# Intergenerational mobility in the very long run: Florence 1427-2011

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**Abstract.** The paper examines intergenerational mobility in the very long run, across generations that are six centuries apart. We exploit a unique dataset containing detailed information at the individual level for all people living in Florence in 1427. These individuals have been associated, using the surnames, to their pseudo-descendants living in Florence in 2011. We find that earnings elasticity is about 0.04, much higher than that predicted by traditional models of intergenerational mobility. We also find evidence of strong real wealth inheritance. These findings are confirmed when we test the robustness of the pseudo-links and address the potential selectivity bias due to the heterogeneous survival rates across families.

**Keywords:** intergenerational mobility, earnings, wealth, professions, informational content of surnames, Florence.

**JEL classification**: J62, N33, D31.

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*"Prestige is an accident that affects human beings. It comes into being and decays inevitably. [...] It reaches its end in a single family within four successive generations"*
Ibn Khaldun

*"Almost all the earnings advantages or disadvantages of ancestors are wiped out in three generations"*
Gary Becker and Nigel Tomes [1]

## 1. Introduction

Most theoretical and empirical studies on intergenerational mobility focus on correlation in socioeconomic status between two successive generations[2] – parents and their children – and share a common view that the economic advantages and disadvantages of ancestors vanish in few generations. In this paper we question this view and empirically document the persistence of socioeconomic status across generations that are six centuries apart. Hence, and surprisingly, the huge political, demographic and economic upheavals occurred in the meanwhile were not enough to untie the Gordian knot of socioeconomic inheritance.

Linking people belonging to generations that are distant each other is difficult because of data limitations. In this paper we exploit a unique dataset containing main socioeconomic variables at the individual level for people living in Florence in 1427. These individuals (the ancestors) have been associated, using surnames, to their pseudo-descendants living in Florence in 2011. Empirically we use a two-sample two-stage least squares (TS2SLS) approach: first, we use the sample of ancestors and regress the log of earnings on a full set of surname dummies (and on age and gender); second, we observe current taxpayers (living in the city of Florence and present in the 2011 tax records) and regress the log of their earnings on those of their ancestors, as predicted by their surname in the first step. The same strategy has been repeated using the log of real wealth or dummies for professions instead of log of earnings as dependent variables.[3]

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[1] Ibn Khaldun was one of the greatest Arab historian and he is considered among the founding fathers of modern sociology, historiography and economics; the citation has been drawn from his influential book *The Muqaddimah* (1377). Becker and Tomes provided, in their seminal contributions, the theoretical framework that represented the main building block of research on intergenerational mobility; the citation has been drawn from Becker and Tomes (1986).

[2] Earnings persistence has been observed in all countries studied so far, although to varying degrees. See Black and Devereux (2011) and Corak (2013) for recent surveys. Chetty et al. (2014) moved the analysis at the local level, providing evidence across commuting zones within the U.S.

[3] Björklund and Jäntti (1997) were the first to apply the TS2SLS approach to intergenerational mobility estimation. Thenceforth the same strategy has been adopted for many country studies, typically using occupation, education and sector of activity to predict pseudo-fathers earnings. On the contrary, Aaronson and Mazumder (2008) used state and year of birth while Olivetti and

We find that the elasticity of descendants' earnings with respect to ancestors' earnings is around 0.04. Stated differently, a one-standard deviation increase in the ancestors' earnings increases the descendants' earnings by 7% of its standard deviation. Intergenerational persistence in real wealth is even stronger. These results suggest that long run mobility is much lower than previously thought. To reconcile our results with those predicted by traditional models of intergenerational mobility, we provide further evidence showing that mobility in the 15th Century was much lower than nowadays; moreover, we also find evidence of dynasties in certain (elite) professions, consistent with status inheritance across multiple generations and, therefore, with an earning elasticity that does not necessarily decline geometrically as commonly thought.

Our empirical findings have two main weaknesses. First, the strength of the pseudo-links may be questioned as we are working with generations that are six centuries apart. However, our pseudo-links are reliable as they are generated in the intersection of surname and geographical localization, by including only people living in Florence. If the same data were available for all Italian cities, our strategy would entails prediction of ancestors' socioeconomic status using interaction between surnames and cities. This is arguably a more demanding and more precise approach to create links across generations than the one adopted in previous studies. Moreover, a rich set of robustness checks, including placebo regressions where we randomly reassign surnames to the descendants, is largely reassuring on the strength of the pseudo-links. Second, family survival rates – and, therefore, the likelihood of finding descendants of Florentine families in the 15th Century among current taxpayers – may vary to a large extent across families. If variation in the survival rate was correlated with current earnings and wealth, this would bias our estimates. To address this issue, we account for survival through a Heckman approach that confirms our main findings.

The main element of novelty of the paper is that we are able to provide evidence on intergenerational mobility in the very long run, linking ancestors and descendants that are six centuries apart (i.e. about 20 generations of 30 years each). Indeed, linking people through several generations has been done rarely.[4] Chan and Boliver (2013) show a statistically significant association between grandparents' and grandchildren's class positions, even after parents' class position is taken into account. Lindahl et al. (2015) use a Swedish data set that links individual earnings (and education) for three generations and find that

Paserman (2015) exploited the information conveyed by first names. These variables, however, are partly endogenous since the choices of first names or state of residence may be related to parental characteristics while surnames are more exogenous markers.

