DISCUSSION PAPER SERIES

DP18006

MULTIGENERATIONAL TRANSMISSION OF WEALTH: FLORENCE 1403-1480

Marianna Belloc, Francesco Drago, Mattia Fochesato and Roberto Galbiati

ECONOMIC HISTORY AND LABOUR ECONOMICS

CEPR

ISSN 0265-8003

MULTIGENERATIONAL TRANSMISSION OF WEALTH: FLORENCE 1403-1480

Marianna Belloc, Francesco Drago, Mattia Fochesato and Roberto Galbiati

Discussion Paper DP18006
Published 20 March 2023
Submitted 16 March 2023

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

MULTIGENERATIONAL TRANSMISSION OF WEALTH: FLORENCE 1403-1480

Abstract

By using hand-collected data on households' wealth assessments, we study multigenerational mobility in Florence during the late Middle Ages. We find that Florentine society was more mobile than one would expect but also that multigenerational mobility was lower than implied by two generations estimates. We reconcile these findings by showing their consistency with a model where wealth transmission is governed by an unobserved latent factor. We also show that, given our estimates, this model is compatible with the long-run persistence obtained by previous studies. Finally, we find that participation in marriage networks and in politics correlates with persistence of the economic status across generations.

JEL Classification: J62, N00

Keywords:

Marianna Belloc - mariannabelloc@uniroma1.it
Sapienza University of Rome and CEPR

Francesco Drago - francesco.drago@unict.it
University of Catania and CEPR

Mattia Fochesato - mattia.fochesato@unibocconi.it
Bocconi University

Roberto Galbiati - roberto.galbiati@sciencespo.fr
CNRS-Department of Economics Sciences Po (DESP, CNRS-SciencesPo) and CEPR

Acknowledgements
We wish to thank the Editor, Camille Landais, and two anonymous referees for their helpful comments and suggestions. We are grateful to Antony Molho and John Padgett for sharing the digitized version of the 1480 Catasto. We thank seminar participants at Bocconi University, University of Nantes, and Sciences Po for helpful discussions. Ilaria Canfailla and Irene Volpi provided outstanding research assistance and archival expertise.

Multigenerational Transmission of Wealth: Florence 1403-1480*

Marianna Belloc† Francesco Drago‡ Mattia Fochesato§ Roberto Galbiati¶

This version: March 15, 2023

Abstract

By using hand-collected data on households' wealth assessments, we study multigenerational mobility in Florence during the late Middle Ages. We find that Florentine society was more mobile than one would expect but also that multigenerational mobility was lower than implied by two generations estimates. We reconcile these findings by showing their consistency with a model where wealth transmission is governed by an unobserved latent factor. We also show that, given our estimates, this model is compatible with the long-run persistence obtained by previous studies. Finally, we find that participation in marriage networks and in politics correlates with persistence of the economic status across generations.

Keywords: Wealth transmission, social mobility, multiple generations, latent factors.

*We wish to thank the Editor, Camille Landais, and two anonymous referees for their helpful comments and suggestions. We are grateful to Antony Molho and John Padgett for sharing the digitized version of the 1480 *Catasto*. We thank seminar participants at Bocconi University, University of Nantes, and Sciences Po for helpful discussions. Ilaria Canfailla and Irene Volpi provided outstanding research assistance and archival expertise.

†Sapienza University of Rome, CESifo & CEPR marianna.belloc@uniroma1.it

‡University of Catania, CEPR & CSEF francesco.drago@unict.it

§Dondena Centre and BIDSA, Bocconi University, mattia.fochesato@unibocconi.it

¶CNRS-SciencesPo, Sciences Economiques & CEPR roberto.galbiati@sciencespo.fr

1 Introduction

The literature on the intergenerational transmission of economic status has recently gained a renewed impetus to derive measures of mobility in contemporary societies (Acciari et al., 2022; Black and Devereux, 2010; Chetty et al., 2014; Guell et al., 2018). In particular, the increased availability of data about multiple generations has allowed economists to investigate the transmission mechanisms of economic resources in the short and in the long run (Adermon et al., 2021; Alesina et al., 2021; Barone and Mocetti, 2021; Braun and Stuhler, 2018; Lindahl et al., 2015; Pfeffer and Killewald, 2018). However, few studies have examined the strength of the persistence of economic status across generations in the very distant past (Clark, 2014; Ager et al., 2021). In this paper, we investigate wealth status transmission across generations by exploiting newly collected data on the universe of Florentine households over almost a century in the late Middle Ages. The considered historical context is that of one of the most important European urban centers of the period, which was undergoing profound social, political, and economic transformations (Goldthwaite, 2009; Najemy, 2006). The analysis of intergenerational economic mobility in the past is not only important *per se* but is also instructive regarding the forces that govern transmission mechanisms across time and is relevant for the interpretation of contemporary empirical patterns.

For this purpose, we have assembled a novel dataset that combines four subsequent wealth assessments. Three of these are available thanks to the work of a previous generation of historians and provide measures of wealth at three points in time: 1403, 1427, and 1480. The last source, which includes the 1457 wealth tax assessments of more than 7,000 Florentine households, has been hand-collected by us and then made compatible with the other sources. The observation of household-level information at time intervals of about 30 years allows us to identify direct links between children, parents, grandparents, and great-grandparents and thus to cover up to four generations. To the best of our knowledge, this has never been done in a study on intergenerational mobility employing historical data dating as far back as six centuries ago.

As measures of economic status, we employ wealth percentile ranks and indicators for the top deciles of the wealth distribution. First, we empirically assess intergenerational mobility across adjacent generations, implementing estimation at the individual (household's head) and family (surname) levels, finding that the correlation coefficients between the children's and parents' generations do not change dramatically across time. Our derived measures of mobility also indicate a society that presents some degree of persistence of wealth transmission but is not totally immobile, being not as far from comparable with the upper bounds of intergenerational wealth correlations in modern societies. For example, our estimated rank-rank wealth correlation falls within the range between 0.4 and 0.5, whereas that found by Adermon et al. (2018) for the 20th century Sweden goes from 0.3 to 0.4, depending on the specification. These results suggest that 14th- and 15th-century urban areas, such as Florence, represented a concrete opportunity for social mobility (Lopez, 1976; Padgett, 2010): this is in line with the views of historians who have abandoned the myth that the Middle Ages was a socially immobile world (Carocci, 2011; Goldthwaite, 1980).

Then, we move on to study multigenerational mobility linking up to four generations. The relevant literature suggests two alternative (not mutually exclusive) models to explain economic status correlation across multiple generations. According to the first approach, grandparents have a direct effect on the fortunes of their grandchildren (the "grandparental effects model", Mare, 2011). According to the second, the transmission of wealth is governed by an unobserved latent factor, which is transferred from generation to generation and is correlated with economic outcomes (the "latent factor model", Clark, 2014). Although the grandparental effects and the latent factor model have different policy implications, they share a number of empirical predictions. First, both models, if used to infer predictions for the long run, systematically imply a lower degree of intergenerational mobility than that derived by iteration of the canonical model across time.[1] Second, once we control for parental wealth, both models imply a positive correlation between grandparents' and children's outcomes (Braun and Stuhler, 2018).[2]

In our analysis, we find empirical support for both predictions. First, when we look at two non-adjacent generations (grandparents and grandchildren), we find that the measured correlation is larger than that implied by the iteration of a simple model of wealth transmission between parents and children, suggesting that persistence in economic status in the medium and long run may be higher than that inferred from a short run analysis. Second, when we consider three adjacent generations (grandparents, fathers, and grandchildren observed in 1427, 1457, and 1480, respectively), we find that the coefficients on the grandparents' generation are large and statistically different from zero. These findings call for an empirical investigation to discriminate between the two alternative approaches, the grandparental effect model and the latent factor model.

With our data, we can gather some evidence in this direction. First, we employ the three-generation (1427, 1457, and 1480) model and exploit the fact that descendants have a lower probability of being

[1] In particular, should the grandparental effects model be the correct one to describe the transmission process, the intergenerational mobility in the long-run would be overestimated by iteration of the canonical two-generation model because we would ignore the effects of grandparents, which is not fully captured by the parents' status. If, in contrast, the correct model was that based on the latent factor, the iterative procedure would erroneously ignore the presence of the endowment (the latent factor) and its role in the process of economic status transmission across generations.

[2] The intuition is that grandparents' outcomes capture part of the omitted latent factor.

in contact with their grandparents the greater the age difference between the two. Therefore, we condition our regression to the age of the grandparents being greater than the median computed when the grandparents' wealth is observed (this median is equal to 57, which coincides with the upper bound of the average age at death in the period under analysis, Cummins, 2017). We find that, even in this case, the estimated effect of the grandparents is sizable suggesting that they may exert an effect on their descendants' economic status even when there is no direct contact. In a similar exercise, we condition our three-generation regressions to the number of household members being greater than the median and find that, again, the correlation between grandparents' and children's outcomes, after controlling for parental outcomes, does not substantially change should we restrict our analysis to families with a large number of children. This result is at odds with a model in which grandparents have a direct effect on children's wealth through, for example, gifts, skills, and inheritance, while is consistent with the latent factor model. Second, we exploit a four-generation model (1403, 1427, 1457, and 1480) and find that we cannot exclude that the wealth outcomes of the great-grandparents' generation had an effect on the great-grandchildren's wealth outcomes. Since, in the period of observation, great-grandparents are very unlikely to might have had direct contact with a generation of individuals who lived 80 years later, this evidence also supports the latent factor model.

Next, using our estimated parameters in the previous exercises, we challenge the available models (the iterative model, the grandparental transmission model, and the latent factor model) to explain the empirical patterns of very long-run wealth status transmission in an out-of-sample prediction analysis. To do this, we implement simulations over a time horizon of about 600 years and compare the predictions with those produced in a recent influential paper by Barone and Mocetti (2021). The authors also focus on the city of Florence and, linking wealth observations from families observed in 1427 and in 2011, find a positive correlation coefficient across about 19 generations. With our data, iterations from the canonical first-order model and the grandparental transmission model show a short longevity of wealth status persistence: achieving decay to zero correlation after seven generations in the first case and after 13 generations in the second. The latent factor model, instead, implemented with our estimated coefficients predicts positive correlation along a horizon of 19 generations (although the implied coefficient turns out lower than that obtained by Barone and Mocetti, 2021), confirming the ultimate sense of their findings: very long-run positive wealth correlations are possible and compatible with direct evidence of multigenerational historical data.

Our results, taken together, suggest that Florence in the late Middle Ages was relatively mobile, but also that wealth status positions tended to be very persistent over a multiple-generations horizon. Moreover, we show that the gathered empirical evidence speaks in favor of the latent factor model, when its predictions are challenged by the data and compared with those of alternative approaches. Although we cannot provide exhaustive evidence of the nature of the latent factor, in the last part of the paper, we explore some hypotheses to better understand what factors might have fostered or hampered wealth status mobility at the time. The analysis is limited by the availability of reliable data for our period of interest; however, we are able to collect some interesting evidence. We start by investigating the possible dimensions at which wealth transmission might occur, occupation, neighborhood, and family, finding no role for the first two and a modest and not statistically significant role for the last one (possibly including network effects or genetics). Then, we explore plausible mechanisms at play, unraveling the role of participation in the Florentine marriage market and the city government. Although this evidence is not conclusive, the unveiled role of social and political networks in affecting wealth status transmission in the past calls for future research. Our analysis is related to a large body of literature on the intergenerational mobility of economic status. The analysis of the process of wealth transmission across generations is more recent than that of income and has attracted much attention in recent years (see, for instance, Piketty, 2014; Piketty et al., 2006). Wealth reflects accumulated income and captures individuals' economic opportunities (Killewald et al., 2017). This observation has motivated recent works on intergenerational mobility, mainly in contemporary societies.[3]

Our multigenerational study of wealth status transmission in Florence in the late Middle Ages contributes to this literature and, in particular, to one that explores the role of latent factors in understanding the dynamics underlying the economic status transmission process between ancestors and offspring. Our findings are consistent with the results by Braun and Stuhler (2018) on the multiple-generations persistence of occupational and educational attainments in Germany and with the results by Clark and Cummins (2015), who use rare surnames to study intergenerational economic mobility in modern England. Both studies find evidence consistent with the latent factor model, implying a higher long-run persistence of economic status than that derived with the iteration of the canonical model across time. Our analysis suggests that similar mechanisms may be at play

[3] Adermon et al. (2018) examine wealth transmission over up to four generations in Sweden, focusing on the role played by inheritance. Boserup et al. (2017) exploit administrative data on three generations in Denmark to investigate intergenerational wealth mobility and its relationship to lifetime economic resources. Pfeffer and Killewald (2018) use survey data to investigate wealth mobility in the U.S.

in very different contexts and for different socioeconomic outcomes and tries to gauge evidence for the nature of the latent factor.[4]

Our focus on the distant past adds to recent results by Ager et al. (2021) on the 19th-century U.S. Their paper shows that the wealthiest slaveholders in the U.S. South lost their wealth after the civil war, but their children recovered almost completely after one generation. Interestingly, our findings unveiling the role of the marriage market in determining the degree of intergenerational wealth persistence are in line with the authors' result that family networks favored former slave owners' wealth recovery. Our paper is also related to work by Padgett (2010), who has investigated the dynamics of the social and political elite composition in the 14th- and 15th-centuries Florence. Like us, Padgett employs census data to measure movement in relative wealth positions; however, he focuses on a surname-level analysis and examines variation in marriage patterns, family structure, and degree of intergenerational mobility across broad political, social, and economic dimensions. We complement and extend his investigation by identifying individual links across generations, measuring multigenerational mobility, and deepening our understanding of economic status transmission models.

