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Selection and evolutionary growth in pre-industrial Germany

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Abstract

Evolutionary growth theory (i.e., Galor and Moav (2002) and Clark (2007)) posits that natural selection set the stage for modern growth. I leverage micro-data from historical Germany to assess the viability of the selection mechanisms. I estimate fertility differentials and the inter-generational transmission of SES. High status couples, proxied by occupation, had 1-2 additional children, and SES was strongly heritable. To explore whether these parameters induce selection, I simulate an overlapping generation model of fertility choice and status transmission. The German parameters do not enable Clark's *survival of the richest*, whereas Galor and Moav's *selection on quality* can arise if the returns to investing in child quality are sufficiently large. Monte Carlo simulations extend the analysis beyond Germany. Survival of the richest requires exceptionally high coefficients of transmission (≈0.87), and selection on quality emerges whenever returns to quality investments translate into higher fertility. Both depend on the strong heritability of the growth-complementary traits.

JEL Classification: O40, J12, J13, J62, N33

Keywords: Socioeconomic Status; Fertility; Inter-generational Mobility; Endogenous Growth Theory; Survival of the Richest. Historical Demography.

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Introduction

Economists have long emphasized the relevance of reproductive inequality, namely fertility differentials by socioeconomic status (SES) (Malthus 1803). If some segments of a population with particular traits or preferences have higher net fertility, a greater share of the next generation will exhibit these features. This is the fundamental building block of evolutionary growth theory (Galor and Moav 2001). Here, reproductive inequality leads to the proliferation of the (potentially growth-inducing) traits and preferences of the reproductively more successful classes. Evolutionary change towards traits that are complementary with economic growth thus contributes (or even causes) the transition to modern economic growth (Galor and Moav 2002; Clark 2007). These processes of evolutionary change can occur via genetic and extragenetic transmission (Lala and Feldman 2024), with authors placing varying wights on these different pathways (Clark 2023). Although such explanations are appealing in their theoretical clarity, their applicability to observed historical processes is unclear (e.g. McCloskey 2008; Dribe and Scalone 2014; Cummins 2020).

Even if we assume that some classes had particularly *growth-inducing* traits – i.e. that these traits are highly correlated with SES – questions remain. Reproductive inequality will only lead to long-term selection if SES and the associated traits are strongly transmitted from one generation to the next.[1] However, we are unsure about (1) the level of reproductive inequality and (2) the degree of inter-generational transmission necessary for sustained selection on these traits. To test the viability of evolutionary growth theory, I focus on the two most prominent theories; Galor and Moav's (2002) *selection on quality* and Clark's (2007) *survival of the richest.* In Galor and Moav (2002) some share of the population have a heritable preference for quality that manifests in a reproductive advantage via higher incomes. In Clark (2007) the rich have a growth-inducing *je ne sais quoi* that is disseminated via their reproductive advantage. I delineate the parameter space for these selection mechanisms, and discuss the general conditions for evolutionary growth.

To this end, I estimate reproductive inequality and inter-generational transmission for pre-Industrial Germany. I then simulate an overlapping generation model of fertility choice and inter-generational transmission to explore which parameter combinations can induce selection. To estimate the parameters, I leverage individual-level life histories from the historical principalities of Wittgenstein in western Germany (Mehldau 2011). This source is extensive in depth, temporal scope, and generational linkage, containing demographic histories for around 150,000 individuals across three centuries (1600-1900). The main threat to estimation is the migration-induced censoring of life histories. This source contains the universe of ecclesiastically recorded demographic events in contingent parishes across two sovereign principalities. Compared to other sources for pre-Industrial demographic behavior in Europe, this minimizes censoring, making this a uniquely suitable source. I proxy SES with individuals' occupational status by using a large language model to map occupational titles to measures of status.[2] More than 24% of men had their occupation

[1] McCloskey (2008) raises a similar critique regarding *survival of the richest.* Clark (2008) responds to this critique and uses back-of-the-envelope calculations to demonstrate that fertility differentials and the high heritability of status could lead to survival of the richest. This paper formalizes these back-of-the-envelope calculations by calculating the magnitude of and threshold conditions for selection.

[2] Using LLM methods, instead of hand-coding occupational titles, has the advantage of reducing researcher degrees of freedom while also improving replicability.

recorded.[3] This compares favorably with frequently used sources for France or England (Wrigley et al. 1997; Henry and Houdaille 1973).

Using these detailed life histories, I can show that high SES couples had between 1 and 2 additional surviving children. This differential is driven by gross fertility, with under-15 mortality level across the SES distribution. I find little movement along the extensive margin of fertility; childlessness and celibacy did not vary by SES. Based on a simple decomposition exercise, 83% of the effect of SES on gross fertility is attributable to variation in mother's age at marriage (starting), with variation in the length of the average birth interval (spacing) accounting for the remainder. Instead of interpreting this as evidence for deliberate fertility control, I argue that labor migration among poorer husbands mechanically increased the average birth interval. Fertility differentials of this magnitude create significant selection pressure on SES. The degree to which this pressure affects the composition of society depends on the heritability of SES. To this end, I draw on work by Stuhler (2012) to estimate the coefficient of transmission. I estimate multi-generational elasticities of SES across one, two, and three generations. These elasticities are attenuated by measurement error. A ratio estimator identifies the unattenuated coefficient of inter-generational transmission. In the full sample the coefficient of transmission is equal to 0.63.

Aside from their relevance in describing the social and demographic patterns of pre-industrial Germany, these results contribute to the broader debates about the origins of modern economic growth. I formulate a simple overlapping generation model of fertility choice and inter-generational transmission of status. By simulating this model for the estimated parameters, I show that the German demographic regime could not sustain *survival of the richest*. I find that the story for *selection on quality* is more complex; if the income returns were greater than the fertility cost of investing in child quality, selection pressure on quality preferences emerges. I generalize these results by simulating several 100,000 parameter combinations. The selection mechanism underpinning survival of the richest is contingent on exceptionally high heritability of SES – across simulations, the threshold coefficient of transmission that produces a 50% increase in mean endowment over 20 generations is 0.87. In terms of fertility differentials and status transmission, the parameter space for selection on quality is larger. However, selection depends on more conditions. Chiefly, the fertility returns to quality – via higher incomes – need to be large enough to offset the fertility cost of investing in quality. If this condition is met, and preferences for quality are strongly heritable, lineages with a quality preference out-reproduce the rest. More generally, I show that the conditions for evolutionary growth are (1) a *slight* reproductive advantage for the trait, and (2) a *high* heritability for the trait. Although the former conditions was likely met, the viability of the second is more contentious.