[4] See Solon (2014) for theoretical models accounting for mobility across multiple generations.

persistence is much stronger across three generations than predicted from simple models for two generations. More closely to our paper, Collado et al. (2012) and Clark and Cummins (2014) exploited the distribution of surnames to estimate social mobility in the long run. Collado et al. (2012), using data from two Spanish regions, find that socioeconomic status at the end of the 20th Century still depends on the socioeconomic status of one's great-great grandparents; however, they also suggest that the correlation vanishes after five generations. Clark and Cummins (2014) use the distribution of rare surnames in England and find significant correlation between the wealth of families that are five generations apart.[5]

Beyond the large time span, such a very strong persistence of socioeconomic status is even more striking given the huge political, demographic and economic upheavals that occurred in the city across centuries. On the political ground, Florence passed from a self-governed and independent city-state (see Figure 1) to a city like any other within a larger State (with the Italian unification in 1861). Regarding demography, the population in the city was fairly stable between 1400 and 1800 and experienced a huge increase in the 19th and 20th Centuries (see Figure 2a). Finally, the GDP per capita was basically flat in the pre-industrial era while it recorded an exceptionally high growth rate during the 20th Century (see Figure 2b), accompanied by industrial revolution, tertiarization and, finally, by the technological revolution.

Our empirical analysis also has other prominent strengths. First, we consider different socioeconomic outcomes including earnings, wealth and professions. Second, ancestors' socioeconomic status has been predicted using surnames at the city level, thus generating more precise links across generations with respect to other studies that use names or surnames at the national level. Third, the huge heterogeneity and "localism" of Italian surnames further strengthens the quality of the pseudo-links. Fourth, the Italian Renaissance offers a unique background to trace family dynasties and investigate the transmission of inequalities across centuries. Indeed, Florence in the 15th Century was already an advanced and complex society, characterized by a significant level of inequality and by a rich variety of professions and occupational stratification.

The rest of the paper is structured as follows. Section 2 presents the empirical strategy. Section 3 provides background information and describes the data and the variables. Section 4 shows the empirical results. Section 5 concludes.

[5] In the data used by Clark and Cummins (2014), the wealth is estimated at death, thus ignoring inter-vivos transfers. Our data, on the contrary, have the advantage of being available when individual is an adult. Moreover, we can control for the evolution of the outcome variable in the lifecycle by adding age among the controls.

## 2. Empirical strategy

The main requirement when analyzing socioeconomic mobility is an appropriate data set that spans over generations. Unfortunately, such a suitable dataset is not easily available and this is even more true if we consider generations that are centuries apart. To overcome the problem, we adopt an approach that combines information from two separate samples (TS2SLS) and whose properties are discussed in Inoue and Solon (2010).

In the first sample we have information about ancestors' socioeconomic status (say earnings) and their surnames, and we run the following regression:

$$y_i^a = \delta S_i^a + \gamma X_i^a + \mu_i^a \quad (1)$$

where $y_i$ is the log of earnings of individual $i$ living in Florence in the 15th Century, $X_i^a$ is a vector of controls such as age and gender and $S_i^a$ is a set of dummies for each surname.

In the second sample we have information about pseudo-descendants, i.e. taxpayers currently living in Florence, the regression of interest is:

$$y_i^d = \beta(\hat{\delta} S_i^d) + \rho X_i^d + \mu_i^d \quad (2)$$

where $y_i^d$ is the log of earnings of individual $i$ currently living in Florence, $X_i^d$ is as above a vector of controls for age and gender and $\hat{\delta} S_i^d$ is the log of ancestors' earnings imputed using surnames and the coefficients estimated in equation (1); the $\beta$ is the TS2SLS estimate of intergenerational elasticity.

However, for reasons of data availability (see more on this below), we run a slightly modified regression:

$$y_k^d = \beta(\hat{\delta} S_k^d) + \rho X_k^d + \mu_k^d \quad (3)$$

where earnings and other controls in the second sample are collapsed at the surname level (indexed by $k$) and taken at their means. To replicate the original population, regressions are weighted by the frequency of surnames.

# 3. Data and descriptive analysis

## 3.1 Data sources

Florence originated as a Roman city, and later, after a long period as a flourishing trading and banking medieval commune, it was the birthplace of the Italian Renaissance. According to the *Encyclopedia Britannica*, it was politically, economically, and culturally one of the most important cities in the world from the 14th to 16th centuries.[6] In 1427, in the midst of the fiscal crisis provoked by the protracted wars with Milan, the Priors of the Republic decreed an entirely new tax survey that applied to citizens of Florence and to inhabitants of the Florentine districts (1427 Census, henceforth). The assessments were entrusted to a commission of ten officials, and their staff, and were largely complete within a few months, although revisions continued during 1428 and 1429. It has been acknowledged as one of the most comprehensive tax surveys to be conducted in the pre-modern Western Europe.[7]

The 1427 Census represents the first sample, containing information on socioeconomic status of the ancestors. Indeed, the dataset reports for each household, among other variables, the name and the surname of the head of the household, occupation at 2-digit level, assets (i.e. value of real property and of private and public investments), age and gender. The data were enriched with estimates on earnings, attributed to each person on the basis of occupations and the associated skill group.[8]

The 2011 tax records represent the second sample, containing information on socioeconomic status of the pseudo-descendants. From tax records, we draw information on incomes and main demographic characteristics (age and gender). Income items reported on personal tax returns include salaries and pensions, self-employment income, real estate income, and other smaller income items. In order to comply with the privacy protection rules, the variables have been collapsed at the surname level and only surnames with a frequency equal to 5 or above have been included. We define as earnings the total income net of real estate incomes while real wealth has been estimated from real estate incomes.[9]

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[6] The Medici, the most renowned rulers, gathered to court the best artists, writers and scientists of the time such as Botticelli, Dante, Galileo, Leonardo da Vinci, Michelangelo and Machiavelli.

[7] The documentary sources are fully described in Herlihy and Klapisch-Zuber (1985).

[8] Data on earnings were kindly provided by Peter Lindert (University of Davis). See the document gpih.ucdavis.edu/files/BLW/Tuscany_1427.doc for further information. The same data were also used in Milanovic et al. (2011) for an analysis on inequality in pre-industrial societies.