Finally, our work is related to the existing historical literature that has documented social and economic mobility in pre-modern and industrializing Western Europe by exploiting information contained in historical and tax records. Regarding the last two centuries, van de Putte et al. (2009) examine the relationship between modernization and societal openness by employing information on marriage registers in industrializing Belgium, whereas van Leeuwen et al. (2015) reconstruct the occupation patterns across multiple generations in 18th- to 20th-century France. Looking at the earlier periods, Hanus (2012) exploits tax registers on income earned across generations in the 16th-century Low Countries, whereas Payling (1992) study intergenerational transmission of wealth among the elites in late Medieval rural England. We contribute to this literature by linking directly, for the first time, wealth observations of family members across multiple generations in an urban center of the late Middle Ages.

This paper is organized as follows. In Section 2, we describe the historical background and the data used in the paper. In Section 3, we illustrate measures of intergenerational mobility, discuss the comparison between different estimators, and present our results for two adjacent generations. Section 4 shows our findings on multigenerational mobility, explores alternative models proposed by

[4] Unlike Clark and Cummins (2015), we use census level data on wealth and show that the use of a surname-level analysis implemented with two generations only may fail to correctly identify the parameters in the latent factor model since the transmission of economic status takes place not only between extended families (households sharing the surname) but also within families.

the literature, and evaluates their relative performance. In Section 5, we analyze the mechanisms of wealth status transmission considering possible factors affecting mobility in our context. Section 6 provides concluding remarks.

2 Historical background and data

The inhabitants of the city of Florence gained political independence and established an independent republic in the 12th century. During the 15th century, the city became the cradle of the Italian Renaissance and underwent a series of political changes that interacted with important transformations of the fiscal system; together, these dynamics shaped the socioeconomic structure of the city (Najemy, 2006). This historical period was also marked by tensions among prominent Florentine families, which deeply influenced the functioning of the Republican institutions (we study these dynamics more extensively in Belloc et al., 2022).

In the first decades of the 15th century, Florence experienced a long phase of foreign pressure on the political independence of the city and, consequently, faced increasing military expenditures to maintain its sovereignty (Molho, 1971). To cope with the mounting fiscal burden and introduce an objective system to allocate it to citizens, in 1427, the Republic decreed the first universal wealth assessment, commonly known as *Catasto* (Herlihy and Klapisch-Zuber, 1975, pp.10-13).[5] Each head of a household, whether residing in the city or in the countryside controlled by Florence, had to declare their names (first name and patronymic) and their surname, age, neighborhood of residence, occupation, as well as the number of members in their households and a complete list of wealth items: liquidity, contracts of private and public credit, and the value of real estate owned, including land.[6] The declarations for the 9,780 non-exempted households residing in the city are available thanks to the pioneering work of historians, David Herlihy and Christiane Klapisch-Zuber, who conducted a detailed study of the 1427 *Catasto* (Herlihy and Klapisch-Zuber, 1975), and to the subsequent reorganization and digitization of the document by Robert Burr Litchfield and Anthony Molho (Herlihy et al., 2002).

During the 15th century, new registers were redacted in 1435, 1451, 1457/58, 1469, 1480, and 1495 (Procacci, 1996). Among those that have survived, we had access to the 1457/58 *Catasto* and to the 1480 *Catasto*. The first is the most complete register and was not available in digitized form until now. The register covers sociodemographic and economic information that can be compared

[5]Ecclesiastics and citizens with no or temporary residence were the only categories exempted from the assessment.

[6]While the movable properties were assessed at their market values, real estate was evaluated by the rent it could produce, which was capitalized as 7% of its total value. For example, the value of property that would have produced a yearly rent of 7 gold Florins was estimated to have a total value of 100 gold Florins.

with information included in the 1427 census. We have conducted a direct historical analysis of the declarations included in the original copies of the 48 volumes of the *Catasto del 1457-Portate dei Cittadini* held in Florence's State Archive. Through this research, we have realized a digital version of the document that reports for the 7,455 non-exempted households in the city of Florence the same pieces of information (excluding individual age) reported by the digital version of the 1427 *Catasto*: names and surname, neighborhood of residence, occupation, number of members in the household, and wealth items, including real estate. Importantly for our purposes, and in addition to the previous register, each record reports a third name (the avonymic) in addition to the first two names (the first name and the patronymic) and the surname.[7]

The 1480 *Catasto* reports for each of the 8,413 non-exempted urban households useful sociodemographic information, including three names (the first name, the patronymic, and the avonymic) and the surname, the neighborhood of residence, the occupation, and regarding wealth the value of real estate (Molho, 1994). This register was digitized by Anthony Molho.[8] Its characteristics were first studied by Procacci (1996).

To exploit a fourth observation in time, we employ the 1403 *Prestanze* register as an additional source of information. The *Prestanze* were forced loans exacted by the Republic from the most affluent Florentine citizens. Martines (1963) lists the 150 richest "lenders" in each of the four Florentine neighborhoods, approximately representing the top decile of the city's wealth distribution. His register reports, for the included households, the (two and rarely three) names of the household head, the surname, the neighborhood of residence, (seldom) the occupation, and the value of the loan. This source, although representing an imperfect proxy for wealth status, allows us to extend our analysis to four generations.

Finally, to disentangle the factors that facilitated or limited intergenerational wealth status mobility, we collected two additional datasets. The first source, compiled and kindly shared by John Padgett (Padgett, 2010), provides information about the marriage networks in the city of Florence. The key variable measures the level of structural cohesion of a family in the marriage network (Moody and White, 2003). By structural cohesion, the author means "the minimum number of links, anywhere in the network, that have to be severed in order to disconnect any particular node (perhaps including its neighbors) from the rest of the network"(Padgett, 2010, p.374-375). In practice, for each family, the variable can assume an integer value (between zero and eight), which indicates how many marriage links need to be broken up to detach the family from the marriage

[7]When the avonymic was missing, we have complemented this information by employing the additional sources, such as Herlihy et al. (2000).

[8]We thank Anthony Molho and John Padgett, who kindly shared the digital version with us.

network. The higher the structural cohesion variable for a family, the more central the family in the marriage network. Families with an indicator value equal to two are defined by Padgett (2010) as participating to the marriage market, and those with an indicator value equal to or greater than four are denoted as "core".[9]

The second source regards the political participation of Florentine citizens in the government of the city over the period of interest. At that time, the city political office assignment was based on a system combining elections and sortition called *Tratte*. The records of the citizens who had access to political offices has been digitized by Herlihy et al. (2000), who relied on the original documents called the *Giornali delle Tratte* held in the Florentine State Archive. Each record reports the complete list of the names and surname of the citizen selected for a specific office, the date of drawing, and other information. For our analysis, we extract information about the time interval in which individuals had access to an office (in particular, we define dummy variables equal to one if an individual held at least one office before 1427, or before 1457, and to zero otherwise).

To combine the various datasets, after archival work and visual inspection of the various records (see Appendix A), we identify families according to their surname and individuals according to their (two or three) names and surname.[10] In particular, to build connections across generations and establish *direct* (fathers-sons, grandfathers-grandchildren) links, we employ the surname, the patronymic, and the avonymic. For instance, in the 1480 *Catasto*, we observe *Niccolo* (first name) *Bartolomeo* (patronymic) *Sandro* (avonymic) *Bandini*, in the 1457 *Catasto* we find *Bartolomeo* (first name) *Sandro* (patronymic) *Giovanni* (avonymic) *Bandini*, and finally in the 1427 *Catasto* we find report *Sandro* (first name) *Giovanni* (patronymic) *Bandini*. We then identified *Niccolo* (whose wealth we observe in 1480) as son of *Bartolomeo* (observed in 1457) and grandchildren of *Sandro* (observed in 1427). The *Bandini* family was also included in the 1403 *Prestanze* register. For future use, note that in the dataset each record corresponds to the head of the household; thus individual and household observations coincide, whereas by family we mean all the individuals with the same surname. Accordingly, we call the links identified across individuals who share a common surname (family) *indirect*.

Finally, as we will see in Subsection 3.2, as a measure of wealth outcomes, we employ real estate percentile ranks and real estate top deciles. The choice of real estate as a proxy for wealth is imposed

[9]The variable is constructed for the Florentine families who were tied to the marriage networks in seven sub-periods, each of which is year: 1282-1317, 1318-1347, 1348-1377, 1378-1403, 1404-1433, 1434-1463, and 1464-1493.

[10]Before merge, we verified that the spelling of names and surnames followed the same rules. We visually inspected the most similar records and evaluated their correspondence case by case (details in Appendix A). Note that the names of households included in the 1480 *Catasto* are formed by only five letters, differently from the names included in the other registers which range up to 11 letters. In the merging process, names are then cropped to five letters when necessary. Surnames always have up to 11 letters.

by the fact that it is the only asset that we observe over the three available *Catasti*.[11] The use of relative wealth positions in place of the absolute levels of wealth is motivated by the need to avoid any complications with the conversions of the values across time.

3 Mobility across adjacent generations

3.1 Empirical specifications

A first approach to measuring intergenerational mobility consists in estimating the following standard regression:

$$y_{ijt} = \beta_0 + \beta_{-1} y_{ijt-1} + u_{ijt}, \tag{1}$$

where y_{ijt} and y_{ijt-1} are the wealth outcomes for household i (individual) with surname j (family) in generations t and $t-1$, respectively, and u_{ijt} denotes the error term. In some recent applications, exploiting contemporary administrative datasets, for instance, information on family lineage is known, and this allows us to connect each child of the t generation to his/her parent in the $t-1$ generation. In the context of our application, which exploits data from six centuries ago, instead direct links between children and their ancestors are unknown and can be inferred only by matching individual and family information across censuses, as we explained in Section 2. When part of this information is missing (the patronymic, for example), we have an omitted link between the population of parents (generation at time $t-1$) and the population of children (generation at time t). In such a case, model (1) can be estimated only on a sub-sample of the universe, call it the *matched sample* (the sample of individuals observed in t that we are able to match with their ancestors observed in $t-1$).

A second approach consists in considering a variation of model (1) to estimate the so-called "grouping estimator" (Santavirta and Stuhler, 2021). Namely, the parent's wealth outcome in the previous regression is replaced by the group mean at the surname (family) level:

$$y_{ijt} = \pi_0 + \pi_{-1} \bar{y}_{jt-1} + v_{ijt}, \tag{2}$$

where $\bar{y}_{jt-1}$ is the family mean of wealth outcomes of individuals with surname j in generation $t-1$ and v_{ijt} is the error term. When model (2) is estimated on the matched sample, $\bar{y}_{jt-1}$ includes

[11] We do not employ income as a measure of economic outcomes, as other studies do (see, for instance, Chetty et al., 2014), because of data limitations. Starting from wealth assessments, reliable income estimates for the period would require data on items, such as cattle and home-ownership, and professional activities, that are available in the dataset only for 1427 (Milanovic et al., 2011).

information on the *matched* parents with surname j, that is, individuals observed from generation $t-1$ who have been linked to at least one child observed in t. However, model (2) does not require that direct links are identified to be estimated, and it can be run on a larger sample. We define the *extended sample* as the sub-population of individuals observed at time t for which *at least* one relative is observed at time $t-1$ (an individual with the same surname). The *extended sample* is larger than the *matched sample*, as it includes direct as well as indirect links between children and their ancestors in the previous generation who are not necessarily their parents. The first advantage of employing the *extended sample* is that it allows to extend our analysis to a larger share of the universe of the children with respect to the *matched sample.* The second advantage is that it allows to make meaningful inferences from modifications of model (2) by including outcomes from waves at $t-2$ and $t-3$, even when direct links with grandfathers and great-grandfathers are not available (or are too few).

Then, it is important to discuss how β_{-1} and π_{-1} compare with each other when we employ the matched or extended sample. When the two parameters are estimated using the matched sample, π_{-1} is expected to be greater than β_{-1} as long as surname j has informative content about child i with surname j's outcome over and above the direct effect of his/her parent. To see this, consider the *long* regression (Santavirta and Stuhler, 2021), which includes the wealth outcome of household i with surname j in generation $t-1$ and the family group mean also in $t-1$:

$$y_{ijt} = \pi_0 + \pi'_{-1} y_{ijt-1} + \pi''_{-1} \bar{y}_{jt-1} + w_{ijt}, \tag{3}$$

where π''_{-1} captures any family effect at the j level on the child's wealth outcome after the impact of i's parental wealth outcome has been controlled for; w_{ijt} denotes the error term. As shown by Santavirta and Stuhler (2021), as the covariance between y_{ijt-1} and its family mean $\bar{y}_{jt-1}$ ($cov(\bar{y}_{jt-1}, y_{ijt-1})$) is smaller than the variance of y_{ijt-1} ($var(y_{ijt-1})$), it is easy to see that

$$\pi_{-1} = \pi'_{-1} + \pi''_{-1} = \beta_{-1} + \pi''_{-1}\left(1 - \frac{cov(\bar{y}_{jt-1}, y_{ijt-1})}{var(y_{ijt-1})}\right) > \beta_{-1}, \tag{4}$$

if and only if $\pi''_{-1} > 0$, that is, as long as the surname has additional informational content about children's wealth outcomes above that of their parents. The second part of equation (4) establishes a relationship between the surname-level estimator π_{-1} from model (2) and the individual-level estimator β_{-1} from model (1), the first part decomposes the surname level estimator π_{-1} into a family (j) effect captured by π''_{-1} and an individual (i) effect captured by π'_{-1}.

The comparison between β_{-1} estimated employing the matched sample and π_{-1} estimated employing the extended sample is more complicated. As a matter of fact, as the two coefficients are obtained from different samples, any meaningful comparison between them should be made under the assumption that $\hat{\beta}_{-1}$ is an unbiased representation of the underlying parameter on the *extended sample* (that is, the case in which we were able to observe for all the children registered in wave t their parents registered in $t-1$). Under this assumption, there are two competing forces that lead $\hat{\pi}_{-1}$ estimated in the *extended sample* to be larger or smaller than $\hat{\beta}_{-1}$ estimated in the *matched sample* (see also Santavirta and Stuhler, 2021).