Related Literature. This paper contributes to the debate on the viability of evolutionary growth theory (Galor and Moav 2002; Clark 2007).[4] Instead of focusing on the transition to modern growth, I focus on the underlying selection mechanisms. Although several papers estimate fertility differentials or heritability in the context of evolutionary growth (e.g. Boberg-Fazlic et al. 2011; Clark

[3] All results are robust to excluding this unobserved category, to including it as unobserved, or to assigning individuals to the lowest SES.

[4] Another strand of literature discusses the relevance of reproductive inequality in contemporary settings (de la Croix and Doepke 2003; Doepke 2004; Vogl 2016).

and Cummins 2015; Clark and Cummins 2014; de la Croix et al. 2019), this literature stops short of demonstrating whether these parameters are sufficient for selection to take place.[5][6] I use Monte Carlo simulations to identify the conditions for selection under Galor and Moav (2002) and Clark's (2007) theories. My results favor the mechanism underpinning selection on quality over survival of the richest. Qualitatively, this work is most similar to contributions illustrating that medium fertility families had an evolutionary advantage in the long-run (Galor and Klemp 2019; Hu 2025). By testing the demographic feasibility of evolutionary growth theories, this paper contributes to our understanding of the transition from economic stagnation to growth.[7]

This literature overlaps with work testing Malthusian theory.[8] Malthus makes formal predictions about the relationships between wealth, fertility, and mortality (Malthus 1803). He predicts lower gross fertility (preventive check) and higher childhood mortality (positive check) among poorer couples (Malthus 1803). Several studies examine these associations at the individual-level. For Europe, previous studies focus on England (Clark and Hamilton 2006; Boberg-Fazlic et al. 2011; Kelly and Ó Gráda 2014; Clark and Cummins 2015; Cummins et al. 2016; de la Croix et al. 2019) and France (Weir 1995; Cummins 2020).[9] By exploring these associations in Germany, this paper expands our knowledge of the demographic history of Europe. France and England are the vanguards of demographic change and industrialization, respectively. Understanding how these associations shaped the demographic regime in a case removed from these extremes is an important step towards a more holistic understanding of demographic regimes of pre-industrial Europe. The fertility differentials I estimate are comparable to the "super-fertility" of the rich in England, instead of the moderate advantage the richest enjoyed in pre-revolutionary France (Cummins 2020, p. 15).

Lastly, my findings contribute to a rich literature on social mobility. While several studies explore historical social mobility (Crew 1973; Kaelble 1984; Van Leeuwen and Maas 1996), the German case before 1900 is largely absent from the recent literature. Advancements in methodology and data availability led to a proliferation of estimates of social mobility for Anglo-American countries (Miles 1999; Mitch 2005; Mazumder 2005; Long and Ferrie 2013; Clark and Cummins 2014; Braun and Stuhler 2018; Clark, Cummins, and Curtis 2023; Zhu 2024; Pérez 2019; Ward 2023, e.g.). I contribute the first estimate of inter-generational transmission from pre-Industrial Germany. I estimate that the coefficient of transmission was 0.63 (1650-1850). Albeit high, implying limited mobility, the estimate falls below the proposed universal coefficient of ≈0.8 by Clark (2014) and is much closer to estimates for early-20th-century Germany by Braun and Stuhler (2018).

[5] Klemp and Weisdorf (2019) test another tenet central to endogenous growth theory. They explore the relationship between medium fecundity and human capital in pre-Industrial England.

[6] de la Croix et al. (2019) include back-of-the-envelope calculations to show that their estimates would lead to a significant expansion of the middle-class. However, their calculations assume perfect inter-generational transmission.

[7] Another strand of literature uses genotyped DNA samples and GWAS poly-genic scores to identify evidence for genetic selection (Piffer and Connor 2025). But questions regarding population stratification (Hellwege et al. 2017) (i.e., where random variation in genotypes across environments drive spurious associations between genotype and environment-dependent phenotype) and the portability problem (Matthews 2022), the limited out-of-sample applicability of poly-genic scores) raises important concerns about the reliability of these findings.)

[8] Given the population level predictions of the Malthusian model and the scarcity of individual-level records, macro-level inquiry – estimating the relationship between vital rates and real wages at a population level – prevails (Lee and Anderson 2002; Crafts and Mills 2009; Fernihough 2013; Pfister and Fertig 2020). Another strand of this literature uses historical event analysis to evaluate the contemporaneous individual-level demographic response to economic pressure and the variation of the latter across social groups (Bengtsson et al. 2004; Thiehoff 2015).

[9] Several papers tested the individual-level dynamics of the Malthusian model outside of Europe (Feng et al. 1995; Lee and Feng 1999; Campbell and Lee 2002; Bandyopadhyay and Green 2013; Lee and Park 2019; Kumon and Saleh 2023; Hu 2023).

The paper progresses as follows. The next section introduces the data I assembled to estimate German parameters. In section three, I estimate reproductive inequality and the underlying mechanism. Section four presents estimates of inter-generational transmission of SES. Section five describes the overlapping generation model and discusses the results of the simulation exercise. Section six concludes.

2 Data and Background

Studying pre-industrial demographic behavior requires a set of sources distinct from those employed for later epochs. Census or population registry data of sufficient granularity are seldom available prior to the mid-19th century (Campbell 2015). In this paper, I leverage the *community reconstitution* for the historical principalities of Wittgenstein (Mehldau 2011). Community reconstitutions contain linked life histories for all members of a specific 'community'.[10] Life histories are based on ecclesiastical records of baptism, marriages, and deaths. Due to the labor-intensive process of linking demographic events, reconstitutions tend to focus on singular, or at most, a collection of parishes and rarely capture urban populations (Blanc 2023). The Wittgenstein reconstitution sets itself apart by containing the universe of ecclesiastically recorded demographic events across two sovereign principalities. Additionally, compared to other genealogical sources, the exceptional scientific rigor (citing the specific source for each demographic event) makes this reconstitution particularly valuable. The dataset encompasses 150,000 individuals across 42,000 couples. The core of the study draws on the complete registers of 16 parishes (11 Reformed-protestant, 1 Lutheran-protestant, 4 Roman-catholic) (Mehldau 2011).

