Nepotism vs. Intergenerational Transmission of Human Capital in Academia (1088-1800)

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Nepotism vs. Intergenerational Transmission of Human Capital in Academia (1088–1800)*

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Abstract

We argue that the waning of nepotism in academia bolstered scientific production in pre-industrial Europe. We build a database of families of scholars (1088–1800), measure their scientific output, and develop a general method to disentangle nepotism from inherited human capital—two determinants of occupational persistence. This requires jointly addressing measurement error in human capital proxies and sample selection bias arising from nepotism. Our method exploits multi-generation correlations together with parent-child distributional differences to identify the structural parameters of a first-order Markov process of human capital transmission with nepotism. We find an intergenerational human capital elasticity of 0.59, higher than that suggested by parent-child elasticities, yet lower than multi-generation estimates ignoring nepotism. In early academia, 40 percent of scholars' sons achieved their position because of nepotism. Nepotism was lower in science than in law and in Protestant than in Catholic institutions, and declined substantially during the Scientific Revolution and the Enlightenment—two periods of buoyant scientific advancement.

Keywords: *Intergenerational mobility, human capital transmission, nepotism, upper-tail human capital, pre-industrial Europe, simulated method of moments.*

JEL Codes: *C31, E24, J1*

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1 Introduction

Universities and scientific academies are often seen as being essential for having brought Europe through the Commercial Revolution (Cantoni and Yuchtman 2014), Scientific Revolution (Applebaum 2003), and Enlightenment (Mokyr 2009). Yet, these institutions are not immune to criticism: some remained attached to old paradigms, others sold diplomas, and many accepted appointments and nominations of relatives.[1] This may indicate that children benefited from their parents' social connections and used them to get jobs ahead of better qualified candidates (henceforth, nepotism). That said, family dynasties are common in high-talent occupations,[2] which may be optimal if talent is scarce and children's human capital depends on parental investments, inherited knowledge, abilities, and skills (henceforth, inherited human capital). Disentangling inherited human capital from nepotism is important as their economic implications are fundamentally different: while inherited human capital increases productivity, nepotism leads to a misallocation of talent. Such misallocation is particularly damaging in high-talent markets (Murphy, Shleifer, and Vishny 1991) where it can affect the production of ideas, and in turn technological progress and economic development (Mokyr 2002).

However, disentangling inherited human capital from nepotism is challenging from an econometric perspective. The reason is that these two elements are associated with two different biases: on the one hand, inherited human capital is only imperfectly reflected in socio-economic outcomes, which can lead to measurement error. Recent studies suggest that this bias can be large: Earnings, wealth, or occupation are considerably more persistent across multiple generations than suggested by parent-child elasticities[3] because children inherit a set of unobserved endowments (e.g., human capital, ability, genetic advantages) which are later transformed into observed outcomes with measurement error.[4] On the other

[1] See Dulieu (1983) on Montpellier's medical faculty, Slottved and Tamm (2009) on the University of Copenhagen, and Connor (1947) on the Cassini dynasty at the Paris Observatory and the French Academy of Sciences.

[2] Examples include doctors (Lentz and Laband 1989), lawyers (Laband and Lentz 1992; Raitano and Vona 2018), politicians (Dal Bó, Dal Bó, and Snyder 2009), inventors (Bell et al. 2018), CEOs (Pérez-González 2006; Bennedsen et al. 2007), pharmacists (Mocetti 2016), self-employed (Dunn and Holtz-Eakin 2000), liberal professions (Aina and Nicoletti 2018; Mocetti et al. 2018), and university professors (Durante, Labartino, and Perotti 2011).

[3] Güell, Rodríguez Mora, and Telmer (2015), Clark (2015), Clark and Cummins (2015), Lindahl et al. (2015), Braun and Stuhler (2018). For reviews on parent-child elasticities, see Solon (1999), Corak (2006), and Black and Devereux (2011).

[4] Alternatively, it has been suggested that grandparents can have independent effects on their grandchildren (Mare 2011; Zeng and Xie 2014; Lindahl et al. 2015; Adermon, Lindahl, and Waldenström 2018; Long and Ferrie 2018; Colagrossi, d'Hombres, and Schnepf 2019).

hand, nepotism introduces a different econometric bias: selection. For example, nepotism can bias intergenerational mobility estimates by generating barriers of entry to certain occupations. Traditional estimates that bundle inherited human capital and nepotism do not address both biases jointly, and hence, provide unreliable estimates of intergenerational inequality.

In this paper, we develop a general method to disentangle inherited human capital from nepotism and examine its implications for talent allocation and the production of ideas in pre-industrial Europe. We build a dataset with families of scholars in 1088–1800 and their scientific output. Using our novel method, we show that human capital endowments were inherited with an intergenerational elasticity of 0.59—higher than suggested by father-son correlations in scientific publications, and lower than estimates proposed in the literature that omit nepotism. Hence, in settings where nepotism is prevalent, failing to account for it can overstate the true rate of persistence of human capital endowments. We find that forty percent of scholars' sons were themselves scholars because of nepotism before the Scientific Revolution. Nepotism declined dramatically in the Scientific Revolution and the Enlightenment, when families of scholars emerged as a by-product of inherited human capital. This suggests that nepotism distorted the production of ideas and that removing this barrier was crucial for Europe's scientific advancements before the Industrial Revolution.

Our first contribution is to propose a general method to disentangle human capital transmission from nepotism. We argue that standard two-generation elasticities in socio-economic outcomes provide biased estimates of the transmission of underlying endowments like human capital due to (i) measurement error in these underlying endowments and (ii) selection bias arising from nepotism. While the literature has addressed each of these biases separately, we develop a new method to jointly address them. We use two sets of moments to characterize intergenerational persistence: one standard in the literature, another new. The first is correlations in observed outcomes across multiple generations, which have been used to address measurement error.[5] Under the assumption that measurement error is constant across generations, these multi-generation correlations reflect the transmission of (unobserved) underlying human-capital endowments. The second set of moments are distributional differences in observed outcomes between fathers and sons in the same occupation. We consider an occupation which selects individuals from the upper-tail of the human-capital distribution and where the entry criterion may be different for sons of insiders. In this setting, father-son distributional differences

[5]Lindahl et al. (2015), Braun and Stuhler (2018).

may be the result of two forces: on the one hand, if human capital strongly reverts to the mean, the sons of individuals at the top of the human-capital distribution will perform worse than their fathers.[6] On the other hand, nepotism lowers the selected sons' human capital relative to that of the selected fathers. Even when human capital slowly reverts to the mean, this generates distributional differences in observed outcomes across generations, especially at the bottom of the distribution, i.e., closer to the selection thresholds. Hence, the excess distributional differences, net of reversion to the mean, can be used to identify nepotism.[7]

Our second contribution is to quantify nepotism vs. inherited human capital in explaining the prevalence of families in pre-industrial academia, as well as its effects on talent allocation, scientific production, and upper-tail human capital accumulation. We build a new dataset of $1,440$ lineages of scholars in 100 universities and 40 scientific academies in pre-industrial Europe. We do so by using university catalogues and secondary sources, such as books on the histories of the universities and compendia of university professors. We then match the names found with old biographical dictionaries (e.g., Michaud 1811) and online encyclopedias.[8] Our database contains $1,257$ fathers and $1,440$ sons who were members of the same university or scientific academy in 1088–1800. We also observe 145 families with three or more generations of scholars. Finally, we use WorldCat to count the number of library holdings by or about each author. By using library holdings in modern libraries, we measure the size as well as the long-term relevance of a scholar's scientific output (henceforth, publications). Publications is an outcome variable that is noisily correlated with inherited human capital endowments.

We document two facts for lineages of scholars in pre-industrial Europe. The first fact is a high elasticity of publications across generations: we estimate a 0.35 elasticity on the intensive margin, comparable, e.g., to the elasticity of wealth in pre-modern agricultural societies (Borgerhoff Mulder et al. 2009). However, lineages with at least three generations of scholars display larger elasticities than predicted by the iteration of the two-generation elasticity. This suggests that the underlying human-capital endowments determining publications were strongly transmitted from parents to children—probably at a higher rate than father-son correlations in publications reflect. This is consistent with a slow rate of reversion

[6] To gauge how much do distributional differences depend on mean reversion, we follow the literature and assume stationarity in the distribution of human capital over all potential scholars.

[7] In addition, we use the fact that an increase in nepotism (measurement error): increases (does not) the variance of the sons' outcomes relative to their fathers' and increases (reduces) how well father-son correlations in outcomes reflect human capital transmission.

[8] E.g., *Allgemeine Deutsche Biographie*, *Treccani*, and Dictionary of National Biography.

to the mean in human capital. The second fact is that the publications' distribution of fathers first-order stochastically dominates that of sons. The distributional differences are large, especially below the median. This suggests that, compared to selected sons, selected fathers had substantially higher human capital endowments, which then translated into a better publication record. As argued above, this difference in endowments could be the result of a fast rate of reversion to the mean in human capital. That said, the high inter-generational elasticities in observed publications (fact 1) suggest a slow rate of reversion to the mean, which is hard to reconcile with the large distributional differences between fathers and sons (fact 2). We reconcile these two apparently contradictory facts with nepotism, which allowed sons of scholars to become scholars even when their human capital endowments were low. Formally, we use these two facts to estimate the structural parameters of a first-order Markov process of endowments transmission (Clark and Cummins 2015; Braun and Stuhler 2018), extended to account for nepotism. Using the Simulated Method of Moments, we obtain estimates for nepotism and the rate at which children inherited their parent's human capital.

Our first result is that nepotism was quantitatively important in universities and scientific academies—especially before the Scientific Revolution. Between 1088 and 1800, one in twenty-five scholars developed his career in the same university or scientific academy as his father.[9] We estimate that the son of a scholar could become a scholar even if his human capital was 2.2 standard deviations lower than the average potential scholar, and 2.1 standard deviations lower than the marginal outsider scholar. Before the Scientific Revolution, 40 percent of scholars' sons would not have become scholars under the same criteria than outsiders. This distorted the production of ideas: A counterfactual exercise suggests that removing nepotism would increase the scientific output of the average scholar in our dataset by 65 percent before the Scientific Revolution. Nepotism is only the tip of the iceberg of favouritism towards other relatives, friends, and acquaintances. Hence, these inefficiencies are likely a lower-bound estimate of talent misallocation in early academia.

We document a large decline in nepotism in the Scientific Revolution (1543–1687) and the Enlightenment (1687–1800). Nepotism declined from forty percent before 1543 to 14-16% in the Scientific Revolution and to 3.8% in the Enlightenment. This was the result of the foundation of modern, meritocratic institutions and not of structural reforms in existing institutions. Nepotism was not prevalent

[9]This figure is based on 35,999 known scholars from the 111 institutions with better data coverage. It excludes catholic priests in theology, who did not have legitimate children.

in Protestant universities and scientific academies. In contrast, Catholic institutions were less open and relied heavily on knowledge transmission within families. This partially explains the divergent path of Catholic and Protestant universities after the Reformation (Merton 1938). We also show that nepotism was higher in law and physician's faculties than in sciences, more prominent for sons appointed during their father's lifetime and for sons in their father's field of study, and similar in universities and scientific academies. Finally, we validate our identification strategy with a falsification test: we consider fathers and sons appointed at different institutions, and hence, not subject to nepotism.

Altogether, this suggests that nepotism resulted in a misallocation of talent, distorted the production of ideas, and slowed the accumulation of upper-tail human capital. Eventually, modern, open universities were established, contributing to Europe's scientific advancements before the Industrial Revolution.

Our second result is that human capital endowments were transmitted with an intergenerational elasticity of 0.59. This value is higher than what father-son correlations in observed outcomes (publications) would suggest. Yet our estimate is in the lower range of elasticities estimated elsewhere via multiple generations, group-averages, or the informational content of surnames. We show that in our setting, where nepotism and selection are prevalent, standard multi-generation estimates overstate the true rate of persistence of human capital endowments—that is, the persistence of endowments, talents, skills, etc. affecting children's productivity. Similarly, if we set nepotism to zero, our method delivers large intergenerational elasticities, close to the 0.7–0.8 range estimated by Clark (2015). Finally, our findings do not support Clark's hypothesis that the rate of persistence is constant through different historical periods. The transmission of human capital endowments and nepotism follow an inverse relationship over time: after the Scientific Revolution, nepotism declined but lineages of scholars did not disappear; they became meritocratic. This suggests that institutional factors can affect the intergenerational transmission of occupations even if family dynasties persist.

Relative to the existing literature, we make the following contributions. First, we show that to obtain reliable intergenerational elasticities it is crucial to jointly address measurement error in a child's inherited endowments and the selection bias arising from nepotism. One branch of the literature addresses measurement error by using multiple generations (Lindahl et al. 2015; Braun and Stuhler 2018; Colagrossi, d'Hombres, and Schnepf 2019), group-averages for siblings (Braun and Stuhler 2018), rare surnames (Clark and Cummins 2015), the informational content of surnames (Güell, Rodríguez Mora, and Telmer 2015), or horizontal kinship correlations (Collado, Ortuno-Ortin, and Stuhler 2018). We show that, by ignoring selection in the form of nepotism, multi-generation estimates can overstate the persistence of endowments like human capital, abilities, or genetic advantages.[10] Another branch of literature quantifies nepotism in top professions (e.g., doctors, lawyers, politicians) by exploiting natural experiments that altered the importance of connections to accessing jobs.[11] By looking at a snapshot, these papers cannot characterize long-run persistence or address measurement error in children's inherited human capital. In addition, our findings shed new light on the debate about whether intergenerational mobility is associated with the economic environment (Chetty et al. 2014; Güell et al. 2018) or is constant across historical periods Clark (2015). Finally, scholars constitute a well-defined universe of individuals at the top of the human capital distribution. Hence, we provide new evidence on the rate of mean-reversion in upper-tail human capital in pre-industrial Europe. We find a slow rate of mean reversion, especially for later periods. This lends credence to Galor and Moav (2002) and Galor and Michalopoulos (2012), who show that natural selection of growth-promoting traits (e.g., upper-tail human capital) is more likely when parents pass on such traits, genetically or culturally, with a high probability.[12]

Second, our proposed method circumvents some of the data requirements that have limited the study of intergenerational persistence. Previous methods require census-like data with links across multiple generations, horizontal kinship relations or the entire surname distribution. Such data may be difficult to obtain, particularly in historical settings. Our method only requires observing a well-defined universe, e.g., an occupation. Similarly, we can estimate nepotism across time and space, beyond the specific instances in which a natural experiment is available.

Third, our paper is related to a literature on patronage and favouritism. This literature considers family ties but also other social and geographic connections between principals and agents. Hence, the focus is on disentangling favouritism[13] from the principal's private information about the unobserved abilities of connected agents. One approach is to exploit the fact that promotions of connected candidates look more random to the econometrician due to the principal's private

[10] A related literature uses twins, adoptees, and natural experiments to test whether intergenerational associations are genetically inherited (selection) or depend on parental investments (causation). See Holmlund, Lindahl, and Plug 2011 and Black and Devereux 2011 for reviews. Differently, we address the selection bias resulting from of nepotism to disentangle it from human capital endowments—but not whether such endowments are determined by nature or nurture.

[11] See references in footnote 2.

[12] They typically assume an intergenerational elasticity of one for growth-promoting traits.

[13] Favouritism (nepotism) is the promotion of connected agents (relatives) with weaker criteria.

information (Bramoullé and Huremović 2018). Another approach is to compare objective performance measures of connected and unconnected agents. For example, scholars appointed by someone with home-town ties (Fisman et al. 2018) or evaluated by an acquaintance (Zinovyeva and Bagues 2015) underperform unconnected individuals in, respectively, the Chinese Academy of Science and among Full Professors in Spain. In contrast, Voth and Xu (2019) find evidence against favouritism in the British Navy. By narrowing the focus to parent-child ties, we can disentangle favouritism from the transmission of human capital across generations.

Fourth, our empirical application sheds new light on a growing literature that highlights the importance of upper-tail human capital for economic growth in pre-industrial Europe. This literature argues that upper-tail human capital—such as the knowledge produced at universities—is important to explain the Commercial Revolution (Cantoni and Yuchtman 2014), the rise of new Science after the adoption of the printing press (Dittmar 2019), and the Industrial Revolution (Mokyr 2002; Galor and Moav 2002; Mokyr 2016; Squicciarini and Voigtländer 2015). We contribute to this literature by identifying two important aspects affecting the production of scientific knowledge: the transmission of human capital across generations and nepotism. Our results suggest that periods of rapid advancement in sciences were associated with lower degrees of nepotism in universities and scientific academies. This finding supports the hypothesis by Greif (2006) and de la Croix, Doepke, and Mokyr (2018), that the dissemination of new productive knowledge in pre-industrial European corporations was not slowed down by narrow family networks or kin groups. That said, we find that human capital transmission within nuclear families was important. We also shed new light on the divergent path of Catholic and Protestant universities after the Reformation. We show that nepotism and the transmission of knowledge within families of scholars may have played an important role beyond traditional explanations based on religious values (Merton 1938) or institutional factors (Landes 1998). More generally, our results relate to a large literature showing that distortions in high-talent markets can drastically affect the production of ideas. Examples of such distortions include family-successions of CEOs (Pérez-González 2006; Bennedsen et al. 2007) and lack of exposure to innovation (Bell et al. 2018).

The article proceeds as follows: Section 2 discusses methods for measuring intergenerational persistence and our model with nepotism. Section 3 presents the institutional background, the data, and two stylized facts about scholar's lineages. Identification and main results are in Section 4. Sections 5 and 6 contains validation exercises, heterogeneous effects, and robustness. Section 7 concludes.

2 Methods

Here we discuss different methods for measuring intergenerational persistence and highlight two potential biases. We then present our general model with nepotism.

2.1 Parent-child elasticities

To study the extent to which inequalities are transmitted across generations, economists typically estimate coefficient b in:

$$y_{i,t+1} = b\, y_{i,t} + e_{i,t+1} \ , \tag{1}$$

where i indexes families, t parents, and t+1 children. The outcome y reflects social status (e.g., income, wealth, education, occupation) and is in logarithms. b is the intergenerational elasticity of outcome y. It determines the speed at which outcomes revert to the mean. To see this, note that the half-life of y (the generations until the gap to the mean halves) is $t_{\frac{1}{2}} = -\frac{\ln(2)}{\ln(|b|)}$, which depends negatively on b.

Table B1 in the Appendix shows estimates of b in the literature.[14] Parent-child elasticities vary across time and space, but are generally below 0.5. This implies a half-life of $t_{\frac{1}{2}} = 1$. That is, half the gap to the mean is filled after one generation. In three generations, almost all advantages will revert to the mean.

2.2 Measurement error bias

Recent studies looking at multiple generations show that, in the long-run, social status is more persistent than suggested by parent-child elasticities. One possibility is that there is a highly-persistent inherited endowment that wealth, income, or occupation only reflect noisily. Children do not inherit their socio-economic outcomes directly from their parents. Instead, children inherit an unobserved human capital endowment h (e.g., knowledge, skills, genes, preferences) which then transforms into the observed outcome y imperfectly. This is modelled as a first-order Markov process of endowments transmission where endowments are observed with measurement error (Clark and Cummins 2015; Braun and Stuhler 2018):

$$h_{i,t+1} = \beta h_{i,t} + u_{i,t+1} \ , \tag{2}$$

$$y_{i,t+1} = h_{i,t+1} + \varepsilon_{i,t+1} \ , \tag{3}$$

where $h_{i,t} \sim N(\mu_h, \sigma_h^2)$ and $u_{i,t+1}$ and $\varepsilon_{i,t+1}$ are independent noise terms. The coefficient β captures the extent to which the parents' endowment h is inherited

[14] For a more thorough review, see Solon (1999), Corak (2006), and Black and Devereux (2011).

by their children. In this sense, β is the parameter governing the true rate of persistence of social status across generations. In contrast, Equation (3) determines how well this endowment is reflected in the observed outcome y. A larger variance in the noise term, σ_ε^2, is associated with a lower observability of the endowment h.

The intergenerational elasticity of outcome y estimated from equation (1) is:

$$E(\hat{b}) = \beta \, \frac{\sigma_h^2}{\sigma_h^2 + \sigma_\varepsilon^2} := \beta \; \theta,$$

where $\theta < 1$ is an attenuation bias for β.

Several methods have been used to identify the true rate of persistence, β. One is to exploit correlations in y across multiple generations.[15] According to the first-order Markov process described above, the elasticity of outcome y is $\beta\theta$ between parents, t, and children, $t+1$, and $\beta^2\theta$ between grandparents, t, and grandchildren, $t+2$ (as long as the signal-to-noise ratio is stable across generations). Hence, the ratio of these elasticities identifies β. Intuitively, β is identified because the endowment h is inherited, but the estimation bias θ is not—it is the same across two or three generations. Another identification strategy for β is to estimate intergenerational regressions of equation (1)'s form with group-average data for siblings (Braun and Stuhler 2018) or for people sharing rare surnames (Clark and Cummins 2015). By grouping individuals with similar inherited endowments, the noise term ε is averaged away. Güell, Rodríguez Mora, and Telmer (2015) propose to identify β through the informational content of rare surnames (ICS)—a moment capturing how much individual surnames explain the total variance of individual outcomes.[16] This method only requires cross-sectional data, i.e., it does not require linking data across generations. Similarly, Collado, Ortuno-Ortin, and Stuhler (2018) estimate β using horizontal kinship correlations in the cross-section.

Table B1 in the Appendix reports estimates of β from these different approaches. The estimates range between 0.49 and 0.90, and hence are substantially larger than the parent-child elasticities b. Furthermore, Clark (2015)'s comprehensive evidence suggests that β is close to a "universal constant" across societies and historical periods. This finding is disputed by studies using the ICS (Güell et al. 2018) or multi-generation links (Lindahl et al. 2015; Braun and Stuhler 2018; Colagrossi, d'Hombres, and Schnepf 2019) instead of surname-averages.

In light of this evidence, the unobserved endowment that children inherit from their parents has often been interpreted as skills, preferences, or even genes. First,

[15] Lindahl et al. (2015), Braun and Stuhler (2018), Colagrossi, d'Hombres, and Schnepf (2019).

[16] The ICS is the difference in the R^2 of a regressions of y on a vector of dummies indicating surnames vs. a regression in which this vector indicates "fake" surnames. This moment is used to structurally estimate the true rate of persistence in education.

because these endowments reflect well the measurement error problem described here: wealth, income, education, etc. only reflect skills and innate abilities with noise. Second, because if β is a universal constant, it should reflect nature rather than nurture. In other words, if β does not vary substantially across time and space, an obvious conclusion is that institutions, social policies, or processes of structural economic transformation cannot affect social mobility in the long run.

We argue that these estimates may be subject to another source of bias in settings where favouritism or nepotism are prevalent. That is, where those with power and influence give preference to friends and relatives ahead of better-qualified outsiders. For example, estimates of occupational or wage persistence may be affected by the fact that certain jobs have higher entry barriers for outsiders than for sons of insiders. Econometrically, this introduces a different bias: selection.

2.3 Selection bias

Beyond measurement error, parent-child elasticities may be subject to sample selection: whether observations are sampled or not may be correlated with the unobserved endowment h inherited by children.

This additional source of bias is is inherent to data used to evaluate social mobility. It is present in applications that focus on a subgroup of the population, e.g., one occupation and those leaving wills. Specifically, in certain occupations relatives of insiders may be more likely to be observed. This kind of selection bias is typically addressed using natural experiments.[17] Similarly, wealth elasticities rely on wills and probate records, where only those leaving wealth above a minimum legal requirement are sampled (Clark and Cummins 2015). This sampling criterion is likely to be correlated with h, an individual's inherited endowments (e.g., social competence, skills, genes). Sample selection may also arise in applications covering the entire population (Lindahl et al. 2015; Braun and Stuhler 2018). In census data linking several generations, families are not observed if a generation migrates or dies before outcomes are realized (e.g., wage, occupational choice). This attrition can be correlated with the underlying endowment h. Finally, life-history data collected retrospectively may suffer from recall bias. This bias depends on h if families with large endowments have better knowledge of their ancestors.

To see how selection affects intergenerational elasticity estimates, let s be a selection indicator such that $s_i = 1$ if family i is used in the estimation, and $s_i = 0$

[17] See footnote 2 for detailed references.

if it is not. The intergenerational elasticity of y estimated from equation (1) is:

$$E(\hat{b}) = b + \frac{\text{Cov}\,(s_i y_{i,t},\ \ s_i e_{i,t+1})}{\text{Var}\,(s_i y_{i,t})}\ .$$

If $\text{Cov}\,(s_i y_{i,t},\ \ s_i e_{i,t+1}) = 0$, then $\hat{b}$ is an unbiased estimate of b and a biased estimate of β due to measurement error, i.e., $\hat{b} = \theta\beta$. If the selection indicator s_i is correlated with the underlying endowment transmitted across generations, $h_{i,t}$ and $h_{i,t+1}$, then the condition above is violated and $\hat{b}$ is a biased estimate of b.

These two biases are fundamentally different. As described above, measurement error can be corrected using multiple generations. The reason is that across n generations, the underlying endowment is inherited $n-1$ times at a rate β but only twice transformed into the observed outcome y with measurement error. This is not true for the selection bias, which depends on the h, and hence is 'inherited' $n-1$ times. For example, consider grandparent-grandchild (and parent-child) correlations in outcomes: The correlations depend on β—which is inherited twice (once), on the measurement error with which h is twice (twice) transformed into y, and on the selection bias—which is also 'inherited' twice (once). Hence, the ratio of grandparent-grandchild to parent-child correlations does not correct for selection. Moreover, if selection changes over time (e.g., due to changes in the prevalence of nepotism) the selection bias may differ across two and three generations. In other words, the ratio of grandparent-grandchild to parent-child correlations may provide upward or downward biased estimates of β.[18]

Henceforth, we restrict our analysis to sample selection—the bias emerging when inherited human capital is correlated to whether families are sampled or not. Another selection issue is whether human capital endowments (h) are genetically inherited (selection) or are determined by parental investments (causation). See Holmlund, Lindahl, and Plug (2011) and Black and Devereux (2011) for reviews.[19] We abstract from this selection story as our main purpose is to disentangle nepotism from human capital endowments, regardless of whether the latter are determined by nature or nurture. That said, in our empirical application it is possible that a scholar strategically invests in the human capital of his most endowed son, i.e., the son with higher chances of becoming a scholar *ex ante*. Unfortunately, we only observe the children of scholars who become scholars themselves. Hence, we

[18]Formally, this ratio is an upward biased estimate of β if $\frac{\text{Cov}(s_i y_{i,t},\ s_i e_{i,t+2})}{\text{Cov}(s_i y_{i,t},\ s_i e_{i,t+1})} > 1$.