[9] Specifically, from the Survey of Household Income and Wealth carried out by the Bank of Italy (1) we selected people living in the province of Florence, (2) we regressed the log of real assets on age,

## 3.2 The origin and the distribution of surnames

Pseudo-links between ancestors and their descendants are generated using (implicitly) geographical localization – since we consider people living in Florence in both samples – and exploiting the informational content of surnames.

Italians surnames have some interesting peculiarities. Surnames were inherited from one generation to the next, through the patriline, and most Italians began to assume hereditary surnames in the 15th Century. Some surnames derived from one's father names (patronymics) through the use of the Latin genitive (e.g. Mattei means son of Matteo)[10] or formed by the preposition of "di"/"de" followed by the name (e.g. Di Matteo or De Matteo is the son of Matteo). The origin or residence of the family gave rise to many surnames such as the habitat – Della Valle (i.e. "of the valley") – specific places – Romano (i.e. "Roman") – or nearby landmarks – Piazza (i.e. "square"). Ancestors' occupation (or utensils associated to the occupation) was also a widespread source of surnames, such as Medici ("medical doctors"), Martelli ("hammer") or Forni ("ovens"). Finally, nicknames, typically referring to physical attributes, also gave rise to some family names, e.g. Basso ("short"). The huge variety of surnames was amplified by the extraordinary linguistic diversity at the local level. Indeed, there are surnames' ending that are region specific. For example, in Veneto many surnames end with "n" (e.g. Benetton), in Campania with "iello" (e.g. Borriello), in Sardinia with "u" or "s" (e.g. Soru and Marras) and in Tuscany with "ai" or "ucci" (e.g. Bollai and Balducci).

In sum, there are two striking features. First, in Italy there is a large number of surnames, likely one of the largest collections of surnames of any ethnicity in the world. This is associated to a high fractionalization: the first 100 most frequent surnames account only for 7% of overall population against 22% in England. Second, and unsurprisingly, the surnames present in our samples are highly Florence-specific: on average, the ratio between the surname share in Florence and the corresponding figure at the national level, which measures a specialization index centered in 1, is nearly 6. Therefore, the informational content of surname is presumably much higher than elsewhere, supporting our empirical strategy in the identification of the pseudo-links.

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gender and incomes from building (actual and imputed rents) and (3) we stored the coefficients. Then we imputed real wealth for individuals included in the tax records using age, gender, real estate incomes and the coefficients estimated and stored above.

[10] The large number of Italian surnames ending in "i" is also due to the medieval habit of identifying families by the name of the ancestors in the plural (which have an "i" suffix in Italian).

### 3.3 Descriptive analysis

In the 1427 Census there are about 10,000 families, corresponding to nearly 40,000 individuals. Descriptive statistics reported in Table 1 refer to household heads that were predominantly males. Earnings and real wealth were equal, on average, to 36 and 291 florins, respectively. Moreover, the two variables were characterized by an unequal distribution across families: the Gini index was about 35% for earnings and nearly 80% for real wealth. The occupational structure was highly stratified as well. Twelve artist guilds that regulated the trades were the basis of Florence's commercial success; their members were wealthy and held influential positions in society and politics. The most powerful guilds were those that represented textile workers (much of Florence's wealth was dependent on the manufacture or trade of cloth, primarily wool). Goldsmiths, in turn, were also organized into guilds and were among the wealthiest people in the city. The vibrant economic activity favored the development of lettered bureaucrats and professionals, such as lawyers, judges, medical doctors and pharmacists (the oldest pharmacy in Europe was set up in Florence). Finally, many Florentine families were successful bankers (e.g. Bardi, Medici and Peruzzi); they were known throughout Europe as well, for they established banking houses in other important cities such as London, Geneva, and Bruges. The local currency, the florin, was the strongest currency and the most traded in Europe.

For about half of the surnames listed in the 1427 Census we found pseudo-descendants in the 2011 tax records.[11] They correspond to about 800 surnames and 52,000 taxpayers. On average they earn about 24,000 Euros per year and the real wealth is estimated to be nearly 60,000 Euros.[12]

Table 2 provides a first descriptive assessment of persistence: we report for the top 5 and bottom 5 surnames among current taxpayers, the modal value of the occupation and the percentiles in the earnings and wealth distribution in the 15ht Century (surnames are replaced by capital letters for confidentiality reasons). The richest surnames among current taxpayers were already 6 centuries ago at the top of the socioeconomic ladder: they were lawyers or member of the wool, silk and shoemakers guilds; their earnings and wealth were often well above the median. On the contrary, the poorest surnames had less prestigious occupations and their earnings and wealth were below the median in most cases.

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[11] The creation of pseudo-links through surnames has been pursued with some degree of flexibility, to account for slight modification in the surnames across centuries. For example, current taxpayers with surnames such as “Mattei” or “Di Matteo” are considered descendants of “Matteo”.

[12] Florence continues to be one of the wealthiest cities in Italy and the value added per capita in the province is about 20% higher than the national average.

# 4. Results

## 4.1 Main results

In the first stage we regress log of ancestors' earnings on surnames, as shown in equation (1), using 1427 Census data. We find that surnames accounts for about 10% of the total variation in log of earnings and 17% of the total variation in log of wealth. These results support the hypothesis that surnames carry information about the father's socioeconomic status.[13] Coefficients for surnames estimated in the first stage are then used to predict ancestors' earnings and wealth for taxpayers included in the 2011 tax records.

Table 3 presents our TS2SLS estimates of the intergenerational earnings elasticity, as shown in equation (3).[14] We consider three different empirical specifications, with the first including only the predicted ancestors' earnings, the second and the third adding age and age and gender, respectively. The earnings elasticity is fairly stable across specification, with a magnitude around 0.04, and it is statistically significant at 5% level. Table 4 replicates the estimation with respect to the wealth elasticity. The parameter ranges from 0.02 to 0.03 and it is, again, highly significant (mostly at 1% level). This first set of results documents a surprisingly high persistence of earnings and wealth across six centuries.