Notably, the approach of the Wittgenstein reconstitution is micro-historical. Instead of looking at a broad sample of remote parishes, I observe one cluster of neighboring parishes. This is advantageous since much early-modern migration occurred over short distances (e.g., neighboring parish); hence, in my sample, fewer life histories are censored by migration (Clark 1979; Patten 1976). Moreover, Wittgenstein constitutes a valuable case study of rural German demographic behavior. Before the Reichsdeputationshauptschluss of 1803, the territory was split between the two principalities of Sayn-Wittgenstein-Hohenstein in the south and Sayn-Wittgenstein-Berleburg in the north (Köbler 2007).[11] Protestantism was adopted early; most of the population was Reformed Protestant, with a sizable Lutheran minority and smaller Roman Catholic and Jewish ones. Given its mountainous geography, extensive forests, and low agricultural suitability, Wittgenstein was characterized by fragmented farming instead of larger estates. Compounded by a partible inheritance structure, this meant that most inhabitants practiced some degree of subsistence agriculture. In the later part of our study period, the first-order geography, which had initially retarded Wittgensteins development, favored the development of proto-forestry and metallurgy industries. Wittgenstein's main export was charcoal, primarily to its more industrialized neighbors. In addition to artisans, a small textile cottage industry constituted an additional source of employment (Klein 1936;

[10] Community reconstitutions are the non-academic analog to family reconstitutions, often compiled by hobby genealogists (Knodel and Shorter 1976).

[11] A substantial step in the secularization and mediatization of the late Holy Roman Empire initiated to compensate German principalities for the loss of territory left of the Rhine to Napoleonic France.

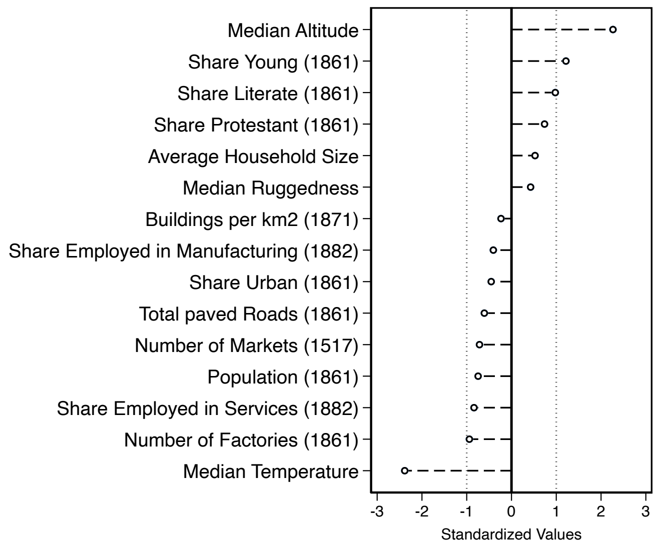

Figure 1: Wittgenstein: Socioeconomic observables compared to west Prussian average.
Source: Galloway Prussia Database, iPEHD Prussia Database, Princes and Townspeople: A Collection of Historical Statistics on German Territories and Cities (Markets). Map created using ArcGIS.

Fremdling 1986).

Still, although it was located on the border of the economically dynamic Rhineland, its infrastructural backwardness and geographical remoteness partially isolated Wittgenstein from modernizing tendencies (Klein 1936). Figure 1 compares Wittgenstein with other western Prussian counties at the end of the 19th century across several socio-economic observables. With the exception of geographic variables (temperature and altitude), most others are within one standard deviation of the mean county. The picture of late 19th-century Wittgenstein that emerges is one of a somewhat economically backward region, with a young and relatively more educated population. Although it would be misguided to claim that these principalities are wholly representative of German demographic behavior, these traits of Wittgenstein – subsistence agriculture and the development of proto-industry – make it a pertinent case for understanding demographic behavior and change in rural Germany.

Exclusion conditions. Since community reconstitutions often link records from outside the core area of the study, they are at risk of over-sampling genealogies of particular interest to contributors or greater ease of access. The Wittgenstein one-place study contains complete reconstitutions for the 16 parishes of Wittgenstein and partial reconstitutions from other parishes (mostly neighboring Siegen). Although the reconstitution contains records from as early as 1525, observations from before 1600 are excluded. An 1876 law transferring the responsibility for recording demographic events from ecclesiastic to secular institutions marks the end of parish registers as a complete source. To ensure that I observe full fertility histories, only marriages prior to 1850 are included when I estimate fertility differentials. When estimating inter-generational transmission, the sample is restricted to son's that married before 1876. Throughout, to ensure estimates are not biased by

Table 1: Summary Statistics

Panel A: Demographic Variables						
	Mean	Std. dev	Min.	Max.	N	Level
Gross Fertility	5.18	3.00	0	17	10323	Couple
Net Fertility	3.58	2.33	0	12	10323	Couple
P(Childless)	0.06	0.23	0	1	10323	Couple
Marriage Age: Mother	24.98	5.88	11	72	10323	Couple
Marriage Age: Father	28.66	6.16	10	75	10323	Couple
Age at last birth: Mother	37.50	6.24	15	55	9731	Couple
Birth-interval (avg. months)	35.33	15.36	0	388	8978	Couple
HISCAM^h	59.71	14.31	41	99	5325	Couple
P(AgeDeath $\leq$ 5)	0.25	0.43	0	1	54018	Birth
P(AgeDeath $\leq$ 15)	0.30	0.46	0	1	54018	Birth
HISCAM^f	60.50	13.80	41	99	27700	Birth

Panel B: Intergenerational Transmission				
Variable	Generation	Mean	Std. dev	N
	G3 (son)	4.04	0.18	5143
ln(HISCAM)	G2 (father)	4.07	0.20	5143
	G1 (grandfather)	4.10	0.21	3274

Notes: Panel A presents summary statistics for the most all relevant variables used in the estimation of reproductive inequality. Variables are observed either at the level of the couple or the level of the birth. At the birth level HISCAM is the occupational status of the father, and at the couple level it is the occupational status of the husband. Further variation in sample size is the result of inclusion restrictions discussed in section 2. Panel B presents summary statistics for the estimation of intergenerational transmission of status. The variable of interest is log occupational status with each row corresponding to a generation in the linked sample.

the effect of remarriage, only bachelor-spinster marriages are included.

When estimating reproductive inequality, I include only couples whose marriages were recorded in the core parishes, constituting the full reconstitution at the heart of the source. Individuals are not observed across their full lifetime but instead only enter observation at discrete instances when specific demographic events occur. Since migration is an unobserved event, I need to account for the migration-induced censoring of life histories (Campbell 2015). To this end, only non- and in-migrants prior to marriage are included.[12] These restrictions result in a sample of 10,323 couples and 54,018 births (see Panel A, Table 1).