[19]Different strategies have been used to address this kind of selection, ranging from twin studies (Behrman and Rosenzweig 2002), adoptees (Plug 2004; Björklund, Lindahl, and Plug 2006; Sacerdote 2007; Majlesi et al. 2019; Fagereng, Mogstad, and Ronning), and policy changes that affect parents' outcomes exogenously (Black, Devereux, and Salvanes 2005).

cannot use sibling comparisons to address this issue. That said, under this type of selection, our estimates would understate the rate of mean reversion in scholars' human capital and overstate nepotism—which we already estimate to be low in periods of rapid scientific advancement.

2.4 Model with nepotism

To address measurement error and selection, we develop a new model that incorporates nepotism into the standard first-order Markov process of endowments transmission described above. This section presents this model using the terminology of our empirical application.

We consider a population of potential scholars who are heterogeneous with respect to their human capital. The human capital of each potential scholar depends on a human capital endowment inherited from his father[20] and on random ability shocks. Individuals with high human capital are selected to be a scholar. To account for the possibility of nepotism, we allow this selection criterion to be different for sons of scholars. Once an individual becomes a scholar, his unobserved human capital translates into an observed outcome, publications, with noise.

Specifically, each potential scholar is indexed by $i \in \mathbb{I}$, their family, and by $\mathbf{t} = \{t, t+1, ...\}$, their generation. A potential scholar in generation t of family i is endowed with an unobserved human capital $h_{i,t}$ (in logarithms). This is distributed according to a normal distribution with mean μ_h and standard deviation σ_h:

$$h_{i,t} \sim N(\mu_h, \sigma_h^2) \ . \tag{4}$$

The offspring of this generation, indexed $t+1$, partly inherit the unobserved human capital endowment under a first-order Markov process:

$$h_{i,t+1} = \beta h_{i,t} + u_{i,t+1} \ , \tag{5}$$

where β is the intergenerational human capital elasticity and $u_{i,t+1}$ is an i.i.d. ability shock affecting generation $t+1$, which has a normal distribution, $N(\mu_u, \sigma_u^2)$.

At each generation, only a selected group of potential scholars actually become scholars. Specifically, only those with human capital above $\tau \in \mathbb{R}$ become scholars. We account for the possibility of nepotism by allowing sons of scholars to become scholars if their human capital is above $\tau - \nu$. If $\nu \geq 0$, then the selection process into becoming a scholar is subject to nepotism. Formally, the set $\mathbb{P}$ denotes lineages

[20] In our empirical application we do not observe mothers. Under the assumption of positive assortative matching, though, the endowment inherited from father and mother is similar.

of observed scholars, i.e., families in which father and son became scholars:

$$\mathbb{P} = \{i \mid h_{i,t} > \tau, h_{i,t+1} > \tau - \nu\} \subset \mathbb{I} \ . \tag{6}$$

As in Section 2.2, human capital is transformed into an observable outcome y with measurement error. In our case, scholars use their (unobservable) human capital to produce scientific knowledge in the form of (observable) publications. We depart from the previous literature and consider two sources of measurement error: one on the intensive margin, another on the extensive margin. On the one hand, we consider idiosyncrasies in the publication process, shocks to an individual's health, luck, etc. that can affect a scholar's number of publications independently of his human capital. On the other hand, in our empirical application we need to account for the possibility that some publications might be lost or are not held in modern libraries any more. That is, that we are more likely to observe the publications of a scholar with a larger record of publications. Formally, the publications for fathers, $y_{i,t}$, and sons, $y_{i,t}$, in the set of scholar lineages $\mathbb{P}$ are:

$$y_t = h_t + \varepsilon \quad \text{if} \quad h_t + \varepsilon > \kappa, \quad y_t = 0 \text{ otherwise} \tag{7}$$

$$y_{t+1} = h_{t+1} + \epsilon \quad \text{if} \quad h_{t+1} + \epsilon > \kappa, \quad y_{t+1} = 0 \text{ otherwise} \tag{8}$$

where $\epsilon_{i,t}$, $\epsilon_{i,t+1} \sim N(0, \sigma_e^2)$ are mean-preserving shocks affecting how human capital translates into publications. Parameter κ is the minimum number of publications to observe a scholar's publications. The former captures measurement error on the intensive margin, the latter on the extensive margin.

We assume that human capital among the population of potential scholars is stationary. This assumption allows us to put some structure into how much of the distributional differences between fathers and sons can be explained by pure reversion to the mean—that is, independently of nepotism. Formally we assume that, conditional on the model's parameters being constant, the human capital of generations t and $t+1$ is drawn from the same distribution. Formally, $h_{i,t} \sim N(\mu_h, \sigma_h^2)$ and $h_{i,t+1} = \beta h_{i,t} + u_{i,t+1}$ implies $h_{i,t+1} \sim N(\beta\mu_h + \mu_u, \beta^2\sigma_h^2 + \sigma_u^2)$. Imposing stationarity leads to the following two restrictions:

$$\mu_u = (1-\beta)\mu_h \tag{9}$$

$$\sigma_u^2 = (1-\beta^2)\sigma_h^2 \ . \tag{10}$$

Using these stationarity conditions, we can re-write equation (5) as:

$$h_{i,t+1} = \beta h_{i,t} + (1-\beta)\mu_h + \omega_{i,t+1} \ , \tag{11}$$

where $\omega_{i,t+1}$ is a shock distributed according to $N(0, (1-\beta^2)\sigma_h^2)$.

Equation (11) suggests that a son inherits a fraction β of his father's human capital, draws a fraction $(1-\beta)$ from the population mean, and is subject to a mean-preserving shock ω. Hence, β determines the speed at which inherited human capital advantages revert to the mean. For low values of β, the rate of mean reversion will be large—and so will the distributional differences across generations independently of nepotism. Note, however, that this describes the mean-reversion process among *potential* scholars; the set of observed families is determined by equation (6). Hence, estimates of equation (11) need to address issues related to selection and nepotism. Estimation is further complicated by measurement error, i.e., the fact that h is only imperfectly proxied by y (see eq. (7) and (8)). Next, we describe our data and how we identify our model's parameters.

3 Institutional background and data

In this section we describe the recruitment process in universities and academies, present our data, and document two stylized facts on nepotism and the transmission of human capital across generations.

3.1 Recruitment

Although norms varied across universities and academies, the recruitment process shared some general characteristics. The recruitment of university professors typically involved the faculty and an external authority. Specifically, the faculty proposed to appoint a candidate to a chair and the authority (e.g., Monarch, Church, Municipality, Corporation) approved it. Most chairs were filled by public competition, but professors' appointments were sometimes transferred to a representative of the authorities (Rashdall 1958: vol 2, p. 192). For example, the University of Copenhagen initially appointed its professors. Following the introduction of Absolute Monarchy in 1660, these appointments had to be approved by the King. Both steps of the recruitment process were subject to nepotism. Slottved and Tamm 2009: pp. 42-43, argues that Thomas Bartholin (1616–80) used his social connections at the University of Copenhagen as well as at the court to promote his relatives' careers. On the one hand, his permanent position as Dean of the Medical Faculty gave him influence over matters of importance at the University, particularly over appointments. On the other hand, Bartholin ingratiated himself with the King's chancellor, who also served as Chancellor of the University.

In academies, new members were elected by co-option—that is, they were elected at the discretion of existing members. In general, a member (or a group of members) sponsored an external candidate. All academy members then voted whether to accept this candidate (Foster and Rücker 1897). The available election certificates of Royal Society fellows shows that fathers never sponsored their sons. This suggests that, if there was nepotism, it was the result of fathers influencing the vote of their fellows rather than directly sponsoring their sons. In some academies, the candidates had to submit a written work for evaluation (Galand 2009). As in universities, the nomination of new academy members was sometimes subject to the approval of external authorities. For example, in the French and Spanish Academies, the votes for new members had to be approved by the King.

Besides chaired professors and ordinary academy members, we find in our database a myriad of other scholarly positions. This includes university regents in France, docents in Germany, or fellows in England, and different academy memberships (e.g., corresponding member, honorary member, free member). These positions were used as a stepping stone to a university chair or an academy membership. Recruitment rules for these intermediate positions varied across institutions, but in general they involved insiders; i.e., faculty or academy members.

3.2 Data: Original sources and coverage

We build a new database of families of scholars in pre-industrial Europe. Our database contains $1,257$ fathers and $1,440$ sons who were members of the same university or scientific academy. We also observe 145 families with three or more generations of scholars. We cover 100 universities and 40 scientific academies[21] in 1088–1800. We measure scientific output using the number of publications by or about each individual that are available in libraries today. We also collect scholars' birth and death year, date of appointment, and field of study. Next, we describe the sources used and the coverage of our dataset.

Linages of scholars. To reconstruct the lineages of scholars in pre-industrial Europe, we use two sources of information. First, we use secondary sources on each university and scientific academy. These include catalogues of members, scholars' biographies and bibliographies, and books on the history of each university or academy. Second, we use biographical dictionaries and encyclopedias about universities or about the regions where universities were located. Altogether, these

[21] This includes some important language academies, e.g., the Académie Française, the Accademia della Crusca, and the Real Academia Española.

sources allow us to code fathers and sons who were members of the same university or academy. We also code multi-generation lineages, e.g., the Chicoyneau and Mögling families—who had, respectively, four and six generations of scholars at the University of Montpellier and at Tübingen (see Appendix A1).

Table 1 reports the ten institutions with more lineages of scholars. The first is the University of Bologna. Mazzetti (1847) provides a comprehensive list of professors since the University's foundation and a brief biography. This, together with the Treccani encyclopedia, allows us to reconstruct family relations among Bologna scholars. The second largest institution is the Royal Society. This academy has an online list of past members. We identify family relations from various biographical dictionaries, e.g., the Dictionary of National Biography. For other universities, there is neither a members' catalogue nor a book on the history of the institution. This is the case of the University of Avignon, which became important thanks to the Avignon papacy.[22] A sample of professors was drawn by combining various sources: Laval (1889) for the medical faculty, Fournier (1892) and Teule (1887) for lawyers, and Duhamel (1895) for rectors. To reconstruct family relations, professors are matched with the biographical dictionary of the Department of Vaucluse, France (Barjavel 1841). In our data, the University of Tübingen is the institution in the Holy Roman Empire with more scholar lineages. Conrad (1960) provides a list of all chair holders.[23] We established family links using the *Allgemeine Deutsche Biographie*. Specifically, we checked manually whether professors with similar names were related. The second largest academy in our dataset is the Leopoldina, Germany's National Academy of Sciences. It provides an online list of members which we linked to the *Allgemeine Deutsche Biographie* and other encyclopedia to establish family relations. Appendix A details the primary sources used for all the 100 universities and 40 scientific academies covered.[24]

Other information. We complement the list of scholar lineages with information on their birth, nomination, death year and field of study. We consider four fields: lawyers, physicians, theologians, and scientists. These categories correspond to the three higher faculties of early universities plus the arts faculty, where scientists gained importance over time. This information is sometimes provided by the catalogues of scholars. In many cases, however, we rely on other biographical sources. Overall, we find the birth year for 77% of the observations, the death

[22] Alice Fabre compiled Avignon's lawyers and rectors for de la Croix et al. (2020).

[23] The list was digitalized by Robert Stelter for de la Croix et al. (2020).

[24] In 33 institutions, we observe only one family. These families were mentioned in sources about other institutions. That said, these families are only 2.3 percent of our sample; their exclusion does not affect the moments used in our estimations (descriptives available upon request).

TABLE 1: Institutions with the largest number of lineages.

Institution (dates)	N	Main Sources	Bio. dictionary†
Univ. of Bologna (1088-)	171	Mazzetti (1847)	Treccani
Royal Society (1660-)	76	www.royalsociety.org/	DNB
Uni. of Avignon (1303-1793)	58	Laval (1889), Fournier (1892) Teule (1887), Duhamel (1895)	Barjavel (1841)
Uni. of Padova (1222-)	49	Facciolati (1757)	Treccani
Uni. of Copenhagen (1475-)	47	Slottved (1978)	www.geni.com
Uni. of Tübingen (1476-)	47	Conrad (1960)	ADB
Uni. of Basel (1460-)	45	Herzog (1780)	Michaud (1811)
Leopoldina (1652-)	40	www.leopoldina.org/	ADB
Uni. of Montpellier (1289-1793)	34	Dulieu (1975, 1979, 1983)	Clerc (2006)
Uni. of Leipzig (1409-)	31	Hehl (2017)	ADB

Notes: ADB: Allgemeine Deutsche Biographie; DNB: Dictionary of National Biography; Treccani: Enciclopedia italiana; N: number of lineages; †Main biographic dictionary used.

year for 88%, the nomination date for 91%, and the field of study for all scholars. Finally, we collect information at the institution level: we use Frijhoff (1996) and McClellan (1985) to record the foundation date of universities and scientific academies as well as its religious affiliation after the Protestant reformation.

Scientific output. We link each scholar to his entry in the WorldCat service—an online catalogue of the library holdings of more than 10,000 libraries worldwide. Our measure of a scholar's scientific output is the total number of library holdings of his publications. This includes all copies of books, volumes, issues, or documents he wrote that are available in WorldCat libraries today. It also includes publications about his work written by a different author. Hence, our measure captures both the size and the relevance of a scholar's scientific production today.

Chaney (2020) shows that WorldCat provides a good approximation to the population of known European authors. He compares the Universal Short Title Catalogue (USTC) of St. Andrews (2019)[25] to the references in the Virtual International Authority File (VIAF), on which WorldCat is based. Chaney successfully locates 81% of USTC authors in the VIAF. We do not find WorldCat entries for 36.7% of sons and for 29.5% of fathers. Given WorldCat's coverage, these scholars likely never published. That, said, we account for the possible loss of some publications over time. To do so, throughout the paper we separate the inten-

[25] https://ustc.ac.uk/

sive margin (i.e., publications conditional on being listed in WorldCat) from the extensive margin (i.e., whether a scholar is listed in WorldCat).

Example. To illustrate how the data was collected, Figure A3 in Appendix A1 considers Honoré Bicais and his son Michel, both professors at the University of Aix. As explained above, the University of Aix does not have a historical catalogue of professors. Honoré Bicais is recovered by de la Croix and Fabre (2019) from Belin's *Histoire de l'Ancienne Universite de Provence* (1905). This source also mentions that Michel became professor at Aix in medicine. Birth and death year comes from a biographical dictionary of people in Aix's department.[26] Again, Honoré's biography mentions his son, saying he succeeded Honoré "in his chair and in his reputation." Finally, we link Honoré and Michel Bicais to their WorldCat entries. WorldCat considers different spellings of the family name (Bicais, Bicaise, Bicays, and the latinized Bicaisius and Bicaissius), which facilitates the matching. Honoré Bicais was a prolific scholar: there are 293 library holdings on books originally published by him. In contrast, modern libraries only hold 16 library holdings of his son Michel's work. While Michel succeeded his father in his chair, it is less clear that he did so too in his academic reputation.

Coverage. Sons who worked in the same institution as their fathers represent around 4% of the known faculty between 1088 and 1800—although there is a lot of heterogeneity across time and institutions.[27]

We cover most of Europe. Figure 1 shows a map of the institutions in our dataset (green circles). In north-west and central Europe, we cover 27 universities (and 6 academies) in the Holy Roman Empire, 26 (and 16) in France, 6 (and 4) in England and Scotland, and 7 universities in the Netherlands. For southern Europe, the data mostly comes from 15 universities and 9 academies in Italy. We also cover universities in eastern (e.g., Moscow, St. Petersburg) and northern Europe (e.g., Copenhagen, Lund, Turku, Uppsala). Universities had, on average, 10 families of scholars. The map also displays birth places (orange for fathers, red for sons): most scholars originate from north-west and central Europe and from Italy.

The dataset spans 800 years from 1088—the year of the foundation of the University of Bologna—to 1800. More than half of the universities in our dataset were established before 1500, e.g., the University of Paris (officially established in 1200, but starting before), Oxford (1200), Cambridge (1209), Salamanca (1218), Prague (1348). That said, most scholars under analysis are from after the 1400s. Figure 2

[26] *Les Bouches-du-Rhône, Encyclopédie Départementale* by Masson (1931).

[27] This is based on institutions with better data coverage (i.e., at least two families) and excludes catholic priests in theology faculties, who did not have legitimate children.

FIGURE 1: Geographical distribution of scholars' lineages

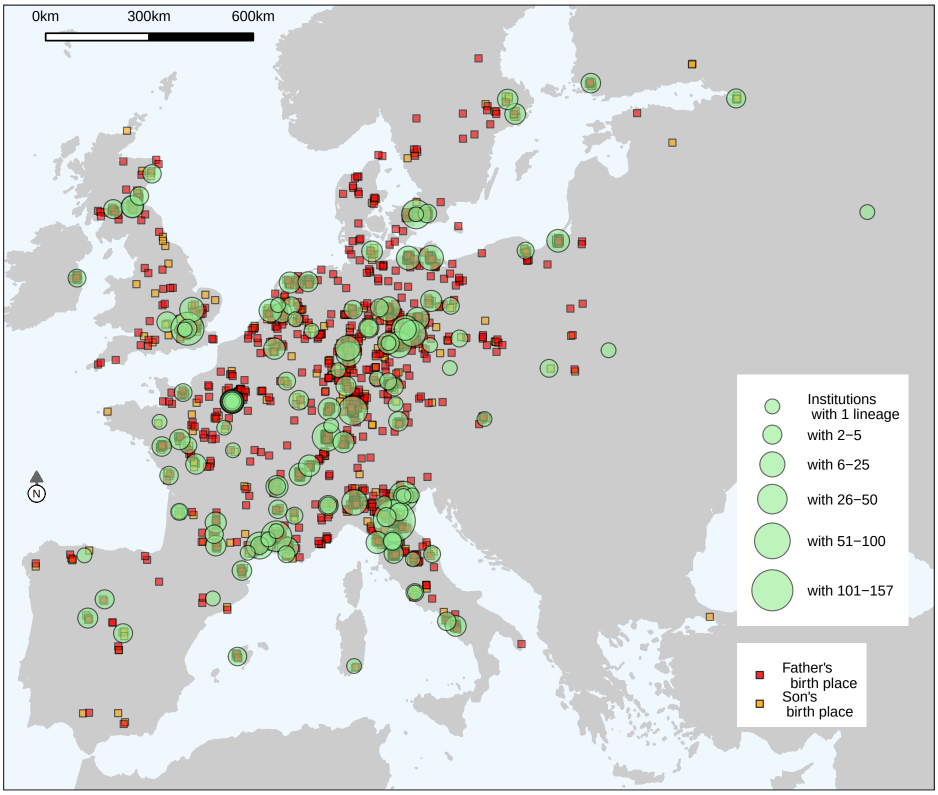
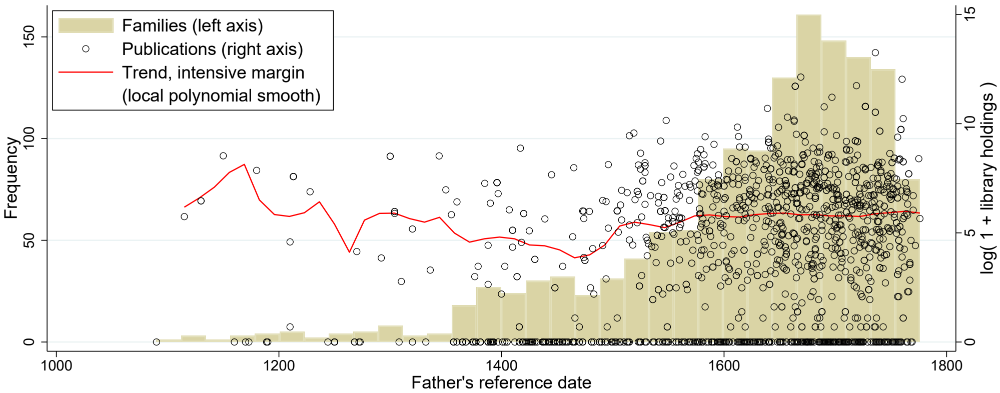


FIGURE 2: Number of scholar families and father's publications



Notes: Reference date based on birth year, nomination year, or approximative activity year.

plots the number of scholar lineages over time. Before 1400, we observe around 90 families. This number increases after 1400 and peaks during the Scientific Revolution. The Figure also plots publications over time. Specifically, we consider the logarithm of one plus the library holdings in WorldCat by and about fathers (the figure is similar for sons). Observed publications increase after the invention of the printing press around 1450. That said, there is no upward trend in publications, conditional on being positive (see appendix F for details).

3.3 Evidence on nepotism and human capital transmission

Anecdotal evidence suggests that both nepotism and the human capital transmitted from fathers to sons mattered for pre-industrial scholars' careers. For example, Jean Bauhin (1541–1613), professor in Basel, holds a remarkable publication record: there are 1,180 library holdings of his work. Michaud's *Biographie Universelle* emphasizes how Jean Bauhin's knowledge was inherited from his father, also a professor in Basel:

> Jean Bauhin (1541–1613) learned very early the ancient languages and humanities. His father, Jean Bauhin, was his first master in the study of medicine and of all the underlying sciences.

This contrasts with the case of the Benavente family at the University of Salamanca. Juan Alfonso Benavente has 96 publications available in WorldCat libraries today. According to the *Diccionario Biográfico Español*, he used his power and influence to pass down his chair to his son Diego Alfonso:

> After sixty years of teaching canon law in Salamanca, Juan Alfonso Benavente (–1478) retired in 1463. He retained his chair and his lectures were taught by substitutes, including his son Diego Alfonso Benavente (c. 1430–1512). Finally, on 1477, Benavente resigned his chair on the enforceable condition that his son was appointed to it.

Diego Alfonso Benavente proved less productive than his father. He only has one publication, a compendium of his father's work.

Table 2 documents two stylized facts for lineages of scholars in pre-industrial Europe. These facts reflect the patterns outlined by the examples above: on the one hand, sons strongly inherited underlying endowments, e.g., human capital, from their fathers, which were later reflected in their publication outcomes. On the other hand, nepotism was also present among pre-industrial scholars.

Fact 1: High elasticity of publications across generations. Table 2, Panel A presents father-son correlations in publications, measured as the logarithm of 1 + the number of library holdings. We distinguish correlations conditional on both father and son having at least one observed publication (intensive margin) from the proportion of lineages where father and son have zero publications (extensive margin). The correlation on the intensive margin is 0.35 (see Figure 3 for details). This implies that an increase of one percent in a father's publications is associated with an increase of 0.35 percent in his son's publications. This elasticity of scholar's publications is comparable to the the elasticity of wealth in pre-modern agricultural societies (Borgerhoff Mulder et al. 2009) and of educational attainment in modern

TABLE 2: Moments used in the estimation.

		value	s.e.	obs.
A. Intergenerational correlations				
Father-son, intensive margin	$\rho(y_t, y_{t+1} \mid_{y_t, y_{t+1}>0})$	0.35	0.04	795
Father-son with zero pubs.	$\Pr(y_t{=}0 \wedge y_{t+1}{=}0)$	0.22	0.01	1,440
Grandfather-grandson, intensive margin	$\rho(y_t, y_{t+2} \mid_{y_t, y_{t+2}>0})$	0.20	0.18	74
B. Father-son distributional differences				
Fathers with zero pubs.	$\Pr(y_t{=}0)$	0.29	0.01	1,257
Sons with zero pubs.	$\Pr(y_{t+1}{=}0)$	0.37	0.01	1,440
Fathers median	$Q50(y_t)$	4.43	0.16	1,257
Sons median	$Q50(y_{t+1})$	3.18	0.21	1,440
Fathers 75th percentile	$Q75(y_t)$	6.79	0.08	1,257
Sons 75th percentile	$Q75(y_{t+1})$	5.90	0.10	1,440
Fathers 95th percentile	$Q95(y_t)$	8.67	0.13	1,257
Sons 95th percentile	$Q95(y_{t+1})$	7.90	0.07	1,440
Fathers mean	$E(y_t)$	4.03	0.09	1,257
Sons mean	$E(y_{t+1})$	3.20	0.08	1,440

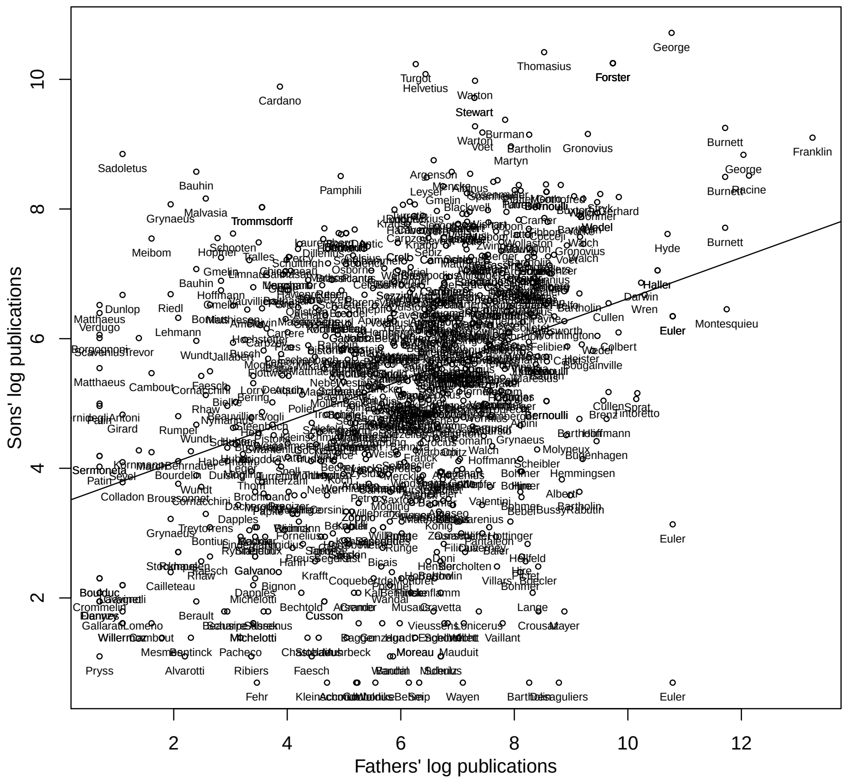
Notes: The baseline sample are families in which the father and the son are scholars; y: publications (log of 1 + library holdings by or about each author).