On the one hand, $\hat{\pi}_{-1}$ could be larger than $\hat{\beta}_{-1}$, because, as we have explained before, the former estimates the effect of the parents' wealth outcomes (also captured by $\hat{\beta}_{-1}$) plus that of the family outcomes (if any) over and above the parental wealth outcomes. In this case, the difference between $\hat{\pi}_{-1}$ and $\hat{\beta}_{-1}$ is an increasing function of this family effect. On the other hand, $\hat{\pi}_{-1}$ could be smaller than $\hat{\beta}_{-1}$, because in the *extended sample* some direct links might be missing, implying that the former coefficient would underestimate the effect of the parents' generation on children's outcomes. In this case, the difference between $\hat{\pi}_{-1}$ and $\hat{\beta}_{-1}$ is a decreasing function of the share of the direct links identified in the population. In conclusion, whether $\hat{\pi}_{-1}$ is larger or smaller than $\hat{\beta}_{-1}$ is an empirical question that depends on the informational content of the family and the share of direct links identified in the extended sample.

3.2 Baseline results

With this discussion in mind, we now present the results from the estimation of model (1) (*matched sample*) and model (2) (*matched sample* and *extended sample*). We start by considering rank-rank specifications, as in Dahl and DeLeire (2008), Chetty et al. (2014), and Acciari et al. (2022). Therefore, for example, looking at model (1), we investigate how the percentage rank position of individual (household's head) i from family j in the wealth distribution of generation t, y_{ijt}, is predicted by the percentage rank position of his/her parent's rank position observed in generation $t-1$, y_{ijt-1}.[12] The estimated slope parameter measures the "relative mobility", that is, the correlation between ranks in two subsequent generations within the same family. A large $\hat{\beta}_{-1}$ denotes a strong persistence in wealth positions across generations. By combining $\hat{\beta}_0$ with $\hat{\beta}_{-1}$, we can measure the degree of "absolute mobility" (Chetty et al., 2014): the expected percentage rank position of households observed in t for any given percentage rank position in the previous generation's

[12]Estimates of the intergenerational elasticity of wealth and income are typically nonlinear and sensitive to outliers and observations with zero wealth. The rank-rank specification overcomes these problems (Chetty et al., 2014).

wealth distribution in $t-1$. Moreover, given the linearity of the rank-rank relationship, the average percentage rank (in the population distribution) of a household below the median of the wealth distribution is considered to be equal to the rank of a household in the first quartile. Thus, the expected percentage rank of a household with a parent below the median of the wealth distribution will be $\hat{\beta}_0 + 25 \times \hat{\beta}_{-1}$. This measure conveys information about the "absolute upward mobility" (Chetty et al., 2014).[13]

Table 1 about here.

The results for two subsequent censuses, t and $t-1$ (1427-1457 (Panel A) and 1457-1480 (Panel B)) are reported in Table 1. Columns (1)-(2) and (5)-(6) report the estimated coefficients from models (1) and (2), respectively, on the matched sample, while columns (3) and (7) show the estimated coefficients from model (2) obtained from the extended sample. In columns (4) and (8), the focus is restricted to uncommon surnames, namely, those that in the extended sample have a frequency lower than the first quartile of the coeval surname distribution and for which the likelihood of identifying direct links is expected to be higher. Each column also reports the average frequency of surnames, the number of families (surnames) in each sample employed for estimation, and the fraction of the children's population observed in the respective census (1457 or 1480) captured by the sample used for estimation (our percentages compare to those reported by Ager et al., 2021, of about 17%).

In the individual-level specification, whose results are reported in columns (1) and (5), the slope coefficients, β_{-1}, for the two subsequent censuses are precisely estimated and remarkably similar: 0.483 (between 1427 and 1457) and 0.487 (between 1457 and 1480). The estimated intercepts, $\hat{\beta}_0$, go from 24.802 (between 1427 and 1457) to 27.232 (between 1457 and 1480). Exploiting these figures, the absolute upward mobility totals 36.887 ($24.802 + 25 \times 0.483$) in 1457 and remains very similar in 1480 (39.407). These numbers imply that a household in a family with a rank below the median of the wealth distribution in the parents' generation at $t-1$ should be expected to have a percentage rank approximately between 37 and 39.

We can rationalize the observed differences between the remaining coefficients (listed in columns (2)-(4) and (6)-(9)) and those reported in columns (1) and (5), relying on the discussion reported

[13] Chetty et al. (2014) and Acciari et al. (2022), in their analysis, compare the estimated absolute upward mobility across regions or provinces. In our study, based on one city only, if we could recover the entire set of links for the full sample, we would observe an average percentile rank equal to 50; the intercept would then be equal to $50 - 50 \times \hat{\beta}_{-1}$. As we explained, however, we are able to identify only a subset of the family links in our data; thus, in our samples, the average percentile rank may differ from 50. In conclusion, the estimated intercept and slope coefficient are not transformations of the same underlying object.

in Subsection 3.1. First, the point estimates for $\hat{\pi}_{-1}$ in the matched sample (columns (2) and (6)) are larger than those found for $\hat{\beta}_{-1}$ in both periods, suggesting that in the rank-rank relationship, the family has an additional informative value over and above that of the parent. Instead, the comparison of $\hat{\pi}_{-1}$ in the extended sample (columns (3) and (7)) and $\hat{\beta}_{-1}$ (matched sample) gives mixed conclusions: in the 1427-1457 period, $\hat{\beta}_{-1}$ is larger than $\hat{\pi}_{-1}$, while in the 1457-1480 period, the opposite holds. As explained in Subsection 3.1, it is possible that in the most recent period, the extended sample contains more direct links than the previous one or that, *ceteris paribus*, the family effect in the extended sample is stronger in 1457-1480 than in 1427-1457. Importantly, the π_{-1} coefficients estimated on the extended sample are in the same ballpark of the estimated β_{-1} coefficients, thus suggesting that the results obtained on the extended sample might be deemed reliable. Finally, when we move from column (3) to column (4) and from column (7) to column (8), we observe an unsurprising, but modest, increase in $\hat{\pi}_{-1}$, the reason being that by focusing on less frequent surnames, we increase the likelihood of identifying direct links in the extended sample.

Then, we explore intergenerational mobility at the top of the distribution. To do so, we estimate equation (1) as a linear probability model where y_{ijt} and y_{ijt-1} are binary indicators for having individual i with surname j in the top decile of the wealth distributions, respectively, in t and $t-1$. Similarly, we estimate equation (2) by employing the correspondent top decile indicators as wealth outcomes. The results are reported in Table 1 for the two subsequent periods, 1427-1457 (Panel C) and 1457-1480 (Panel D).

The estimated intercept, $\hat{\beta}_0$, captures the average probability of being in the top decile of the wealth distribution for an individual conditional on having his/her parent with a wealth status below the top decile. In contrast, the estimated slope, $\hat{\beta}_{-1}$, captures the correlation between the probabilities of being in the top wealth decile across two subsequent generations.[14] The picture emerging from our results is that of a society that presents some degree of persistence, captured by a relatively large $\hat{\beta}_{-1}$ in Panels C and D of Table 1, but that is not completely immobile at the top of the distribution. In the individual-level specification (columns (1) and (5)), the unconditional probability of being at the top decile is equal to 0.117 in the 1427-1457 period and 0.070 in 1457-1480, while the estimated slope coefficients are 0.216 and 0.282, respectively.

As the literature on intergenerational mobility focuses mainly on the transmission of income and socioeconomic status, to place our baseline results in a broader context, we can compare our findings with a few recent studies that focus on the intergenerational transmission of wealth in

[14]The slope coefficients can also be interpreted as the difference in probability of being in the top decile for a child with and without a parent at the top of the distribution.

modern societies. Using Swedish data and a sample matching parents and children, Adermon et al. (2018) report percentile rank correlation between two-adjacent generations in the range between 0.30 and 0.40. Black et al. (2020), also employing data from Sweden but considering adopted children, find an intergenerational wealth correlation of 0.27. Pfeffer and Killewald (2018), examining U.S. data, find an average rank slope correlation in the range 0.31-0.39, a result in line with a previous study by Charles and Hurst (2003). Despite these coefficients being smaller than that returned by our estimated parent-child percentage rank correlation, from a comparative perspective, Florentine society in the late Middle Ages does not seem to be dramatically less mobile than recent societies. The fact that Florence at that time was not an immobile society, as one might expect, has been noted by historians and social scientists alike (Lopez, 1976; Padgett, 2010), contributing to abandoning the myth of the Middle Ages as a socially immobile world (Carocci, 2011; Goldthwaite, 1980).

4 Models of wealth transmission across multiple generations

4.1 Persistence across two non-adjacent generations

The analysis in the previous section focused on two-generation models. We now exploit the presence of multiple generations in our data and additional information about the demographic characteristics of the households to further explore the mechanism of wealth status transmission across time and infer predictions for the long run.

Applying standard iteration, the simple relationship in model (1) implies that, after m generations, the correlation between the first and the last generation would be equal to β_{-1}^{m} (under the assumption of constant correlation) or to the product of the correlation coefficients (in the case of variable correlation across time). Following this procedure, the implied long-run correlation between the wealth outcomes of the grandchildren's generation registered in 1480 and those of grandparents' generation observed in 1427, $\tilde{\beta}_{-2}$, would turn out as shown in Panels A and B of Table 2 (bootstrapped standard errors with 1,000 replications reported). For instance, the predicted coefficient in the first column of Panel A, 0.235, is given by 0.483×0.487 from columns (1) and (5) of Table 1.

As discussed by several authors, most notably by Solon (2018), these extrapolations are likely to neglect important factors underlying the process of wealth status transmission and might lead to overestimating long-run intergenerational mobility. To verify this, we compare the predicted coefficients in Panels A and B of Table 2 with those estimated from the following (individual- level and surname-level) regressions:

$$y_{ijt} = \beta_0 + \beta_{-2} y_{ijt-2} + u_{ijt}, \tag{5}$$

$$y_{ijt} = \pi_0 + \pi_{-2} \bar{y}_{jt-2} + v_{ijt}, \tag{6}$$

where the notation is as in models (1) and (2), respectively, and y_{it} and y_{it-2} refer to the wealth outcomes of sons in 1480 and grandfathers in 1427, respectively. Panels C (percentile ranks) and D (top deciles) of Table 2 report the estimation output. Columns (1) and (5) show the results for model (5) and the matched sample. Columns (2) and (6) list estimated coefficients from model (6) and, again, the matched sample. The remaining columns report estimation output from model (6) and the extended sample, with and without restriction to uncommon surnames, as previously discussed.

As one can see, the estimated coefficients, $\hat{\beta}_{-2}$ and $\hat{\pi}_{-2}$, are systematically larger than the corresponding coefficients obtained from the iteration, $\tilde{\beta}_{-2}$ and $\tilde{\pi}_{-2}$, suggesting that extrapolation from a simple two-generation model, such as model (1), leads to overestimating the degree of mobility in the long run. In the last part of Table 2 (Panels E and F), we also test the equality between the coefficients and find that, despite the limited amount of observations, the coefficient differences are, with few exceptions, different from zero at conventional levels of statistical significance.

Table 2 about here.

4.2 Multigenerational models

The literature suggests two alternative approaches consistent with the empirical finding that the estimated correlation coefficient between two non-adjacent generations turns out larger than that implied by iterating the canonical autoregressive model (for a discussion, see Solon, 2018). The first is the "grandparental effects model", in which the impact of grandparents on their descendants' economic status is predicted to be direct. For instance, according to this approach, grandparents transfer knowledge or material resources directly to their grandchildren (e.g., Mare, 2011). Therefore, the coefficient on the $t-2$ generation outcomes, β_{-2} in model (5) (or π_{-2} in model (6), depending on the adopted specification) would absorb these effects that are not captured by β_{-1} in model (1) (π_{-1} in model (2)) and its iteration over two periods. In the direct grandparental effects model, we expect a positive coefficient on the $t-2$ generation outcomes conditional on the effects coming from the $t-1$ generation.

The second approach is the "latent factor model" (Clark, 2014), in which economic status is transmitted indirectly from one generation to another through an endowment model. Accordingly, it predicts that some variable (call it the "latent factor"; for example, preferences, ability, and human capital) exists that is imperfectly correlated with wealth and is inherited across generations. Denoting the latent factor by e_{it} (endowment), the underlying transmission process would be (see also Braun and Stuhler, 2018):

$$
\begin{aligned}
y_{it} &= \rho e_{it} + \epsilon_{it}, \\
e_{it} &= \lambda e_{it-1} + \zeta_{it},
\end{aligned}
\tag{7}
$$

where ρ and λ are the transferability and heritability parameters and are assumed to be less than or equal to one, while ϵ_{it} and ζ_{it} are error terms.[15] When $\rho = 1$, λ is equal to β_{-1} in model (1). In this case, the slope coefficient β_{-2} in model (5) would be equal to $\lambda^2{=}\beta_{-1}^2$, and thus $\hat{\beta}_{-1}$ obtained from model (1) can be correctly employed for iteration to predict mobility over two periods and, more generally, across multiple generations. In contrast, when $\rho < 1$, and the observed data-generating process follows model (7), the slope coefficient β_{-1} of model (1) turns out equal to $\rho^2\lambda$, and the slope coefficient β_{-2} of model (5) is equal to $\rho^2\lambda^2$.[16] Thus, if the latent factor model governs actual transmission of wealth status across generations, by iterating model (1) over two periods, we always obtain an implied correlation, $(\rho^2\lambda)^2$, which leads to overestimating the true degree of mobility (underestimating the true degree of correlation), $\rho^2\lambda^2$. Importantly, as also shown by Braun and Stuhler (2018), when data on multiple generations are available, we can empirically assess the parameters λ and ρ by exploiting the relations above.

The reason why, under a latent factor model, the true correlation between wealth outcomes between m non-adjacent generations is underestimated when inferred by iteration of model (1) can be summarized as follows: in this approach, what is passed on from parents to children is not wealth itself (as we would impose by iterating) but, rather, the endowment (the latent factor) that is transmitted from generation to generation (m times) according to the autocorrelation parameter λ and, then, transformed (*once*) into wealth for each of the two generations according to the parameter ρ, which is possibly smaller than one. Therefore, shocks to the wealth status of intermediate

[15]For the sake of simplicity, when discussing the latent factor model, we suppress the subscript j indicating the family (surname), although the endowment can also be regarded as a factor transmitted at the family level.