We cannot directly compare the two elasticities because the size of the coefficients partly depends on the mean and the variance of the independent variable. To address this issue, in Table 5 we compare the magnitude of the two elasticities by estimating equation (3) on the same sample and computing the standardized beta coefficients. It turns out that that the size of the wealth elasticity largely exceeds that of earnings elasticity either without controlling for sex and age (columns 1-2) or including those controls (columns 3-4). According to our preferred specification, a one-standard deviation increase in the ancestors' earnings increases the descendants' earnings by 6.7% of its standard deviation. The corresponding figure for real wealth is 9.7%. Therefore wealth persistence is higher than earnings' persistence and this is an expected result as real wealth can be transmitted across generations more easily and more directly.

Table 6 provides a first set of robustness checks. First we address tax evasion. Our dependent variables are based on tax records that, as well known, may suffer from a severe underestimation due to tax evasion. In the first two

[13] Further evidence on this point will be discussed later.

[14] Standard errors have been bootstrapped with 1,000 replications in order to that take into account the fact that the key regressor is generated.

columns we upwardly revise the variables from tax records with the correction factors suggested by Marino and Zizza (2011).[15] Results are unchanged and this may be explained by the fact that tax evasion might influence our results only if it is correlated with pseudo-ancestors' earnings (or wealth), which is clearly a very unlikely possibility. Second we address outliers as the distributions of earnings and wealth have long tails that might drive the results. In the last two columns we trim both the dependent variable and the key regressor at the 1% and the 99% level and we re-estimated equation (3): again, the estimates of positive and significant intergenerational elasticities are fully confirmed.

### 4.2 Robustness of pseudo-links

Our empirical strategy relies on the assumption that the probability that one taxpayer (randomly) taken from the 2011 tax record is a descendant of one taxpayer (randomly) selected from the 1427 Census is strictly higher if the two share the same surname.

At least two facts challenge our working hypothesis. First, people sharing the same surname may well not belong to the same family. Our test is then based on the idea that the more a surname is common the less sharing the surname is informative about the actual kinship. In the first two columns of Table 7 we re-estimate equation (3) by weighting observations with the inverse of the relative frequency in 1427, so giving more weight to rare surnames. Our results are largely confirmed. The second threat to our assumption rests on the fact that the city of Florence is not a closed system. For instance, take a surname in 1427, say "Bardi". Even if "Bardi" was a rare surname in 1427 it may well happen that in recent years a (non-descendant) immigrant named "Bardi" settled in Florence from outside. Our methodology treats erroneously the latter as a pseudo-descendant of the former. We minimize such a risk in the last two columns of Table 7 where we split our key parameters by interacting them with a dummy variable that equals 1 for more typical Florentine surname and 0 otherwise.[16] The results are reassuring: elasticities are larger for more Florence-specific surnames.

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[15] Marino and Zizza (2011) compares incomes from tax records with those collected through the Survey of Household Income and Wealth. This approach is based on the hypothesis that as the survey questionnaire is multipurpose and replying is not compulsory, it is likely that respondents do not feel threatened or suspicious and would hence reply truthfully. On this basis, they provide for each income types a proxy of tax evasion (as measured by the difference between income from the survey and income from the fiscal source).

[16] The measure for Florence-specific surnames is given by the ratio between the surname share in Florence and the corresponding figure at the national level. In the table we consider more typical Florentine surnames those with a value above the median.

The two exercises discussed above *indirectly* test the robustness of pseudo-links. We complement them with a *direct* test that goes as follows. We randomly reassigned surnames to taxpayers in 2011 and re-estimate the TS2SLS intergenerational elasticities. If the positive correlations we detect are not related to the lineage (whose measurement might be affected by error) but emerge by chance, we should find that our estimates are not statistically different from those stemming from a random reshuffling of surnames. Figure 3 shows the distribution of estimated earnings elasticity for 1 million replications. The two dashed vertical lines are the 95$^{th}$ and the 99$^{th}$ percentiles while the red line indicates the position of the estimate based on real surnames. These results provide a clear graphical representation of the informational content of surnames and the goodness of the pseudo-links: the simulated p-value in this exercise is lower than 1%. Figure 4 shows the corresponding results for wealth where the outcome of the check is even more telling.

### 4.3 Selectivity bias due to families' survival rate

The analysis of intergenerational mobility in the long run points out to a demographic issue since families' survival rate depends on basic demographic processes that transform populations from one generation to the next. Moreover, reproduction, marriage, fertility, migration, and mortality may differ across people with different socioeconomic background.

As far as migration is concerned, some of the families recorded in the 1427 Census might have decided to migrate in the following centuries. Since they are not necessarily a random sample of the original population (Borjas, 1987), this might bias our estimates.[17] Analogously, dynasty's reproduction rate (i.e. fertility/mortality rate) may be correlated with income and/or wealth. Jones et al. (2010) show a strong and robust negative relationship between income and fertility, though they also argue that in the agrarian (pre-industrialization) economies the reverse could have been possible, as documented for example in Clark and Cummins (2009). On the other side, it is reasonable to expect that the wealthiest families were those better equipped to survive across centuries (and therefore those that can be matched to the current tax records). How do we address these issues?

First, we provide descriptive evidence of the distribution of earnings and wealth in 1427, between the families who are still present in the tax records of

[17] Borjas (1987) provided a theoretical model to predict whether migrants are drawn mainly from the upper or lower tail of the skill (i.e. income) distribution. This, in turn, depends on income distributions in both the sending and the destination regions.