For inter-generational transmission, I impose less severe inclusion restrictions. To estimate status elasticities, I need to observe occupation for two subsequent generations (GX & G[X-1]). Fathers (sons) who are linked to sons (fathers) outside the core parishes do not bias the estimates. Delger and Kok (1998) outlines how marriage registers – observing both father and son's status at the instant of the son's marriage – underestimate mobility due to the difference in career progression. My sample is limited to fathers (G2) that I observe at marriage (either in or outside of Wittgenstein) and their legitimate children (G3), mitigating this source of bias. Since my sample is fully hand-linked, I avoid concerns regarding false-positives from automated record linkage (Bailey et al. 2020;

[12] I also run regressions based on a sample that is only restricted by mothers death, allowing for the out-migration of fathers. This has a negligible effect on results; hence, only the stricter restriction is reported throughout. For a full discussion of how migration can color my results, see Appendix B.

Table 2: Status Classes

Class	**Classification Rule:** Capital			**Summary Statistics**		
	Human	Economic/Land	Social	N Couples	N Births	E(HISCAM)
Lower	1	0	1	429	1883	47.22
Lower-middle	2	1	2	1020	5009	52.50
Upper-middle	3	2	3	3342	17441	60.50
Upper	4	3/4	4	770	4231	71.83

Notes: The table summarizes class definitions based on the classification of occupations by a LLM according to three forms of capital and reports associated sample sizes and expected HISCAM (occupational status). In classification: 0-None, 1-Low, 2-Modest, 3-High, 4-Very High.

Anbinder et al. 2021). Still, identifying the coefficient of transmission in a latent variable model requires linked data across three generations. Leveraging the linkage depth of the reconstitution, I link backwards along the paternal line to find grandfathers (G1). The estimation sample contains 5,143 sonfather (G3-G2) and 3,274 songrandfather (G3-G1) links (see Panel B, Table 1).

2.1 Occupational Status

At the level of couples, SES is approximated by husband's occupational status.[13] In other regressions status is measured by own, husband's, or father's status ($\text{Status}_i^{i/h/f}$).

To reduce researcher degrees of freedom and improve replicability, occupational descriptions are mapped to occupational status using natural-language methods. After minimal preprocessing, occupational descriptions are parsed by a large language model (LLM) (`claude-3-haiku-20240307`), yielding 2,568 unique occupational titles. A separate model (`claude-sonnet-4-20250514`) is used to (1) translate occupational titles and (2) assign them to discrete status classes.[14] The LLM makes assignments based on the (1) human capital, (2) economic capital or land, and (3) social capital requirements of different occupations. Table 2 summarizes the classification rules and reports summary statistics for the classes.[15]

In addition to discrete status classes, occupational titles are also mapped to a continuous measure (0-100) of occupational status (HISCAM). To this end, I employ a fine-tuned version of the `OccCANINE` classifier model by Dahl and Vedel (2024) to code all translated occupational titles into HISCO, a standard historical occupational classification scheme that maps onto HISCAM scores. HISCAM is based on the observed stratification of social interactions in historical societies; as such, it is distinct from class schemes that assign occupations to social groups based on the post-factum conceptualization of status (Lambert et al. 2013).[16] For a subset of individuals, I observe multiple occupations. Whether due to occupational mobility, differing occupational names, or because

[13] In the patriarchal context of rural pre-industrial Germany, male income was the main determinant of household income.
[14] I also run a classification prompt that assigns each occupation to one of ten discrete occupational categories. The two approaches yield similar results and the same overall fertility gradient. However, to aid interpretability, and because a ranking across a larger number of categories is more contentious, I prefer and report estimates using the four status classes. My results also replicate when using the seven occupation categories proposed by Clark and Hamilton (2006). See Table A2.
[15] Table A3 reports the ten most common occupations per class.
[16] Throughout, I use the universal HISCAM scale, since the German-specific scale relies on a small sample.

people pursue multiple occupations. When using HISCAM, I average across these observations to reduce measurement error in occupational status. When using the discrete categories, I use a random draw of available occupations.[17]

I validate the LLM mapping by comparing it to a hand-mapping of occupations. In the absence of a ground-truth mapping, this is the second-best approach to validation. Inter-rater agreement measures between the mappings indicate substantial agreement (Cohens κ=0.62) and correlations between different status measures are high across the board (see Table A1). Additionally, I demonstrate that results are robust to using the hand-mapping.

3 Reproductive Inequality

This section estimates the degree of reproductive inequality – the fertility differential between the highest and lowest SES couples. After estimating the degree of reproductive inequality, I discuss the mechanisms underpinning class differences and account for measurement error using a partial identification strategy.

3.1 Estimation

Reproductive inequality is defined as the differential in net fertility between couples of high and low SES. Net fertility is a composite of how many children were born (Malthusian preventive check) and how many died before reaching reproductive age (positive check). To understand how these three demographic outcomes – gross fertility, under-15 mortality, and net fertility – vary in SES, I estimate the following econometric model.

$$Y_i = \alpha_p + \tau_t + \beta \cdot STATUS_i + \epsilon_{i,t,p} \quad (1)$$

where Y_i is the outcome of interest. i indexes the couple or, when estimating mortality, the individual birth. The model includes parish α_p and decade τ_t fixed effects to account for local reporting practices and temporal differences. The exposure variable $STATUS_i$ is a measure of SES; discrete status categories $\sum STAT_i$ or a continuous logged measure $\ln(\text{HISCAM}_i)$. All baseline regressions are estimated using OLS, and standard errors are clustered at the parish level.[18]

Gross fertility is the number of children ever born to a couple. Childhood mortality is estimated at the individual level, where Y_i is an indicator variable equal to one if the age at death is younger than 15.[19] Estimation at the individual-level ensures that mortality differentials are isolated from

[17] Results are robust to using their highest or lowest status occupation. See Table A2.

[18] The results are robust to estimation using negative binomial (for fertility) and logistic (for under-15 mortality) models; See Table A4. I cluster at the parish level since demographic events and occupations are recorded at the level of the parish, and unobserved parish-specific factors can create within-parish correlation. To further account for this I show that my results are robust to clustering at the approximate level of the priest (Parish $\times$ Decade) in Table A5.

[19] I account for the under-reporting of infant deaths by using a repeat-naming approach (Houdaille 1976; Cummins 2020). In pre-modern Europe, when a child died, the subsequent child was often given the same forename. Therefore, where a child has a subsequent sibling of the same name and is not linked to a burial record, it is assumed to have died as an infant.