[16]From model (7), this result can be easily obtained by noting that the slope coefficient between y_{it} and y_{it-1} is equal to $\rho^2\lambda$ (under the assumption of normalization of the variances of e_{it} and y_{it} to one). Similarly, the slope coefficient between y_{it} and y_{it-2} (β_{-2}) is equal to ρ^2 times the slope coefficient between e_{it} and e_{it-2} that equals λ^2. More generally, the slope coefficient between y_{it} and y_{it-m} is equal to $\rho^2\lambda^m$.

generations ($t-1$, $t-2$, ... $t-m+1$) do not affect the correlation between the wealth status of generation t and that of generation $t-m$.[17]

Both approaches, the grandparental effects and the latent factor model, not only imply a higher long-run correlation than that implied by extrapolation from model (1) but also predict a positive coefficient on the grandparents' outcomes, y_{t-2}, in the following (individual-level and surname-level) models:

$$y_{ijt} = \gamma_0 + \gamma_{-1} y_{ijt-1} + \gamma_{-2} y_{ijt-2} + \eta_{ijt}, \tag{8}$$

$$y_{ijt} = \delta_0 + \delta_{-1} \bar{y}_{jt-1} + \delta_{-2} \bar{y}_{jt-2} + \theta_{ijt}, \tag{9}$$

which are modifications of models (1) and (2) by including outcomes from generation $t-2$ (y_{jt-2} and $\bar{y}_{jt-2}$). If the true data-generating process followed the latent factor model, the parameters γ_{-2} and δ_{-2} would turn out to be positive because they would capture part of the variation of the latent factor that is omitted in regressions (8) and (9) because ρ is less than one (see Clark and Cummins, 2015).

The results from the estimation of models (8) and (9) using data for the three adjacent generations observed in 1480, 1457, and 1427 are listed in Panels A (percentile ranks) and B (top deciles) of Table 3. It is shown that the coefficients on the wealth positions of generations in $t-1$ and $t-2$ ($\hat{\gamma}_{-1}$ and $\hat{\gamma}_{-2}$ or $\hat{\delta}_{-1}$ and $\hat{\delta}_{-2}$, depending on the specification) are sizable and statistically significant. For instance, looking at individual-level results from the matched sample, reported in columns (1) and (5), the parents' and grandparents' coefficients turn out equal to 0.284 and 0.254, respectively, when we employ the wealth percentile ranks as wealth outcomes, and to 0.087 and 0.134, respectively, when the top deciles are considered. Turning to consider results from the extended sample, displayed in columns (3) and (7), we observe larger estimated coefficients associated with the $t-1$ generation and equal to 0.471 and 0.302 for the percentile ranks and the top deciles, respectively. Estimated coefficients on the $t-2$ generation wealth positions are smaller but still statistically significant, equal to 0.092 and 0.081, and more in line with other studies examining multigenerational mobility (see, in particular, Braun and Stuhler, 2018, and Adermon et al., 2018).

Table 3 about here.

[17] Consider, for instance, an individual living in period $t-1$ who inherits a large endowment and comes from affluent parents living in period $t-2$ but, for any random reason, does not achieve a relatively high wealth status in his/her life. As, according to the latent factor model, this individual will pass on to his/her offspring the endowment and not wealth itself, it is still possible that the wealth status of the grandchildrens' generation will be positively correlated with that of the grandfathers. Therefore, the persistence of economic status across generations living at t and $t-2$ turns out higher than what we would infer from looking at the mobility between adjacent generations two by two.

4.3 Latent factor model versus grandparental effects model

Discriminating between the direct grandparental effects approach and the latent factor model is challenging because they are observationally in many respects equivalent. Nonetheless, we exploit the complementary information included in our dataset and the presence of multiple generations to collect some evidence in favor of or against the two mechanisms of wealth status transmission.

Table 4 about here.

First, employing the three-generation model, we exploit data availability on the household's age in the 1427 *Catasto* and estimate model (8) by splitting the sample according to the age of the grandparents. Following the historical literature that documents the mean age at death of European elites in the early modern era of 57 years (Cummins, 2017), we adopt 57 as the threshold age: grandparents who report an age above this threshold in the 1427 *Catasto* are very unlikely to have had direct contact with descendants observed in the 1480 *Catasto*. As we can see from columns (2) and (4) of Panel A in Table 4, we still observe a sizable estimated $\hat{\gamma}_{-2}$ for children who are unlikely to have met their grandparent. This evidence is consistent with the idea that the effect of grandparental outcomes observed in Table 3, at least in part, operates through a latent factor.

Second, we exploit the information included in the 1457 *Catasto* on the number of family members living with their parents. This number is expected to reflect the number of grandchildren of the grandparents observed in 1427. If the grandparents had a direct effect on their grandchildren registered in 1480, we expect to obtain a larger effect in families where the number of grandchildren is relatively smaller. The idea is that whatever grandparents pass to their grandchildren, for example material wealth in the form of gifts, inheritance, or skills, the amount of this endowment that benefited each grandchild decreases with the number of recipients. This should imply a lower expected correlation between grandparents' and grandchildren's wealth outcomes, conditional on the parents wealth, for the more numerous families. In contrast, the transmission mechanism of a latent factor in model (7) should not be affected by the number of grandchildren. In Panel B of Table 4, we split the sample according to the median number of household members in 1457 equal to 7. As one can observe, there is not a clear pattern indicating that the estimated coefficient on grandparents' outcomes, $\hat{\gamma}_{-2}$, is systematically smaller for grandchildren who potentially shared their grandparental interactions with many other household members of their generation.

Finally, we exploit information on a fourth generation of households available in our dataset obtained from the 1403 *Prestanze* registers and run modification of models (8) and (9) after including the great-grandparents' generation wealth outcomes, y_{ijt-3} and $\bar{y}_{ijt-3}$, respectively. As explained in Section 2, these data allow us only to infer which individuals were in the top decile of the 1403 wealth distribution; thus, we can implement this exercise only for top deciles and consider the period 1403-1427-1457-1480.[18] Since a direct effect of great-grandparents observed as household heads in 1403 on descendants observed in 1480 is implausible in the Middle Ages, a positive coefficient on y_{ijt-3} ($\bar{y}_{ijt-3}$) is expected to capture unobserved characteristics at the parental level, thus supporting the latent factor model and challenging the hypothesis that a direct effect between ancestors and their offspring drives the correlation between wealth outcomes of the two non-adjacent generations. In Table 5, we present the results of this exercise. When we use the matched sample (columns (1) and (2)), we obtain very small estimated coefficients, $\hat{\gamma}_{-3}$ and $\hat{\delta}_{-3}$, which turn out not statistically different from zero: with a limited number of observations, there is a too limited amount of variation in y_{ijt-3} ($\hat{y}_{ijt-3}$), conditionally on y_{ijt-1} and y_{ijt-2}, to identify the great-grandparents' effect. Instead, in the extended sample (columns (3) and (4)), we find a sizable and statistically significant coefficient on y_{ijt-3} ($\bar{y}_{ijt-3}$). Thus, we are induced not to reject the hypothesis that the effect of great-grandparents' wealth outcomes on great-grandchildren's wealth outcomes is non-negligible, again corroborating the latent factor model.

Table 5 about here.

Given the evidence reported above, we can empirically assess the heritability and transferability parameters of model (7), λ and ρ. As discussed in the previous section, given that, with three generations $\lambda = \beta_{-2}/\beta_{-1}$ and $\rho = (\beta^2_{-1}/\beta_{-2})^{1/2}$, employing $\hat{\beta}_{-1}$ reported in column (5) of Panel B of Table 1 and $\hat{\beta}_{-2}$ reported in column (1) of Panel C of Table 2, we obtain $\tilde{\lambda} = 0.895$ [0.251], $\tilde{\rho} = 0.738$ [0.121] (bootstrap s.e. from 1,000 replications in brackets). Although the estimated λ found with our data is statistically different from zero, we cannot exclude that it is different from those found by the existing literature at conventional levels of statistical significance, relying on coefficient test based on 1,000 bootstrap replications (for example, Clark, 2014 finds the implied λ to be equal to 0.75 for modern England, while Braun and Stuhler, 2018 report a range between 0.494

[18] Notice that, as explained in Section 2, the *Prestanze* allows us to know only the inclusion of households in the top decile and not to observe the whole wealth distribution. Furthermore, consider that, since the 1427 *Catasto* reports only two names (first name and patronymic), beyond the surname, of the household head, the matching procedure for the identification of direct links could rely only on the surname and one name (avonymic in 1457 or patronymic in 1427) to be matched with the surname and the first name in 1403. This procedure would not be very reliable because individuals from the same family often have the same first name; thus, at least two names are necessary for identification. To minimize mismatches and to maximize the number of observations to employ in estimation, we then define y_{ijt-3} to be equal to one if at least one household in family j is registered in the *Prestanze* registers, and to zero otherwise.

and 0.699 for 20th-century Germany).[19] It is worth noting that a high intergenerational persistence of the latent factor in Middle Ages Florence is not at odds with a relatively high intergenerational mobility in the short run. Idiosyncratic shocks to individual wealth may increase mobility in the short run despite a high persistence of the latent factor, a circumstance that seems plausible in a society, which lacked social protection institutions. Indeed, our estimated $\tilde{\rho} = 0.738$ implies that about 45% of cross-sectional variation in wealth should be explained by variation in shocks orthogonal to the latent factor.[20]

4.4 Predictions for the long run

In this subsection, we evaluate the implications of the estimated parameters presented so far for intergenerational mobility in the long run. In particular, we employ our estimated coefficients for out-of-sample predictions and compare them with the long-run estimated correlation coefficients offered by recent related literature. Barone and Mocetti (2021), in their assessment of the economic status persistence across six centuries in Florence, find estimated percentage wealth rank-rank coefficients between 1427 and 2011 (19 generations according to their computations) that range between 0.120 and 0.082.[21]

We implement this analysis by employing individual-level estimation coefficients reported in the previous sections. To iterate model (1) over a time horizon of up to 19 generations, we consider $\hat{\beta}_{-1}$ estimated for wealth percentile ranks and for 1480-1457, reported in column (1) of Panel B of Table 1, equal to 0.487 (should we adopt the corresponding coefficient estimated for 1457-1427 results would not change in any significant way). As for the grandparental transmission model (8), we employ estimated coefficients, $\hat{\gamma}_{-1}$ and $\hat{\gamma}_{-2}$, for 1480-1457-1427 in column (1) of Table 3: 0.284 and 0.254.

Finally, exploiting the implied heritability and transferability parameters, $\hat{\lambda}$ and $\hat{\rho}$, reported at the end of the last subsection, we iterate the latent factor model (7) over 19 generations (as we have seen in footnote 16, $\beta_{-m} = \rho^2\lambda^m$). To extrapolate predictions out of sample, we need to make assumptions on how correlations between adjacent generations change over time after 1480. As a conservative approximation (first scenario), we consider these parameters to be time invariant. As an alternative hypothesis (second scenario), we assume λ to progressively decline over time at a

[19] While Adermon et al. (2018) do not focus on the latent factor model, their multigenerational analysis on wealth in Sweden implies a λ parameter of about 0.7.

[20] Considering the first equation of model (7) and the normalization of the variances of y_{it} and e_{it} to one, we have that the variance of y_{it} equals $\rho^2 + var(\epsilon_{it})$.

[21] While Barone and Mocetti (2021) implement their estimates on income and wealth data, the most sensible comparison with our results is with their estimated parameters on wealth percentile ranks reported in Panel B of Table 3 of their paper.

degree of 1% after each generation (we maintain ρ constant, but results would not be significantly affected should we assume it to change over time).

Figure 1 about here.

The results are depicted in Figure 1, where the range of estimates reported by Barone and Mocetti (2021) is indicated by the shaded area. As one can see, the correlation coefficients across m generations computed adopting the first two approaches show quite short longevity in the wealth status transmission process: about seven generations the iterative model and about 13 generations the grandparental model. In contrast, the latent factor model predicts persistence for a longer time: this approach, with our data, implies a positive wealth status correlation coefficient up to 17 generations in the second scenario and even after 19 generations in the first scenario. The latter predictions are also somehow closer to estimation results by Barone and Mocetti (2021), achieving the lower bound of their range after 14 generations.

Although in this exercise the implied intergenerational economic mobility is higher than that predicted by Barone and Mocetti (2021), the fact that, even under the assumption of constant parameters, we still find a positive degree of persistence after 19 generations is consistent with the ultimate sense of their findings, namely, a rank-rank wealth status coefficient that is non-negligible after almost six centuries.

5 Mechanisms of wealth status transmission

Previous findings suggest that the persistence of economic status across generations in 15th-century Florence is consistent with the transmission process of a latent factor from ancestors to offspring. While identifying the nature of this latent factor is challenging with our data, in this section, we investigate the underlying mechanisms by attempting to rule in and out alternative hypotheses that might be plausible in our context. We do this with the matched sample that allows us to perform a household-level analysis. Our exercise is driven by data availability and by the historical literature on our period of interest.

5.1 Occupation, spatial, and family heterogeneity

Wealth status transmission between two generations can occur in different dimensions. The first possibility is that, within some professional categories, parents pass on skills, abilities, and business connections to the next generation, thus creating professional dynasties. Under this hypothesis, the process of wealth status transmission would be driven by differences across groups of families that share the same prevalent parental occupation. The second hypothesis is that individuals with similar socioeconomic statuses tend to locate spatially (in the same neighborhood, for instance) close to each other and to reciprocally help within the spatial boundaries defining their group. In this case, the relevant variation to estimate mobility would be between neighborhoods. More generally, wealth status transmission might be driven by any mechanism working at the family level, including inheritance of the genetic endowment or any factors that are related to time-invariant family characteristics. In this case, our results would be explained by the variation in the process of economic status transmission between families, thus households with the same surname.