Sweden (Lindahl et al. 2015). As for the extensive margin, in 22 percent of families both father and son have zero publications. In sum, publication records were persistent across two generations. This suggests that endowments determining publications, e.g., human capital, were partly transmitted from parents to children.

In addition, lineages with three generations of scholars display high correlations in publications on the intensive margin. The correlation between grandfathers and grandsons is 0.20. This number is larger than predicted by the iteration of the two-generation correlation, i.e., $0.35^2 = 0.12$. In other words, underlying endowments are probably more persistent than suggested by father-son correlations.

Fact 2: The publication's distribution of fathers first order stochastically dominates (FOSD) that of sons. In Panel B, we present ten moments describing the empirical distribution of publications for fathers and sons. As before, we use the logarithm of 1 + the number of library holdings. On the bottom end of the distribution of scholars, we find that 37 percent of sons had zero publications. The corresponding percentage for fathers is 29 percent. The average father has twice as many publications as the average son (55 vs. 24, in levels). Fathers also have

Figure 3: Father-son correlation in publications



Notes: The sample are 795 father-son dyads in academia where both have at least one publication. Log-publications are log of 1 + library holdings by or about each author.

twice as many publications as their sons in the 75th and the 95th percentile of the distribution. The differences are larger at the median: there, fathers published more than three times more than sons (83 vs. 23, in levels).[28]

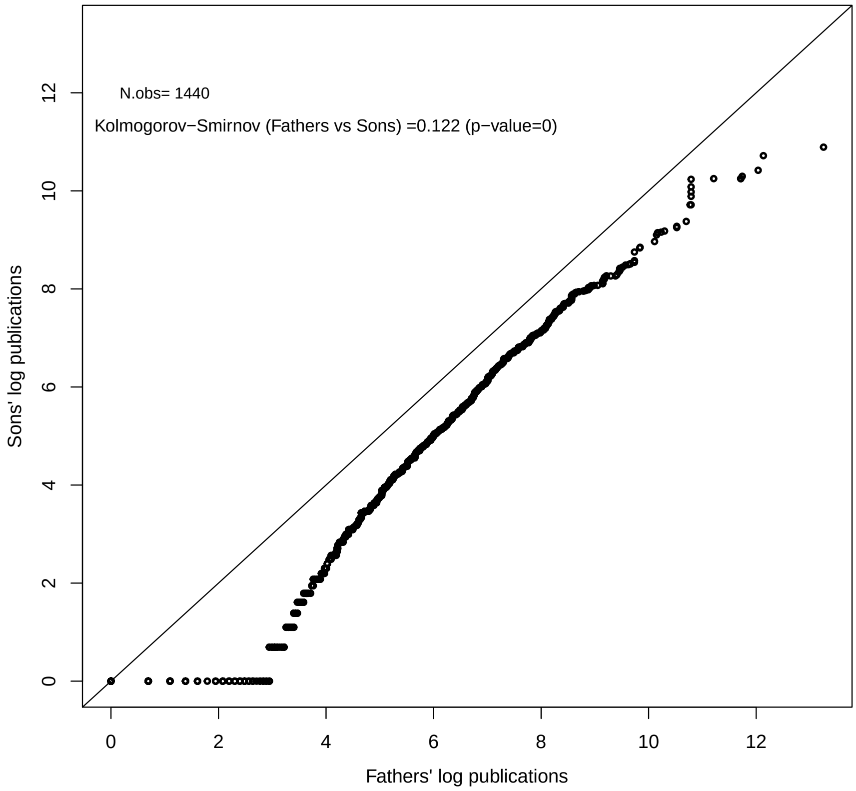
To illustrate these differences, Figure 4 presents a QQ-plot; a plot of the quantiles of the father's distribution against the quantiles of the son's distribution. If the two distributions were similar, the points would lie on the 45 degree line. Differently, we observe that in all quantiles fathers have larger publication records. That is, the father's publication distribution FOSD that of their sons.[29] In addition, the distributional differences are stronger at the bottom of the distribution.

The large distributional differences suggest that, compared to sons, fathers had higher endowments of human capital, which translated into a better publication record. Partly, the difference in human capital endowments between fathers and sons can be explained by reversion to the mean. We are looking at a sample of individuals at the top of the human capital distribution, and hence, if there is

[28]Specifically, the differences in levels are $\exp(4.03) - 1 = 55.3$ vs. $\exp(3.20) - 1 = 23.5$ in the mean and $\exp(4.43) - 1 = 82.9$ vs. $\exp(3.18) - 1 = 23.0$ in the median.

[29]A Kolmogorov-Smirnov test confirms that the distributions are different.

Figure 4: Quantile-quantile plot



Notes: The sample are 1,440 families of scholars. Publications are the log of 1 + the number of library holdings by or about each author.

reversion to the mean, sons should to some extent be worse than fathers. That said, the rate of mean reversion needed to explain away the observed distributional differences is implausibly high, especially in light of the high correlation in publications across generations (fact 1). Instead, much of these distributional differences likely reflect nepotism. That is, that fathers may have used their power and influence in the profession to allocate jobs to their sons ahead of outsiders, even when the former had low human capital endowments. For example, Figure E1 in the appendix uses data from de la Croix (2021) to compare scholar's sons to outsiders—that is, scholars whose parents were not academics. The figure shows that sons of scholars had a worse publication record not only than their fathers, but also than outsiders. Even when human capital slowly reverts to the mean, this kind of nepotism generates father-son distributional differences in observed outcomes, especially at the bottom of the distribution, i.e., closer to the selection thresholds. We can use these excess distributional differences, net of reversion to the mean, to identify nepotism.

In sum, the strong father-son correlations in observed publications (fact 1) suggest that the rate of mean-reversion in human capital is slow. In contrast, the distributional differences alone (fact 2) seem to suggest that human capital reverts to the mean rapidly. We argue that these two apparently contradictory facts can be reconciled with the existence of nepotism, which allows sons of scholars to become scholars with low human capital endowments.

4 Identification of parameters and main results

4.1 Identification

The model's main parameters are the intergenerational elasticity of human capital, β, and nepotism, ν. In addition, the parameters σ_e and κ capture the extent to which the human capital endowment translates into the observed publications, and μ_u and σ_u capture random ability shocks affecting each generation's human capital. These four parameters determine, in combination, the measurement error problem described above. Finally, μ_h and σ_h shape the human capital distribution and τ the selection into being a scholar independent of nepotism.

We estimate these parameters using a minimum distance estimation procedure. Specifically, we identify β, ν, σ_e, κ, μ_h, and σ_h by minimizing the distance between 13 simulated and empirical moments summarized in Table 2. The remaining parameters, μ_u and σ_u, are pinned down from the stationarity conditions (9) and (10). We assume $\tau = 0$ without loss of generality.

The empirical moments used in the estimation can be grouped into two categories: First, as is standard in the literature, we consider three moments capturing correlations in observed outcomes across generations. Specifically, we consider the father-son correlation in publications conditional on both having at least one observed publication (intensive margin) and the proportion of families where father and son have zero publications (extensive margin). When observed, we also consider the grandfather-grandson correlation in the intensive margin. Second, we depart from the previous literature and consider ten moments describing the empirical distribution of publications for fathers and sons. These moments are the mean, the median, the 75th and 95th percentiles, and the proportion of zeros in the distribution of publications.

Next, we describe how these moments identify the model's parameters. Father-son correlations provide biased estimates of β due to measurement error, governed by σ_e and κ, and due to selection in the form of nepotism, ν. We address both biases by comparing not only observed *outcomes* across generations, but also the corresponding *distributions*. These comparisons respond differently to measurement error and nepotism, and hence can be used to identify the model's parameters. In terms of observed *outcomes*, an increase in measurement error reduces the extent to which father-son correlations reflect β (see Section 2.2). The reason is that measurement error alters these correlations but not the underlying human capital endowments. In contrast, an increase in nepotism alters the human capital distributions for selected fathers and sons, and also the corresponding father-son correlations. Hence, these correlations may become more informative of β.

In terms of observed *distributions*, nepotism and measurement error also have different implications. Measurement error is not associated with differences in the distribution of the observed outcome y across generations. In contrast, nepotism lowers the selected sons' human capital relative to that of their fathers. This generates distributional differences across generations (beyond those generated by reversion to the mean), as suggested by Figure 4. Intuitively, the distributional differences generated by nepotism are stronger at the bottom of the distribution, i.e., closer to the selection thresholds. Our estimation strategy, hence, will put additional weight on the proportion of father's and sons with zero publications. In addition, the variance of the distributions—captured by the 75th and 95th percentiles—also helps to disentangle measurement error from nepotism: an increase in measurement error increases the variance of both distributions, while an increase in nepotism increases the variance of the sons' distribution relatively more. In theory, this allows to correct for measurement error without resorting to grandfather-grandson correlations. That said, in our empirical application measurement error is governed by two parameters, σ_e and κ. This additional moment, i.e. grandfather-grandson correlations, helps to identify σ_e and κ separately.[30]

In sum, our identification strategy exploits the fact that an increase in the degree of nepotism (measurement error):

(i) generates (does not generate) father-son distributional differences;

(ii) increases (does not increase) the variance of sons' outcomes vs. their fathers';

(iii) increases (reduces) the information that father-son correlations convey about intergenerational human capital transmission.

Hence, by comparing both outcomes and distributions across generations, we can disentangle measurement error from selection and identify our model's parameters. In Appendix C, we further illustrate our identification strategy with simulations.

[30] In other words, for datasets in which κ is not binding, the measurement error bias is governed by one parameter, σ_e. This can be identified with the variance of the observed outcome's distribution across generations, without resorting to grandfather-grandson correlations.

4.2 Minimum distance estimation

Formally, we use the following minimum distance estimation procedure:

$$\min_{p} V(p) = \sum_{j} \lambda_j \left(\frac{\hat{m}_j(p) - m_j}{\sigma_{m_j}} \right)^2 \tag{12}$$

where j indexes each of the 13 moments described above, $p' = [\beta \nu \ \sigma_e \ \kappa \ \mu_h \ \sigma_h]$ is the vector of model's parameters, m is an empirical moment, $\hat{m}(p)$ is a simulated moment, σ_{m_j} is the standard deviation of empirical moment j, and λ_j is the weight of moment j. As explained above, λ_j attaches higher weights to two moments which are most useful for identification: the proportion of fathers and sons with zero publications. We also attach additional weight to the standard moment in the literature: the father-son correlation in publications (in the intensive margin). Specifically, λ_j is arbitrarily large for these three moments, and $\lambda_j = 1$ otherwise.

The above estimation problem belongs to the family of the Simulated Method of Moments (Gourieroux, Monfort, and Renault 1993; Smith 2008), a structural estimation technique used when the theoretical moments cannot be computed explicitly and need to be simulated. To compute the vector of the simulated moments, we proceed as follows. We draw 50,000 families consisting of three generations: father, son, and grandson. Each generation's human capital and publications are calculated as described in equations (4), (5), (7), and (8). We then compute our simulated moments from a sample of families in which fathers and sons meet the criteria to become scholars, i.e., equation (6). To calculate grandfather-grandson correlations, we further restrict the simulated sample to families in which scholar's grandsons also meet the (nepotic) criteria to become scholars, i.e., $h_{t+2} > \tau - \nu$.

We then minimize the objective function $V(p)$ using the Differential Evolution algorithm (Price, Storn, and Lampinen 2006) as implemented in R by Mullen et al. (2011). To compute standard errors, we draw 200 random samples from the original data with replacement. For each bootstrap sample, we generate the 13 moments and estimate the corresponding parameters. We then use these bootstrapped estimates to compute the standard errors.

4.3 Aggregate results (1088–1800)

Table 3 presents the identified parameters for the entire period 1088 to 1800. The most important estimates are ν (nepotism) and β (intergenerational elasticity of human capital). In sum, we find that one in six scholar's sons became scholars thanks to nepotism and that human capital was inherited with an intergenerational elasticity of 0.59. Next, we discuss the identified parameters in detail.

Nepotism. We find that nepotism was non-negligible among university scholars in pre-industrial Europe. To interpret the magnitude of ν, note that the son of a scholar becomes a scholar if his human capital is above $\tau - \nu = -7.515$. This number is substantially lower than the estimated mean human capital in the population of potential scholars, $\mu_h = 2.383$, and than the human capital an outsider requires to become a scholar, $\tau = 0$. To see this, note that we estimate a standard deviation of $\sigma_h = 3.616$ for the human capital of potential scholars. This implies that the son of a scholar could become a scholar even if his human capital was 2.2 standard deviations lower than the average potential scholar, and 2.1 standard deviations lower than the marginal outsider scholar.

Alternatively, we quantify the magnitude of nepotism through two counterfactual exercises. First, we simulate our model with the estimated parameters and remove nepotism by setting $\nu = 0$. That is, we impose the same selection criteria for sons of scholars and outsiders. Our simulations suggest that, in 1088–1800, around sixteen percent of sons of scholars were nepotic scholars who would not have become scholars under the same selection criteria as outsiders. Second, we evaluate the impact of nepotism on scientific production. We identify the nepotic scholars from the previous counterfactual exercise and replace them with an average potential scholar. We find that this would increase by 19 percent the scientific output of the average scholar in the simulated economy.

Table 3: Identified parameters.

Parameter		value	s.e.
Intergenerational elasticity of human capital	β	0.594	0.043
Nepotism	ν	7.515	1.630
Std. deviation of shock to publications	σ_e	0.340	0.148
Threshold of observable publications	κ	2.144	0.152
Mean of human capital distribution	μ_h	2.383	0.402
Std. deviation of human capital distribution	σ_h	3.616	0.202

Notes: τ normalized to 0; s.e. obtained by estimating parameters on 200 bootstrapped samples with replacement; degrees of overidentification: 6

Human capital transmission. We estimate an intergenerational elasticity of human capital, β, equal to 0.59. This implies that, in lineages of scholars, sons inherited 59 percent of their father's human capital. Relative to the existing literature, this value is higher than the elasticities in wealth, earnings, or education estimated through parent-child correlations (see Table B1). This finding supports the hypothesis that the underlying endowments transmitted across generations (in this case, human capital) are more persistent than suggested by parent-child correlations in outcomes (Clark 2015).

That said, our estimate of β implies a substantially lower persistence than estimates based on comparing average outcomes across surname groups, which cluster around 0.75 (Clark 2015). In addition, our estimate is near the bottom of the range of estimates using multiple-generation correlations (Braun and Stuhler 2018) and the informational content of surnames (Güell, Rodríguez Mora, and Telmer 2015). As explained in Section 2.2, these estimates are based on methods that address the measurement error bias in parent-child correlations but that ignore selection and nepotism. In other words, the divergence in estimates for β may stem from the selection bias inherent to nepotism (see Section 2.3). Of course, it could also be that our lower elasticities are specific to our empirical application.

To evaluate these possibilities empirically, we use our data on pre-industrial scholars to calculate intergenerational elasticities using two standard methods in the literature. The results are in Table 4. First, we estimate a standard elasticity based on regressing sons' outcomes on fathers' outcomes. Specifically, we estimate b from equation (1), where outcome y is the logarithm of 1 + number of publications. The estimated coefficient is $\hat{b} = 0.478$, which implies that an increase of one percent in a father's publications is associated with an increase of 0.5 percent in his son's publications. This strong persistence of publication attainment across two generations is comparable, e.g., to the persistence of education attainment in Germany (Braun and Stuhler 2018). That said, this elasticity is lower than our model's estimate for $\beta = 0.59$. The discrepancy is more striking when we compare our β-estimate to elasticities in the intensive margin, b_I.[31] Altogether, this suggests that the measurement error and the selection bias inherent to father-son regressions leads to an attenuation bias. In other words, human capital, the endowment determining a scholar's outcomes that children inherit from their parents, is more persistent than what parent-child correlations in publications suggest.

Next, we compare our β-estimates to those obtained using the multiple generations method proposed by Braun and Stuhler (2018). They argue that – in the absence of selection – the elasticity in outcomes across n generations is $\beta^n\ \theta$, where $\theta = \sigma_h^2\ /\ (\sigma_h^2 + \sigma_\varepsilon^2)$ is the measurement error bias. Hence, the ratio between the grandfather-grandson elasticity ($n = 2$) and father-son elasticity ($n = 1$) identifies

[31] A means t-test rejects the null that our model's β is the same as the estimates $\hat{b}$ and $\hat{b}_I$.

TABLE 4: Intergenerational elasticites amongs scholars, different methods.

method		value	s.e.	N	reference
Two-generations, all	$\hat{b}$	0.478	0.021	1,440	Equation (1)
Two-gener., intensive marg.	$\hat{b}_I$	0.345	0.031	795	Equation (1)
Multiple-generations	$\hat{\beta}$	0.751	0.086	183	Braun and Stuhler (2018)
Multiple-generations	$\hat{\beta}_A$	0.679	0.080	183	Braun and Stuhler (2018)
Model's β	β	0.594	0.046	1,440	-

Notes: The sample are 1,440 scholars and their fathers. In row 2, this is restricted to 795 families in which both father and son have at least one publication. In rows 3 and 4, the sample are 183 scholars (G3), their fathers (G2), and grandfathers (G1); $\hat{\beta} = b_{G1-G3} \,/\, b_{G2-G3}$ and $\hat{\beta}_A = b_{G1-G3} \,/\, average\left(b_{G1-G2}, b_{G2-G3}\right)$, where $b_{Gi-Gj} = cov(y_{Gi}, y_{Gj}) \,/\, var(y_{Gi})$ is the elasticity of publications between generations Gi and Gj. Bootstrapped standard errors in parenthesis.

β. We use our sample of lineages with three generations to estimate this ratio. Specifically, we use 183 scholars (generation 3) with their fathers (generation 2) and one of their grandfathers (generation 1) in academia. We report estimates of $\hat{\beta}$, the ratio of the elasticity between generations 1 and 3 to the elasticity between generations 2 and 3. We also report $\hat{\beta_A}$, the ratio of the elasticity between generations 1 and 3 to the average elasticity between generations 2 and 3 and generations 1 and 2. These methods yield a β between 0.679 and 0.751, a substantially larger value than our model-based β and close to the estimates of Clark (2015). This suggests that in empirical applications where nepotism is prevalent, the multiple-generation β-estimates proposed by the literature can be upward biased.

Other parameters. We find that the distribution of human capital in the population of potential scholars has a mean of $\mu_h = 2.383$ and a standard deviation of $\sigma_h = 3.616$. Since we normalized $\tau = 0$, this implies that the average potential scholar can become a scholar, but not those with human capital one standard deviation lower than the mean—unless their fathers are scholars. Using stationarity conditions (9) and (10), we pin down $\mu_u = 0.967$ and $\sigma_u = 2.909$. That is, the mean and the standard deviation of the random ability shocks to a (potential) scholar's human capital, independent of his inherited endowments.

As for the production function of scientific output, we find an imperfect relation between human capital and publications. The shock affecting how scholar's human capital translates into publications, ϵ, has a standard deviation of $\sigma_e = 0.340$. This number is lower that the standard deviation of the human capital distribution (σ_h) and of the random ability shocks (σ_u). That said, publications are a noisy proxy for human capital. We estimate a relatively high $\kappa = 2.144$. This implies that the publication record of pre-industrial scholars who published three works ($\exp \kappa - 1$) is likely to be unobserved in our data. In other words, observing zero publications may reflect a scholar's low level of human capital or the fact that some of his publications have been lost and are not held in modern libraries.

4.4 Model fit

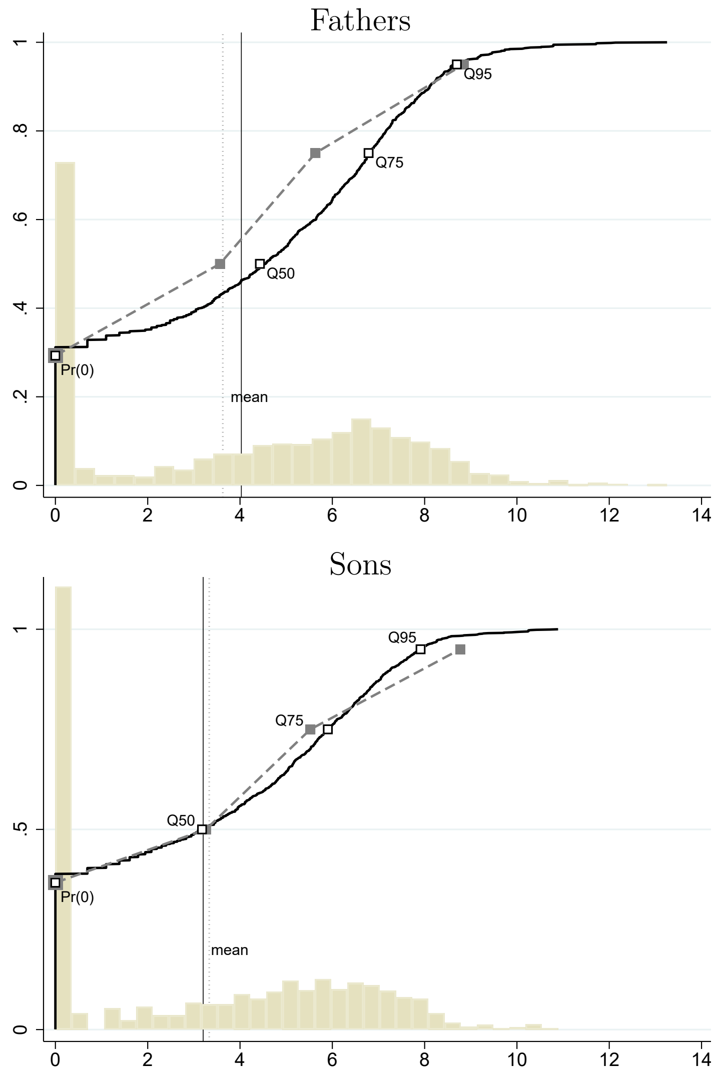
Next, we compare the empirical moments to those simulated by our model. Here we show that we match the father-son distributional differences (Fact 2). Appendix D shows that we also reproduce the high elasticity of publications across generations (Fact 1) and the empirical observation that the grandfather-grandson correlation is larger than predicted by iterating the two-generation correlation.

Figure 5 shows the distributional differences between fathers and sons. Specifically, we plot the histogram for the logarithm of 1 + number of publications, the empirical cdf, and the simulated mean, median, 75th and 95th percentile, and the proportion of zeros. We fit both distributions: we perfectly match the proportion of fathers and sons with zero publications. These are the two moments to which our objective function attaches additional weight (see eq. (12)). We also match their means, medians, 75th and 95th percentiles. For fathers, we underestimate the number of publications, especially in the 75th percentile.

Importantly, we reproduce Fact 2: The fathers' simulated distribution of publications first order stochastically dominates that of sons. We match the fact that fewer fathers have zero publications, that fathers on average published more than sons, and that the median father and the father on the 75th and 95th percentile published more than the corresponding sons. We also reproduce the empirical observation that the gap between fathers' and sons' publications is more prominent at the bottom of the distribution: our simulated moments reflect larger father-son gaps in the proportion of zero publications, the mean, and the median than in the 75th and 95th percentile. For example, the gap between fathers and sons (in levels) in the median is more than two times larger than in the 75th percentile.

Nepotism is crucial for reproducing the father-son distributional differences in publications. To show this, we estimate an alternative model ignoring the selection bias emerging from nepotism. We set $\nu = \tau = 0$, that is, we assume that sons of scholars were selected into becoming a scholar under the same criteria as outsiders. Note that, in this alternative model, the only force that can generate distributional differences is mean reversion—since scholars are at the top of the human capital

FIGURE 5: Publication's distribution, lineages of scholars



Notes: This figure displays the histogram and the cdf of fathers' and sons' publications. Data (black), simulated moments (grey), and moments (labels).

distribution, reversion to the mean will worsen the sons' publications relative to that of their fathers. This effect should be larger for top scholars' sons than for average scholars' sons. Table D1 (appendix D) presents the estimated parameters and the simulated moments. Consistent with our theoretical prediction, the model without nepotism is able to reproduce some distributional differences at the top: in the 95th percentile, sons perform slightly worse than their fathers. That said, this alternative model fails to match Fact 2, that is, that the fathers' distribution of publications first order stochastically dominates that of sons: the simulated mean, median, and the proportion of non-zero publications are not larger for fathers than for sons. In other words, the observed distributional differences are hard to reconcile with a model of mean reversion that ignores nepotism.

The alternative model estimates a substantially larger β than our baseline model. When we ignore nepotism we find an intergenerational elasticity of 0.72, close to the 0.75 estimate by Clark (2015) and to the 0.68-0.75 estimate that we obtained applying standard multi-generation estimates to our data (see Table 4). This strongly suggests that ignoring the selection bias arising from nepotism can overstate the rate at which children inherit their parents' underlying endowments.

4.5 Results over time

So far we have shown that, between 1088 and 1800, sixteen percent of scholars' sons became scholars because of nepotism, which reduced scientific output by 19 percent. These aggregate effects, however, mask interesting dynamics. Next, we evaluate whether periods of rapid scientific advancement are associated with a decline in nepotism, and hence, a better allocation of talent in academia. We narrow our focus to the two proclaimed roots of all modern technological advances: the Scientific Revolution (Wootton 2015) and the Enlightenment (Mokyr 2009).

