail Botvinnik, Vasily Smyslov, Mikhail Tal, Tigran Petrosian, Boris Spassky, Robert James Fischer, Anatoly Karpov, Gary Kasparov, Alexander Khalifman, Viswanathan Anand, Ruslan Ponomariov, Rustam Kasimdzhanov, Veselin Topalov, Vladimir Kramnik, and Magnus Carlsen.

[‡]The move-by-move evaluation follows that by Alliot (53).

$$\bar{P}_{ig} = f(A_{ig}, C_i, T_{ig}) + X_{ig}\gamma + \phi_i + \varepsilon_{ig}, \quad [1]$$

where $f(\cdot)$ represents a function of age A_{ig}, birth cohort C_i, and calendar year T_{ig}. The specification includes controls for player–game-specific characteristics X_{ig} (color, number of moves, and average complexity of the game as measured by the search depth of the chess engine). For reasons of clarity regarding the interpretation of our results, we use standardized control variables (mean zero and SD one). In order to account for unobserved heterogeneity that might influence the results systematically, the empirical analysis includes player dummies ϕ_i, which account for all time constant player characteristics, thereby identifying the age pattern from within-person variation in age. We denote the error term by ε_{ig}.

In the analysis, we consider both parametric and nonparametric specifications of $f(A_{ig}, C_i, T_{ig})$. As a benchmark, we specify fully flexible univariate age, birth cohort, and calendar year profiles in specifications without additional controls.

In multivariate regressions, we model age as a third-order polynomial:

$$f(A_{ig}|C_i = c, T_{ig} = t) = \beta_1 A_{ig} + \beta_2 A_{ig}^2/10 + \beta_3 A_{ig}^3/100.$$

As an alternative, we estimate specifications with age groups.

It is well known that the effects of age, cohort, and period cannot be disentangled without additional assumptions. Since the focus of this paper is on the changes of performance over the life cycle across periods and cohorts, and not about the absolute performance at a given time or for a given cohort, we combine periods as well as age cohorts into groups. This grouping allows identifying age, period–group, and cohort–group effects. Moreover, since we are interested in changes in performance across cohorts and over time, we focus on interaction terms of the age profile with birth cohort groups and calendar periods.

Data Availability. Replication data and code have been deposited in Harvard Dataverse (https://doi.org/10.7910/DVN/DZC0MT).

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