Figure 2 about here.

In Figure 2, we plot, for the two periods considered, the baseline estimated slope coefficients ($\hat{\beta}_{-1}$ from model (1) reported in Table 1) and the estimation output after including fixed effects for the prevalent family occupation in the parental generation. As one can see, the estimated coefficients remain almost unchanged in size, suggesting that in our data, there are no relevant factors working at the occupation level that lock wealth-relative positions within some professional dynasties and not in others (the regression output is reported in columns (2) and (5) of Table B.1).

Second, we investigate whether the estimated degree of intergenerational mobility in wealth outcomes could depend on spatial proximity among families. Households similar in cultural traits or economic status tend to settle in the same neighborhood, and this fact might trigger economic status transmission mechanisms at the local level. The results depicted in Figure 2 are obtained after including in model (1) the parental neighborhood of residence fixed effects (in the period of interest, Florence was divided into 16 neighborhoods, the *gonfaloni*). Again, the estimated coefficients are not smaller than the baseline ones (regression output in columns (3) and (6) of Table B.1).

Finally, we explore the broader role of heterogeneity at the family level by including in model (1) surname fixed effects. The results are also illustrated in Figure 2 (regression output in Table B.1 of Appendix B). A graphical inspection reveals that the inclusion of family fixed effects leads to a modest drop in the point estimates, suggesting that the economic status transmission is not mainly driven by genetic endowment or other time-invariant family characteristics consistently with findings by Ager et al. (2021) for the 19th-century U.S. Overall, our results hint at the presence of a latent factor transmission process at the household level.

5.2 The role of the marriage network and political participation

We now investigate the possible mechanisms that generate intergenerational mobility or economic status persistence. Our data allow us to look at two possible, not mutually exclusive, dimensions of interest: the marriage market and the political participation.

Figure 3 about here.

As suggested by Padgett (2010), Florentine families used the marriage system to create networks of economic and social interests. Accordingly, we investigate whether joining the marriage market promoted or hampered social mobility.[22] In Figure 3, we plot the estimated slope coefficient from model (1), splitting our sample into two groups. The first sample includes households from families that joined the marriage market (*cohesion* indicator, described in Section 2, changes from zero or one to a number equal to or larger than two) in the period of observation before that of wealth status registration (periods for the *cohesion* indicator defined by Padgett, 2010), namely, 1404-1433 when we consider the 1427-1457 period and 1434-1463 when we look at the 1457-1480 period.[23] The second includes those that had always been in or out the market (the value of the *cohesion* indicator does not change to cross the critical value of two). In the figure, we also report the baseline slope coefficient obtained with the full sample for which we observe a valid entry for the *cohesion* indicator (regression output in Table B.2 in Appendix B). As one can see, especially for the 1427-1457 period, mobility within the sample of families that joined the marriage market in the previous period of observation is higher than that estimated for the other group.[24] This exercise, consistent with Padgett (2010) and Molho (1971), indicates that access to the network of the interconnected Florentine families could be a source of mobility.

Figure 4 about here.

Second, being part of the political elite can be a channel for establishing connections and acquiring prestige and visibility; thus, the political participation of parents and ancestors might play a relevant role in explaining the process of wealth status transmission.

The political context, in the period of interest, was that of the Republic, whose government was formed by three main offices, the Standard-bearer of Justice and eight Priors, and two colleges, 12

[22]Botticini (1999) also examines in great detail the functioning of the marriage market in Tuscany in the period under analysis and, in particular, unveils the possibility of marriage links between individuals from different wealth statuses.

[23]Note that the variable that captures entry into the marriage market is collected at the family level.

[24]In Table B.3 in Appendix B, we also see that households belonging to families that have always been in the marriage market have a higher intergenerational correlation of wealth.

Good Men and 16 Standard-bearers of the Companies (Brucker, 1977). As discussed in Section 2, the office assignment mechanism was based on a mix of elections and lottery (so-called *Tratte*, see Belloc et al., 2022, for details). The system was clearly oligarchic, because to be elected citizens must be included on special lists; thus being part of the network of notable families in the city was a necessary condition for election (Padgett and Ansell, 1993). However, the *Tratte* system made political participation relatively open.[25] To investigate the role of political participation, we need to build individual-level variables that cover information on both parent and grandparent; thus, because of data limitations, we are induced to focus on the generation of children observed in 1480.[26]

We start by building a variable that captures the entry in the political elite: it is an indicator that is equal to one if an individual's father was part of the political elite (held at least one political office among those mentioned above before 1457) and his/her grandparent was not (in the period before 1427), and to zero otherwise. Then, we split the sample according to the values of this variable and estimate model (1). The results are reported in Figure 4 and show that the group of sons that had a father (but not a grandfather) in politics is characterized by higher intergenerational mobility measured by percentile ranks, although the difference in estimated coefficients is not statistically significant (regression output reported in Panels A and B of Table B.4 of Appendix B). This evidence is consistent with the idea that entry into the political network might open an opportunity for intergenerational economic mobility. In contrast, there is no difference in mobility rates across samples when we analyze mobility at the top of the distribution.

Figure 5 about here.

Next, we explore potential complementarities between entering into the political elite and being at the core of the family network of the marriage market. Following Padgett (2010), we define families as central in the network if they have a cohesion indicator (see Section 2) equal to or larger than four. The results of our exercise are reported in Figure 5 and reveal that, in the group of "core" families in $t-1$, there is a difference between the slope coefficients for individuals whose father (but not the grandparent) entered into the political elite and the other households (regression output reported in Table B.5 of Appendix B). This difference is null when we consider families outside the core. This evidence suggests that participation in politics might favor mobility only for families who

[25]As discussed in Belloc et al. (2022), this system was eventually captured by the Medici family starting in the third decade of the 15th century.

[26]Remember that we do not observe the avonymic in 1427, thus we cannot identify individuals living in 1403, but only families.

are centrally connected in the city social network. Again, no conclusion can be drawn by looking at the top deciles.

We conclude our analysis by looking at political dynasties. Accordingly, we define an indicator that is equal to one if both the father and the grandfather held political offices in their relevant periods (before than 1457 and 1427, respectively). The emerging picture from Figure 6, when looking at percentile ranks (left panel) is that households whose ancestors were members of political dynasties have a higher persistence of wealth status compared to other households (regression output reported in Panels C and D of Table B.4 of Appendix B). Taken together, these results provide suggestive evidence that, in late medieval Florence, intergenerational economic mobility for households was associated with the possibility of having access to the political network, and then persistence of the economic status was favored by staying in the network.

Figure 6 about here.

6 Conclusions

This study contributes to the literature on intergenerational mobility of economic status by providing the first analysis of wealth outcome transmission over multiple generations in the late Middle Ages. Our data, covering four subsequent generations observed for a period of about one century, allow us to improve our understanding of the process of economic outcomes transmission recently documented by many scholars (Solon, 2018; Chetty et al., 2014; Black and Devereux, 2010) and complement research on the very long-run persistence of economic status implemented in other papers (Barone and Mocetti, 2021).

The picture of Florence at the dawn of the Renaissance that emerges from our analysis is one of a relatively mobile society. We find correlation coefficients across generations in the range of 0.4-0.5 when we consider wealth percentile ranks and in the range of 0.2-0.3 when we investigate economic status mobility at the top of the wealth distributions. Our study also digs into the transmission mechanisms exploring predictions and relative performance of alternative theoretical approaches offered by the relevant literature, the canonical first-order autoregressive model, the grandparental effect model, and the latent factor model, finding support for the latter.

Our estimates are also used to look at the very long run and lead us to confirm that, under a latent factor model approach, although the implied correlation coefficient is smaller than that estimated by Barone and Mocetti (2021), the longevity of wealth status persistence might be predicted to remain positive along a time horizon of 19 generations. Finally, we analyze several hypotheses regarding the nature of the factors underlying the transmission of economic status and unveil the role played, in our context, by social (marriages) and political (participation in the city government) networks.

Although these results are far from conclusive, our work advances knowledge of economic status mobility across generations and calls for future research through archival work to further clarify the underlying mechanisms.

References

Acciari, P., A. Polo, and G. L. Violante (2022). "And yet it moves": Intergenerational mobility in Italy. *American Economic Journal: Applied Economics 14*(3), 118–163.

Adermon, A., M. Lindahl, and D. Waldenström (2018). Intergenerational wealth mobility and the role of inheritance: Evidence from multiple generations. *Economic Journal 128*(612), F482–F513.

Adermon, A., M. Lindhal, and M. Palme (2021). Dynastic human capital, inequality, and intergenerational mobility. *American Economic Review 111*(5), 1523–1538.

Ager, P., L. Boustan, and K. Eriksson (2021). The intergenerational effects of a large wealth shock: White southerners after the civil war. *American Economic Review 111*(11), 3767–3794.

Alesina, A., S. Hohmann, S. Michalopoulos, and E. Papaioannou (2021). Intergenerational mobility in Africa. *Econometrica 89*(1), 1–35.

Barone, G. and S. Mocetti (2021). Intergenerational mobility in the very long run: Florence 1427–2011. *Review of Economic Studies 88*(4), 1863–1891.

Belloc, M., F. Drago, M. Fochesato, and R. Galbiati (2022). Wealth accumulation and institutional capture; the rise of the Medici and the fall of the Florentine republic. *CEPR - Discussion Paper* (17456).

Black, S. and P. Devereux (2010). Recent developments in intergenerational mobility. In O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, pp. 1487–1541. Amsterdam: Elsevier.

Black, S., P. Devereux, P. Lundborg, and K. Majlesi (2020). Poor little rich kids? the determinants of the intergenerational transmission of wealth. *Review of Economic Studies 84*(7), 1683–1725.

Boserup, S. H., W. Kopczuk, and C. T. Kreiner (2017). Intergenerational wealth formation over the life cycle: Evidence from Danish wealth records, 1984-2013. *Columbia University*, 1–37.

Botticini, M. (1999). Loveless economy? intergenerational altruism and the marriage market in a tuscan town, 1415-1436. *Journal of Economic History 59*(1), 104–121.

Braun, T. S. and J. Stuhler (2018). The transmission on inequality across multiple generations: Testing recent theories with evidence from Germany. *Economic Journal* (128), 576–611.

Brucker, G. (1977). *The Civic World of Early Renaissance Florence.* Princeton: Princeton University Press.

Carocci, S. (2011). Social mobility and the Middle Ages. *Continuity and Change 26*(3), 367–404.

Charles, K. and E. Hurst (2003). The correlation of wealth across generations. *Journal of Political Economy*.

Chetty, R., N. Hendren, P. Kline, and E. Saez (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *Quarterly Journal of Economics 129*(4), 1553–1623.

Clark, G. (2014). *The Son Also Rises: Surnames and the History of Social Mobility.* Princeton: Princeton University Press.

Clark, G. and N. Cummins (2015). Intergenerational wealth mobility in England, 1858-2012: surnames and social mobility. *Economic Journal 125*, 61–85.

Cummins, N. (2017). Lifespans of the european elite, 800-1800. *Journal of Economic History 77*(2), 406–439.

Dahl, M. W. and T. DeLeire (2008). *The association between children's earnings and fathers' lifetime earnings: estimates using administrative data.* University of Wisconsin-Madison, Institute for Research on Poverty.

Goldthwaite, R. A. (1980). *The Building of Renaissance Florence: An Economic and Social History.* Johns Hopkins University Press.

Goldthwaite, R. A. (2009). *The Economy of Renaissance Florence.* Johns Hopkins University Press.

Guell, M., M. Pellizzari, G. Pica, and J. Rodríguez Mora (2018). Correlating social mobility and economic outcomes. *Economic Journal 128*(612), 353–403.

Hanus, J. (2012). Economic growth and income mobility in the sixteenth-century Low Countries. *Journal of European Economic History 11*(1), 1–41.

Herlihy, D., R. Burr Litchfield, A. Molho, and R. Barducci (2002). Florentine Renaissance Resources: Online Tratte of Office Holders, 1282-1532.

Herlihy, D. and C. Klapisch-Zuber (1975). *Tuscans and Their Families: A Study of the Florentine Catasto of 1427.* Yale University Press.

Herlihy, D., C. Klapisch-Zuber, B. Litchfield, A. Molho, and R. B. . (2000). Online tratte of office holders.

Herlihy, D., C. Klapisch-Zuber, B. Litchfield, A. Molho, and R. Barducci (2002). Online *Catasto* of 1427. Version 1.3.

Killewald, A., F. Pfeffer, and J. Schachner (2017). Wealth inequality and accumulation. *Annual Review of Sociology 43*, 379–404.

Lindahl, M., M. Palme, S. Sandgren Massih, and A. Sjögren (2015). Long-term intergenerational persistence of human capital. *Journal of Human Resources 50*, 1–33.

Lopez, R. (1976). *The Commercial Revolution of the Middle Ages, 950-1350.* Cambridge University Press.

Mare, R. D. (2011). A multigenerational view of inequality. *Demography 48*, 1–23.

Martines, L. (1963). *The Social World of Florentine Humanists, 1390-1460.* Princeton University Press.

Milanovic, B., P. Lindert, and J. Williamson (2011). Pre-industrial inequality. *Economic Journal 121*(551), 255–272.

Molho, A. (1971). *Florentine Public Finances in the Early Renaissance, 1400-1433.* Cambridge: Harvard University Press.

Molho, A. (1994). *Marriage Alliance in Late Medieval Florence.* Cambridge: Harvard University Press.

Moody, J. and D. R. White (2003). Structural cohesion and embeddedness: A hierarchical concept of social groups. *American Sociological Review 68*(103-27).

Najemy, J. M. (2006). *A History of Florence, 1200-1575.* Blackwell Publishing.

Padgett, J. and C. Ansell (1993). Robust action and the rise of the Medici, 1400-1434. *American Journal of Sociology 98*(6), 1259–1319.