We divide our families of scholars into four periods based on the father's reference date. We use standard dates marking the Scientific Revolution and the Enlightenment: **(i)** before 1543, when Copernicus published *De revolutionibus orbium coelestium*; **(ii)** 1543–1632, the beginning of the Scientific Revolution, which focused on recovering the ancients' knowledge; **(iii)** 1632–1687, the Scientific Revolution, from Galileo's *Dialogue Concerning the Two Chief World Systems* to Newton's 1687 *Principia*; and **(iv)** 1687–1800, the age of Enlightenment.

For the sake of illustration, Appendix Figure E2 presents QQ-plots for the father-son distribution of publications across historical periods. For all periods, the father's publication record dominates their son's. That said, distributional differences are substantially reduced in the Scientific Revolution and almost disappear in the Enlightenment. This suggests that, over time, selected sons became more similar to their fathers in terms of underlying endowments, e.g., human capital.

This was due to a decline in nepotism. Table 5 shows the results of estimating our model for each period separately. As before, we quantify nepotism through two counterfactual exercises. First, we simulate our model with the estimated parameters and remove nepotism by setting $\nu = 0$. Before 1543, almost forty percent of the sons of scholars would not have become scholars under the same selection criteria as outsiders. This percentage is dramatically reduced to 14-16 percent during the Scientific Revolution, and drops to only 3.8 percent during the Enlightenment. Second, we replace nepotic scholars for average potential scholars before the Scientific Revolution. We find that this would have increased the scientific production of the average scholar by 65 percent. Altogether, this two exercises suggest that the increase in scientific production during the Scientific Revolution and the Enlightenment goes hand in hand with a decline in nepotism in universities and scientific academies.

TABLE 5: Results over time.

	β	ν	σ_e	κ	μ_h	σ_h	% nep	N
Pre-Scientific Rev. (1088-1543)	0.42	7.86	1.73	2.70	-0.48	3.75	39.89	288
Scientific Revolution (1543-1632)	0.59	6.63	0.35	2.09	2.58	3.46	14.38	305
Scientific Revolution (1633-1687)	0.58	9.44	0.32	1.51	2.44	3.81	16.31	343
Enlightenment (1688-1800)	0.59	5.61	0.19	2.75	4.34	2.68	3.78	502
Institution established pre-1534	0.61	5.45	0.53	2.37	2.35	3.29	14.38	604
Institution established post-1534	0.54	5.69	0.25	1.69	4.33	3.06	5.89	548

The decline of nepotism could be the result of two different processes: one possibility is that *existing* universities and academies undertook structural reforms to eliminate nepotism from their hiring decisions. Another possibility is that *new* institutions were established under more modern, meritocratic principles. The evidence supports the latter. In Table 5, we compare families of scholars in institutions established before and after 1543, the start of the Scientific Revolution (see appendix Figure E3 for the QQ-plot). We only consider families of scholars after 1543 such that both groups are comparable. We find that nepotism was three times smaller in new universities and scientific academies than in institutions which had been funded before the Scientific Revolution (14.38 vs 5.89 percent).

Finally, this analysis allows us to shed new light on Clark's (2015) hypothesis that β, the rate at which children inherit endowments from their parents, is close to a universal constant over time. Our findings do not support this hypothesis. Our β-estimate ranges from 0.42 before 1543 to 0.59 in 1688–1800. Interestingly, we find an increasing trend over time. During the Scientific Revolution (1543–1632), scholars inherited human capital and other underlying endowments from their parents at a higher rate than pre-1543 scholars. Similarly, the Enlightenment (1715–1789) is characterized by a persistent transmission of underlying endowments within lineages of scholars. These findings suggest that the intergenerational transmission of human capital endowments is subject to changes in the environment. In other words, among pre-industrial scholars, β reflects nature but also nurture.

Altogether, our estimates show an inverse relationship between nepotism and

β, the rate at which scholars inherited their parents' human capital. In early academia, families of scholars emerged as a result of nepotism: scholars used their power and influence to appoint their sons, even those who had low human capital. With the Scientific Revolution and the Enlightenment nepotism lost prevalence but scholar lineages did not disappear. The reason is that sons of scholars inherited large human capital endowments from their parents, giving them a natural advantage over outsiders. In other words, lineages of scholars became more meritocratic. This suggests that the establishment of open universities and the emergence of meritocratic lineages in pre-industrial Europe was a stepping stone to the production of new ideas and to the accumulation of upper-tail human capital.

5 Validation and heterogeneity

In this section, we perform a validation test on an alternative sample where, *ex ante*, we expect no nepotism. We then explore heterogeneous effects in Protestant vs. catholic institutions, by field of study, by sons nominated before vs. after their father's death, and by universities vs. academies.

5.1 Validation using families at different universities

Our baseline sample considers fathers and sons in the same university or scientific academy. *Ex ante*, one would expect sons who also held positions at a different institution than their fathers to be more meritocratic; they should reflect a strong transmission of human capital across generations and not nepotism. The reason is that social connections may be more important for obtaining a job where one's father is employed than in a different university or scientific academy.

We exploit this to conduct a validation test. We estimate our model for an alternative sample of 410 scholars who were appointed to at least one different university or scientific academy than their fathers. Sixty-eight percent of these families are also in the baseline sample—that is, they held positions in the same and in different institutions. The remaining 32 percent are families in which fathers and sons were never in the same institution. Since we expect these lineages to be meritocratic, a large estimate for our nepotism parameter would falsify our identification strategy. It would suggest that our nepotism parameter captures other elements of the university's hiring process—e.g., information frictions affecting scholars' sons and outsiders differently. Similarly, a large nepotism estimate would suggest that broader trends outside academia—to which both our baseline and validation sample are exposed—are important for our results over time.

Table 6 provides empirical moments and estimates for this alternative sample. As expected, fathers and sons appointed to at least one different institution have a better publication record: the share of fathers and sons with zero publications is higher in the baseline sample, and the mean, median, 75th and 95th percentile are higher for fathers and sons in different institutions. Importantly, the distribution of publications of fathers no longer first-order stochastically dominates that of sons. In fact, for families in different institutions, sons outperform their fathers. Finally, the father-son correlation is lower for families in different institutions.

Nepotism was negligible when sons were appointed to a different institution than their fathers: the parameter ν is close to zero.[32] Admittedly, this estimate has large standard error. Nevertheless, it suggests that the (unobserved) human capital required to become a scholar was not statistically different for fathers and sons when they were appointed to different institutions. Consistently, our model simulations show that, for this alternative sample, only 0.1 percent of scholars' sons were scholars because of nepotism. Finally, families of scholars in different institutions transmitted their human capital endowments with an elasticity of 0.62.

Other than validating our identification strategy, this result is interesting in its own right. It shows that mobile families where fathers and sons had appointments in different institutions were not the result of nepotism. This suggests that the establishment of an academic market with hiring across universities (de la Croix et al. 2020) might have fostered modern, open universities not subject to nepotism.

5.2 Protestant reformation

Here we narrow the focus on a historical event often deemed crucial for the rise of modern science: the Protestant Reformation. Merton (1938) argued that there was a direct link between Protestantism and the Scientific Revolution; Protestant values encouraged scientific research because they showed God's influence on the world. Similarly, other authors have argued that in Catholic regimes, the Scientific Revolution was hindered by the closure and censure imposed by the Counter-Reformation (Lenski 1963; Landes 1998).[33] We shed new light on this debate by

[32]For this estimation, we restricted ν to be greater than or equal to zero.

[33]Lenski argued that, after the Reformation, Catholic leaders identified intellectual autonomy with Protestantism and heresy (p. 176): "In the centuries before the Reformation, southern Europe was a centre of learning and intellectual inquiry [...] The Protestant Reformation, however, changed the rules. It gave a big boost to literacy, spawned dissents and heresies, and promoted the scepticism and refusal of authority that is at the heart of the scientific endeavour. The Catholic countries, instead of meeting the challenge, responded by closure and censure."

Table 6: Fathers and sons at different universities.

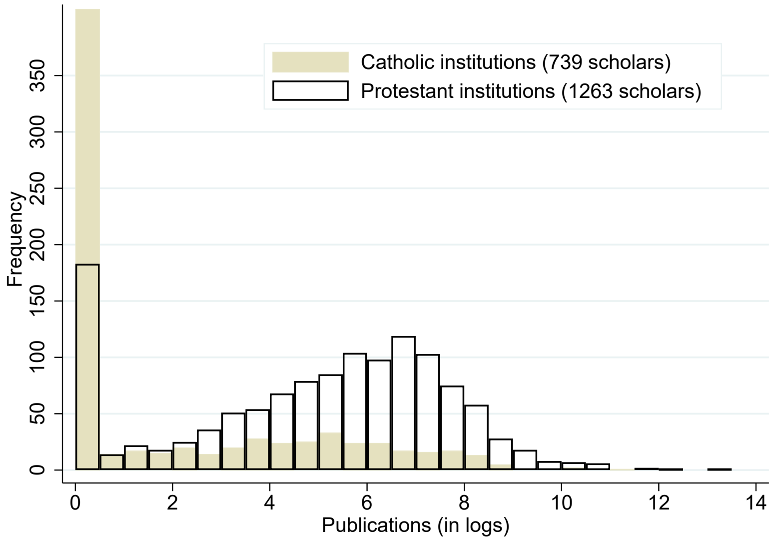
		Baseline sample		Different universities	
Parameters					
Interg. elasticity human capital	β	0.59	(0.04)	0.62	(0.14)
Nepotism	ν	7.52	(1.63)	0.05	(2.07)
S.D. shock to publications	σ_e	0.34	(0.15)	1.46	(0.47)
Threshold observable publications	κ	2.14	(0.15)	3.06	(0.62)
Mean human capital distribution	μ_h	2.38	(0.40)	5.99	(0.32)
S.D. human capital distribution	σ_h	3.62	(0.20)	2.00	(0.23)
% nepotism		15.6%		0.11%	
Data moments					
Fathers with zero publications		0.29		0.15	
Sons with zero publications		0.37		0.10	
Median, fathers		4.43		5.49	
Median, sons		3.18		6.37	
75th percentile, fathers		6.79		7.09	
75th percentile, sons		5.90		7.40	
95th percentile, fathers		8.67		8.80	
95th percentile, sons		7.90		8.98	
Mean, fathers		4.03		4.92	
Mean, sons		3.20		5.69	
Father-son correlation†		0.35		0.32	
Father-son with zero publications		0.22		0.04	
Grandfather-grandson correlation†		0.20		-0.02	
N (sons)		1,440		410	

Notes: †on the intensive margin. SE from 100 bootstrapped samples with replacement.

showing that differences in the scientific output of Protestant vs. Catholic universities are associated with differences in both nepotism and in the transmission of human capital across generations of scholars.

Figure 6 shows that scholars in our dataset (i.e., those belonging to a lineage of scholars) were more productive in Protestant than in Catholic institutions. Specifically, we sort scholars according to the religious affiliation of their university or scientific academy. We exclude all lineages before 1527—when the first Protestant university was created in Marburg. The figure shows that 55 percent of scholars in Catholic institutions had zero publications. The corresponding percentage was 14.5 in Protestant institutions. Conditional on having at least one publication, the average scholar in a Protestant institution had thrice the number of publications than the average scholar in a Catholic institution (93 vs. 295 in levels). Differences are also visible at the upper-tail of scientific production. For example, we observe a much higher frequency of Protestant scholars with more than 1,000 library holdings (more than 7 log-publications).

FIGURE 6: Publications, by institution's religious affiliation.



Notes: The sample are 2,002 scholars who (1) were nominated after 1527 and (2) belong to a scholar's lineage. Log-publications are the log of 1 + library holdings by or about each author.

The larger scientific output in Protestant institutions is associated with lower levels of nepotism. Table 7, Panel A shows the estimated parameters for Protestant and Catholic universities.[34] We find that β was almost twice as large in Catholic than in Protestant institutions. In other words, relative to Protestant institutions, Catholic institutions relied on the human capital and abilities that children inherited from their parents. That said, lineages of scholars in Catholic universities were a by-product of nepotism. We simulate our model with the estimated parameters in each subgroup and remove nepotism by setting $\nu = 0$. Our simulation exercise suggests that, in Catholic institutions, 29 percent of the sons of scholars were nepotic scholars. Nepotism was much less prevalent in Protestant universities: there, we only identify 4 percent of scholars' sons as nepotic.

The difference in nepotism between Catholics and Protestants accounts for substantial differences in scientific output. We perform a counterfactual exercise in which we replace nepotic scholars for average potential scholars. By removing nepotism, the publications of the average scholar increase by 42 percent in catholic institutions and by only 4.3 percent in Protestant institutions. This accounts for 18.7 percent of the Catholic-Protestant gap in mean publications.[35]

[34] See Figure E4 in the appendix for the corresponding QQ plot.

[35] The Protestant-Catholic gap in the son's mean log-publications is 2.9. Removing nepotism increases publications by 4.3 and 42%, leading to a counterfactual gap of 2.47 log-publications.

One important concern is that many scholars in theology were ordained priests or pastors. These scholars could marry and have sons following them in their position only in Protestant institutions. In addition, nepotism was low in theology, as appointments often required the approval of Church authorities external to the university. We rule out that Protestant institutions appear more meritocratic because of this composition effect. To do so, we exclude theology scholars from Protestant institutions (row 3).[36] Estimated parameters are robust, and the percentage of nepotic sons in Protestant institutions is unchanged (4.3 vs. 4.7).

Table 7: Heterogeneity.

	β	ν	σ_e	κ	μ_h	σ_h	% nep	N
A. University's religion (after 1527)								
Catholic	0.73	8.08	0.63	2.14	-0.99	3.97	29.48	424
Protestant	0.46	6.50	0.16	1.79	4.61	2.79	4.08	753
Protestant (excl. theology)	0.45	5.40	0.20	1.84	4.56	2.84	4.73	562
B. Field of study (of fathers)								
Lawyer	0.74	3.86	1.61	2.56	-0.72	3.87	25.37	357
Physician	0.61	7.75	0.63	2.08	1.58	3.80	19.83	423
Theologian	0.48	4.49	0.26	1.82	4.69	2.62	2.99	206
Scientist	0.58	8.08	0.33	2.00	3.89	3.35	8.38	231
Father & son in same field	0.65	7.18	0.37	2.08	1.53	3.94	19.18	1053
Father & son in diff. field	0.52	9.38	0.28	2.05	3.58	3.20	9.42	387
C. Son appointment date								
After father's death	0.55	5.93	0.50	2.10	3.23	3.19	10.48	606
Before father's death	0.65	7.09	0.37	1.73	1.95	4.03	17.38	602
D. Universities vs. Academies								
Universities	0.61	4.41	0.26	2.25	3.14	3.22	10.17	841
Academies	0.55	7.19	0.29	1.70	3.80	3.49	9.47	311

In sum, these results suggest that Catholic universities fell behind their Protestant counterparts after the Reformation, and that nepotism and inherited human capital were crucial factors behind this divergence. First, the dissemination of knowledge in Catholic universities relied heavily on the transmission of knowledge within families. As argued by Greif (2006) and de la Croix, Doepke, and Mokyr (2018), this can lead to distortions ultimately affecting the production of ideas. Second, nepotism was considerably smaller in Protestant institutions. This improved the allocation of talent in Protestant academia, and hence, contributed to the advancement of science and the accumulation of upper-tail human capital.

[36] In Catholic institutions, priests are already excluded from the sample by construction.

5.3 Results by field of study

Here, we estimate the prevalence of nepotism and the strength of human capital transmission in different fields of study. This is important as different types of upper-tail human capital may have different implications. For example, Murphy, Shleifer, and Vishny (1991) and Maloney and Valencia Caicedo (2017) emphasize the importance of engineers for modern economic development. In medieval Europe, university training in Roman law helped in establishing markets during the Commercial Revolution (Cantoni and Yuchtman 2014). During the Scientific Revolution, research and teaching in science gained importance within the faculty of arts, which also encompassed philosophy, music, and history.[37]

We consider four fields: science (arts), law (canon and Roman law), medicine (including pharmacy and surgery), and theology.[38] Table 7, Panel B presents estimates by field.[39] Specifically, lineages are sorted into fields according to the father's field of study. Nepotism was most prevalent in law faculties and among physicians. Our simulations suggest that 25.4 percent of law scholars' sons and 19.8 percent of physicians' sons became scholars thanks to nepotism. This is in line with Lentz and Laband (1989), Mocetti (2016), and Raitano and Vona (2018), who find high levels of nepotism for modern lawyers, pharmacists, and doctors. We find that 8.4 percent of scientists' sons were nepotic scholars, suggesting that applied sciences were more open to newcomers. This reinforces our previous finding that the Scientific Revolution, a period when science gained importance, was associated with a decline in nepotism. Finally, nepotism was low in theology. This reflects the fact that such appointments often required approval by Church authorities, and hence, universities had less discretion in filling such positions (see Section 3.1).

The transmission of human capital across generations ranges between 0.48 among (Protestant) theologians and 0.74 amongst lawyers. As stressed in Section 4.5, this finding does not support the hypothesis that β is a universal constant, but instead is shaped by different institutional environments.

This data also allows us to compare sons who followed their father's footsteps in the same field of study with those who published or taught in a different field. This exercise is interesting in two respects: first, one would expect families in the same field to be less meritocratic—a son's inherited social connections may be more important for obtaining a job in the same faculty as his father (science, law,

[37] Some faculties of arts, however, missed on fields such as cartography and astronomy. This led scientists like Copernicus, Kepler, or Galileo to quit their universities (Pedersen 1996).

[38] We omit other fields belonging to the faculty of arts, e.g., Hebrew, Philosophy, and Rhetoric.

[39] See Appendix Figure E5 for the corresponding QQ plot.

medicine, and theology). Second, comparing these two types of families allows us to separate the transmission of general human capital from the transmission of human capital specific to the father's field of study.[40]

Table 7 presents the results.[41] As expected, families with fathers and sons in different fields were more meritocratic: they had larger human-capital endowments (μ_h 3.58 vs. 1.53) and were less nepotic. In contrast, we estimate that 19.2 percent of scholars sons became scholars in their father's field because of nepotism; more than twice the percentage of nepotism for families in different fields.

We also find a stronger transmission of human capital between fathers and sons in the same field. For them, we estimate a β of 0.65, thirteen percentage points larger than for families in different fields. This difference can be attributed to the transmission of field-specific human capital. That said, the fact that human capital was also strongly inherited by sons who ended up working in a different field than their parents highlights the importance of general human capital.

Finally, this finding adds credence to our identification strategy. Although, in general, we find that nepotism and inherited human capital are negatively related (see Table 5 and discussion), this is not an artificial by-product of our model or of our estimation strategy. In settings where we expect both high transmission of human capital and high nepotism—such as among fathers and sons in the same field—our estimates for β and for nepotism are positively related.

5.4 Son's nomination date

Nepotism can take two forms: one the one hand, fathers may use their social connections and influence in the profession to nominate their sons—in this case, to a university chair. On the other hand, influential scholars may secure university chairs as part of their family's assets. Under this scenario, chairs may have been inherited by children upon their father's death. Next, we distinguish these two expressions of nepotism by estimating our model for two sets of lineages: lineages in which the son was nominated before vs. after his father's death.

Table 7, Panel C presents the estimated parameters for these two subgroups. Our model simulations suggest that 17.4 percent of sons nominated during their father's lifetime were nepotic scholars. That is, had they been outsiders, they would not have been nominated. Alternatively, we find nepotism in 10.5 percent

[40] In our framework, human capital is any inherited endowment affecting productivity, including the knowledge acquired from one's parents—which can be general or specific human capital.

[41] Some fathers and sons published in more than one field. We consider them to be in the same field if any of their multiple fields of study coincided.

of sons nominated after their father's death. This suggests that, in our setting, nepotism is characterized by fathers using their social connections to nominate their sons rather than by fathers passing down their chairs upon their death as part of the inheritance—although the later form of nepotism is not negligible.

Finally, note that the transmission of human capital was stronger in lineages where the son was nominated during his father's lifetime. For them, we estimate a β of 0.65, ten percentage points larger than for lineages in which the son was nominated after his father's death. This suggests that scholars nominated at an early age strongly inherited their parents' human capital endowments.

5.5 Universities vs. Academies

During the Scientific Revolution, some saw universities as an obstacle to modernity. For example, Manuel (1968) described Cambridge as "an intellectual desert, in which a solitary man [Newton] constructed a system of the world." In contrast, many scholars became members of the academies created during the Scientific Revolution, e.g., Académie des Sciences (1666), the Royal Society of London (1662), and the Academia Leopoldina (1677). These academies formalized the Republic of Letters and were a key engine of cultural change (Mokyr 2016).

Here we examine whether academies were the (only) modern, meritocratic research institutions during the Scientific Revolution. Table 7, Panel D compares families of scholars in universities vs. academies after the start of the Scientific Revolution in 1543.[42] Our estimated parameters are similar for universities and academies. With regards to nepotism, our simulations suggest that one in ten sons of university professors got a job at a university because of nepotism. The same proportion as in academies. These findings do not support the negative views about universities during the Scientific Revolution. Nepotism declined as a result of the establishment of new academies, but also in newly established universities (see Table 5), paving the way for Europe's scientific advancements after 1543.

6 Robustness

We perform several robustness checks. This section briefly describes them; the detailed results are available in the online appendix.

Stationarity. In our estimation, we assume that the human capital distribution is stationary among potential scholars. This assumption is standard in the

[42]See Figure E7 in the appendix for the corresponding QQ plot.

literature, but its importance to estimate the transmission of endowments across generations is rarely discussed (Nybom and Stuhler 2019). Appendix F presents evidence supporting this assumption in our setting. We examine trends among potential scholars using a dataset on 42,954 scholars—not only fathers and sons—collected by de la Croix (2021). The mean and the standard error of publications, our proxy for human capital, are stable over time, suggesting a stationary human capital distribution. The appendix also shows that under stationarity our nepotism estimates are conservative, lower-bound estimates. The reason is that our estimation uses father-son distributional differences to identify nepotism but does not attribute all these differences to it. We allow for distributional differences to be the result of a second force: mean reversion. That is, that top scholar's sons may be "naturally" worse than their fathers, even if no nepotism is involved. In a non-stationary environment where the human capital distribution improves over time, mean reversion would explain less of the father-son distributional differences in publications. Hence, our (already large) nepotism estimates would have to be larger to match the observed distributional differences.

Shocks from fat-tailed distributions. In our estimation, we assume that shocks affecting human capital are drawn from a normal distribution—like most of the literature. An attractive alternative to normality consists in drawing shocks from fat-tailed distributions, giving higher likelihood to the emergence of geniuses. In Appendix G we re-estimate our model under different distributional assumptions. We show that, although fat tailed distributions for human capital shocks seem *a priori* to be appealing, they do not fit the data well, which is very normally distributed after all. Our nepotism estimates are however robust to assuming fat-tailed shocks, although the estimated intergenerational persistence is not.

Linear β. We assume that β is linear, that is, that parents at the top and bottom of the human capital distribution transmit their endowments at the same rate. This assumption would be violated, for example, if successful fathers could spend less time with their children, reducing their human capital transmission systematically.[43] Appendix H shows evidence in support of our assumption. The parent-child elasticity of publications—one of the moments used to identify β—is indeed linear. Specifically, OLS elasticity estimates (akin to our targeted moments) are identical to elasticities estimated non-parametrically. The latter allow elasticities to be different across families with different publication records, and

[43] Note that this would generate father-son distributional differences in publications, especially, at the top of the distribution. Instead, we identify nepotism mainly from differences at the bottom of the distribution (Section 4). Hence, our estimates for nepotism are robust to this scenario.

hence, with different human capital endowments.

Publication threshold. To capture measurement error on the extensive margin of publications, our model considers κ, the minimum number of works to observe a scholar's publications. Admittedly, this parameter may differ across scholars. For example, the work of a famous scholar's son may capture the attention of publishers more easily—even if it is of lower quality. Appendix I examines whether this can explain away our results on nepotism. We re-estimate our model allowing the publication threshold κ to be lower for scholars' sons. Our estimates are robust.

Measure of publications. Our preferred measure of publications is the number of library holdings by or about each scholar in modern libraries. The reason is that library holdings capture both the size and the relevance of a scholar's scientific production today. In Appendix J, we show that results are robust to using unique works instead of the total library holdings. To do so, we re-estimate our model targeting moments based on this alternative measure. We find a β of 0.576 and that 15.4% of scholars' sons were nepotic, very similar to our baseline results.

7 Conclusions

From the Bernoullis to the Eulers, families of scholars have been common in academia since the foundation of the first medieval university in 1088. In this paper, we have shown that this was the result of two factors: First, scholars' sons benefited from their fathers' connections to receive nominations to academic positions in their fathers' university. Between 1088 and 1800, one in six scholars' sons were nepotic scholars. They became academics even when their underlying human capital was 2.1 standard deviations lower than that of marginal outsider scholars. Second, scholars transmitted to their sons a set of underlying endowments, i.e., human capital, that were crucial to produce scientific knowledge. Our estimates suggest a large intergenerational elasticity of such endowments, as high as 0.59.

To disentangle the importance of nepotism vs. inherited human capital endowments, we proposed a new method to characterize intergenerational persistence. Our method exploits two sets of moments: one standard in the literature—correlations in observed outcomes across multiple generations—another novel—distributional differences between adjacent generations in the same occupation. We argue that, under a standard first-order Markov process of human capital endowments' transmission, a slow rate of reversion to the mean strengthens the correlations across generations and (should) reduce the distributional differences between fathers and sons. When this distributional differences are larger than predicted by reversion to the mean, it reflects the fact that the observed parents and children are selected under different criteria, i.e., nepotism. In other words, excess parent-child distributional differences within a top occupation can be used to identify and to quantify the prevalence of nepotism.