Table 3: Reproductive Inequality

	Gross Fertility		$1(\text{AgeDeath} \leq 15)$		Net Fertility	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(HISCAM)	1.335***		-0.039*		1.140***	
	(0.215)		(0.021)		(0.182)	
Lower-middle Class		0.518**		0.009		0.325***
		(0.197)		(0.017)		(0.104)
Upper-middle Class		0.900***		0.007		0.594***
		(0.129)		(0.015)		(0.077)
Upper Class		1.165***		0.000		0.823***
		(0.204)		(0.014)		(0.168)
Mean DV	5.144	5.136	0.298	0.298	3.594	3.587
Observations	5325	5561	27700	28874	5325	5561
Parishes (clusters)	16	16	16	16	16	16
R^2	0.035	0.036	0.008	0.007	0.034	0.033

Robust clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table reports OLS estimates for the association between SES and demographic outcomes. In columns (1), (3), and (5) the exposure variable is ln(HISCAM) – logged continuous occupational status – and in all other columns SES is operationalised as discrete status categories, with "lower class" being the reference category. The outcome variable in columns (1) and (2) is gross fertility measured at the couple level. Columns (3) and (4) are estimated at the birth level and the outcome variable is a indicator variable equal to one if the child died prior to turning 15. Here status is measured using father's status. Columns (5) and (6) present estimates for net fertility, gross fertility minus adjusted under-15 mortality, and are estimated at the couple level. All regressions include parish and marriage/birth decade fixed effects.

fertility effects.[20] This approach assumes that I observe child-deaths prior to 15 even where I do not observe the full life history, since children were likely to live with their parents up to 15. Last, net fertility is gross fertility minus adjusted under-15 mortality at the couple level.

Table 3 reports the results. Columns (1) and (2) demonstrate a pronounced and significant positive association between SES and gross fertility. The coefficient for ln(HISCAM) implies that doubling HISCAM from the lower-bound of the status distribution (40) to the top decile (80) would increase gross fertility by $1.335 \times \ln(80/40) = 0.925$. Column (2) reveals an even more pronounced fertility differential; couples of the highest status class had 1.165 additional children compared to those of the lowest class. HISCAM and the status classes capture distinct dimensions of SES. Thereafter, this small difference (21.6%) in the estimates of the fertility differential is unsurprising. The relationship between SES and fertility is non-linear across the 4 status categories. The predicted fertility for the lower-middle class is $\times 1.12$ higher than that of the lower class, but the advantage of the upper class over the upper-middle class shrinks to $\times 1.05$. The log-linear specification in column (1) accounts for this non-linearity: the effect of SES on fertility levels off at higher SES. This concavity is consistent with biological constraints on fertility. Assuming couples begin childbearing at age 25, continue until age 45, and maintain an average birth interval of 3 years, the maximum expected fertility is 6.7 births.[21] As couples approach this limit, the marginal effect of SES becomes

I compare siblings based on the string distance (jaro-winkler) between names. This approach enables me to also catch cases where parents reused names for the other gender, e.g., Peter (male) and Petra (female).

[20] Since the proportion of children dying is a function of both childhood mortality and gross marital fertility, estimation at the couple level introduces bias if a status gradient in fertility is present. Even if the probability of a child dying is equivalent across status groups, variation in the denominator could introduce spuriously significant associations between status and mortality.

[21] Calculated as (StoppingAge-StartingAge)/SpacingTime.

mechanically constrained. Moreover, in a classic model of fertility choice where preferences are defined across consumption and children, higher-SES (income) couples may have a preference for consumption, reducing the marginal effect of SES (income) on fertility.

The association between under-15 mortality and SES is estimated using a linear probability model. The coefficients correspond approximately to changes in the probability of death for all births. All estimates in (4) are statistically insignificant. The only significant coefficient – at the 10% level – found in column (3) is economically small. Children born to couples of the lowest SES have a probability of 0.31, as opposed to a probability of 0.29 for the highest status decile. These results imply that under-15 mortality did not vary across SES in a meaningful way. This finding is consistent with evidence from France and England (Boberg-Fazlic et al. 2011; Clark and Cummins 2015; Cummins 2020). Given the dominance of infectious diseases as causes of under-15 mortality, the absence of an association is unsurprising. The better living standards of higher SES couples did little to curb high childhood mortality from infectious diseases. SES and income only became relevant in periods of sustained resource shortages when children of wealthier couples were less exposed to malnutrition. Kelly and Ó Gráda (2014) finds that in late-medieval England, a SES-gradient in mortality only emerged in periods of sustained famine. In a similar vein, Malthus himself noted that the status-gradient in mortality acted only as a "last most dreadful resource of nature" during periods of pronounced resource scarcity (Malthus 1803).

Given the absence of an association between under-15 mortality and SES, the gradient in net fertility closely mirrors that in gross fertility. Based on the coefficient in column (4), couples in the top decile had $1.140 \times \ln(80/40) = 0.790$ additional surviving children. According to the discrete categories, the highest-SES class had 0.823 additional surviving children.

3.2 Mechanism

Extensive Margin. Baudin et al. (2015) decomposes group level fertility into an intensive and extensive margin. The intensive margin corresponds to the number of surviving children per reproductive unit (couple). The extensive margin is determined by the share of all potential reproductive units that do not have children, namely couples that remain childless and individuals who remain celibate. de la Croix et al. (2019) demonstrates that the extensive margin affected reproductive inequality in England; here, when accounting for celibacy and childlessness, the middle-class had the highest fertility. To explore whether this is the case in Germany, I regress indicator variables for childlessness and celibacy on ln(HISCAM) in a linear probability model. I find that the extensive margin of fertility did not vary in SES. Instead, reproductive inequality operated fully through the intensive margin.[22]

Intensive Margin. The intensive margin of gross fertility is a function of when reproductive behavior begins (*starting*), when reproductive behavior ceases (*stopping*), and how frequently births occur within this period (*spacing*). To understand the relevance of these factors in my sample, I regress mother's age at marriage, age at last birth, and birth intervals on husband's occupational

[22] For a fuller discussion, see Appendix C.