Padgett, J. F. (2010). Open elite? Social mobility, marriage, and family in Florence, 1282-1494. *Renaissance Quarterly 63*, 357–411.

Payling, S. (1992). Social mobility, demographic change, and landed society in late medieval England. *The Economic History Review 45*(1), 51–73.

Pfeffer, F. T. and A. Killewald (2018). Generations of advantage. Multigenerational correlations in family wealth. *Social Forces 96*(4), 1411–1442.

Piketty, T. (2014). *Capital in the Twenty-First Century.* Cambridge Massachusetts: The Belknap Press of Harvard University Press.

Piketty, T., G. Postel-Vinay, and J. Rosenthal (2006). Wealth concentration in a developing economy: Paris and France, 1807-1994. *American Economic Review 96*(1), 236–256.

Procacci, U. (1996). *Studio sul Catasto Fiorentino.* Olschki, Florence.

Santavirta, T. and J. Stuhler (2021). Name-based estimators of intergenerational mobility. Technical Report, Stockholm University.

Solon, G. (2018). What do we know so far about multigenerational mobility. *Economic Journal 128*, F340–F352.

van de Putte, B., M. Oris, and K. Matthijs (2009). Marrying out of the lower classes in nineteenth century belgium. *Continuity and Change 24*(3), 421–453.

van Leeuwen, M., I. Maas, D. Rebaudo, and J.-P. Pelissier (2015). Social mobility in France 1720-1986: Effects of war, revolution and economic change. *Journal of Social History*.

Tables and figures

Table 1: Wealth status transmission across two adjacent generations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reg. coefficient:	Panel A: Percentile ranks 1457-1427				Panel B: Percentile ranks 1480-1457			
$\hat{\beta}_{-1}$	0.483				0.487			
	(0.059)				(0.036)			
$\hat{\beta}_0$	24.802				27.232			
	(5.156)				(2.942)			
$\hat{\pi}_{-1}$		0.600	0.393	0.410		0.533	0.510	0.529
		(0.065)	(0.038)	(0.053)		(0.045)	(0.031)	(0.045)
$\hat{\pi}_0$		15.301	34.678	31.457		23.805	28.163	25.337
		(5.599)	(2.698)	(3.635)		(3.492)	(2.090)	(2.860)
R-squared	0.845	0.844	0.812	0.799	0.867	0.858	0.823	0.806
Reg. coefficient:	Panel C: Top deciles 1457-1427				Panel D: Top deciles 1480-1457			
$\hat{\beta}_{-1}$	0.216				0.282			
	(0.035)				(0.031)			
$\hat{\beta}_0$	0.117				0.070			
	(0.016)				(0.013)			
$\hat{\pi}_{-1}$		0.218	0.298	0.354		0.307	0.350	0.361
		(0.041)	(0.037)	(0.059)		(0.040)	(0.037)	(0.050)
$\hat{\pi}_0$		0.116	0.130	0.106		0.061	0.085	0.084
		(0.018)	(0.010)	(0.014)		(0.014)	(0.009)	(0.011)
R-squared	0.266	0.246	0.242	0.247	0.286	0.254	0.221	0.231
Analysis level	Individual	Surname	Surname	Surname	Individual	Surname	Surname	Surname
Sample	Matched	Matched	Extended	Extended	Matched	Matched	Extended	Extended
Uncommon surnames	No	No	No	Yes	No	No	No	Yes
Observations	768	768	2,900	731	1,005	1,005	3,422	884
Number of surnames	326	326	671	417	370	370	664	416
% of full sample (sons)	19.7	19.7	74.5	18.8	24.9	24.9	84.8	21.9
Avg. freq. of surnames	2.4	2.4	4.3	1.8	2.7	2.7	5.2	2.1

Notes. Columns (1) and (5): coefficients estimated from equation (1); columns (2)-(4) and (6)-(8): coefficients estimated from equation (2). Percentile rank (Panels A and B) in t is the rank position of individual (family) i (j) in the wealth distribution of generation t. Top decile (Panels C and D) in t is a dummy variable equal to one if individual (family) i (j) is in the top decile of the wealth distribution of generation t, and to zero otherwise. Uncommon surnames occur with frequency smaller than the first quartile of the surname distribution. Family clustered s.e. in parentheses.

Table 2: Wealth status transmission across two non-adjacent generations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implied correlation:	Panel A: Percentile ranks 1480-1427				Panel B: Top deciles 1480-1427			
$\tilde{\beta}_{-2}$	0.235				0.061			
	[0.033]				[0.010]			
$\tilde{\pi}_{-2}$		0.320	0.200	0.217		0.067	0.104	0.128
		[0.044]	[0.021]	[0.032]		[0.013]	[0.013]	[0.026]
Reg. coefficient:	Panel C: Percentile ranks 1480-1427				Panel D: Top deciles 1480-1427			
$\hat{\beta}_{-2}$	0.436				0.155			
	(0.119)				(0.044)			
$\hat{\beta}_0$	27.845				0.043			
	(10.694)				(0.021)			
$\hat{\pi}_{-2}$		0.512	0.302	0.290		0.161	0.186	0.196
		(0.118)	(0.037)	(0.048)		(0.053)	(0.034)	(0.048)
$\hat{\pi}_0$		21.241	40.134	38.578		0.040	0.124	0.115
		(10.549)	(2.587)	(3.275)		(0.025)	(0.011)	(0.013)
R-squared	0.870	0.872	0.810	0.780	0.178	0.173	0.193	0.182
Coeff. difference:	Panel E: Percentile ranks 1480-1427				Panel F: Top deciles 1480-1427			
$\hat{\beta}_{-2} - \tilde{\beta}_{-2}$	0.201				0.094			
	[0.117]				[0.039]			
$\hat{\pi}_{-2} - \tilde{\pi}_{-2}$		0.193	0.101	0.073		0.094	0.081	0.068
		[0.118]	[0.035]	[0.048]		[0.044]	[0.025]	[0.040]
Analysis level	Individual	Surname	Surname	Surname	Individual	Surname	Surname	Surname
Sample	Matched	Matched	Extended	Extended	Matched	Matched	Extended	Extended
Uncommon surnames	No	No	No	Yes	No	No	No	Yes
Observations	223	223	3,194	1,011	223	223	3,194	1,011
Number of surnames	115	115	600	414	115	115	600	414
% of full sample (sons)	5.5	5.5	79.2	25.1	5.5	5.5	79.2	25.1
Avg. freq. of surnames	1.9	1.9	5.3	2.4	1.9	1.9	5.3	2.4

Notes. Columns (1) and (5): coeff.s estimated from equation (5); columns (2)-(4) and (6)-(8): coeff.s estimated from eq. (6). Perc. rank (Panels A, C, and E) in t is the rank position of individual (family) i (j) in the wealth distribution of generation t. Top decile (Panels B, D, and F) in t is a dummy variable equal to one if individual (family) i (j) is in the top decile of the wealth distribution of generation t, and to zero otherwise. Uncommon surnames occur with frequency smaller than the first quartile of the surname distribution. Family clustered s.e. in parentheses; bootstrap s.e. from 1,000 replications in brackets.

Table 3: Wealth status transmission across three adjacent generations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reg. coefficient:	Panel A. Percentile ranks 1480-1457-1427				Panel B. Top deciles 1480-1457-1427			
$\hat{\gamma}_{-1}$	0.284				0.087			
	(0.087)				(0.048)			
$\hat{\gamma}_{-2}$	0.254				0.134			
	(0.120)				(0.050)			
$\hat{\gamma}_0$	21.567				0.020			
	(8.535)				(0.020)			
$\hat{\delta}_{-1}$		0.349	0.471	0.479		0.101	0.302	0.336
		(0.113)	(0.040)	(0.051)		(0.072)	(0.041)	(0.051)
$\hat{\delta}_{-2}$		0.336	0.092	0.110		0.136	0.081	0.094
		(0.113)	(0.039)	(0.048)		(0.060)	(0.034)	(0.042)
$\hat{\delta}_0$		9.073	24.184	21.482		0.008	0.075	0.076
		(9.038)	(2.728)	(3.522)		(0.026)	(0.011)	(0.013)
R-squared	0.877	0.878	0.824	0.811	0.191	0.183	0.222	0.246
Analysis level	Individual	Surname	Surname	Surname	Individual	Surname	Surname	Surname
Sample	Matched	Matched	Extended	Extended	Matched	Matched	Extended	Extended
Uncommon surnames	No	No	No	Yes	No	No	No	Yes
Observations	223	223	3,077	909	223	223	3,077	909
Number of surnames	115	115	536	352	115	115	536	352
% of full sample (sons)	5.5	5.5	76.3	22.5	5.5	5.5	76.3	22.5
Avg. freq. of surnames	1.9	1.9	5.7	2.6	1.9	1.9	5.7	2.6

Notes. Columns (1) and (5): coefficients estimated from equation (8); columns (2)-(4) and (6)-(8): coefficients estimated from equation (9). Percentile rank (Panel A) in t is the rank position of individual (family) i (j) in the wealth distribution of generation t. Top decile (Panel B) in t is a dummy variable equal to one if individual (family) i (j) is in the top decile of the wealth distribution of generation t, and to zero otherwise. Uncommon surnames occur with frequency smaller than the first quartile of the surname distribution. Family clustered s.e. in parentheses.

Table 4: Wealth status transmission across three adjacent generations: Heterogeneity

	(1)	(2)	(3)	(4)
Reg. coefficients:	Panel A. Percentile ranks		Panel B. Top deciles	
$\hat{\gamma}_{-1}$	0.299	0.282	0.163	0.050
	(0.112)	(0.152)	(0.082)	(0.056)
$\hat{\gamma}_{-2}$	0.325	0.204	0.179	0.094
	(0.211)	(0.152)	(0.073)	(0.050)
$\hat{\gamma}_{0}$	15.365	24.613	0.021	0.008
	(16.133)	(9.795)	(0.030)	(0.022)
R-squared	0.863	0.895	0.271	0.128
Observations	113	110	113	110
Grandparents' age	≤ 57	> 57	≤ 57	> 57
Number of surnames	71	54	71	54
% of full sample (sons)	2.8	2.7	2.8	2.7
Avg. freq. of surnames	1.9	2.4	1.9	2.4
Reg. coefficients:	Panel C. Percentile ranks		Panel D. Top deciles	
$\hat{\gamma}_{-1}$	0.314	0.319	0.260	0.007
	(0.112)	(0.130)	(0.098)	(0.054)
$\hat{\gamma}_{-2}$	0.200	0.362	0.160	0.164
	(0.124)	(0.257)	(0.080)	(0.049)
$\hat{\gamma}_{0}$	26.278	6.679	0.011	-0.002
	(9.407)	(18.492)	(0.032)	(0.018)
R-squared	0.867	0.890	0.287	0.167
Observations	108	115	108	115
Household's members	≤ 7	> 7	≤ 7	> 7
Number of surnames	80	54	80	54
% of full sample (sons)	2.7	2.9	2.7	2.9
Avg. freq. of surnames	1.9	2.6	1.9	2.6

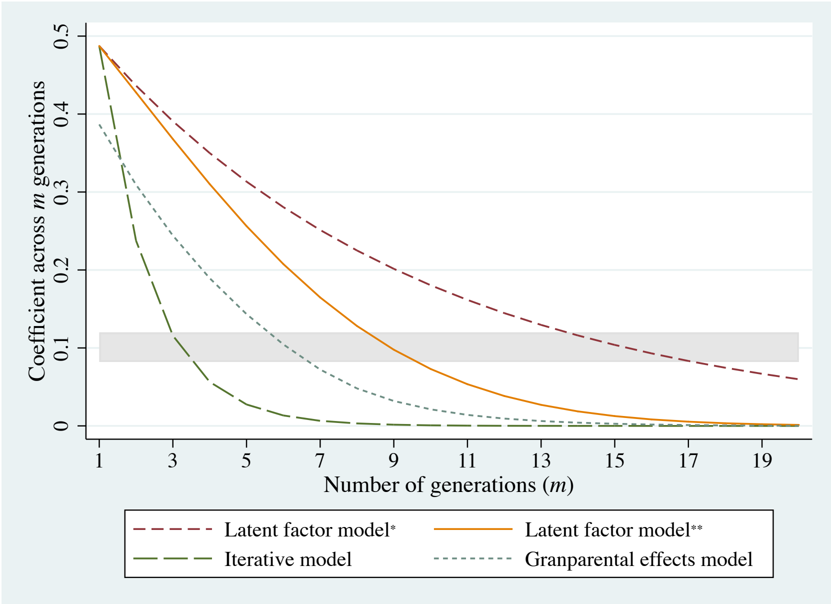
Notes. Coefficients estimated from equation (8). Percentile rank (Panels A and C) in t is the rank position of individual i in the wealth distribution of generation t. Top decile (Panels B and D) in t is a dummy variable equal to one if individual i is in the top decile of the wealth distribution of generation t, and to zero otherwise. Panels A and B report the split sample according to the median age of the grandfathers in 1427; panels C and D report the split sample according to the median number of family members in 1457. All columns refer to individual level analysis and matched sample. Family clustered s.e. in parentheses.