Our results have two important implications for measuring the rate of intergenerational persistence. First, we argue that estimates that bundle the transmission of underlying endowments and nepotism together may provide biased estimates of the true rate of intergenerational persistence. The reason is that each of these two elements is associated with a different econometric bias: measurement error and selection. Our estimate for the transmission of underlying human capital endowments is higher than estimates ignoring both biases—i.e., parent-child correlations—but in the lower range of estimates ignoring selection—i.e., multi-generational correlations, group averages, or the informational content of surnames. Specifically, when we omit nepotism, we estimate large intergenerational human capital elasticities among scholars, close to the 0.7–0.8 range estimated by Clark (2015). Hence, failing to account for nepotism can overstate the true rate of persistence of underlying human capital endowments.

Second, our proposed method circumvents some of the data requirements that have limited the study of intergenerational persistence in historical contexts. By modelling selection explicitly, our method only requires the use of data from a well-defined universe, for example, a top occupation. Historical data of such occupations, e.g., scholars, artisans, artists, or government officers, is more common than the census-type evidence required by some of the alternative methods proposed by the literature (Güell, Rodríguez Mora, and Telmer 2015, Lindahl et al. 2015, Braun and Stuhler 2018, Collado, Ortuno-Ortin, and Stuhler 2018). Finally, relative to the literature examining the concentration of certain families in top occupations, our approach allows us to estimate nepotism across time and space, beyond the specific instances in which a natural experiment is available.

Finally, this paper sheds new light on the production of upper-tail human capital and its importance for pre-industrial Europe's take-off (Cantoni and Yuchtman 2014, Mokyr 2002, 2016, Squicciarini and Voigtländer 2015, de la Croix, Doepke, and Mokyr 2018). Our findings suggest that the transmission of human capital within the family and nepotism follow an inverse relationship over time. Periods of advancement in sciences, like the Scientific Revolution or the Enlightenment, were associated with lower degrees of nepotism in universities and scientific academies—especially, those adhering to Protestantism. In contrast, nepotism is prevalent in periods of stagnation and in Catholic institutions that fell behind in the production of scientific knowledge. Although nepotism only concerns fathers and sons, it is likely to reflect other forms of favouritism towards relatives, friends, and acquaintances. Hence, the high levels of nepotism might reflect broader inefficiencies and talent misallocation in early academia. Altogether, our evidence suggests that during the Scientific Revolution and the Enlightenment some of these inefficiencies were removed and that the resulting modern, open universities were crucial to Europe's scientific advancements. The extent to which these changes explain Europe's rise to riches is an intriguing question for future research.

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Nepotism vs. Intergenerational Transmission of Human Capital in Academia (1088–1800) Online appendix

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A Data appendix

This appendix lists the data sources used to construct our dataset and presents to examples: one to illustrate multiple-generation lineages of scholars (the Chicoyneau and Mögling dynasties), another to illustrate our data collection process (Honoré Bicais and his son Michel).

A1 Examples

Multi-generation lineages of scholars. Our database contains 145 families with three or more generations of scholars at the same university or scientific academy. For the sake of illustration, Figure A1 shows one of these dynasties of scholars: the Chicoyneau. The Chicoyneaus had four generations of scholars, all employed at the University of Montpellier. For almost a century (from 1659 to 1758), there was at least one Chicoyneau at the University of Montpellier. This lineage was reconstructed using Dulieu (1983). Note that some Chicoyneaus developed a prolific career. For example, François Chicoyneau (1672-1752) was a professor at Montpellier and was also appointed at the Académie des Sciences. Other members of the dynasty were appointed professor at very early ages. The last member of the dynasty, Jean-François Chicoyneau (born in 1737), was made a professor in 1752—that is, at the tender at age of 15. In principle, dynasties like the Chicoyneaus may emerge because human capital was strongly transmitted across generations, because of nepotism, or because of a combination of both.

Similarly, Figure A2 displays another multi-generation lineage of scholars: the Mögling family at the University of Tübingen (Conrad 1960). This lineage spans six generations, from the sixteenth to the eighteenth century. The first three generations were professors in medicine. After Johan David Mögling (1650-1695), however, the family switch to law (in section 5.3 of the main text, we exploit such field switches). In the first and fifth generation, the lineage members held a professorship elsewhere: Daniel Mögling (1546-1603) at Heidelberg, Johan Friedrich Mögling (1690-1766) at Giessen.

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FIGURE A1: The Chicoyneau dynasty.

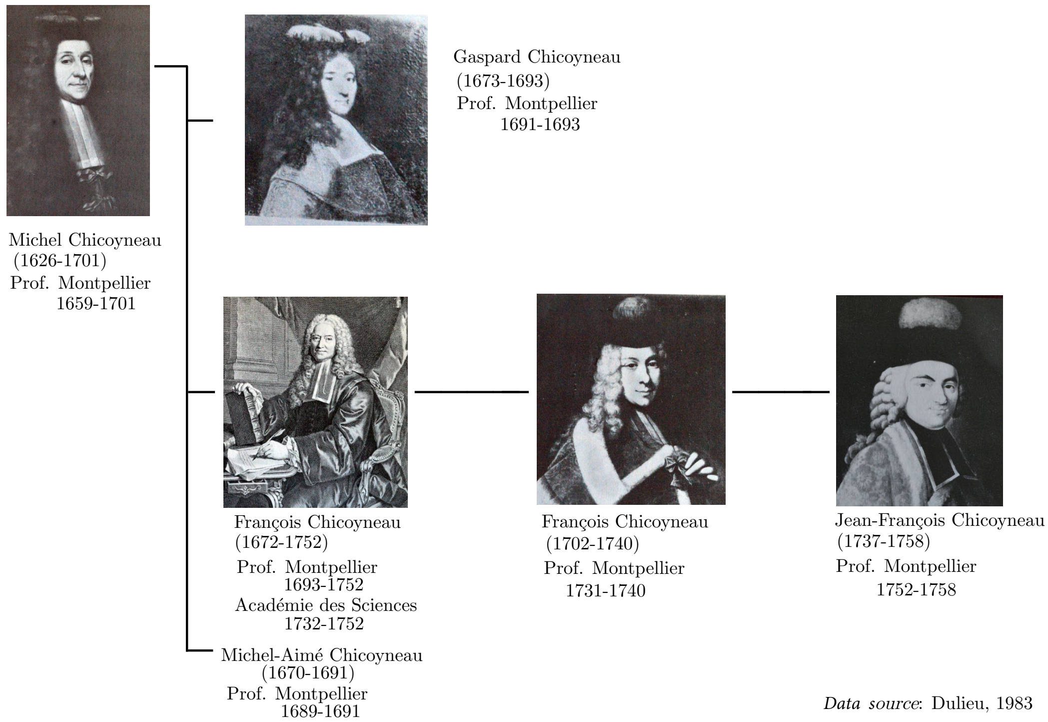
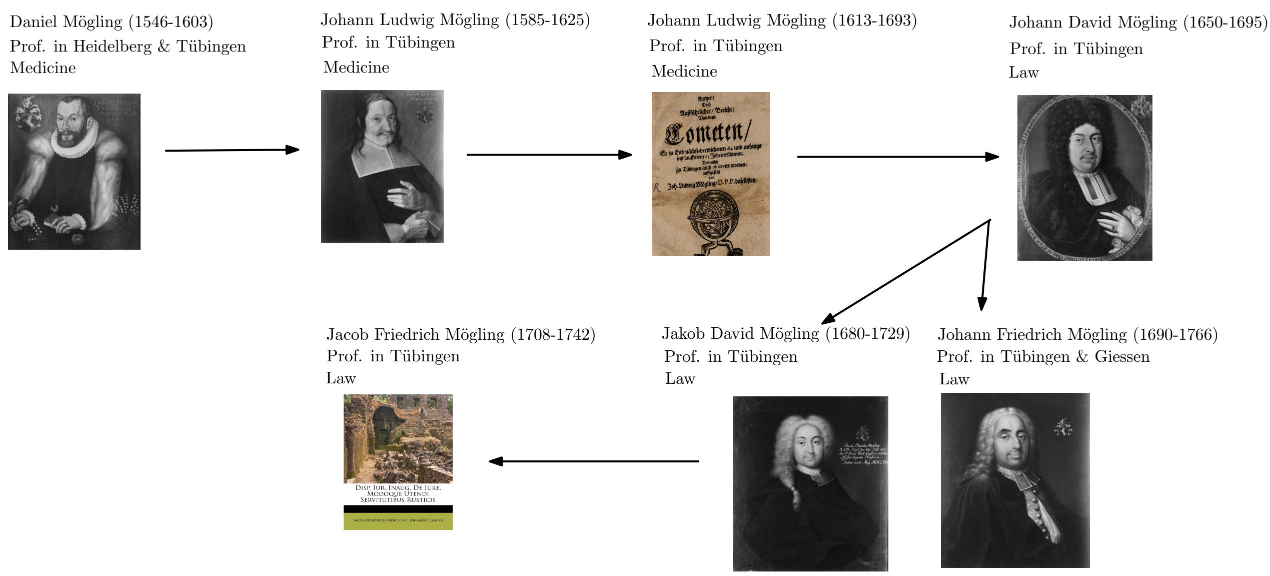


FIGURE A2: The Mögling dynasty.



In the main text, we exploit these multi-generation lineages to address measurement error in estimates for the transmission of human capital. Specifically, we use multi-generation lineages to compute correlations in observed publications across multiple generations. Elsewhere it has been shown that, under the assumption that measurement error is constant across generations, these multi-generation correlations reflect the transmission of (unobserved) underlying human-capital endowments (see section 2.2). In other words, multi-generation lineages help us tackle the measurement error bias in parent-child publication elasticities.

Data collection example - Honoré and Michel Bicais. In Section 3 on the main text, we illustrate the data collection process by using the example of Honoré Bicais and his son Michel, both professors at the University of Aix.

FIGURE A3: Example of data collection - Honoré and Michel Bicais.

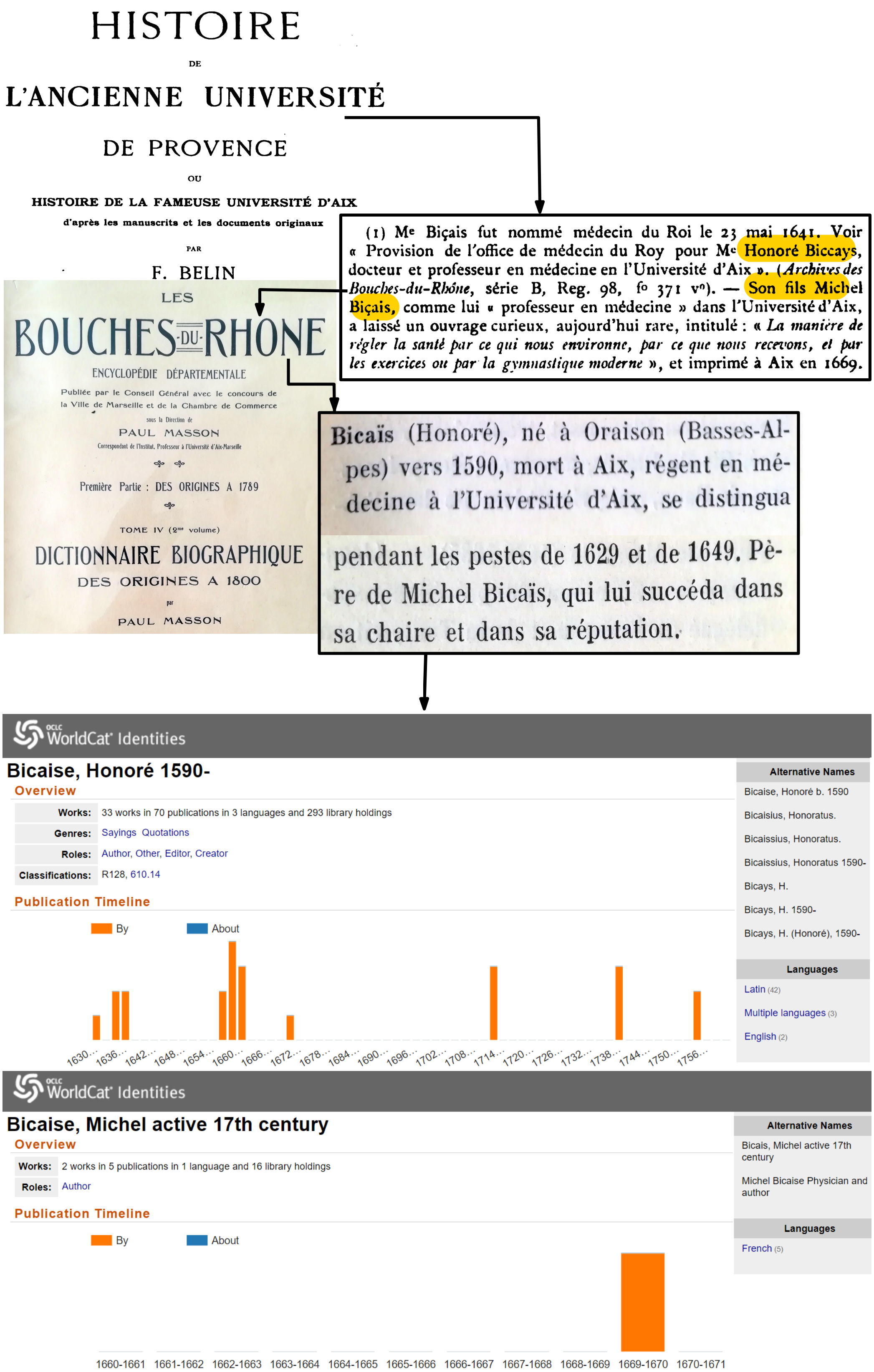


Figure A3 shows the different sources mentioned in the main text: **(a)** Honoré Bicais' biography from Belin's *Histoire de l'Ancienne Universite de Provence* (1905) — used to identify Honoré (and Michel) as professors at the University of Aix; **(b)** The biographical dictionary of Aix's Department, *Les Bouches-du-Rhône, Encyclopédie Départementale* by (Mason 1931) — used to retrieve birth years and the quote that Michel Bicais succeeded his father in "in his chair and in his reputation;" and **(c)** Honoré and Michel Bicais' WorldCat entries — used to measure their scientific output in the form of library holdings by or about them in modern libraries.

A2 Data sources

Table A1 lists the data sources used to construct our dataset on lineages of scholars. Specifically, it provides the name, location, foundation date (and, when applicable, closure date), number of scholar lineages, and the sources used for each of the 100 universities and 40 scientific academies included in our database.

Table A1: Number of families (father-son) by institution (1/6)

Institution	City	Cntry	Dates		Nb.	Sources
University of Bologna	Bologna	ITA	1088		171	Mazzetti (1847)
Royal Society of London (⋯)	London	GBR	1660		76	https://royalsociety.org/
University of Avignon	Avignon	FRA	1303	1793	58	Laval (1889), Fournier (1892), Teule (1887), Duhamel (1895), Barjavel (1841)
University of Padua	Padova	ITA	1222		49	Pesenti (1984), Casellato and Rea (2002), Facciolati (1757),Del Negro (2015)
University of Copenhagen	København	DNK	1475		47	Slottved (1978)
University of Tubingen	Tübingen	DEU	1476		47	Conrad (1960)
University of Basel	Basel	CHE	1460		45	Herzog (1780), Junius Institute (2013), Michaud (1811)
Academy of Sciences Leopoldina	Halle	DEU	1652		40	http://www.leopoldina.org/
University of Montpellier	Montpellier	FRA	1289	1793	34	Astruc (1767), Dulieu (1975, 1979, 1983), Clerc (2006)
Leipzig University	Leipzig	DEU	1409		31	Hehl (2017)
University of Jena	Jena	DEU	1558		30	Günther (1858)
Univ. of Pavia	Pavia	ITA	1361		27	Raggi (1879)
University of Marburg	Marburg	DEU	1527		25	Gundlach and Auerbach (1927)
University of Greifswald	Greifswald	DEU	1456		24	
University of Giessen	Gießen	DEU	1607		24	Haupt and Lehnert (1907)
University of Helmstedt	Helmstedt	DEU	1575	1809	22	Gleixner (2019)
University of Cambridge	Cambridge	GBR	1209		22	Walker (1927), Venn (1922)
French Academy of Sciences	Paris	FRA	1666	1793	18	http://www.academie-sciences.fr
University of Paris	Paris	FRA	1200	1793	19	Antonetti (2013), Courtenay (1999), Hazon and Bertrand (1778)
University of Rostock	Rostock	DEU	1419		19	Krüger (2019)
University of Wittenberg	Wittenberg	DEU	1502	1813	16	Kohnle and Kusche (2016)
Leiden University	Leiden	NLD	1575		16	Leiden (2019)
University of Königsberg	Kaliningrad	RUS	1544		15	Naragon (2006)
University of Strasbourg	Strasbourg	FRA	1538		14	Berger-Levrault (1890)
University of Edinburgh	Edinburgh	GBR	1582		14	Junius Institute (2013), Grant (1884)

TABLE A1: Number of families (father-son) by institution (2/6)

Institution	City	Cntry	Dates		Nb.	Sources
University of Geneva	Genève	CHE	1559		14	Junius Institute (2013), Borgeaud (1900)
Académie royale d'architecture	Paris	FRA	1671	1793	14	www.cths.fr
Académie Royale (···) de Lyon	Lyon	FRA	1700	1790	13	https://academie-sbla-lyon.fr/Academiciens/, Bréghot Du Lut and Péricaud (1839)
Collège Royal	Paris	FRA	1530		13	de France (2018)
University of Halle	Halle (Saale)	DEU	1694	1817	13	https://www.catalogus-professorum-halensis.de
University of Pisa	Pisa	ITA	1343		13	Fabroni (1791)
Academy of(···) Mainz	Erfurt	DEU	1754		12	Kiefer (2004)
University of Aix	Aix-en-Provence	FRA	1409	1793	11	Belin (1896), Belin (1905), Fleury and Dumas (1929), Masson (1931), de la Croix and Fabre (2019)
Accademia Fiorentina	Firenze	ITA	1540	1783	11	Boutier (2017)
University of Louvain	Leuven	BEL	1425	1797	8	Ram (1861), Nève (1856), Brants (1906), Lamberts and Roegiers (1990)
University of Lausanne	Lausanne	CHE	1537		1	Junius Institute (2013),Kiener and Robert (2005)
University of Franeker	Franeker	NLD	1585	1811	10	Feenstra, Ahsmann, and Veen (2003)
Royal Prussian Academy of Sciences	Berlin	DEU	1700		10	BBAW (2019)
University of Cahors	Cahors	FRA	1332	1751	10	Ferté (1975)
Royal Society of Edinburgh	Edinburgh	GBR	1783		10	RSE (2006)
Académie des inscriptions (···)	Paris	FRA	1663		10	Boutier (2018)
Collegium Carolinum	Zurich	CHE	1525		10	Junius Institute (2013), Attinger, Godet, and Türler (1928)
Royal Swedish Academy of Sciences	Stockholm	SWE	1739		9	http://www.kva.se
University of Salerno	Salerno	ITA	1231		9	Sinno (1921), De Renzi (1857)
University of Kiel	Kiel	DEU	1652		9	Volbehr and Weyl (1956)
University of Poitiers	Poitiers	FRA	1431	1793	8	Boissonade (1932)
University of Oxford	Oxford	GBR	1200		8	Emden (1959), Foster (1891)
Uppsala University	Uppsala	SWE	1477		8	Von Bahr (1945), Astro.uu.se (2011)
University of Göttingen	Göttingen	DEU	1734		8	Ebel (1962)

Table A1: Number of families (father-son) by institution (3/6)

Institution	City	Cntry	Dates		Nb.	Sources
University of Angers	Angers	FRA	1250	1793	8	Rangeard and Lemarchand (1868), de Lens (1880), Denéchère and Matz (2012), Port (1876)
University of Toulouse	Toulouse	FRA	1229	1793	8	Deloume (1890), Barbot (1905), Lamothe-Langon (1823)
Utrecht University	Utrecht	NLD	1636		7	Dorsman (2011)
Jardin Royal des Plantes Méd.	Paris	FRA	1635	1793	7	Jaussaud and Brygoo (2004)
Heidelberg University	Heidelberg	DEU	1386		7	Drüll (1991), Drüll (2002)
French Academy	Paris	FRA	1635		7	http://www.academie-francaise.fr/
University of Groningen	Groningen	NLD	1612		7	https://hoogleraren.ub.rug.nl/
Societas Privatas Taurinensis	Torino	ITA	1757	1792	7	https://www.accademiadellescienze.it/accademia/soci/
University of Salamanca	Salamanca	ESP	1218		7	Addy (1966), Rodríguez San Pedro Bezares (2004), Arteaga (1917)
Accademia dei Ricovrati	Padova	ITA	1599		6	https://www.bl.uk/catalogues/ItalianAcademies/
University of Siena	Siena	ITA	1246		6	Frova, Catoni, and Renzi (2001)
University of Perpignan	Perpignan	FRA	1350	1793	6	Carmignani (2017), Capeille (1914),Izarn (1991)
Bavarian Academy of (· · ·)	München	DEU	1759		6	https://badw.de/en/community-of-scholars/
Åbo Akademi University	Turku	FIN	1640		6	
University of Nantes	Nantes	FRA	1460	1793	6	Chenon (1890), Grünblatt (1961)
University of Pont-à-Mousson	Pont-à-Mousson	FRA	1572	1768	6	Martin (1891)
“Mersenne” Academy	Paris	FRA	1635	1648	6	de Coste (1649)
Academy of St Petersburg	Saint-Petersburg	RUS	1724	1917	5	
University of Glasgow	Glasgow	GBR	1451		6	Coutts (1909), University of Glasgow (2020)
Royal Spanish Academy	Madrid	ESP	1713		5	https://www.rae.es/la-institucion/los-academicos/
Royal College of Physicians	London	GBR	1518		4	Munk (1878)
University of Modena	Modena	ITA	1175		5	Mor and Di Pietro (1975)
Uiversity of Valladolid	Valladolid	ESP	1280		5	Alcocer Martinéz (1918)
University of Rinteln	Rinteln	DEU	1620	1809	4	Hänsel (1971)
University of Valence	Valence	FRA	1452	1793	4	Brun-Durand (1901), Nadal (1861)

TABLE A1: Number of families (father-son) by institution (4/6)

Institution	City	Cntry	Dates		Nb.	Sources
University of Lund	Lund	SWE	1666		4	Tersmeden (2015)
University of St Andrews	Saint-Andrews	GBR	1411		1	Smart (2004)
Majorcan cartographic school	Palma	ESP	1330	1500	4	http://www.cresquesproject.net
University of Aberdeen	Aberdeen	GBR	1495		4	Anderson (1893)
Académie (.) de la Rochelle	La Rochelle	FRA	1732	1744	4	https://cths.fr/an/societe.php?id=682
Accademia della Crusca	Firenze	ITA	1583		4	Parodi (1983)
Universty of Naples	Napoli	ITA	1224		4	Origlia Paolino (1754)
University of Montauban	Montauban	FRA	1598	1659	4	Bourchenin (1882)
Académie d'agriculture de France	Paris	FRA	1761	1793	4	https://cths.fr/an/societe.php?id=502
University of Altdorf	Altdorf bei Nürnberg	DEU	1578	1809	3	Flessa (1969)
Société Royale des Sciences	Montpellier	FRA	1706	1793	3	Dulieu (1983)
University of Ferrara	Ferrara	ITA	1391		3	
University of Harderwijk	Harderwijk	NLD	1647	1811	3	van Epen (1904)
University of Caen	Caen	FRA	1432	1793	3	de Pontville (1997a)
Académie des arts et belles lettres	Caen	FRA	1705	1793	3	de Pontville (1997b)
Braunschweig University (· · ·)	Braunschweig	DEU	1745		3	Albrecht (1986)
Jagiellonian University	Krakow	POL	1364		3	Pietrzyk and Marcinek (2000), http://www.archiwum.uj.edu.pl/
University of Rome	Roma	ITA	1303		3	Renazzi (1803)
Gottingen Academy of Sciences	Göttingen	DEU	1752		3	Krahnke (2001)
University of Sedan	Sedan	FRA	1599	1681	3	Bourchenin (1882)
University of Dublin	Dublin	IRL	1592		3	Kirkpatrick (1912)
University of Saumur	Saumur	FRA	1596	1685	2	Bourchenin (1882)
Académie des belles-lettres, (· · ·)	Marseille	FRA	1726	1793	2	
University of Torino	Torino	ITA	1404		2	
University of Florence	Firenze	ITA	1321	1515	2	
Viadrina European University	Frankfurt (Oder)	DEU	1506	1811	2	Junius Institute (2013)
Universite of Die	Die	FRA	1601	1684	2	Bourchenin (1882)

Table A1: Number of families (father-son) by institution (5/6)

Institution	City	Cntry	Dates		Nb.	Sources
University of Macerata	Macerata	ITA	1540		2	Serangeli (2010)
Académie des Sciences et belles lettres	Bordeaux	FRA	1712	1793	2	
Academy of Gorlitz	Gorlitz	DEU	1773		2	https://www.olgdw.de/gesellschaft/mitgliederservice/
Agriculture Society of Lyon	Lyon	FRA	1761		2	http://www.cths.fr/an/societe.php?id=2815
University of Erlangen	Erlangen	DEU	1742		2	Wachter (2009)
Danzig Research Society	Gdansk	POL	1743	1936	2	Schumann (1893)
University of Mainz	Mainz	DEU	1476	1792	1	Benzing (1986)
Academy of the Unknown	Venezia	ITA	1626	1661	1	https://www.bl.uk/catalogues/ItalianAcademies/
Athenaeum Illustre of Amsterdam	Amsterdam	NLD	1632	1877	1	http://www.albumacademicum.uva.nl/
Academy of the Burning Ones	Padova	ITA	1540	1545	1	https://www.bl.uk/catalogues/ItalianAcademies/
University of Würzburg	Würzburg	DEU	1402		1	Walter (2010)
Freiberg University ($\cdots$)	Freiberg	DEU	1765		1	
Zamojski Academy	Zamosc	POL	1594	1784	1	
Nijmegen University	Nijmegen	NLD	1655	1679	1	
Veneziana (Seconda Accademia)	Venezia	ITA	1594	1608	1	https://www.bl.uk/catalogues/ItalianAcademies/
University of Orléans	Orléans	FRA	1235	1793	1	Bimbenet (1853), Duijnstee (2010)
University of Perugia	Perugia	ITA	1308		1	
University of Nîmes	Nîmes	FRA	1539	1663	1	Bourchenin (1882)
University of Moscow	Moskow	RUS	1755		1	Andreev and Tsygankov (2010)
Academy of the Invaghiti	Mantova	ITA	1562	1738	1	https://www.bl.uk/catalogues/ItalianAcademies/
University of Rennes	Rennes	FRA	1735	1793	1	Chenon (1890)
University of Freiburg	Freiburg	DEU	1457		1	
University of Prague	Prague	CZE	1348		1	
University of Erfurt	Erfurt	DEU	1379		1	
Royal Botanic Garden	Kew	GBR	1759		1	
University of Bordeaux	Bordeaux	FRA	1441	1793	1	
Academie de Beziers	Béziers	FRA	1723	1793	1	
University of Cervera	Cervera	ESP	1714	1821	1	Rubio y Borras (1914)

TABLE A1: Number of families (father-son) by institution (6/6)

Institution	City	Cntry	Dates		Nb.	Sources
Academy of the Umorists	Roma	ITA	1603	1670	1	https://www.bl.uk/catalogues/ItalianAcademies/
University of Bourges	Bourges	FRA	1464	1793	1	
University of Orange	Orange	FRA	1365		1	
University of Ingolstadt	Ingolstadt	DEU	1459	1800	1	
Society of Observers of Man	Paris	FRA	1799	1804	1	
University of Oviedo	Oviedo	ESP	1574		1	Canella Secades (1873)
Royal Danish Science Society	Copenhagen	DNK	1742		1	
French Academy of Medecine	Paris	FRA	1731	1793	1	
University of Duisburg	Duisbrug	DEU	1654		1	
University of Vienna	Vienna	AUT	1465		1	
University of Cagliari	Cagliari	ITA	1606		1	Tola (1837), Pillosu (2017)

Notes: Missing sources correspond to families which were mentioned in sources about other institutions.