2011 and those who are not. The first row of Table 8 shows that the earnings of surviving surnames are not statistically significant from the others (columns 1-3), nor that their distribution significantly differs. On the other hand this result does not apply to real wealth: surviving families were healthier and differences were not limited to the mean but extend to the whole distribution. This is a quite expected result since inheritance of real wealth (including housing ownership) may be a constraint to geographical moves. In order to take into account that surviving surnames might be a non-random sample and that selection bias might affect our results – a concern that seems more relevant for real wealth – we adopt a two stages Heckman correction. In the first stage we exploit further information recorded in the 1427 Census. Namely, we estimate a probit model with survival rate as a function of two dummies for migrant status (from other Italian cities and from abroad) and of the family size. The migrant status might influence the surname survival because migrants might display a higher propensity to a new mobility episode; family size, on the other hand, has a direct (mechanical) positive effect on the survival rate. The identifying assumption is that these three variables observed in 1427 do not have a direct effect on earnings and wealth in 2011. Table 9 shows that being a migrant from abroad and larger family sizes influence the survival rate and enter with the expected signs. We then compute the inverse Mills ratio to correct the elasticity estimates: Table 10 indicates that the selectivity term is statistically significant only for wealth elasticity. However, and more important for us, the coefficients of interests are very close to the baseline results and, if any, they are slightly upwardly revised.

### 4.4 Discussion of long term persistence

Intergenerational mobility scholars typically presume that correlations across generations decline geometrically (i.e. the correlation between grandparent and child is the square of the parent–child correlation, the correlation between great-grandparent and child is the cube, etc.). If this was true, our estimates, which are referred to about 20 generations, would be not consistent with the prevailing estimates on earnings and wealth mobility.[18] For example, assume the following deterministic law of motion for earnings: $y_t = \beta y_{t-1}$ where $y$ is log of earnings and $\beta$ the earnings elasticity between two successive generations. In Italy, according to Mocetti (2007), $\beta$ is equal to 0.5. Therefore, our earnings elasticity estimate, equal

[18] In the following we focus on earnings elasticity but the same conclusions can be straightforwardly applied also to wealth elasticity.

to 0.04, is consistent with a 4-5 generation span, much less than our case. Different plausible values for $\beta$ cannot remove this inconsistency.

Recent papers have questioned the assumption that the intergenerational transmission process of human capital has a memory of only one period. Indeed, for example, grandparents can directly transmit their cultural capital to their grandchildren through childrearing or other forms of interactions. Similarly, they can directly pass their wealth to their grandchildren. Therefore, recalling the example above, we can modify the law of motion as follows: $y_t = \beta y_{t-1} + \delta y_{t-2}$. If we assume $\beta = 0.5$ and $\delta = 0.25$ – that plausibly represent an upperbound to the true (unobserved) parameters for Italy – then we find that our earnings elasticity estimate (0.04) is consistent with a 8-9 generation span. This law of motion, however, continues to be, by itself, not enough to fully explain our findings.

In the following we discuss two further explanations for the observed persistence across centuries and we provide related empirical evidence.

First, intergenerational mobility in the past might have been lower than nowadays. Considering again our earnings elasticity across 20 generations, this is consistent with a $\beta$ across successive generations equal, on average, to 0.85. This parameter is not necessarily unlikely. Indeed, in the pre-industrial era, the persistence in social standing across generations has been perceived as large, while some scholars tend to believe that industrialization and the rise of capitalism would bring a more fluid society.[19]

In order to provide some empirical support to this claim, we rely on the approach by Güell et al. (2014) who developed a novel measure of intergenerational mobility that needs only cross-sectional data and is based on the informational content of surnames (ICS).[20] Following this methodology, we estimate the ICS in 1427 and we compare these figures with those drawn from Güell et al. (2015) for the province of Florence in the mid of the 2000s. These findings, shown in Figure 5, though they should be interpreted with some cautions given the different nature of the data sources, support the view that intergenerational mobility in the past was (much) lower than nowadays. Moreover, it is reasonable to assume that this immobile society was prevailing from 15th to 19th century.

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[19] See Erikson and Goldthorpe (1992) and Piketty (2000) for a discussion between the liberal and Marxist theory about the degree of intergenerational mobility in the industrial society.

[20] ICS is defined as $ICS \equiv R_D^2 - R_F^2$. The first R-squared ($R_D^2$) is obtained from the regression: $y_{i,s} = D + \mu_{i,s}$ where $y_{i,s}$ is log of incomes of individual $i$ with surname $s$ and $D$ is an S-vector of surname-dummy variables with $D_S = 1$ if individual $i$ has surname $s$ and $D_S = 0$ otherwise. The second R-squared ($R_F^2$) is obtained from the regression $y_{i,s} = F + \mu_{i,s}$ where $F$ is an S-vector of "fake" dummy variables that randomly assign surnames to individuals in a manner that maintains the marginal distribution of surnames.

Second, earnings elasticity might not decline geometrically as commonly thought. Indeed, many social institutions contribute to status inheritance over multiple generations, especially at the bottom (e.g. due to ethnic or social discrimination) and at the top (e.g. membership of exclusive clubs and/or elite professions) of hierarchies. In a society of perfect status inheritance (e.g. a pure caste system) children, parents, grandparents, and earlier ancestors are identical in their social and economic positions; in this society the perfect correlations between each generation make alternative types of intergenerational effects (e.g. children-parents, children-grandparents, etc.) indistinguishable. Taking a slightly different perspective, Zylberberg (2014) underlines the existence of unobservable variables that are transmitted by parents: sons of successful families may preserve the high prospects for their descendants even when their own earnings are not very high. In his theoretical framework, dynasties moves across careers rather than across income levels and a society can modelled as a Markov process in which the transition matrix is block-diagonal: only within-block mobility is allowed (e.g. block of manual jobs vs. block of cognitive jobs). This second explanation is consistent with an earning elasticity that does not decline geometrically and with a society characterized by dynasties in professions.