Table 5: Wealth status transmission across four adjacent generations

	(1)	(2)	(3)	(4)
Reg. coefficients:	Top deciles			
$\hat{\gamma}_{-1}$	0.095			
	(0.049)			
$\hat{\gamma}_{-2}$	0.113			
	(0.048)			
$\hat{\gamma}_{-3}$	0.053			
	(0.047)			
$\hat{\gamma}_{0}$	-0.006			
	(0.027)			
$\hat{\delta}_{-1}$		0.104	0.296	0.326
		(0.073)	(0.041)	(0.050)
$\hat{\delta}_{-2}$		0.118	0.063	0.078
		(0.061)	(0.033)	(0.042)
$\hat{\delta}_{-3}$		0.040	0.035	0.055
		(0.048)	(0.016)	(0.030)
$\hat{\delta}_{0}$		-0.010	0.063	0.067
		(0.033)	(0.012)	(0.014)
R-squared	0.195	0.185	0.223	0.249
Analysis level	Individual	Surname	Surname	Surname
Sample	Matched	Matched	Extended	Extended
Uncommon surnames	No	No	No	Yes
Observations	223	223	3,077	909
Number of surnames	115	115	536	352
% of full sample (sons)	5.5	5.5	76.3	22.5
Avg. freq. of surnames	1.9	1.9	5.7	2.6

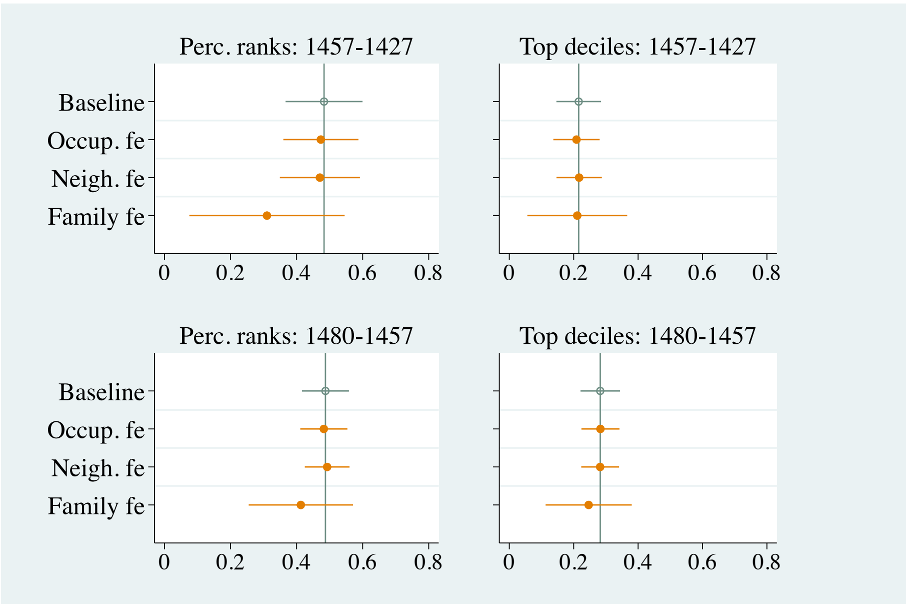
Notes. Coefficients estimated from equation (8) extended to four generations. Top decile in t is a dummy variable equal to one if individual (family) i (j) is in the top decile of the wealth distribution of generation t, and to zero otherwise. Uncommon surnames occur with frequency smaller than the first quartile of the surname distribution. Family clustered s.e. in parentheses.

Figure 1: Prediction of wealth status transmission from alternative models



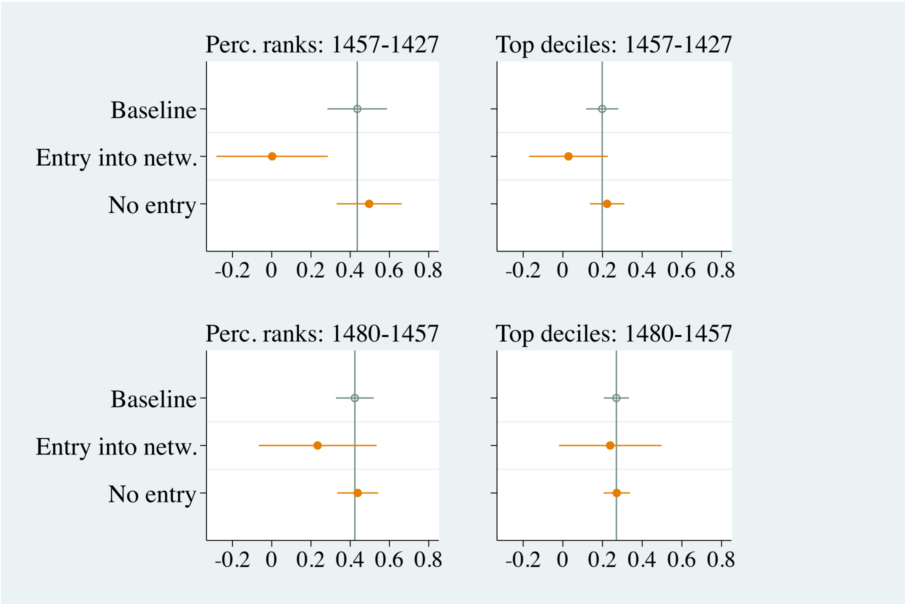
Notes: The picture shows the predicted correlation coefficients across m generations from alternative models employing estimated coefficients from the individual-level analysis: latent factor model, iterative model, and grandparental effects model. Implied coefficients for the latent factor model are $\tilde{\lambda} = 0.895$ [0.251], $\tilde{\rho} = 0.738$ [0.121], bootstrap s.e. from 1,000 replications in brackets. * predictions are obtained assuming constant $\tilde{\lambda}$;** predictions are obtained assuming that $\tilde{\lambda}$ declines by 1% every generation achieving the value of 0.738 after 19 generations. The shaded area depicts the range of the estimated coefficient across 19 generations by Barone and Mocetti (2021).

Figure 2: Wealth status transmission: Family, occupation, and neighborhood fixed effects



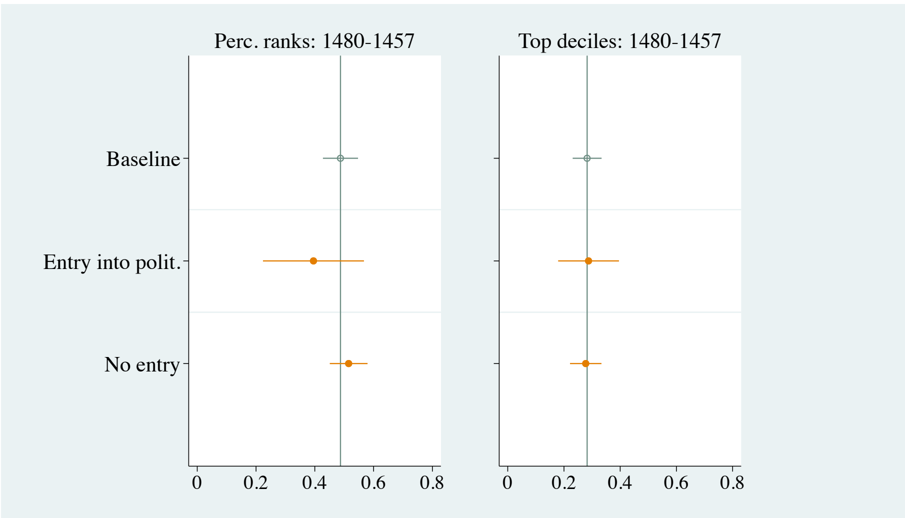
Notes: $\hat{\beta}_{-1}$ is estimated from equation (1) at the individual level on the matched sample with surname, occupation, and neighborhood fixed effects. Percentile rank in t is the rank position of individual i in the wealth distribution of generation t. Top decile in t is a dummy variable equal to one if individual i is in the top decile of the wealth distribution of generation t, and to zero otherwise. Confidence intervals at the 90% level reported; s.e. are family clustered.

Figure 3: Wealth status transmission: Marriage network



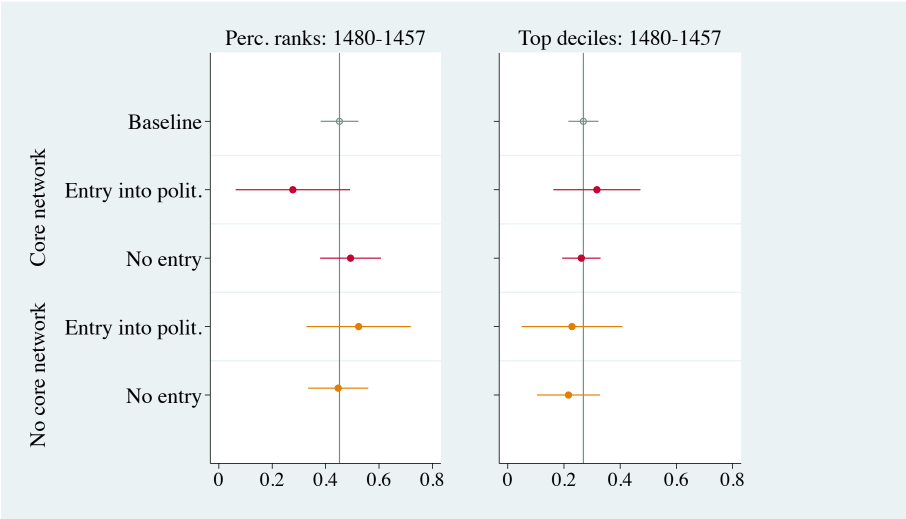
Notes: $\hat{\beta}_{-1}$ is estimated from equation (1) at the individual level on the matched sample after splitting between families that entered into the marriage network in $t-1$ and those that stayed always in or always out. Baseline is the estimated coefficient for the sample with valid entry of *cohesion*. Percentile rank in t is the rank position of individual i in the wealth distribution of generation t. Top decile in t is a dummy variable equal to one if individual i is in the top decile of the wealth distribution of generation t, and to zero otherwise. Confidence intervals at the 90% level reported; s.e. are family clustered.

Figure 4: Wealth status transmission: Political network



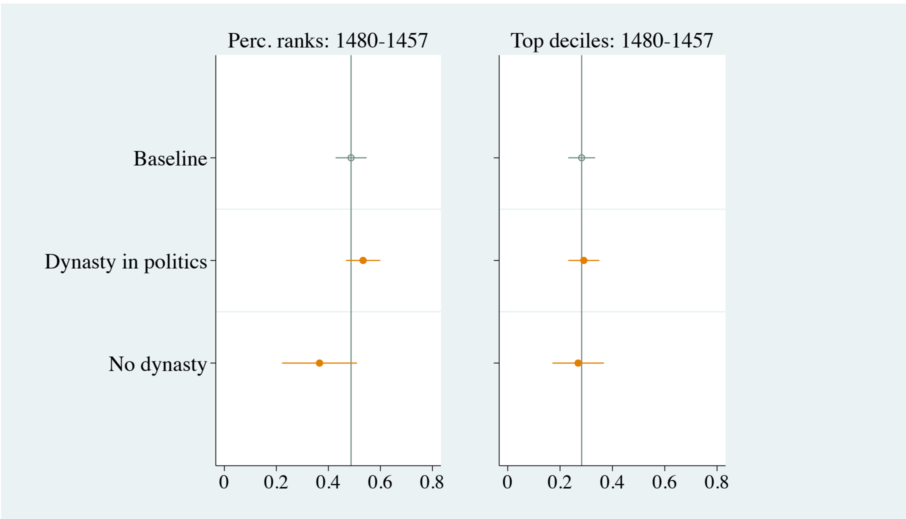
Notes: $\hat{\beta}_{-1}$ is estimated from equation (1) at the individual level on the matched sample after splitting between households who entered into the political elite (parent held at least one political office, grandparent held no political office) and those who stayed always in (both parent and grandparent held at least one political office) or out (neither parent nor grandparent held political office). Percentile rank in t is the rank position of individual i in the wealth distribution of generation t. Top decile in t is a dummy variable equal to one if individual i is in the top decile of the wealth distribution of generation t, and to zero otherwise. Confidence intervals at the 90% level reported; s.e. are family clustered.

Figure 5: Wealth status transmission: Political and marriage networks



Notes: $\hat{\beta}_{-1}$ is estimated from equation (1) at the individual level on the matched sample after splitting between households who entered into the political elite in $t-1$ (parent held at least one political office, grandparent held no political office) and those who stayed always in or out. Each group is further split between families who were at the core of the network in $t-1$ (cohesion indicator larger than or equal to four) and those who were not. Baseline is the estimated coefficient for the sample with valid entry of *cohesion*. Percentile rank in t is the rank position of individual i in the wealth distribution of generation t. Top decile in t is a dummy variable equal to one if individual i is in the top decile of the wealth distribution of generation t, and to zero otherwise. Confidence intervals at the 90% level reported; s.e. are family clustered.

Figure 6: Wealth status transmission: Political dynasties



Notes: $\hat{\beta}_{-1}$ estimated from equation (1) at the individual level on the matched sample after splitting between households who were a political dynasty since $t-2$ (grandparent with at least one political office and parent with at least one political office) and those who were not. Percentile rank in t is the rank position of individual i in the wealth distribution of generation t. Top decile in t is a dummy variable equal to one if individual i is in the top decile of the wealth distribution of generation t, and to zero otherwise. Confidence intervals at the 90% level reported; s.e. are family clustered.

Online appendix (not for publication) for the paper: "Multigenerational Transmission of Wealth: Florence 1403-1480" by Belloc, M., Drago, F., Fochesato, M., and R. Galbiati

A Data appendix: Spelling rules

In preparing the various datasets for the merging procedure, we verified that the spelling of names and surnames followed the same rules. We visually inspected the most similar records and evaluated their correspondence case by case. The spelling rules are defined according to the following sources: Herlihy et al. (2002), Molho (1994), and Padgett (2010). When it appeared that the same name or surname was written with a different rule, we followed the spelling used in the *Tratte* dataset.

Surnames
Concerning surnames, we implemented the following rules.

1. Variants and information on multiple surnames followed Herlihy et al. (2002). (https://cds.library.brown.edu/projects/tratte/doc/TLSNAM1VAR.html). Accordingly, when a family had two or more surnames as reported in Herlihy et al. (2002), we associated individuals always with the same single surname, that coming first in alphabetic order. For instance, ALDOBRANDINI, NERI and DELNERO according to Herlihy et al. (2002) were the same family, in our dataset NERI and DELNERO became ALDOBRANDINI.