B Intergenerational estimates in the literature

This appendix presents estimates for measuring intergenerational persistence in the literature. For a more thorough review, see Solon (1999), Corak (2006), and Black and Devereux (2011).

Specifically, Panel A of Table B1 presents parent-child elasticities, b, estimated from:

$$y_{i,t+1} = b\ y_{i,t} + e_{i,t+1}\ ,$$

where i indexes families, t parents, and $t+1$ children. The outcome y reflects social status (e.g., income, wealth, education, occupation) and is in logarithms.

Panel B of Table B1 reports estimates of β, the extent to which children inherit an unobserved human capital endowment h from their parents (e.g., knowledge, skills, genes, preferences) which then transforms into the observed outcome y imperfectly. One way to model this is as a first-order Markov process (Clark and Cummins 2015; Braun and Stuhler 2018):

$$\begin{aligned} h_{i,t+1} &= \beta h_{i,t} + u_{i,t+1}\ , \\ y_{i,t+1} &= h_{i,t+1} + \varepsilon_{i,t+1}\ , \end{aligned}$$

where $h_{i,t} \sim N(\mu_h, \sigma_h^2)$ and $u_{i,t+1}$ and $\varepsilon_{i,t+1}$ are independent noise terms.

The β-estimates reported in Panel B of Table B1 are obtained through different methods: First, by exploiting correlations in y across multiple generations—specifically, the ratio of the granparent-grandchild elasticity to the parent-child elasticity (see, for example, Lindahl et al. 2015, Braun and Stuhler 2018, and Colagrossi, d'Hombres, and Schnepf 2019).

Second, by estimating intergenerational regressions such as:

$$\hat{y}_{j,t+1} = b\ \hat{y}_{j,t} + \hat{e}_{j,t+1}\ ,$$

with group-average data (j) for siblings (Braun and Stuhler 2018) or for people sharing rare surnames (Clark and Cummins 2015).

Third, through the informational content of rare surnames (ICS)—a moment capturing how much individual surnames explain the total variance of individual outcomes (see Güell, Rodríguez Mora, and Telmer 2015).

Fourth, by using horizontal kinship correlations—e.g., first-, second-cousins, etc.—in cross-sectional data (Collado, Ortuno-Ortin, and Stuhler 2018). All these methods are explained in detail in Section 2.2 of the main text.

Table B1: Persistence of social status in the literature.

Panel A: Estimates of b		
$\hat{b}$	y_t	Country & Source
0.31–0.41	Wealth	Agricultural societies (Borgerhoff Mulder et al. 2009)
0.48–0.59	Wealth	UK (Harbury and Hitchins 1979)
0.225	Wealth	Norway (adoptees) (Fagereng, Mogstad, and Ronning)
0.6	Earnings	USA (Mazumder 2005)
0.34	Earnings	USA (rank-rank correlations) (Chetty et al. 2014)†
0.47	Earnings	USA (Corak 2006)
0.19–0.26	Earnings	Sweden (Jantti et al. 2006)
0.11–0.16	Earnings	Norway (Jantti et al. 2006)
0.46	Education	USA (Hertz et al. 2007)
0.71	Education	UK (Hertz et al. 2007)
0.35	Education	Sweden (Lindahl et al. 2015)
0.35	Body Mass	USA (Classen 2010)
Panel B: Estimates of β		
$\hat{\beta}$	y_t	Data & Source
0.70–0.75	Wealth	UK probate (1858–2012) (Clark and Cummins 2015)
0.70–0.90	Oxbridge	UK (1170–2012) (Clark and Cummins 2014)
0.61–0.65	Occupation	Germany, 3 gen. (Braun and Stuhler 2018)
0.49–0.70	Education	Germany, 4 gen. (Braun and Stuhler 2018)
0.6	Education	Spain, census (Güell, Rodríguez Mora, and Telmer 2015)
0.61	Schooling	Sweden, 4 gen. (Lindahl et al. 2015)
0.49	Earnings	Sweden, 4 gen. (Lindahl et al. 2015)
0.74	Education	EU-28, 3 gen. (Colagrossi, d'Hombres, and Schnepf 2019)
0.8	Education	Spain, census (Collado, Ortuno-Ortin, and Stuhler 2018)

C Identification example

Figure C1 illustrates our identification strategy by simulating our model. We show the simulated distributions of the underlying (human capital) and the observed outcome (publications), father-son correlations in publications and the corresponding QQ plot.

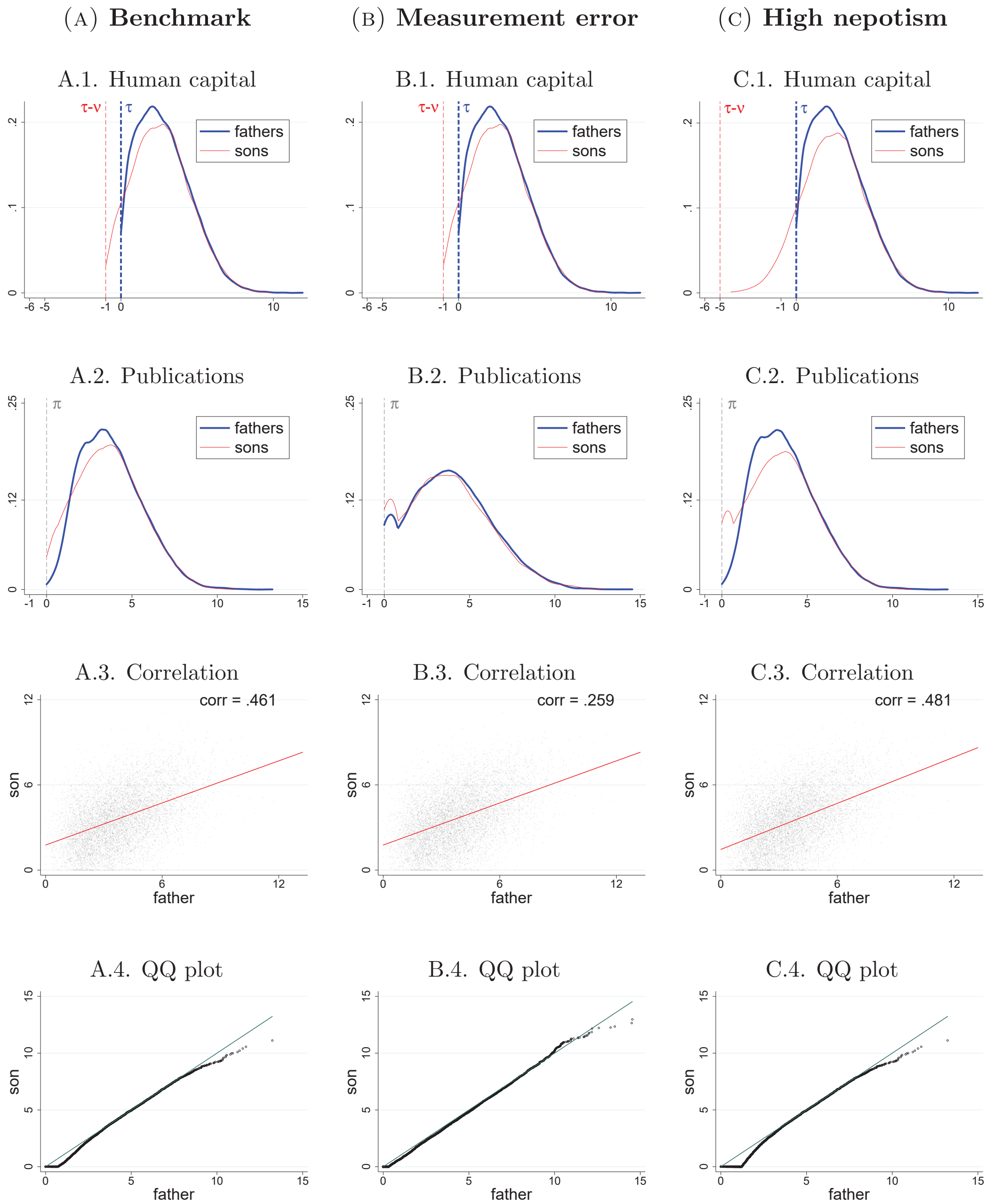
Column A presents a benchmark simulation for 10,000 potential scholars with $\beta = 0.6$, $\nu = -1$, $\tau = 0$, $\mu_e = 1$, $\pi = 0$, $\mu_h = 2$, $\sigma_h^2 = 5$, and $\sigma_e^2 = 0.25$. In Column B, we increase σ_e^2 to 3. That is, we generate measurement error by reducing the extent to which human capital translates into publications. The distribution of h is not altered with respect to the benchmark case, but that of y is: both fathers and sons present a larger mass of zero publications and a larger variance. Since y is similarly affected for fathers and sons, the QQ plot does not reflect distributional differences across generations. However, the increase in measurement error attenuates the father-son correlation in y, which drops from 0.46 to 0.26 with respect to the benchmark case.

Next, Column C increases nepotism with respect to the benchmark case by setting $\nu = -5$. In contrast to the previous exercise, this affects the distribution of both h and y, as sons with low levels of human capital now can become a scholar.[1] This generates distributional differences in observed publications between fathers and sons, reflected in the QQ plot. Most evidently, the mass of sons with zero publications and the variance of sons' publications is now larger than their fathers'. Since nepotism alters both the human capital's and the observed outcome's distribution, father-son correlations become more informative of β than in the benchmark case: the correlation increases from 0.46 to 0.48.

In sum, measurement error and nepotism have different implications for father-son correlations, distributional differences (especially, at the bottom of the distribution), and relative variances of the observed outcome.

[1] The father's h distribution is also affected, albeit to a lesser degree. The reason is that marginal fathers, i.e., fathers with an h just above the threshold τ, are now more likely to be in the set of selected families. Before, these fathers were mostly excluded, as their sons were likely to have low realizations of h, falling below the (nepotic) threshold to become a scholar. Similarly, this may decrease the variance of fathers' publications.

Figure C1: Identification example based on model simulations



Notes: The benchmark simulation is for 10,000 potential scholars with $\beta = 0.6$, $\nu = -1$, $\tau = 0$, $\mu_e = 1$, $\pi = 0$, $\mu_h = 2$, $\sigma_h = 5$, and $\sigma_e = 0.25$. Column B increases σ_e to 3, Column C increases nepotism by setting $\nu = -5$.

D Model fit

This appendix first presents the estimated parameters and the simulated moments for our baseline estimation and for an alternative model ignoring the selection bias emerging from nepotism. Second, we show that our baseline model reproduces the high elasticity of publications across generations (Fact 1) and the empirical fact that the grandfather-grandson correlation is larger than predicted by iterating the two-generation correlation.

Table D1 presents the estimated parameters and the simulated moments for two models: our baseline model (col. 2) and an alternative model ignoring the selection bias emerging from nepotism, that is, setting $\nu = \tau = 0$ (col. 1). As explained in Section 4.4, the baseline model fits father-son distributional differences (Fact 2). In contrast, the alternative model—where mean reversion is the only force generating distributional differences—fails to match Fact 2. In addition, it yields large β-estimates—close to Clark's estimates (Clark 2015) and to what we obtained applying standard multi-generation techniques to our data (Table 4).

Table D1: Simulated and empirical moments for different models.

	Model w/o nepotism	Baseline model	Data
Parameters:			
β	0.72	0.59	.
ν	0	7.52	.
τ	0	0	.
σ_e	1.12	0.34	.
κ	3.70	2.14	.
μ_h	4.47	2.38	.
σ_h	2.00	3.62	.
Moments:			
Fathers with zero pubs.	0.35	0.29	0.29
Sons with zero pubs.	0.36	0.37	0.37
Median, fathers	4.52	3.57	4.43
Median, sons	4.52	3.26	3.18
75th percentile, fathers	6.06	5.64	6.79
75th percentile, sons	6.05	5.53	5.90
95th percentile, fathers	8.23	8.85	8.67
95th percentile, sons	8.19	8.77	7.90
Mean, fathers	3.77	3.63	4.03
Mean, sons	3.76	3.33	3.20
Father-son correlation†	0.35	0.35	0.35
Father-son with zero pubs.	0.20	0.17	0.22
Grandfather-grandson correlation†	0.23	0.17	0.20

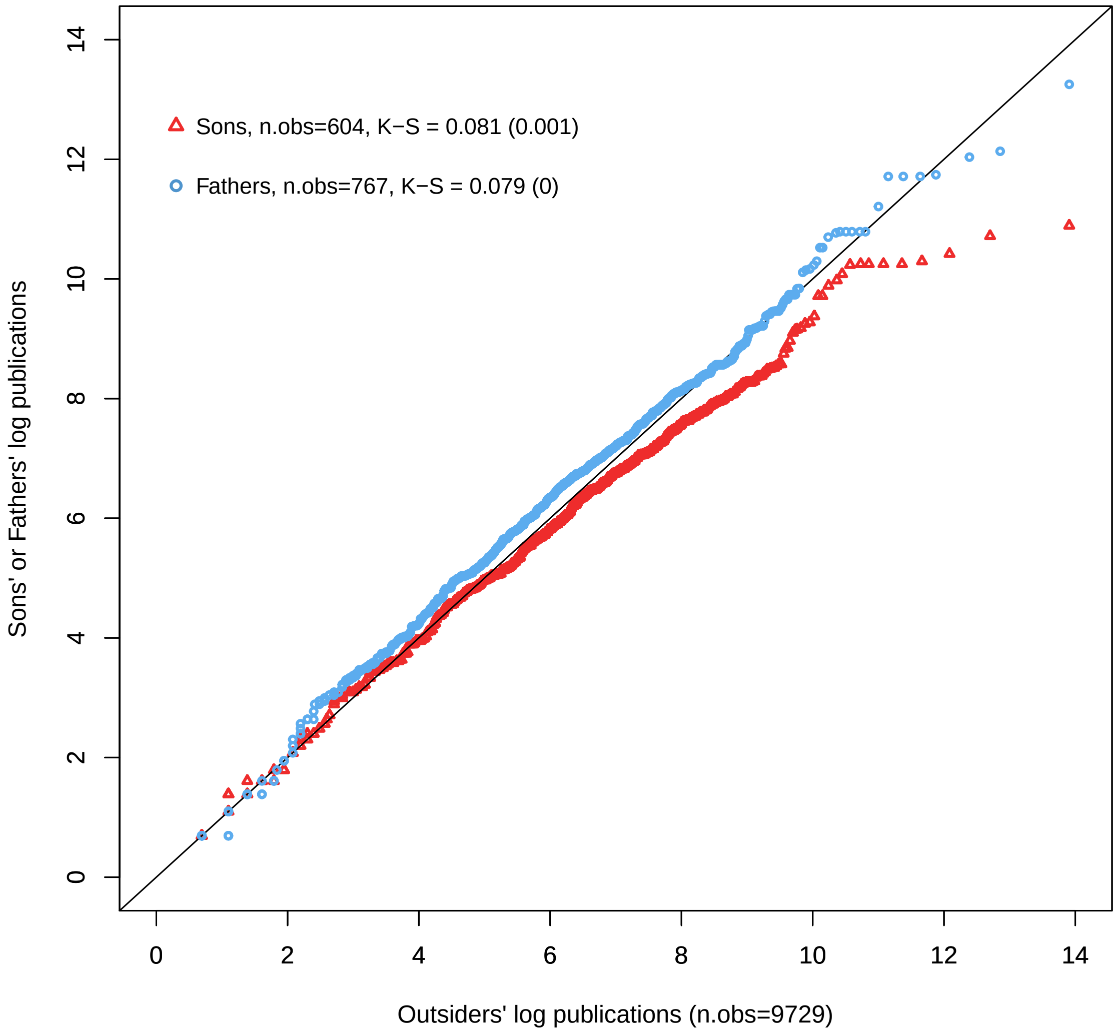
Notes: †correlation on the intensive margin.

Next, we compare the simulated and empirical moments regarding correlations across generations (see bottom rows of Table D1). We reproduce the high elasticity of publications across generations (Fact 1). Our model with nepotism matches the father-son correlation on the intensive margin of publications—that is, conditional on both father and son having at least one observed publication. This is the correlation to which our objective function attaches additional weight. Interestingly, this correlation is below the estimate of β. This implies that father-son correlations in outcomes under-predicts the extent to which children inherit human capital endowments from their parents. Our model with nepotism under-predicts the proportion of families where father and son have zero publications (extensive margin) and the correlation between grandfathers and grandsons in the intensive margin. That said, we match the empirical fact that the grandfather-grandson correlation is larger than predicted by iterating the two-generation correlation. Specifically, our simulated grandfather-grandson correlation is 0.17. In contrast, iterating the simulated two-generation correlation yields $0.35^2 = 0.12$.

E QQ plots

E1 Additional descriptives

Figure E1: Quantile-quantile plot of Fathers, Sons, and Outsiders



Notes: The sample of outsiders are 9,243 scholars whose parents were not academics (source de la Croix 2021). To make the Fathers', Sons', and Outsiders' sample comparable, we restrict them to individuals with a wikipedia and a Woldcat page.

E2 QQ plots for main results

Figure E2: Quantile-quantile plot by historical period

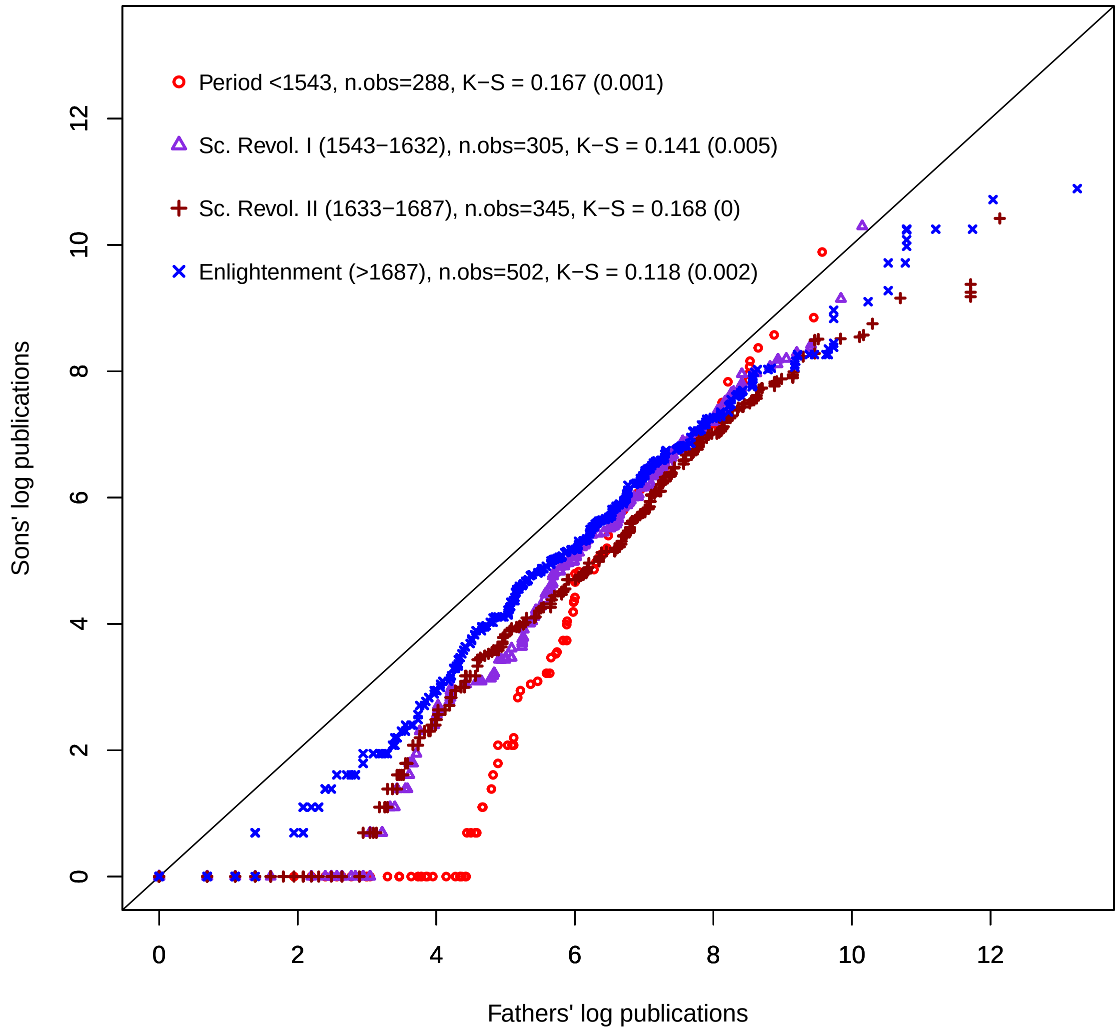
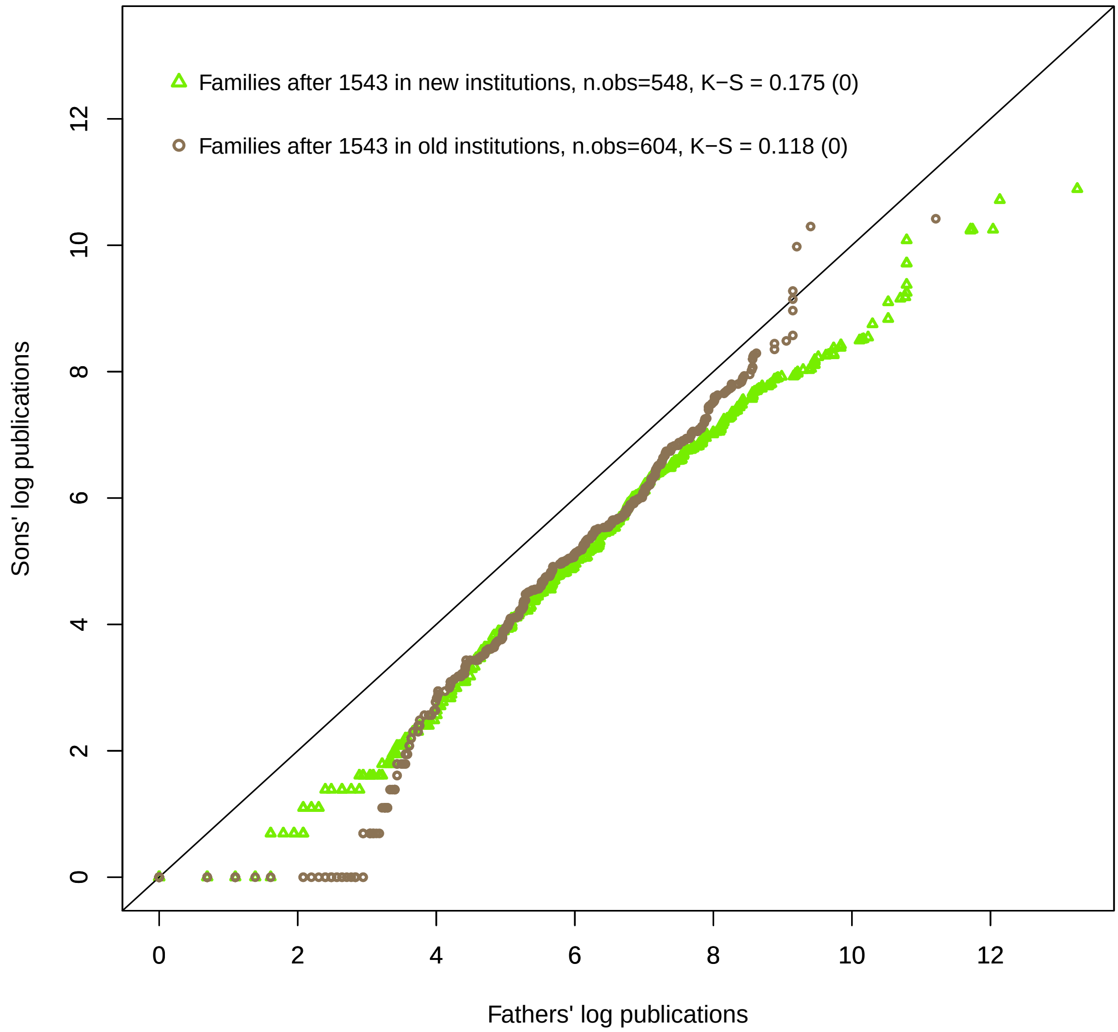