On the empirical side, we show suggestive evidence that some form of dynastic transmission of profession underlies our empirical case. Namely we show that the probability to be employed in a certain elite or niche occupation today is higher the more pseudo-ancestors were employed in the same occupation. We selected 4 professions: lawyers, bankers, medical doctors and pharmacists, and goldsmiths. We consider only these professions for several reasons. First, for reason of data availability, we are forced to focus on professions that already existed in 1427 and for those we have access to publicly available data nowadays. Second, they should be elite or niche profession, consistent with the fact that there should be unobservable variables that favored the career following (e.g. specific human capital or guild privileges). Third, available empirical evidence documents the existence of career dynasties precisely for (some of) these professions.[21]

The empirical strategy is similar to that of equation (2): from the first stage we obtain, for each surname, the probability of being employed in a certain profession. In the second stage we observe individual taxpayer, his/her surname and whether he/she is enrolled in the same profession. The latter information is not directly observable in the tax records and has been built as follows.[22] On one

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[21] See Lentz and Laband (1989) for doctors, Laband and Lentz (1992) for lawyers and Mocetti (2014) for pharmacists.

[22] The dataset with the taxpayers' surname distribution across Italian provinces has been kindly shared by Giovanna Labartino. Public archives for the four professions are: the OR.SO. archive,

hand, we have the full list of taxpayers' surnames in the province of Florence; on the other hand we know, from public archives, how many individuals are employed in a certain profession and have a certain surname. For example, there are 231 taxpayers named "Alessi". From the other sources we know that one "Alessi" works as lawyer, one as doctor and two as goldsmith. Without loss of generality, we define the first "Alessi" as lawyer, the second as medical doctor, the third and the fourth as goldsmiths and the remaining 227 are in a residual category. Results are reported in Table 10. In the first four columns we consider each profession separately and we find a positive and statistically significant correlation for lawyers, bankers and goldsmiths and a positive but not significant correlation for doctors and pharmacists. In the last two columns we pool the professions together and we run the regression with and without profession fixed effects: we continue to find a positive and significant correlation. The impact is clearly small in magnitude – a one-standard deviation increase in the independent variable increases the dependent variable by around 1% of its standard deviation – but it is, again, surprisingly high and strong if evaluated across six centuries.

## 5. Conclusions

We have examined intergenerational mobility in the very long run, exploiting a unique dataset (1427 Census) and a favorable setting for this kind of analysis.

We have found that earnings elasticity, across generations that are six centuries apart, is about 0.04, much higher than that predicted by traditional models of intergenerational mobility. We also find evidence of strong real wealth inheritance. These findings are confirmed when we test the robustness of the pseudo-links and address the potential selectivity bias due to the heterogeneous survival rates across families. We also provide two explanations (and related empirical support) for the surprisingly low level of mobility: first, mobility in the past may have been much lower than nowadays; second, social status and other unobservable variables may also be highly persistent, implying that earnings elasticity might not decline geometrically as commonly thought.

Future research should attend more closely to multigenerational effects and socioeconomic persistence in the long run.

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managed by the Bank of Italy, and containing anagraphic information on members of governing bodies of banks (we restrict the analysis to Tuscan banks); archives of the professional orders for lawyers, doctors and pharmacists, publicly available, and containing anagraphic information on the members of each order (we restrict the analysis to those working in the Florence area); finally, the National Business Register database, containing anagraphic information on members of governing bodies of goldsmith firms and shops (again in the Florence area).

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# Tables

## Table 1. Descriptive statistics

| Variable: | Mean | Standard deviation |
|---|---|---|
| 2011 tax records | | |
| Earnings | 24,234 | 4,929 |
| Real wealth | 59,225 | 26,148 |
| Female | 0.52 | 0.05 |
| Age | 58.4 | 3.0 |
| 1427 Census | | |
| Earnings | 36.2 | 44.8 |
| Real wealth | 291.2 | 705.0 |
| Female | 0.15 | 0.36 |
| Age | 45.9 | 16.9 |

Source: tax records from Florence statistical office (fiscal year 2011) and 1427 Catasto of Florence, provided by Brown University; monetary variables are in Euro in the tax records and in Florentine florin in the 1427 Census.

## Table 2. Persistence in families' socioeconomic status

| Surname | Euros (2011) | Occupation (1427) | % earnings (1427) | % wealth (1427) |
|---|---|---|---|---|
| 5 richest in 2011: | | | | |
| A | 149,547 | Member of shoemakers' guild | 90% | 89% |
| B | 99,254 | Member of silk guild (merchant or weaver) | 97% | 97% |
| C | 95,881 | Member of wool guild (manufacturer or merchant) | 69% | 65% |
| D | 85,862 | Messer (lawyer) | 94% | 93% |
| E | 81,339 | Brick layer, sculptor, stone worker | 38% | 45% |
| 5 poorest in 2011: | | | | |
| V | 12,343 | Goldsmith | 86% | 84% |
| W | 12,287 | Worker in combing, carding and sorting wool | 34% | 53% |
| X | 12,013 | Worker in combing, carding and sorting wool | 30% | 39% |
| Y | 11,358 | Sewer | 43% | 34% |
| Z | 7,528 | Dealer in linen cloth, second-hand clothing | 37% | 49% |

**Table 3. Earnings mobility: baseline**

| Dependent variable: | Log of earnings | Log of earnings | Log of earnings |
|---|---|---|---|
| Log of ancestors' earnings | 0.039** | 0.043** | 0.036** |
| | (0.017) | (0.020) | (0.018) |
| Female | | -0.482*** | -0.467*** |
| | | (0.116) | (0.122) |
| Log of age | | | -0.037 |
| | | | (0.118) |
| Observations | 806 | 806 | 806 |
| R-squared | 0.007 | 0.026 | 0.024 |

Bootstrap standard errors in parentheses (1,000 replications); *** p<0.01, ** p<0.05, * p<0.1