2. Surnames were always truncated to 11 digits, and changed accordingly whenever in the original dataset this rule was not followed (this is true both when the surname reported in the original dataset was longer than 11 digits and when it was shorter -in general 10 digits long- with the last letter missing). For instance, ARDINGHELLI was changed in ARDINGHELL; BOLDRONCINI was changed in BOLDRONCIN; BRACCIOLINI was changed in BRACCIOLIN; DELLANTELL was changed in DALLANTELLA.

3. When multiple variants appear or in case of suspected typo mistakes, surnames were changed to follow the spelling rules in the *Tratte* dataset.

   A non exhaustive list of cases is reported below:

   (a) A letter of the surname is in a different position: for instance, BELFRADELLI and BELFARDELLI.

   (b) There is a double consonant instead of a single consonant (this can happen even twice in the same word): for instance, CERRINI and CERINNI; DAVIZZI and DAVIZI.

   (c) The *H* appears in some variants and not in others: for instance, DELTEGHIA and DELTEGLIA; BARDUCCHI and BARDUCCI.

   (d) There is a different vowel in the same position within the word: for instance, CAVICCIOLI and CAVICCIULI; CEFFINI and CEFFONI; CAMPIOBBESI and CAMPIUBESI.

(e) There is an extra vowel, in general the *I*: for instance, DELCECE and DELCIECE; TERI and TIERI.

(f) The vowel *O* appears in the place of the diphthong *UO* (following the *Tratte* we always kept *UO*): for instance, BONFIGLIO and BUONFIGLIUO.

(g) The prefixes *DE*, *DEGLI*, *DELLA*, *etc* not always appear: for instance, MEDECI and DEMEDICI; BAGLIONE and DELBAGLIONE.

(h) The letter *J* is used instead of *I*: for instance, JACOPI and IACOPI.

(i) A diminutive of the word is used: for instance, SASSOLI and SASSOLINI.

4. In few cases, we suspected typo errors in the *Tratte* dataset and changed them. For instance:

   (a) Both MATTEO BUONACCORSO GIANNI ALDEROTTI and MATTEO BUONACCORSO GIOVANNI ALDEROTTI appear in the dataset. We changed GIANNI in GIOVANNI.

   (b) Both GIOVANNI PIERO VANNI MANNUCCI and VANNI PIERO VANNI MANNUCCI appear in the dataset. We changed VANNI in GIOVANNI.

   (c) Both BUONACCORSO PAOLO CORBELLINI and BUONACCORSO PAOLO CORBELLINI appear in the dataset. We changed CORSELLINI in CORBELLINI.

   (d) Both MAFFEO CANTE CATTANO PITTI and MAFFEO CANTE GUATANO PITTI appear in the dataset. We changed CATTANO in GUATANO.

   (e) Both IACOPO GIOVANNI CIAIO ARRIGUCCI and IACOPO GIOVANNI CIARO ARRIGUCCI appear in the dataset. We changed CIAIO in CIARO.

First names, patronymics, and avonymics

Concerning names, general rules are more difficult to identify because names appeared in several different variants in the various datasets. A non exhaustive list of cases is reported below (the total list of case changes is available upon request):

1. Names were in general truncated to 11 digits, with the exception of the 1480 *Catasto* where they were truncated at 5 digits. Hence, whenever a name from one of the other datasets had to be matched with a name in the 1480 *Catasto*, it was truncated accordingly: for instance, GIOVANNI was changed in GIOVA.

2. The name has a number of diminutives: for instance, GUCCIO, GUCCIONE and GUCCIOZZO.

3. The name appears with double or single consonants: PIEROZZO and PIEROZO, MARCHIONNE and MARCHIONE.

4. *J* is used instead of *I* and *viceversa*: for instance, JACOPO and IACOPO.

5. An extra consonant appears between two vowels in some variants of the name: for instance, PAOLO and PAGOLO.

6. An extra vowel, in general *I*, appears in some variants of the name: for instance, RICCARDO and RICCIARDO.

7. A different consonant appears in the same position within the name: for instance, BERTO and BETTO.

8. A different vowel appears in the same position within the name: for instance, VETTORIO and VITTORIO.

9. The prefix of the name is sometimes omitted: for instance, SALA and DELSALA.

10. *U* is used instead of *O* and *viceversa*: RUBERTO and ROBERTO.

11. The vowel *O* appears in the place of the diphthong *UO* (following the *Tratte* we always kept *UO*): for instance, BONANNO and BUONANNO; AMBROGIO and AMBRUOGIO.

12. There is an extra *H* (sometimes followed by an *E*): INGHELESE and INGLESE; BELCARO and BELCHARO.

13. In the *Tratte* dataset, since woman could not be assigned an office, we suspected female names were typo errors, and changed them in the male version: PIERO and PIERA; ANTONIO and ANTONIA.

14. We always implemented truncation at 11 digits: ALDOBRANDINO and ALDOBRANDIN.

B Supplementary material: Tables and figures

Table B.1: Wealth status transmission across two adjacent generations: Family, occupation, and neighborhood fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Reg. coefficient:	Panel A: Perc. ranks 1457-1427			Panel B: Perc. ranks 1480-1457		
$\hat{\beta}_{-1}$	0.310	0.473	0.470	0.413	0.482	0.492
	(0.120)	(0.058)	(0.062)	(0.080)	(0.036)	(0.034)
R-squared	0.489	0.129	0.143	0.516	0.207	0.220
Reg. coefficient:	Panel C: Top deciles 1457-1427			Panel D: Top deciles 1480-1457		
$\hat{\beta}_{-1}$	0.211	0.209	0.217	0.247	0.283	0.282
	(0.079)	(0.037)	(0.036)	(0.068)	(0.030)	(0.030)
R-squared	0.488	0.087	0.092	0.462	0.145	0.147
Surname fixed effects	Yes	No	No	Yes	No	No
Occupation fixed effects	No	Yes	No	No	Yes	No
Neighborhood fixed effects	No	No	Yes	No	No	Yes
Observations	768	768	768	1,005	1,005	1,005
Number of surnames	326	326	326	370	370	370
Avg. freq. of surnames	2.4	2.4	2.4	2.7	2.7	2.7

Notes. Coefficients estimated from equation (1) at the individual level on the matched sample with surname, occupation, and neighborhood fixed effects (plotted in Figure 2 in the paper). Percentile rank (Panels A and B) in t is the rank position of individual i in the wealth distribution of generation t. Top decile (Panels C and D) in t is a dummy variable equal to one if individual i is in the top decile of the wealth distribution of generation t, and to zero otherwise. Families for which information on neighborhood (occupation) is missing for all family members are associated with a unique neighborhood (occupation) identifier to obtain results reported in columns (2) and (4) ((3) and (6)). Excluding families with missing information on occupation (neighborhood) would not change the results. Family clustered s.e. in parentheses.

Table B.2: Wealth status transmission across two adjacent generations: Marriage network (entry)

	(1)	(2)	(3)	(4)	(5)	(6)
Reg. coefficient:	Panel A: Perc. ranks 1457-1427			Panel B: Perc. ranks 1480-1457		
$\hat{\beta}_{-1}$	0.436	0.002	0.497	0.424	0.234	0.438
	(0.077)	(0.138)	(0.084)	(0.049)	(0.147)	(0.053)
$\hat{\beta}_0$	28.848	60.270	24.555	33.487	44.301	32.531
	(6.931)	(12.567)	(7.543)	(4.105)	(10.027)	(4.498)
R-squared	0.845	0.815	0.851	0.877	0.824	0.881
Reg. coefficient:	Panel C: Top deciles 1457-1427			Panel D: Top deciles 1480-1457		
$\hat{\beta}_{-1}$	0.198	0.029	0.223	0.270	0.239	0.272
	(0.041)	(0.097)	(0.044)	(0.032)	(0.126)	(0.034)
$\hat{\beta}_0$	0.135	0.143	0.134	0.081	0.077	0.082
	(0.022)	(0.070)	(0.023)	(0.018)	(0.044)	(0.019)
R-squared	0.276	0.158	0.296	0.292	0.236	0.296
Baseline	Yes	No	No	Yes	No	No
Entry into network	-	Yes	No	-	Yes	No
Observations	550	70	480	746	58	688
Number of surnames	182	26	156	225	29	196
Avg. freq. of surnames	3.0	2.7	3.1	3.3	2.0	3.5

Notes. Coefficients estimated from equation (1) at the individual level on the matched sample after splitting according to "entry into network" (plotted in Figure 3 in the paper). Percentile rank (Panels A and B) in t is the rank position of individual i in the wealth distribution of generation t. Top decile (Panels C and D) in t is a dummy variable equal to one if individual i is in the top decile of the wealth distribution of generation t, and to zero otherwise. "Entry into network" denotes families that entered the marriage network in $t-1$ (the cohesion indicator changes from zero or one to a number equal to or larger than two). Family clustered s.e. in parentheses.

Table B.3: Wealth status transmission across two adjacent generations: Marriage network (permanence)

	(1)	(2)	(3)	(4)
Reg. coefficient:	Panel A. Perc. ranks 1457-1427		Panel B. Perc. ranks 1480-1457	
β_{-1}	0.510	0.303	0.446	0.160
	(0.094)	(0.202)	(0.057)	(0.193)
β_0	23.382	38.519	31.898	56.251
	(8.461)	(17.494)	(4.847)	(12.134)
R-squared	0.854	0.825	0.879	0.916
Reg. coefficient:	Panel C. Top decile 1457-1427		Panel D. Top decile 1480-1457	
β_{-1}	0.222	0.300	0.275	0.195
	(0.046)	(0.323)	(0.036)	(0.143)
β_0	0.128	0.100	0.086	0.036
	(0.025)	(0.076)	(0.021)	(0.036)
R-squared	0.296	0.250	0.305	0.182
Always in network	Yes	No	Yes	No
Never in network	No	Yes	No	Yes
Observations	422	25	624	41
N. surnames	125	14	164	21
Avg. freq. of surnames	3.4	1.8	3.8	2.0

Notes. Coefficients estimated from equation (1) at the individual level on the matched sample after splitting according to "always/never in network". Percentile rank (Panels A and B) in t is the rank position of individual i in the wealth distribution of generation t. Top decile (Panels C and D) in t is a dummy variable equal to one if individual i is in the top decile of the wealth distribution of generation t, and to zero otherwise. "Always in network" denotes families that were in the network in $t-1$ and $t-2$ (the cohesion indicator is always equal to or larger than two). "Never in network" denotes families that were out of the network in $t-1$ and $t-2$ (the cohesion indicator is always smaller than two). Family clustered s.e. in parentheses.

Table B.4: Wealth status transmission across two adjacent generations: Political network

	(1)	(2)	(3)	(4)
Reg. coefficient:	Panel A. Perc. ranks 1480-1457		Panel B. Top decile 1480-1457	
β_{-1}	0.395	0.515	0.287	0.277
	(0.104)	(0.039)	(0.065)	(0.034)
β_0	33.685	25.570	0.076	0.069
	(8.684)	(3.020)	(0.032)	(0.013)
R-squared	0.846	0.875	0.325	0.267
Entry into politics	Yes	No	Yes	No
Observations	248	757	248	757
Avg. freq. of surnames	4.0	2.9	4.0	2.9
Number of surnames	124	320	124	320
Reg. coefficient:	Panel C. Perc. ranks 1480-1457		Panel D. Top decile 1480-1457	
β_{-1}	0.534	0.366	0.291	0.269
	(0.040)	(0.087)	(0.036)	(0.059)
β_0	24.162	36.477	0.069	0.074
	(3.086)	(7.424)	(0.013)	(0.030)
R-squared	0.875	0.851	0.276	0.304
Dynasty in politics	Yes	No	Yes	No
Observations	701	304	701	304
Number of surnames	316	143	316	143
Avg. freq. of surnames	2.9	4.1	2.9	4.1

Notes. Coefficients estimated from equation (1) at the individual level on the matched after splitting according to "entry in politics" (Panels A and B, plotted in Figure 4) or "dynasty in politics" (Panels C and D, plotted in Figure 6 in the paper). Percentile rank (Panels A and C) in t is the rank position of individual i in the wealth distribution of generation t. Top decile (Panels B and D) in t is a dummy variable equal to one if individual i is in the top decile of the wealth distribution of generation t, and to zero otherwise. "Entry into politics" denotes households whose parents held at least one political office and grandparents held no office. "Dynasty in politics" denotes households whose parents and grandparents both held at least one political office. Family clustered s.e. in parentheses.

Table B.5: Wealth status transmission across two adjacent generations: Political and marriage networks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reg. coefficient:	Panel A: Percentile ranks 1457-1480				Panel B: Top deciles 1457-1480			
$\hat{\beta}_{-1}$	0.277	0.493	0.524	0.447	0.317	0.262	0.228	0.216
	(0.129)	(0.069)	(0.117)	(0.068)	(0.093)	(0.041)	(0.107)	(0.068)
$\hat{\beta}_{0}$	45.481	28.802	20.930	29.483	0.075	0.098	0.054	0.061
	(10.785)	(5.758)	(9.998)	(5.037)	(0.052)	(0.025)	(0.031)	(0.017)
R-squared	0.851	0.895	0.837	0.866	0.370	0.295	0.233	0.195
Entry into politics	Yes	No	Yes	No	Yes	No	Yes	No
Core network	Yes	Yes	No	No	Yes	Yes	No	No
Observations	142	389	95	246	142	389	95	246
Number of surnames	68	114	48	122	68	114	48	122
Avg. freq. of surnames	4.6	4.3	3.7	2.5	4.6	4.3	3.7	2.5

Notes. Coefficients estimated from equation (1) at the individual level on the matched sample after splitting according to "entry into politics" and "core network" (plotted in Figure 5 in the paper). Percentile rank (Panel A) in t is the rank position of individual i in the wealth distribution of generation t. Top decile (Panel B) in t is a dummy variable equal to one if individual i is in the top decile of the wealth distribution of generation t, and to zero otherwise. "Entry into politics" denotes households whose parents held at least one political office and grandparents held no office. "Core" denotes families that were in the core network in $t-1$ (cohesion indicator equal to or larger than four). Family clustered s.e. in parentheses.