Figure E3: Quantile-quantile plot by age of institution



E3 QQ plots for heterogeneity in nepotism

Figure E4: Quantile-quantile plot by religious affiliation

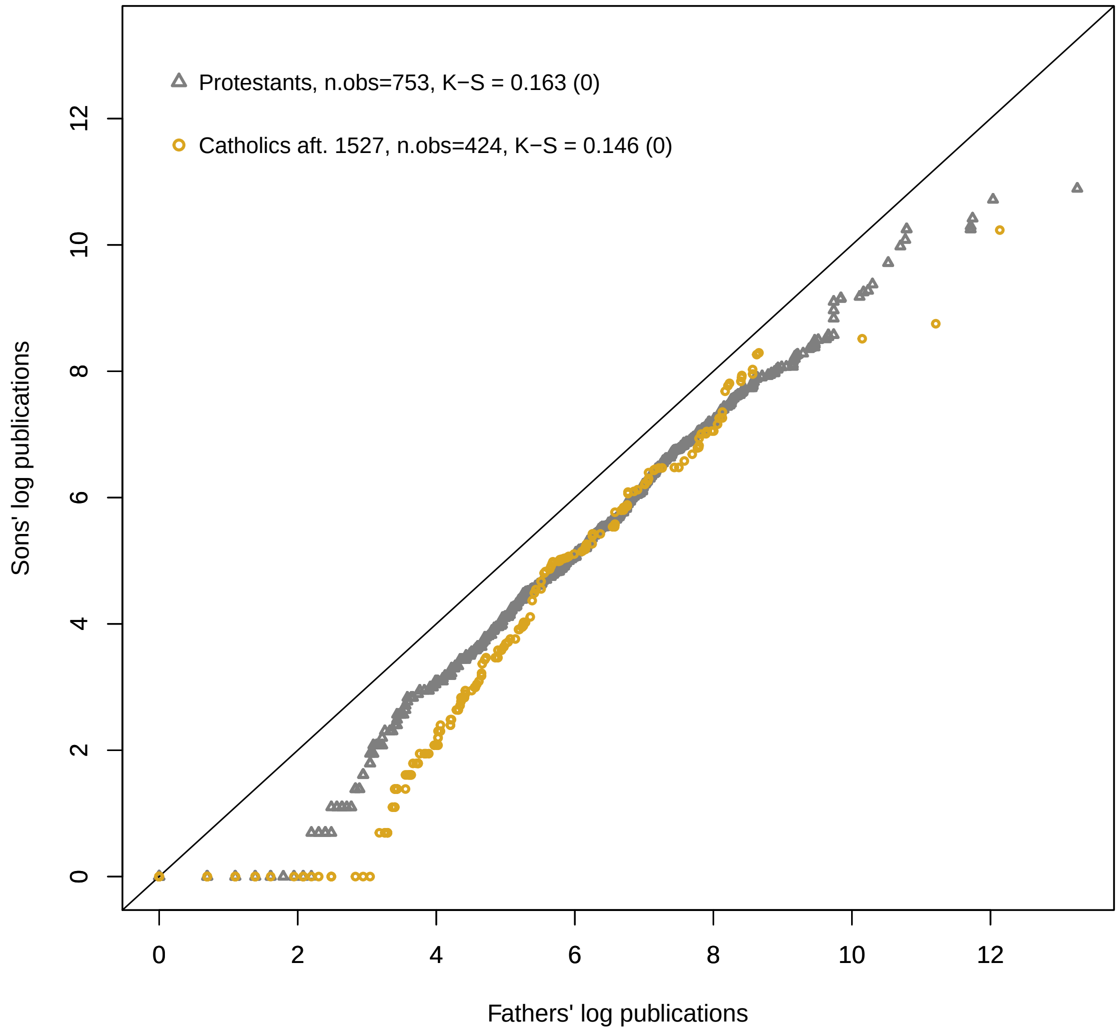


Figure E5: Quantile-quantile plot by field of study

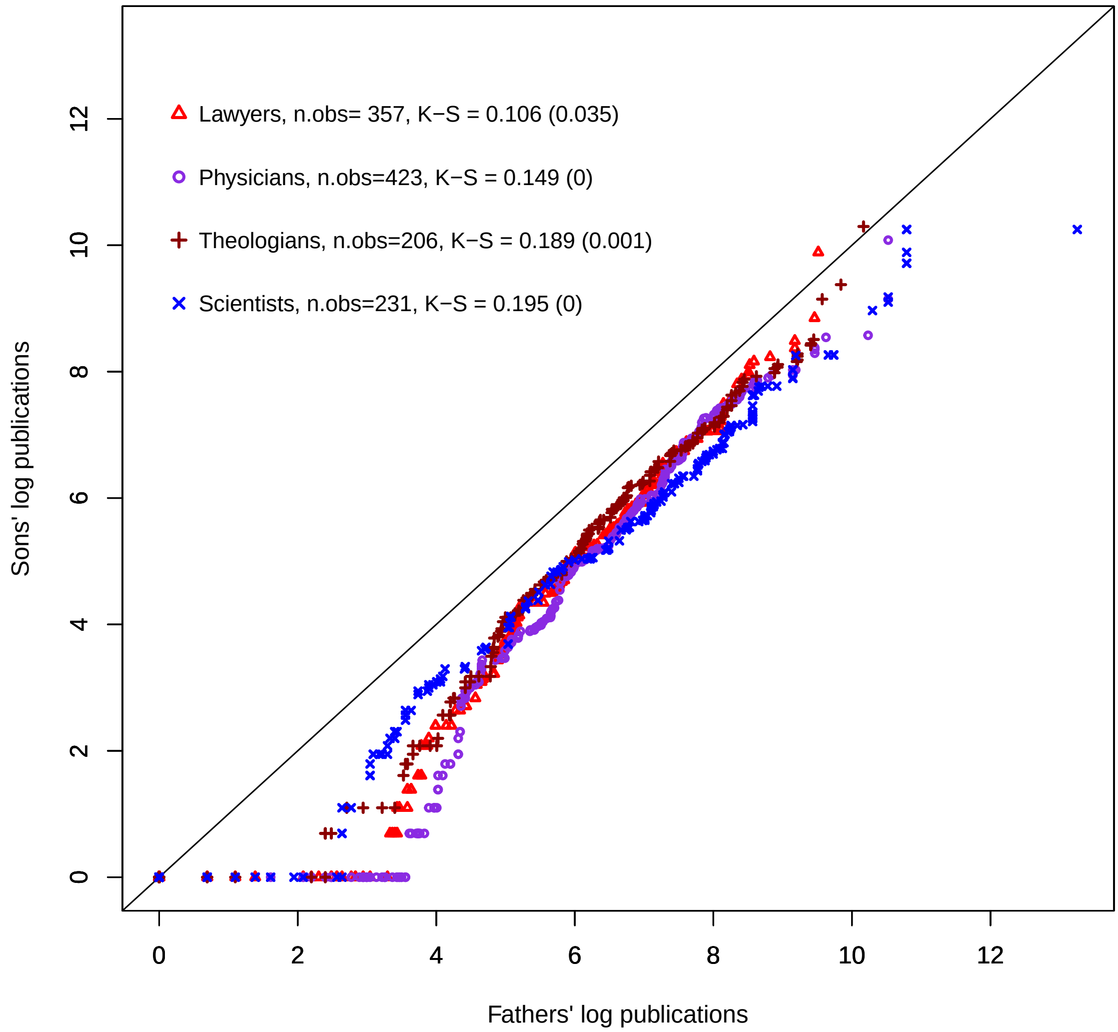


FIGURE E6: Quantile-quantile plot by nomination bef./after father's death

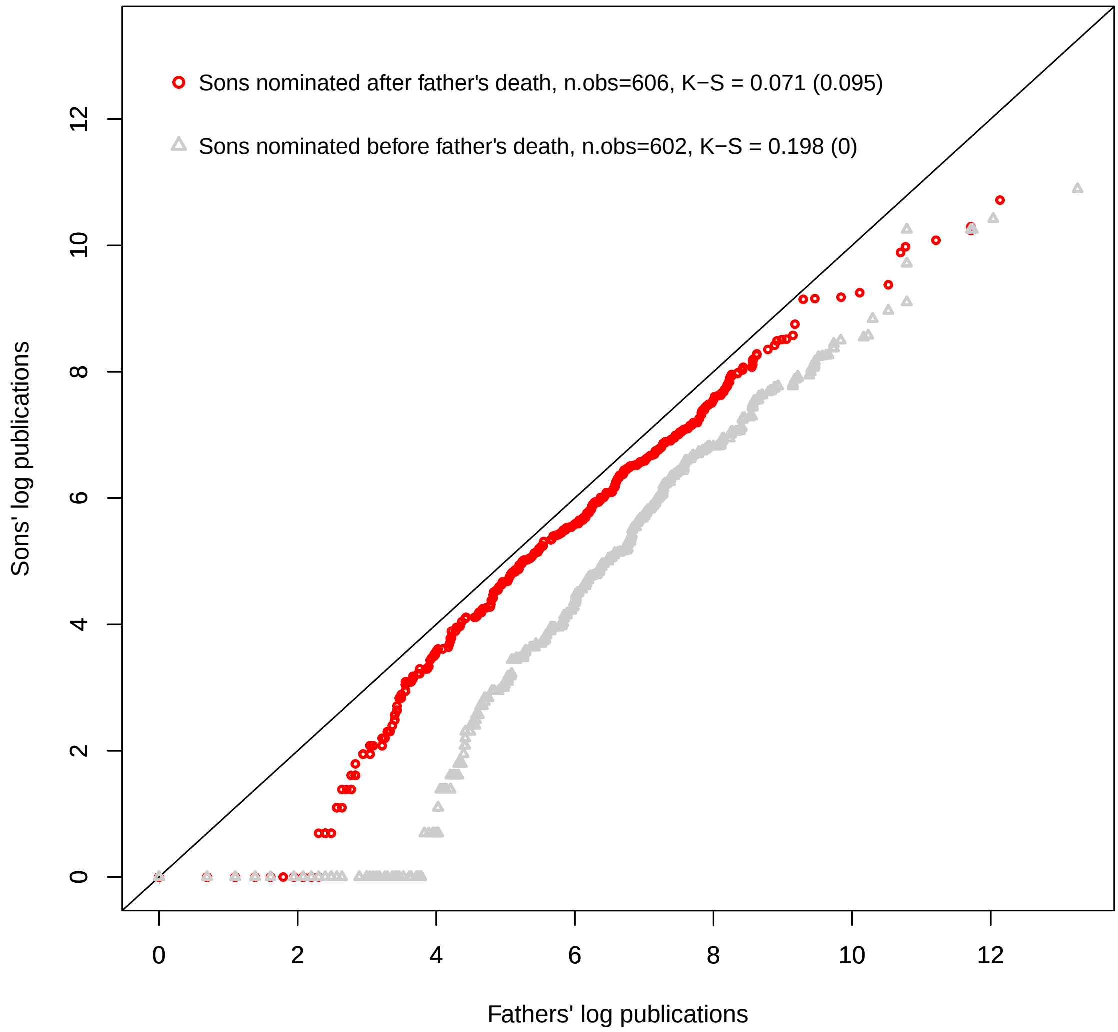
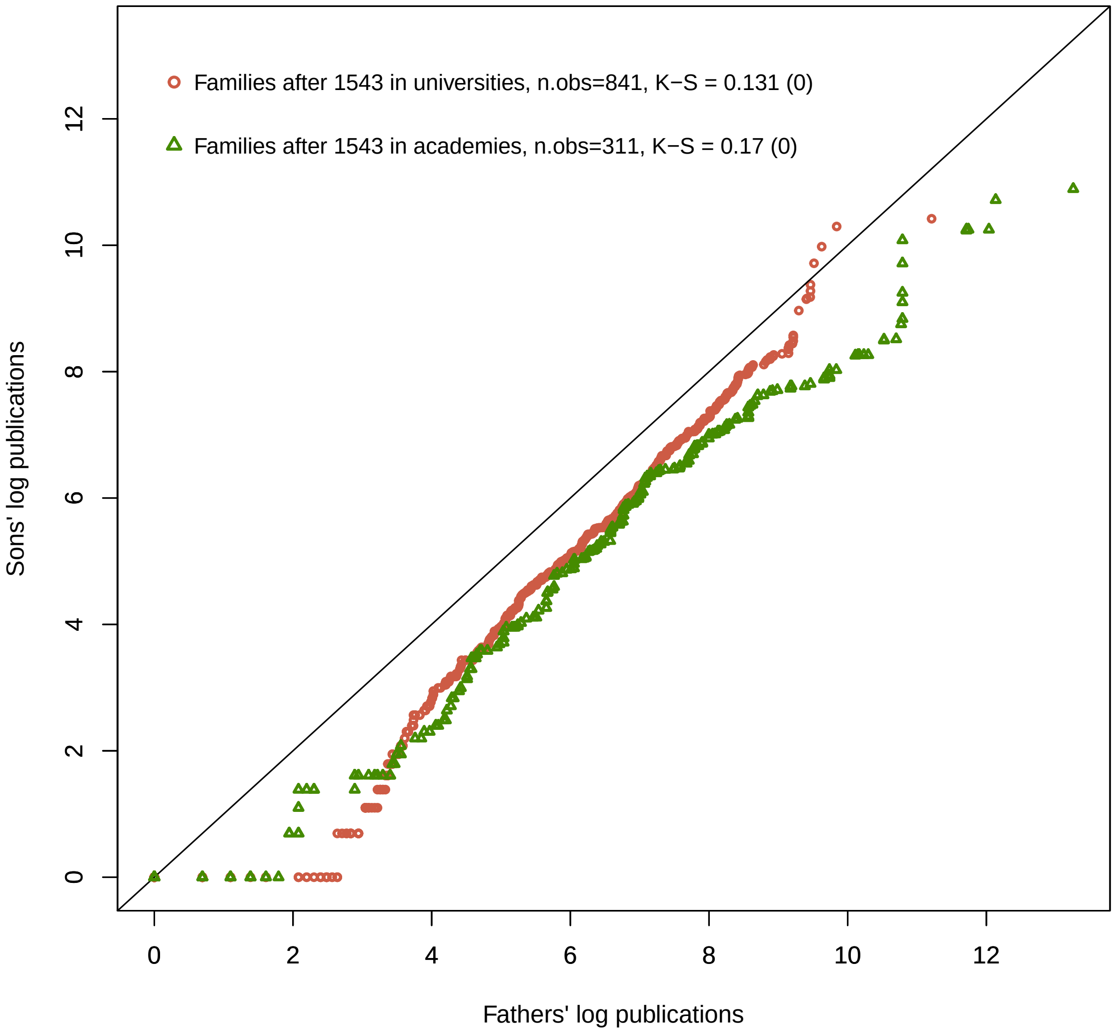


FIGURE E7: Quantile-quantile plot by type of institutions



F Stationarity and time trends in publications

To estimate nepotism and the transmission of human capital across generations, we assume that the human capital distribution is stationary among *potential scholars*. That is, among individuals with high human capital endowments who could potentially become scholars—whether they are observed in our dataset or not. This assumption is standard in the intergenerational transmission literature. That said, estimates for the intergenerational transmission of endowments, e.g., human capital, are often sensitive to this assumption; an issue which is rarely discussed (Nybom and Stuhler 2019). In this appendix, we first discuss the use of the stationarity assumption in the literature and the sensitivity of our β-estimates on human capital transmission to it. Next, we show that, under stationarity, our nepotism estimates are a lower-bound to the true level of nepotism. In other words, assuming a non-stationary environment would lead to higher levels of nepotism than implied by our already large estimates. In addition, we use a dataset on all pre-modern scholars (not only fathers and sons) collected by de la Croix (2021) to examine time trends in observed outcomes. These trends support the stationarity assumptions for both our nepotism and β-estimates.

F1 Stationarity in the intergenerational literature

Theory. Steady-state assumptions play a critical role in the intergenerational transmission literature, especially when the endowments transmitted from parents to children are unobserved (Clark and Cummins 2015; Adermon, Lindahl, and Waldenström 2018; Braun and Stuhler 2018). To see this, consider the first-order Markov process of endowments transmission discussed in Section 2.2:

$$
\begin{aligned}
h_{i,t+1} &= \beta h_{i,t} + u_{i,t+1} \ , \\
y_{i,t+1} &= h_{i,t+1} + \varepsilon_{i,t+1} \ ,
\end{aligned}
$$

where $h_{i,t} \sim N(\mu_{h,t}, \sigma^2_{h,t})$ is an unobserved endowment (human capital) transmitted from parents t to children $t+1$ at a rate β; y is an observed outcome (publications), noisily related to the latent factor h; and $u_{i,t+1}$ and $\varepsilon_{i,t+1}$ are independent noise terms with standard deviation σ_u and σ_e. Note that here we allow the parameters $\mu_{h,t}$ and $\sigma_{h,t}$ to be time dependant. In other words, we do not impose stationarity over the human capital distribution.

As explained in Section 2.2, we can estimate β by exploiting correlations in y across multiple generations.[2] Specifically, the OLS elasticity of outcome y between parents and children (b_1) and the corresponding elasticity between grandparents and grandchildren (b_2) are:

$$
\begin{aligned}
b_1 &= \beta \ \left[\sigma^2_{h,t+1} \ / \ (\sigma^2_{h,t+1} + \sigma^2_{\varepsilon})\right] \ , \\
b_2 &= \beta^2 \ \left[\sigma^2_{h,t+2} \ / \ (\sigma^2_{h,t+2} + \sigma^2_{\varepsilon})\right] \ ,
\end{aligned}
$$

Hence, the ratio b_2/b_1 identifies β under the assumption that $\sigma_{h,t+1} = \sigma_{h,t+2}$. That is, when the signal-to-noise ratio is constant across, at least, three generations: parents, children, and grandchildren. This condition is satisfied by construction when the human capital distribution is stationary. However, as explained in Nybom and Stuhler

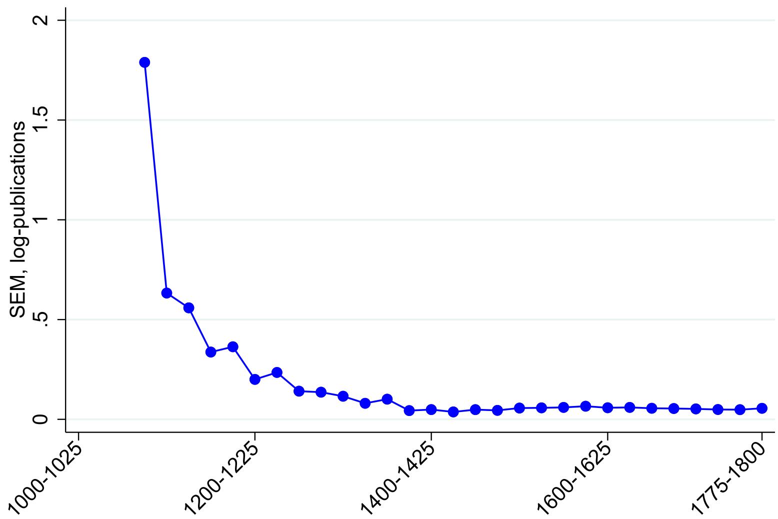
[2] Lindahl et al. (2015), Braun and Stuhler (2018), Colagrossi, d'Hombres, and Schnepf (2019).

(2019), this stationarity assumption is often implicit, and its importance in estimating β is rarely acknowledged in the literature.

Evidence. Next, we present evidence supporting the stationarity assumption that $\sigma_{h,t+1} = \sigma_{h,t+2}$ in our setting. Ideally, we would show that, e.g., the standard deviation of human capital h is constant over time for the entire population of *potential scholars*. Since, by construction, we do not observe h, we will focus on trends in the standard error of the mean for our observed human-capital proxy: publications. To evaluate a population resembling all *potential scholars*, we use the dataset collected by de la Croix (2021) on all pre-modern scholars (not only fathers and sons).

Figure F1 presents trends in the standard error of the mean of publications, in logs. The sample is all scholars in de la Croix (2021) with a reference date between 1088 and 1800.[3] The standard error of the mean is calculated over 25-year intervals. The figure suggests that, after 1350, the standard error of the mean in log-publications is extremely stable. This supports the assumption of a stable variance in the human capital distribution over time, that is, that $\sigma_{h,t+1} = \sigma_{h,t+2}$ is satisfied. Admittedly, the standard error of the mean is much larger before 1350. That said, in our dataset we only observe 33 families where both father and son's reference date is before 1350. In other words, it is unlikely that the large changes in standard error of the mean over time for these few observations are driving our β-estimates.

FIGURE F1: Trend in standard error of the mean, log-publications



Notes: The sample is all scholars in de la Croix (2021) with a reference date between 1088 and 1800. Standard error of the mean in log-publications calculated over 25-year periods.

F2 Stationarity and nepotism

Theory. So far, we have argued that stationarity is a crucial assumption for the estimation of β, the rate at which unobserved human capital endowments are transmitted across generations. Our estimates for nepotism are also sensitive to this assumption.

[3] An individual's reference date is based on available information on his birth year, nomination year, or approximative activity year.

Here we argue that, under stationarity, our nepotism estimates are lower-bound estimates. We then present additional evidence supporting the stationarity assumption in our setting.

Specifically, we identify nepotism by exploiting two sets of moments: First, we exploit correlations in observed outcomes across multiple generations. This moment allows us to uncover the true rate of human capital transmission across generations (see discussion above). This will be important to estimate nepotism. Second, we exploit distributional differences in observed outcomes between fathers and sons who are at the upper-tail of the human-capital distribution. We argue that the observed distributional differences may be the result of two forces: on the one hand, nepotism lowers the selected sons' human capital relative to that of the selected fathers, generating distributional differences in observed publications. That said, not all the distributional differences can be automatically attributed to nepotism. The second force at place is mean-reversion. In detail, if human capital strongly reverts to the mean, the sons of individuals at the top of the human-capital distribution will perform worse than their fathers even if no nepotism is at place.

To gauge how much do distributional differences depend on nepotism and how much on mean-reversion, we follow the literature and assume stationarity in the distribution of human capital over all potential scholars. The stationarity assumption and our first set of moments (which identify the rate of human capital transmission β) allow us to uncover the rate of mean-reversion. That is, how different fathers and sons are supposed to look like in the absence of nepotism. Hence, any excess distributional differences, net of reversion to the mean, can be attributed to nepotism.

Formally, imposing stationarity implies that the difference in human capital between fathers and sons should follow:

$$h_{i,t+1} = \beta h_{i,t} + (1-\beta)\mu_h + \omega_{i,t+1} \ ,$$

where $\omega_{i,t+1}$ is a shock distributed according to $N(0, (1-\beta^2)\sigma_h^2)$. In the absence of nepotism, this differences in human capital would be directly translated into the following differences in publications:

$$y_{i,t} = \max(\kappa, h_{i,t} + \epsilon_{i,t})$$

$$y_{i,t+1} = \max(\kappa, \beta h_{i,t} + (1-\beta)\mu_h + \omega_{i,t+1} + \epsilon_{i,t+1})$$

If the father-son difference in publications is larger than suggested by the previous equations, then an additional force must be in place. A force selecting fathers and sons differently, such that the later can become scholars with lower human capital endowments. In our setting, this additional force is interpreted as nepotism.

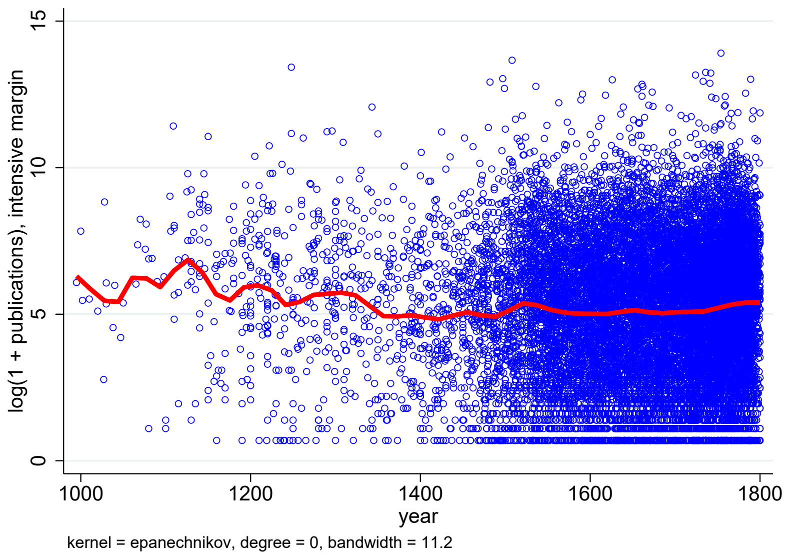
Next let's consider how our nepotism estimates would change in a non-stationary environment. That is, an environment where the human capital distribution changes over time. In our setting, it is reasonable to assume that if the human capital distribution is non-stationary, then it *improves* over time. Under this scenario, we would expect fewer sons with lower human capital than their fathers than under stationarity. This implies that, in the absence of nepotism, we would expect virtually no distributional differences in publications between fathers and sons. In extreme cases, we would even expect the sons publication's distribution to first-order stochastically dominate that of their fathers. Hence, we would need a larger nepotism parameter to reconcile the large observed father-son distributional differences in publications with the small expected differences. In other words, under stationarity, a share of the father-son distributional differences is attributed to nepotism, and another to a second force: mean-reversion. In a non-stationary environment, mean-reversion would explain a lesser share of the father-son distributional differences, and hence, our nepotism estimate would have to be larger. Therefore, we can conclude that, under stationarity, our nepotism estimates are conservative, lower-bound estimates.

Evidence. The fact that our (already large) nepotism estimates are conservative estimates is reassuring. That said, we present additional evidence supporting the stationarity assumption, and hence, that our estimated level of nepotism is not severely downward biased.

As before, ideally we would show that the mean of the human capital distribution, μ_h, is constant over time for the entire population of *potential scholars*. Since, by construction, we do not observe h, we will focus on trends in our observed human-capital proxy: publications. To evaluate a population resembling all *potential scholars*, we use the dataset collected by de la Croix (2021) on all pre-modern scholars (not only fathers and sons).