Table 4: Reproductive Inequality: Measurement Error in SES

	Net Fertility			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
Instrument:			$\ln(\text{HISCAM}_{\text{alt}})$	$\ln(\text{HISCAM}_{\text{g-1}})$
$\ln(\text{HISCAM})$	1.010***			
	(0.177)			
$\ln(\text{HISCAM}_{\text{avg}})$		1.140***		
		(0.182)		
$\ln(\widehat{\text{HISCAM}})$			2.788	2.961***
			(1.710)	(0.641)
Mean DV	3.594	3.594	3.678	3.649
Kleinbergen-Paap F stat			18.194	78.462
Observations	5325	5325	1643	2323
Parishes (clusters)	16	16	14	15

Robust clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table reports OLS and 2SLS estimates for the association between SES and net fertility. The unit of observation is the couple. Columns (1) and (2) are estimated using OLS and use as exposure a random draw of $\ln(\text{HISCAM})$ or the average $\ln(\text{HISCAM})$ respectively. These regressions include both couples with one $\ln(\text{HISCAM})$ and those with multiple. Column (3) and (4) are estimated using 2SLS. In column (3) a random draw of $\ln(\text{HISCAM})$ is instrumented with a second draw among the subpopulation with multiple observed occupations (31%). In column (4) $\ln(\text{HISCAM})$ is instrumented with $\ln(\text{HISCAM}_{g-1})$ of the prior generation among the subset of couples that can be linked backwards (44%). All regressions include parish and marriage/birth decade fixed effects.

status. I discover that both starting and spacing vary in SES. In couples of the top SES decile, women married 3.30 years earlier and had 2.02 months shorter birth intervals. A decomposition exercise reveals that starting was more important, accounting for 83% of the total effect of SES on gross fertility.[23] Historical evidence suggests that differences in birth intervals were not driven by deliberate spacing but were instead the mechanical consequence of local labor markets. Lower SES men often traveled to neighboring principalities to seek out work (Klein 1936). These periods of absence mechanically increase birth intervals for low SES couples, offering a viable explanation for the association between spacing and SES. In aggregate, this suggests that the age at marriage was the main driver of fertility differentials, with a limited role for *mechanical* spacing.

3.3 Measurement Error

One concern when interpreting the magnitude of these differentials is that measurement error in SES – due to data error and status deviations – attenuates my estimates. Although this issue is much acknowledged in the social mobility literature (e.g. Solon 1992; Ward 2023; Zhu 2024), prior studies of historical reproductive inequality do not deal with it directly. Occupational status is a noisy snapshot of latent SES; $OccStatus_i = SES_i + u_i$. If this noise takes the form of classical measurement error – i.e., u_i has mean zero and is uncorrelated with SES – the coefficients $\hat{\beta}_{OLS}$ for reproductive inequality are attenuated (Solon 1992).

[23] For a fuller discussion, see Appendix D.

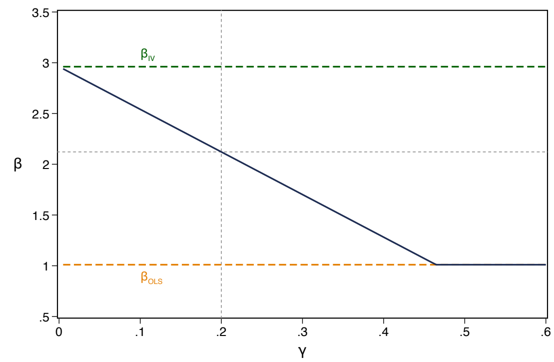

Figure 2: Partial Identification of the Fertility Differential
Notes: This figure depicts the relationship between the unbiased estimate of the fertility differential β and potential violations of the inclusion restriction described by the direct effect of the prior generations SES on fertility γ. The true coefficient is bounded from above by the potentially inflated β_{IV} and from below by the attenuated β_{OLS}.

Two approaches to correct for attenuation bias are (1) averaging across multiple observations of SES per unit, or (2) using a repeated measure of SES as an instrument. The former reduces attenuation, while the latter can fully account for it. However, the repeated measures approach does not work well with reconstitution data; not only is the population with multiple recorded occupations strongly selected, but if multiple are recorded, they are most often not independent measures of the same SES, but instead snapshots at different parts of the status-lifecycle (e.g., marriage and death). Thus, instead of recovering β, the instrumental variable approach estimates a local effect among a selected complier population. In this setting, compliers are couples with very low life-cycle mobility, i.e., the poorest and richest couples who stay poor or rich.[24] To account for this, I implement an strategy and instrument occupational status $OccStatus_{i,g}$ with the occupational status of the prior generation $OccStatus_{i,g-1}$. Father's SES is a strong predictor of one's own SES and thus a relevant instrument.

Table 4 reports estimates obtained using all three strategies. In column (1), the HISCAM is based on a random draw of occupations, where multiple are observed. Column (2) corresponds to the baseline estimate and averages SES across multiple observations. Consistent with measurement error in SES, the point estimate increases by 12.9%. Columns (3) uses a second observed occupation as an instrument; the F *statistic* is low (for a repeat measurement approach), and the point estimate is insignificant. Column (4) reports the estimate from instrumenting with the occupational status of the prior generation. The estimates in column (4) are inflated if the exclusion restriction is violated. If Father's have a direct effect γ on the fertility of their offspring, the exclusion restriction is violated, and β_{IV} is biased by γ/π, where π is the first stage coefficient from regressing $\ln(\text{HISCAM}_{i,g-1})$ on $\ln(\text{HISCAM}_{i,g})$. If the SES of the prior generation affects fertility directly, β_{IV} can be used to bound β from above in a partial identification approach. Since measurement error biases β_{OLS} downwards, we know that $\beta_{OLS} \leq \beta \leq \beta_{IV}$. Figure 2 models this relationship. By considering a realistic range of direct grandfather effects, we can make a best-guess about the true value of β. For example, if we assume a direct grandfather effect of $\gamma = 0.20$ (namely, irrespective of fathers SES, high SES grandparents have 0.20 extra grandchildren), couples of the highest SES decile have a

[24] Additionally, if SES is measured at different ages, the associated measurement error is likely age-dependent and non-classical.

reproductive advantage of $2.122 \times \ln(80/40) = 1.47$.

3.4 Summary

This section presents estimates for reproductive inequality in Germany. When not accounting for measurement error in occupational status, the fertility differential between the lowest and highest status couples was $\ln(80/40) \times 1.01 = 0.70$. Once I account for measurement error, the estimated differential is $\ln(80/40) \times 2.96 = 2.05$. Relaxing the exclusion restriction and allowing for a direct parental-effect on fertility suggests a differential of $\ln(80/40) \times 2.12 = 1.47$. Net fertility differentials are the result of differences in gross fertility; mortality, celibacy, and childlessness do not vary in SES. Mother's age at marriage accounts for the majority of the differential in gross fertility.