**Table 4. Real wealth mobility: baseline**

| Dependent variable: | Log of wealth | Log of wealth | Log of wealth |
|---|---|---|---|
| Log of ancestors' wealth | 0.027*** | 0.026*** | 0.019** |
| | (0.008) | (0.008) | (0.008) |
| Female | | 0.325 | -0.320 |
| | | (0.286) | (0.299) |
| Log of age | | | 2.293*** |
| | | | (0.283) |
| Observations | 679 | 679 | 679 |
| R-squared | 0.018 | 0.019 | 0.101 |

Bootstrap standard errors in parentheses (1,000 replications); *** p<0.01, ** p<0.05, * p<0.1

**Table 5. Comparison between earnings and wealth mobility**

| Dependent variable: | Log of earnings | Log of wealth | Log of earnings | Log of wealth |
|---|---|---|---|---|
| Log of ancestors' earnings/wealth | 0.042** | 0.027*** | 0.038** | 0.019** |
| Standardized beta coefficient | 0.096 | 0.134 | 0.067 | 0.097 |
| | (0.017) | (0.008) | (0.019) | (0.008) |
| Controls | NO | NO | YES | YES |
| Observations | 679 | 679 | 679 | 679 |
| R-squared | 0.009 | 0.018 | 0.030 | 0.101 |

Bootstrap standard errors in parentheses (1,000 replications); controls are female and log of age; *** p<0.01, ** p<0.05, * p<0.1

**Table 6. Income and real wealth mobility: robustness**

| Dependent variable: | Log of earnings | Log of wealth | Log of earnings | Log of wealth |
|---|---|---|---|---|
| Log of ancestors' earnings/wealth | 0.048** | 0.019** | 0.055** | 0.018** |
| | (0.023) | (0.008) | (0.024) | (0.008) |
| Controls | YES | YES | YES | YES |
| Model | correction for tax evasion | correction for tax evasion | trimming | trimming |
| Observations | 806 | 679 | 790 | 667 |
| R-squared | 0.025 | 0.101 | 0.028 | 0.093 |

Bootstrap standard errors in parentheses (1,000 replications); controls are female and log of age; *** p<0.01, ** p<0.05, * p<0.1

**Table 7. Mobility for rare and Florence-specific surnames**

| Dependent variable: | Log of earnings | Log of wealth | Log of earnings | Log of wealth |
|---|---|---|---|---|
| Log of ancestors' earnings/wealth | 0.040* | 0.018* | | |
| | (0.022) | (0.009) | | |
| × Less typical Florentine surnames | | | -0.002 | 0.017* |
| | | | (0.037) | (0.010) |
| × More typical Florentine surnames | | | 0.051** | 0.020* |
| | | | (0.022) | (0.012) |
| Controls | YES | YES | YES | YES |
| Specification | More weights to rare surnames in 1427 | | Differences by low- high- Florence-specific surnames | |
| Observations | 806 | 679 | 806 | 679 |
| R-squared | 0.042 | 0.110 | 0.026 | 0.100 |

Bootstrap standard errors in parentheses (1,000 replications); controls are female and log of age; *** p<0.01, ** p<0.05, * p<0.1

**Table 8. Earnings and wealth distribution by survival rate**

| | matched | unmatched | difference | Kolmogorov-Smirnov |
|---|---|---|---|---|
| Log of ancestors' earnings | 36.2 | 35.9 | 0.305 | 0.009 |
| | | | (0.721) | (0.679) |
| Log of ancestors' wealth | 291.8 | 271.9 | 19.915** | 0.022*** |
| | | | (9.643) | (0.004) |

Matched surnames are those present in both 1427 Census and 2011 tax records; unmatched surnames are those existing in 1427 Census but not in 2011 tax records; standard errors in parenthesis when testing differences in means; p-values in parenthesis for the Kolmogorov-Smirnov test for equality of distributions.

**Table 9. First stage: survival rate**

| Dependent variable: | =1 if survive |
|---|---|
| =1 if migrants from other Italian cities in 1427 | 0.029 |
| | (0.055) |
| =1 if migrants from abroad in 1427 | -0.206*** |
| | (0.037) |
| Size of the family in 1427 | 0.011*** |
| | (0.003) |

Bootstrap standard errors in parentheses (1,000 replications); *** p<0.01, ** p<0.05, * p<0.1

**Table 10. Second stage: selection corrected estimates**

| Dependent variable: | Log of earnings | Log of earnings | Log of wealth | Log of wealth |
|---|---|---|---|---|
| Log of ancestors' earnings/wealth | 0.040** | 0.037** | 0.030*** | 0.023*** |
| | (0.017) | (0.019) | (0.008) | (0.008) |
| Controls | NO | YES | NO | YES |
| Inverse Mills' ratio | 0.036 | -0.002 | 0.504* | 0.534* |
| | (0.128) | (0.122) | (0.295) | (0.285) |
| Observations | 806 | 806 | 679 | 679 |
| R-squared | 0.007 | 0.024 | 0.022 | 0.106 |

Bootstrap standard errors in parentheses (1,000 replications); controls are female and log of age; *** p<0.01, ** p<0.05, * p<0.1