Figure F2 shows the trend in publications (in logs) on the intensive margin. That is, conditional on having at least one publication listed in WorldCat. To calculate trends over time, we use a kernel-weighted local polynomial regression of publications on a scholar's reference date. The figure shows no trend in the intensive margin of publications, supporting our stationarity assumption. If anything, we observe some fluctuations before 1350, but these show no clear trend and are driven by a smaller sample in the earlier periods.

FIGURE F2: Trend in log-publications, intensive margin

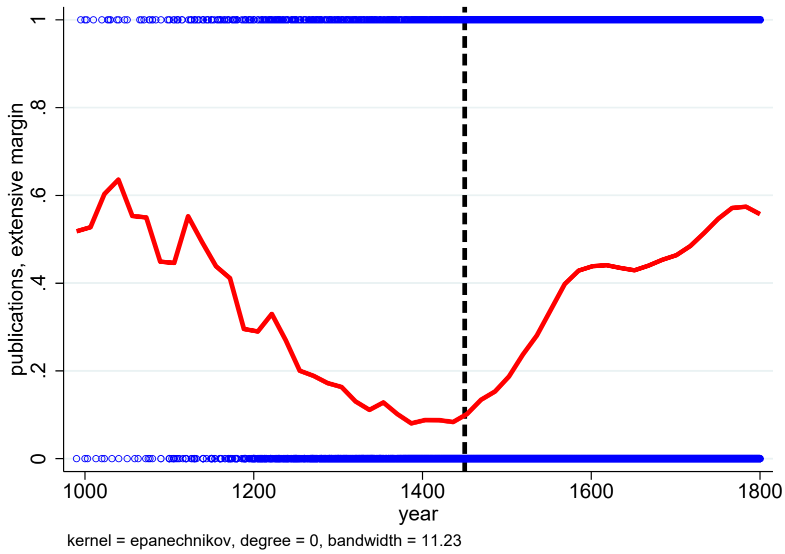


Notes: The sample is all scholars in de la Croix (2021). Trend calculated with a kernel-weighted local polynomial regression of publications (in logs) on a scholar's reference date.

Next, we turn to the extensive margin of publications: that is, whether a scholar has at least one publication listed in WorldCat or not. Figure F3 shows this trend, again calculated using a kernel-weighted local polynomial regression. The figure shows a U-shaped pattern for the extensive margin of publications.

In the initial years, the extensive margin is high because of a selection effect: top scholars are more likely to be observed before 1350. That said, we have a very limited number of observations from this period. We only observe 33 families where both father and son's reference date is before 1350. In other words, it is unlikely that our nepotism estimates are driven by these few observations, even if before 1350 the data does not seem to support our stationarity assumption for the extensive margin of publications.

FIGURE F3: Trend in log-publications, extensive margin



Notes: The sample is all scholars in de la Croix (2021). The dashed line corresponds to the introduction of the printing press.

More importantly, there is a structural break in the extensive margin of publications around the introduction of the printing press (1450). That said, there are several reasons to believe that the trend on the extensive margin of publications after 1450 does not reflect a change in the human capital distribution but a change in the technology for printing and preserving books:

First, it is well-documented that the introduction of the printing press lead to a massive increase in the diffusion and preservation of scholar's books (Dittmar 2019). This alone could explain the observed trend without resort to changes in the human capital distribution. Formally, we believe this trend is related to our parameter κ, the measurement error on the extensive margin of publications, and not to μ_h, the mean of the human capital distribution among potential scholars. This is supported by our higher estimates for κ for earlier periods (see Section 4.5).

Second, it is unlikely that this trend reflects changes in the human capital distribution because such a change would affect the trends in *both* the extensive and the intensive margin of publications. The fact the we only observe a trend in the former suggests that the explanation is related to improvements in the printing and book-preservation technology.

Finally, note that this increasing trend implies that, around 1450, some sons benefited from the existence of the printing press to publish (and preserve) their work. In contrast, we are more likely to observe zero-publications for their fathers, whose output was not printed and may have been lost. Correcting for this bias would increase the observed father-son distributional differences for this period. Hence, would lead to larger nepotism estimates.

In sum, the de la Croix (2021) dataset comprising 42,954 scholars shows no trend on the intensive margin of publications. This supports our stationarity assumption for the human capital distribution. On the extensive margin, we find evidence of a structural break around 1450. That said, this is likely related to the changes brought about by the printing press in terms of book diffusion and preservation, rather than with a change in the human capital distribution.

G Robustness to Distributional Assumptions

The model of intergenerational transmission of wealth is almost always based on normality assumptions on both the initial distribution of wealth $h_{i,t}$ and the distribution of the idiosyncratic shock $u_{i,t+1}$. Given the properties of the normal distribution, and in particular the fact that it is sum stable, the shape of the distribution remains the same across all generations once transformed by Equation 5, $h_{i,t+1} = \beta h_{i,t} + u_{i,t+1}$, only its parameters change. This stability property is not just a theoretical curiosity. Without this property, we face a lack of coherence in modelling, as the initial distribution of human capital could not be rationalized by the model itself, its shape having vanished after one period.

As, in this paper, we are talking about individuals at the very top of the talent distribution, a relevant question is what such distributions mean for the estimated parameters, and could it be that the arguably massive effects estimated for the "nepotism" threshold ν are due to these distributional assumptions? An attractive alternative to normality consists in drawing shocks from fat-tailed distributions, giving higher likelihood to the emergence of geniuses.

When using shocks from fat tailed distributions, one should we aware that some targeted moments commonly used when shocks are normal might not be defined. This is the case for the Pearson correlations and for the mean of the distributions of human capital. We thus define an alternative objective $V_S(p)$ where the Pearson correlation has been replaced by the Spearman rank correlation, which remains well defined with any distribution, and we drop the two means from the objective. We thus have four overidentifying restrictions instead of six. We apply the same SMM algorithm to this new objective keeping the normality assumption on shocks in order to define a new benchmark. Table G1 compares the estimation results under the two different objectives. We first observe that the Spearman correlations ρ_S are very close to their Pearson counterparts ρ. The estimated parameters lead to a slightly higher intergenerational elasticity β, but still within the confidence interval of the benchmark. The standard errors of the parameters are in general smaller with $V_S(p)$, which might indicates that the estimation with $V_S(p)$ is more robust to the exclusion of possible outliers in the bootstrapped samples. The simulated importance of nepotism is very similar across the two columns.

We can now analyze the effect of changing the distribution of shocks. There are three families of distributions where one can write down closed form expressions for the density and verify directly that their shape is preserved (up to scale and shift) under addition: Normal, Cauchy and Levy distributions (Nolan 2003). In this appendix, we implement the Cauchy distribution, which is fat tailed but, unlike the Levy distribution, still defined over $\mathbb{R}$.

The model where shocks are Cauchy is as follows. A potential scholar in generation t of family i is endowed with an unobserved human capital $h_{i,t}$ (in logarithms). This is distributed according to a Cauchy distribution with location x_h and scale parameter γ_h:

$$h_{i,t} \sim \text{Cauchy}(x_h, \gamma_h)$$

The offspring of this generation, indexed $t+1$, partly inherit the unobserved human capital endowment under the first-order Markov process given in Equation (5). The noise term $u_{i,t+1}$ represents an i.i.d. ability shock affecting generation $t+1$, which has a Cauchy distribution, $\text{Cauchy}(x_u, \gamma_u)$.

Table G1: Identified parameters.

Objective:		$V(p)$	$V_S(p)$
Father-son Pearson corr., intensive margin	$\rho(y_t, y_{t+1})$	0.35	
Father-son Spearman cor., intensive margin	$\rho_S(y_t, y_{t+1})$		0.36
Grandfather-grandson, Pearson corr. intensive margin	$\rho(y_t, y_{t+2})$	0.20	
Grandfather-grandson, Spearman corr. intensive margin	$\rho_S(y_t, y_{t+2})$		0.23
Intergenerational elasticity of human capital	β	0.594	0.662
		(0.046)	(0.039)
Nepotism	ν	7.515	6.055
		(1.552)	(1.481)
Std. deviation of shock to publications	σ_e	0.340	0.584
		(0.128)	(0.140)
Threshold of observable publications	κ	2.144	2.033
		(0.159)	(0.139)
Mean of human capital distribution	μ_h	2.383	1.990
		(0.410)	(0.391)
Std. deviation of human capital distribution	σ_h	3.616	3.743
		(0.210)	(0.179)
degrees of overidentification		6	4
percentage of nepotic sons		15.6%	16.2%

Notes: τ normalized to 0. S.E. between parentheses obtained by estimating parameters on 100 bootstrapped samples with replacement

We assume that human capital among the population of potential scholars is stationary. Formally we assume that, conditional on the model's parameters being constant, the human capital of generations t and $t+1$ is drawn from the same distribution. Formally, $h_{i,t} \sim \text{Cauchy}(x_h, \gamma_h)$ and $h_{i,t+1} = \beta h_{i,t} + u_{i,t+1}$ implies $h_{i,t+1} \sim \text{Cauchy}(\beta x_h + x_u, |\beta|\gamma_h + \gamma_u)$.[4] Imposing stationarity leads to the following two restrictions:

$$\begin{aligned} x_u &= (1-\beta)x_h \\ \gamma_u &= (1-|\beta|)\gamma_h \ . \end{aligned}$$

The publications for fathers, $y_{i,t}$, and sons, $y_{i,t+1}$, in the set of scholar lineages $\mathbb{P}$ are still given by Equations (7)-(8) but the shocks $\epsilon_{i,t}$, $\epsilon_{i,t+1} \sim \text{Cauchy}(0, \gamma_e)$ (shocks affecting how human capital translates into publications).

There are three possible variants to the model of the main text (Model I): Cauchy for all shocks (Model II), Cauchy for human capital and Normal for publications (Model III), Normal for human capital and Cauchy for publications. Models II and III are the most appealing ones as they lead to non-normal distribution of human capital. We consider both of them to look at the robustness of the results.

Table G2: Identified parameters under different model assumptions.

Parameter		Mod I	Mod II	Mod III
Intergen. elast. of human capital	β	0.662	0.256	0.446
Nepotism	ν	6.055	9.960	9.387
Std. dev. of shock to publications	σ_e	0.584		2.283
Scale of shock to publications	γ_e		0.010	
Threshold of observable publications	κ	2.033	1.073	0.074
Mean of human capital distrib.	μ_h	1.990		
Location of human capital distrib.	x_h		1.211	0.312
Std. dev. of human capital distrib.	σ_h	3.743		
Scale of human capital distrib.	γ_h		1.102	0.970
value of objective $V(p)$		488	4652	3526
% nepotism		16%	15%	20%

Notes: τ normalized to 0; degrees of overidentification: 6

Table G2 shows the estimation results. Looking first at the value of $V(p)$, it appears clearly that choosing a Cauchy distribution for the shocks to human capital considerably deteriorates the fit for the same degree of overidentification. The reason is that the data cannot be fitted to a distribution with such fat tails. For example, the gap between the 95th quantile and the median for the distribution of publications of sons is 4.726 in the data (from Table D1), 5.622 in the simulation with the Normal distribution, and 7.99 in the simulation with the Cauchy. The two alternative models also lead to a lower value of β, but leave nepotism unchanged.

[4]Because if $X \sim \text{Cauchy}(x_0, \gamma_0)$ we have $kX + \ell \sim \text{Cauchy}(kx_0 + \ell, |k|\gamma_0)$. And if $Y \sim \text{Cauchy}(x_1, \gamma_1)$, $X + Y \sim \text{Cauchy}(x_0 + x_1, \gamma_0 + \gamma_1)$.

To sum up, using fat tailed distributions for shocks to human capital seems *a priori* to be an appealing alternative to the usual normality assumption. They however do not fit the data, which are very normal after all. Moreover, the estimated importance of nepotism is robust to assuming such shocks, although the estimated intergenerational persistence is not.

H Linearity of β

Our estimation assumes that human capital endowments are transmitted linearly. That is, that parents with high and low human capital transmit their endowments at the same rate β. This assumption would be violated, for example, if successful fathers with a high publications' record could spend less time with their children, reducing their human capital transmission systematically. In this appendix, we show empirical evidence suggesting that in our setting this was not the case and, hence, that our assumption is satisfied.

To do so, we examine the parent-child elasticity of publications in the intensive margin. This is one of the moments that we target in our estimation in order to identify β. In fact, a large literature derives estimates of β directly from such parent-child elasticities (see Section 2.1 for details). Specifically, here we compare elasticity estimates obtained using OLS (akin to our targeted moments) to elasticities estimated non-parametrically. The latter allow elasticities to be different in families with different levels of publications, and hence, with different human capital endowments. We find identical estimates using OLS and non-parametric techniques. This strongly suggests that the parent-child elasticity of publications is linear. In other words, it is identical for parents with high and low publications. Altogether, this lends credence to the assumption that human capital endowments are transmitted at the same rate by parents with high and low levels of human capital.

Formally, our OLS elasticity estimates, b^{ols}, correspond to:

$$y_{i,t+1} = c + b^{ols}\ y_{i,t} + e_{i,t+1}\ , \tag{H.1}$$

where $y_{i,t+1}$ and $y_{i,t}$ are the logarithm of 1 + number of publications for, respectively, sons and fathers. The sample is all fathers and sons with at least one publication in WorldCat. That is, b^{ols} captures the publications' elasticity in the intensive margin. Importantly, this assumes that b^{ols} is linear. That is, the publications' elasticity is assumed to be the same for parents with high and low levels of publications.

Conversely, non-parametric estimates for the parent-child publication's elasticity, b^{np}, correspond to:

$$y_{i,t+1} = g(y_{i,t}) + e_{i,t+1}\ , \tag{H.2}$$

where the function $g(.)$ does not follow any given parametric form. Instead, it is derived from the data. In other words, this non-parametric estimation accounts implicitly for any polynomial form for function $g(.)$—i.e., $g(y_{i,t}) = c + \sum_j b_j^{np}\ y_{i,t}^j$ for all $j \in \mathbb{Z}$. Hence, it allows elasticities to be different across families with different levels of publications. The non-parametric elasticity b^{np} corresponds to the marginal effect of $y_{i,t}$.[5]

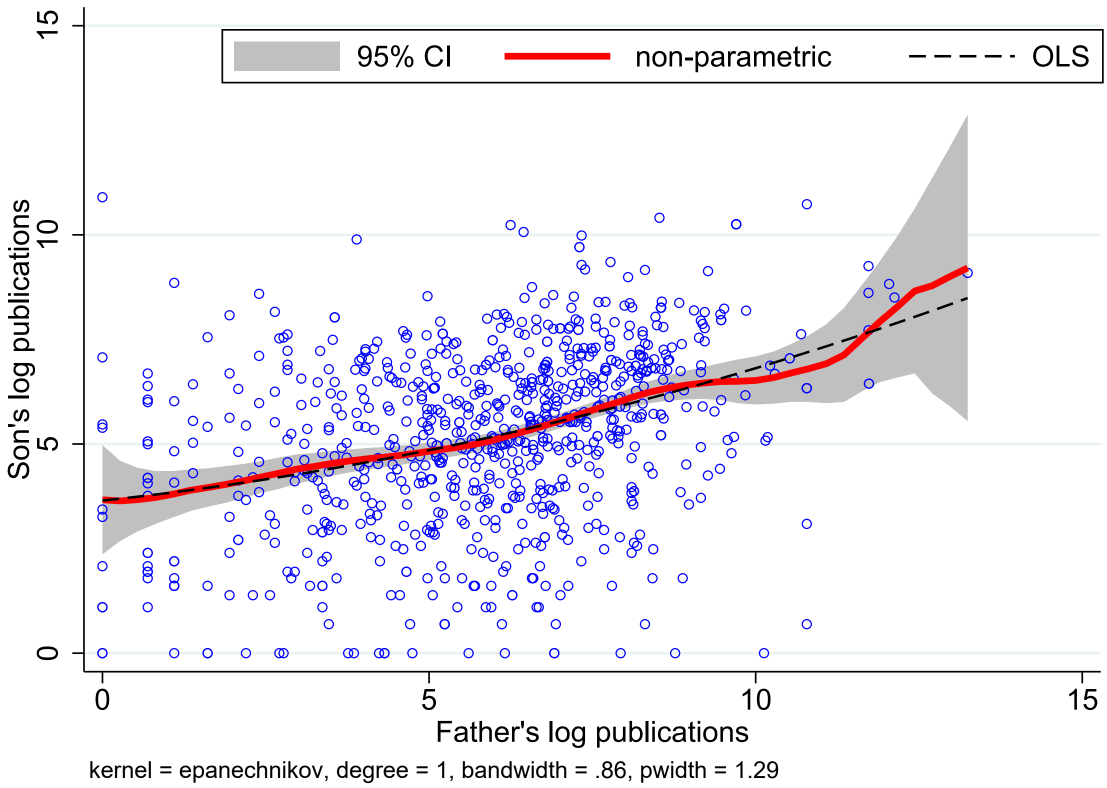
Figure H1 compares OLS and non-parametric elasticity estimates graphically. It shows a scattergram of fathers' (y-axis) and sons' (x-axis) publications, OLS fitted values from Equation (H.1) (dashed line), and non-parametric fitted values and 95% confidence intervals from Equation (H.2) (thick red line and grey area). Specifically, the latter plots the smoothed values of a kernel-weighted local polynomial regression of $y_{i,t+1}$ on $y_{i,t}$. To further capture non-linearities, we choose a polynomial of degree one for the smoothing. The kernel function (epanechnikov), the bandwith, and the

[5] This is obtained as averages of the derivatives.

pilot bandwidth for standard error calculation are set at default values.[6] Finally, note that in this figure the OLS and non-parametric elasticities correspond to the slopes of the plotted lines.

Overall, the figure shows that there is no statistically significant difference between the OLS and non-parametric estimates. This holds true at all levels of father's publications. For example, for fathers with fewer than 1 log-publications ($\leq$ 20 in levels), the fitted OLS and non-parametric values are identical. In turn, the parent-child elasticity in publications (i.e., the slope of the lines) is tightly identified around 0.33 for both estimates. Similarly, for successful fathers with a record of 6 to 10 log-publications (ca. 1,000 to 60,000 in levels), the fitted OLS and non-parametric values are identical. The parent-child elasticity of publications is, as before, tightly identified around 0.33 for both estimates. At the very top of the distribution, we also do not observe significant differences between OLS and non-parametric estimates, although the confidence intervals are wider due to fewer number of observations.

FIGURE H1: Parent-child publications' elasticity (intensive margin), robustness



Notes: The sample are families in which the father and the son are scholars with at least one recorded publication.

Table H1 confirms this pattern for the different periods analyzed in Section 4.5. Specifically, the table shows the OLS (eq. H.1) and non-parametric (eq. H.2) elasticity estimates for the all families with at least one publication (row 1) and for the corresponding families: before the Scientific Revolution (1088–1543); during the Scientific Revolution (1543–1632) and (1632–1687); and during the Enlightenment

[6] The STATA program *lpoly* calculates a rule-of-thumb (ROT) bandwidth estimator. The default pilot bandwidth for standard error is 1.5 times the value of the ROT bandwidth selector.

(1688–1800). The only period where estimates vary is before 1543, although the OLS and non-parametric estimates are not statistically different from each other. This is because the number of observations is small. For the remaining historical periods, the OLS and non-parametric estimates are almost identical. For example, during the Enlightenment the parent-child elasticity is tightly estimated around 0.401 (OLS) and 0.403 (non-parametric).

Table H1: Parent-child publications' elasticity (intensive margin), robustness

	OLS elasticity [1]	non-parametric elasticity [2]	
All	0.333*** (0.030)	0.335*** (0.034)	N=820
Pre-Scientific Revolution (1088–1543)	0.090 (0.111)	0.245 (0.157)	N=70
Scientific Revolution (1543–1632)	0.316*** (0.069)	0.324*** (0.074)	N=173
Scientific Revolution (1632–1687)	0.326*** (0.055)	0.326*** (0.053)	N=229
Enlightenment (1688–1800)	0.401*** (0.046)	0.403*** (0.055)	N=348

Notes: The sample are families in which the father and the son are scholars with at least one recorded publication; Column [1] reports b^{ols} from equation (H.2), column [2] b^{np} from equation (H.1); Non-parametric standard errors obtained with 1,000 bootstrapped replications; *** p<0.01, ** p<0.05, * p<0.1

Altogether, the evidence strongly suggests that the parent-child elasticity of publications is linear. That is, that the elasticity is the same for parents with high and low publication records. This lends creedence to the assumption that human capital endowments are transmitted at a constant rate β by parents with high and low levels of human capital.

I Heterogeneity in publication thresholds

In the benchmark model, κ is the minimum number of publications necessary to observe a scholar's research output. Why would one expect this threshold to be identical for fathers and sons? Could one reasonably assume, instead, that the threshold has to be lower for sons? Isn't a librarian more likely to preserve a text from Pliny the Younger if s/he knows that Pliny the Elder was already a great scholar? If so, how would that affect the findings and the interpretation of parameter estimates?

To answer this question, we define the threshold for sons as κ', possibly lower than the threshold for fathers κ. We estimate the corresponding model. Results are in Table I1. The constraint $\kappa' \leq \kappa$ is saturated, and the estimation is unchanged.

TABLE I1: Identified parameters.

Parameter		benchmark	different κ's
Intergenerational elasticity of human capital	β	0.594	0.582
Nepotism	ν	7.515	7.076
Std. deviation of shock to publications	σ_e	0.340	0.198
Threshold of observable publications - fathers	κ	2.144	2.180
Threshold of observable publications - sons	κ'		2.180
Mean of human capital distribution	μ_h	2.383	2.442
Std. deviation of human capital distribution	σ_h	3.616	3.630

Notes: τ normalized to 0; degrees of overidentification: 6

J Alternative measures of publications

In the main text, we defined publications as the number of library holdings by or about each scholar in modern libraries (WorldCat). We chose this measure for our baseline estimation because it captures two important characteristics of a scholar's work: First, its size. Second, the relevance of a scholar's scientific production today. Although we believe both characteristics to be important, it is interesting to examine the robustness of our results to measuring the size of a scholar's work without resort to its relevance for today. To do so, in this appendix we consider the number of *unique* works by or about each scholar instead of the total number of *library holdings*.

TABLE J1: Targeted moments with alternative measures of publications

	Library holdings (Baseline) [1]	Number of unique works [2]
A. Intergenerational correlations		
Father-son, intensive margin	0.35	0.34
Father-son with zero pubs.	0.22	0.22
Grandfather-grandson, intensive margin	0.20	0.22
B. Father-son distributional differences		
Fathers with zero pubs.	0.29	0.29
Sons with zero pubs.	0.37	0.37
Fathers median	4.43	3.24
Sons median	3.18	2.20
Fathers Q75	6.79	5.23
Sons Q75	5.90	4.46
Fathers Q95	8.67	6.97
Sons Q95	7.90	6.23
Fathers mean	4.03	3.03
Sons mean	3.20	2.38

Notes: The two measures of publications are, respectively, the log of 1 + the total number of library holdings by and about each author and the log of 1 + the number of unique works by and about each scholar.

Table J1 provides empirical moments for this alternative measure. Specifically, it provides inter-generational correlations (Panel A) and father-son distributional differences (Panel B) in publications. These are measured as the logarithm of 1 + the number of library holdings by and about each author (col. [1]) and, alternatively, as the logarithm of 1 + the number of unique works by and about each author. The inter-generational correlations are very similar on the intensive margin, and are equal on the intensive margin by construction.[7] That is, the high inter-generational elas-

[7] Note that we defined the extensive margin as whether a scholar is listed in WorldCat or not. This measure is identical for library holdings and unique works.

ticity (fact 1) is visible both on the number of library holdings and on the number of unique works.

Panel B shows the moments characterizing father-son distributional differences. Note that the levels of each measure are different by construction: the number of unique works is always equal or smaller that the total number of library holdings of these works. Hence, the mean, median, 75th and 95th quantile are lower for our alternative measure. That said, the properties of the distribution and, especially, the father-son distributional differences (fact 2) are robust. To see this, note that the father's median, mean, 75th and 95th quantile are higher than their sons' in both measures. In other words, the distribution of publications of fathers FOSD that of sons both in terms of unique works and in terms of library holdings.

To further check that the properties of the fathers' and sons' distribution are similar, Table J2 shows quantile ratios. The median/Q75 ratio, the median/Q95 ratio, and the median/mean ratio are similar for library holdings and for unique works.

Table J2: Comparison of distributions

		Library holdings (Baseline)	Number of unique works
Q50/Q75	Fathers	0.65	0.62
Q50/Q75	Sons	0.54	0.49
Q50/Q95	Fathers	0.51	0.46
Q50/Q95	Sons	0.40	0.35
Q50/mean	Fathers	1.10	1.07
Q50/mean	Sons	0.99	0.92

Table J3: Identified parameters with alternative measures of publications.

Parameter		Publication measure lib. holdings	nb. works
Intergenerational elasticity of human capital	β	0.594	0.576
Nepotism	ν	7.515	7.399
Std. deviation of shock to publications	σ_e	0.340	0.187
Threshold of observable publications - fathers	κ	2.144	1.721
Mean of human capital distribution	μ_h	2.383	1.953
Std. deviation of human capital distribution	σ_h	3.616	2.832
% nepotic sons		15.6%	15.6%

Notes: τ normalized to 0; degrees of overidentification: 6

Finally, we re-estimate our model targeting two sets of moments: moments defined using library holdings (baseline) and moments defined using the number of unique works (alternative). Table J3 presents the corresponding estimates. Using the number of unique works, we find a β-estimate of 0.576, very similar to our baseline estimate (0.576). Our nepotism estimate, ν is also robust to the measure of publications (7.515 vs 7.399). As in the main text, we quantify nepotism by simulating our model with the estimated parameters and remove nepotism by setting $\nu = 0$. That is, we impose the same selection criteria for sons of scholars and outsiders. Our simulations based on the number of unique works suggest that, in 1088–1800, 15.4% of scholars' sons were nepotic. This estimate is also very similar to our baseline results. In sum, this suggests that our results are not driven by the way we measure publications.

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