Fertility differentials are relevant to evolutionary growth theory because they predict the composition of subsequent reproductive generations. Suppose a population of two equally sized groups and the lower-bound fertility differential. One group has a reproductive advantage of 3.70 over 3.00. Let us assume that people mate only in their own group (perfect assortative mating) and that group status is transmitted perfectly. Within three generations, the group with the reproductive advantage outnumbers the other group by a factor of 1.87. By ten generations (approx. 250 years), this rises to 8.14, with the reproductively successful group constituting 89.1% of the population. Perfect heritability is a strong assumption, but it serves to illustrate the relevance of reproductive inequality. The next section will probe this assumptions.

4 Transmission of SES

In a perfectly mobile society, where parental status has no bearing on the status of children, the selection pressure of reproductive inequality is muted. On the other hand, if, as in the prior example, status is strongly heritable, fertility differentials can change the composition of a population within just a few generations. This section estimates how strongly SES is transmitted across generations to better understand how SES transmission and fertility differentials might interact to induce selection. To estimate the degree of inter-generational transmission, I draw on work by Stuhler (2012) that describes a latent variable model of multi-generational transmission.

4.1 Latent Variable Model

Empirical studies typically estimate inter-generational elasticities β_{-1} by regressing log parental SES ($y_{i,g-1}$) on log offspring SES ($y_{i,g}$). The estimated coefficient captures how strongly SES advantages are passed from parent to offspring. However, interpreting this elasticity as a measure of heritability and extrapolating persistence to multiple generations requires strong assumptions about the SES generating process (Stuhler 2012; Braun and Stuhler 2018; Ward et al. 2025).[25] inter-generational elasticities only have a structural interpretation if there is no noise in the status inheritance process; i.e., status is determined only by parental SES. This is an exceedingly strong assumption; parents shape childhood outcomes via the direct inheritance of traits and preferences; they invest in child quality, SES is shaped by random market forces and choices, and prior generations could have a direct effect on outcomes. We can account for these sources of noise and recover the structural inter-generational transmission of SES in a simple latent variable model (Stuhler 2012).

Model. Assume children inherit some latent variable $x_{i,t}$ from their parents. This latent variable captures direct mechanisms from the parents (e.g., genetic, parental investment, and upbringing) as well as environmental factors (e.g., social/professional network) that are shaped by the parents. For now, we assume that these different facets are inherited as one package according to an inter-generational transmission coefficient λ. Life-time SES ($y_{i,t}$) in turn depends on latent ability ($x_{i,t}$) according to a returns to ability coefficient ρ.

$$y_{i,g} \;=\; \rho\, x_{i,g} \;+\; u_{i,g} \tag{2}$$

$$x_{i,g} \;=\; \lambda\, x_{i,g-1} \;+\; v_{i,g} \tag{3}$$

Let the errors be uncorrelated and independent. $v_{i,g}$ measures endowment luck, while $u_{i,g}$ is a permanent error component that measures market luck and other random deviations from potential SES that arise due to random chance (e.g., injury or war) or individual choice (e.g., the offspring of rich magnates choosing to pursue pottery). Additionally, as we recall from subsection 3.3, we do not observe permanent income/status $y_{i,g}$ directly. Instead, we observe some noisy snapshots $\tilde{y}_{i,g}$ such as occupational status, where $e_{i,t}$ is a transitory error component (Ward et al. 2025). Observed SES is then equal to:

$$\begin{aligned} \tilde{y}_{i,g} &= y_{i,g} + e_{i,g} \\ \tilde{y}_{i,g} &= \rho\, x_{i,g} + u_{i,g} + e_{i,g} \end{aligned} \tag{4}$$

Multi-generational Inheritance. This model implies a structural interpretation of multi-generational elasticities. The slope coefficient from regressing the observed status of a prior generation $\tilde{y}_{i,g-m}$ on the observed status of the current generation $\tilde{y}_{i,g}$ is;

$$\beta_{-1} = \frac{\text{Cov}(\tilde{y}_{i,g}, \tilde{y}_{i,g-m})}{\text{Var}(\tilde{y}_{i,g-m})} \tag{5}$$

If we plug Equation 4 into Equation 5 and generalize to m generations, we obtain:

$$\beta_{-m} = \frac{\rho^2 \sigma_x^2}{\rho^2 \sigma_x^2 + \sigma_u^2 + \sigma_e^2} \cdot \lambda^m \tag{6}$$

[25] Persistence is usually extrapolated to multiple generations by exponentiating the elasticity; i.e., if the inter-generational elasticity $\beta_{-1} = 0.60$, then the multi-generational elasticity across three generations is $\beta_{-3} = \beta_{-1}^3 = 0.21$.

If the variances of underlying ability, the transitory error term, and the permanent error terms are stationary, we can write β_{-m} as the product of an attenuation factor θ and λ^m. Under these additional stationarity assumptions, we can recover the true coefficient of inter-generational transmission via the ratio estimator:

$$\lambda = \frac{\beta_{-m+1}}{\beta_{-m}} \tag{7}$$

.

Assortative Mating. So far, the model assumes a simplified one parent setting where x is only inherited from one parent. Braun and Stuhler (2018) shows that the ratio method still recovers a meaningful inheritance parameter λ if offspring inherit x independently from both parents. Here λ is a reduced form estimate of two components: the average coefficient of transmission across the paternal and maternal lines and the degree of assortative mating. Thus, λ increases in assortative mating. In the absence of perfect assortative mating, λ will understate average heritability $\tilde{\lambda}$ because offspring will inherit different x from either parent. I abstract from incorporating mating patterns. Instead, I interpret λ as a reduced form combination of average inter-generational transmission and assortative mating (Stuhler 2012). However, since assortative mating was high in historical populations (e.g. Clark and Cummins 2022), λ will mostly capture inter-generational transmission.

4.2 Estimation

Identifying Assumptions. Prior to estimating the coefficient of heritability λ, it is worth making explicit the identifying assumptions. First, we assume that the attenuation factor θ is constant across generations. If the data quality changes from one generation to the next, or if permanent deviations from potential status become more likely for certain generations, λ is biased. While it is unlikely that θ changed systematically from one generation to the next, it is important to acknowledge this caveat to the findings. This is particularly relevant when λ is estimated by sub-period; here, generations more closely resemble cohorts that are more prone to systematic differences in θ – i.e., because novel opportunities brought about by industrialization alter ρ.