**Table 10. Probability to belong to a given profession**

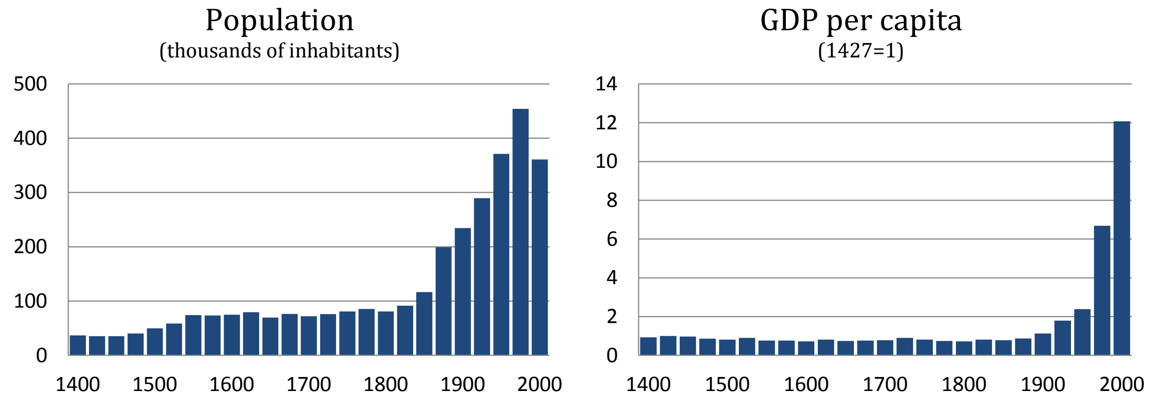
| Dependent variable: | Lawyer | Banker | Doctor or pharmacist | Gold-smith | Pooled professions | Pooled professions |
|---|---|---|---|---|---|---|
| Ancestors employed in the same profession | 0.005** | 0.001* | 0.001 | 0.009** | 0.007*** | 0.003** |
| | (0.002) | (0.001) | (0.002) | (0.004) | (0.002) | (0.001) |
| Profession FE | NO | NO | NO | NO | NO | YES |
| Obs. | 133,193 | 133,193 | 133,193 | 133,193 | 532,772 | 532,772 |
| R-squared | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.003 |

Standard errors clustered at the surname level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

# Figures

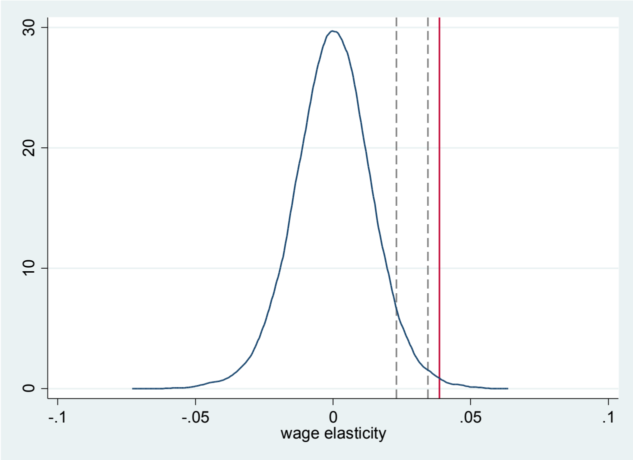
## Figure 1. Italian city-states in the 1400


## Figure 2. Population and GDP per capita in the long run



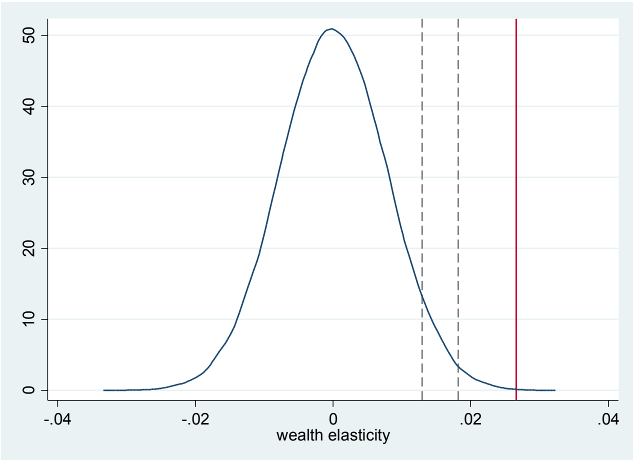

Figures for population refer to the city of Florence (authors' elaborations on data drawn from http://www.paolomalanima.it/ and Census data from 1861 on); figures for GDP per capita refer to the Italian Centre-North and are drawn again from http://www.paolomalanima.it/).

## Figure 3. Earnings mobility with randomly assigned surnames



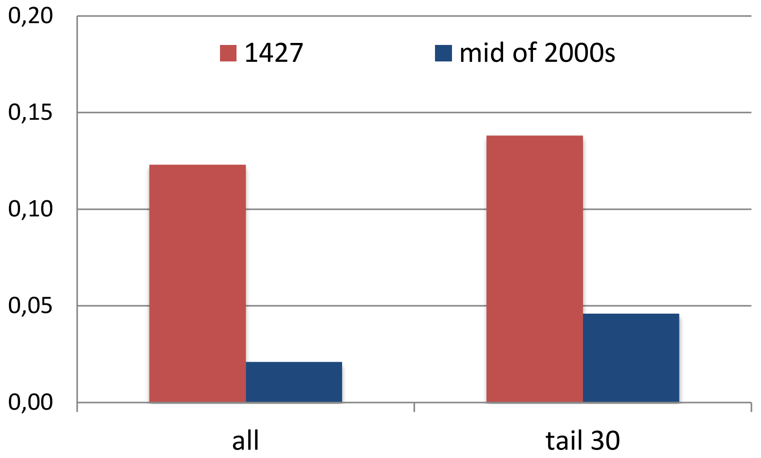

Distribution of estimated earnings elasticity randomly matching ancestors' and descendants' earnings; dashed lines represent 95° and 99° percentile, red line represents the earnings elasticity properly matching ancestors and descendants through surnames.

## Figure 4. Wealth mobility with randomly assigned surnames




Distribution of estimated wealth elasticity randomly matching ancestors' and descendants' wealth; dashed lines represent 95° and 99° percentile, red line represents the wealth elasticity properly matching ancestors and descendants through surnames.

**Figure 5. Income persistence in Florence: 1427 vs. 2000s**




Histograms represent the pseudo-ICS estimated using the approach by Güell et al. (2014); figures for Florence in the 1427 are based on authors' elaborations; figures for Florence in the mid of the 2000s are drawn from Güell et al. (2015); "tail 30" refers to individuals whose surname contains less than 30 people.