Second, the model assumes that status inheritance only spans one generation. Although grandparent effects have received growing attention (Mare 2011; Ferrie et al. 2021), others argue that they are statistical artifacts of the latent variable model (Braun and Stuhler 2018; Ward et al. 2025). The common approaches for identifying grandparent effects are to test for excess persistence, i.e., $\beta_{-2} > \beta_{-1}^2$, or to specify multi-generational AR(2) regressions that test whether $\tilde{y}_{i,g-2}$ is significant conditional on $\tilde{y}_{i,g-1}$. In the presence of measurement error, both approaches identify spurious grandfather effects (Ward et al. 2025).[26] Ergo, if the latent variable model holds, correcting for measurement error should increase β_{-1} while decreasing the relative magnitude of multi-generational effects. I estimate multi-generational transmission in Appendix E; the pattern across coefficients suggests that grandfather effects are driven by measurement error. Thus, I am confident in making the identifying assumption of no grandfather effects.

[26]The first approach overstates the grandparent effect by construction because $\beta_{-2} = \theta\lambda^2 \;>\; \beta_{-1}^2 = \theta^2\lambda^2 \quad \text{if} \quad \theta < 1$. The second approach suffers a similar fate; coefficients are spuriously large and significant due to spill-over bias from the signal for the parental latent variable (Modalsli and Vosters 2024).

Coefficient of Transmission. The latent factor model in subsection 4.1 implies that we can identify λ – the true coefficient of transmission, free from both permanent and transitory measurement error – by using the ratio estimator in Equation 7. Table 5 reports estimates of λ for different subsamples. The first two columns report the number of multi-generational links that are used to estimate the elasticities across one β_{-1} and two β_{-2} generations. The coefficients are estimated according to Equation A1 and reported in the two subsequent columns. The final column contains estimates for the coefficient of transmission $\widehat{\lambda}$. The first row reports results for the full sample, with all possible links. In subsequent rows, the sample is restricted to observations where I observe both the father's (G2) and grandfather's (G3) SES. I also split the sample based on the birth year of the youngest generation (G1). Rows three and four report the results for the pre- and post-1800 samples.

Table 5: Estimates of Intergenerational Transmission

	(1)	(2)	(3)	(4)	(5)	(6)
	N: G3–G4	N: G2–G4	$\hat{\beta}_{-1}$	$\hat{\beta}_{-2}$	$\widehat{\lambda}$	SE($\widehat{\lambda}$)
Full	5146	3274	0.304	0.192	0.631***	(0.067)
Restricted	3274	3274	0.324	0.192	0.593***	(0.069)
Early (pre-1800)	1677	1677	0.339	0.208	0.614***	(0.071)
Late (post-1800)	1597	1597	0.290	0.159	0.549***	(0.121)

Clustered bootstrapped standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table reports estimates of $\lambda = \beta_2/\beta_1$ for different samples. N:G3-G4 and N:G2-G4 denote the number of father-son and grandfather-son links used to estimate β_{-1} and β_{-2} respectively. The unit of observation is a paternal lineage. Standard errors are bootstrapped using 1000 clustered re-samplings. The first row uses all available links, the second restricts to observations with both G3-G4 and G2-G4 links. The last two rows split the sample based on the birth-year of the youngest generation (G4).

Across the board, the estimated coefficient of transmission is significantly larger than the intergenerational elasticities. Although this supports the contention that social mobility was lower than conventional estimation strategies imply, these estimates do not support Clark's hypothesis that the degree of persistence is constant across time and space at around 0.75–0.80 (Clark 2014). Not only is the coefficient for Germany lower than that for England, but it is also not stable over time when splitting the sample in two. As discussed, this time variation could be the product of differences in the attenuation factor across cohorts. In this scenario, we are not estimating the true coefficient of transmission but rather a product of the ratio between cohort specific attenuation factors and the coefficient. However, as argued by Braun and Stuhler (2018), changes in θ would have to be substantive and idiosyncratic to alter λ by as much as observed. Nonetheless, I cannot rule out that time-variation in $\widehat{\lambda}$ is driven by cohort-specific variation in θ. Since generations in the full-sample do not correspond to cohorts, the headline sample is less prone to this type of bias.

The coefficient of transmission for pre-Industrial Germany is strikingly similar to estimates for 20th century Germany by Braun and Stuhler (2018). In Figure 3, I plot the estimates from (Braun and Stuhler 2018) alongside estimates based on 100-year rolling windows from my sample. In the Wittgenstein sample, social mobility increased gradually across the 18th century before a more marked increase in the first half of the 19th century. The Braun and Stuhler (2018) estimates pick up a century later, with social mobility at a comparable level to that of the early 19th century. Given different types of sources – genealogical data versus survey data – the similarity of the estimates is all the more remarkable. Social mobility may have oscillated in the intervening century, as it did in

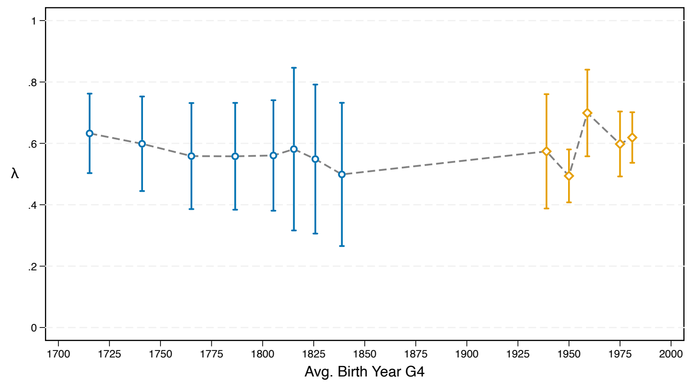

Figure 3: Trend in the Coefficient of inter-generational Transmission
Notes: This figure plots estimates of λ based on a rolling 100 year window from my sample alongside estimates from the 20th century from Braun and Stuhler (2018).

the 18th century, but the set of estimates suggests a stable range of 0.55–0.65 across three centuries. Understanding what drives the fluctuations in social mobility observed in Figure 3 is an interesting avenue for future research.

4.3 Summary

This section presents the first estimates for the coefficient of transmission for pre-Industrial Germany. At a coefficient of 0.63, latent status was strongly heritable. The difference between simple inter-generational correlations ($\beta_{-1} = 0.304$) and the estimated coefficient of transmission ($\lambda = 0.631$) is marked. The former implies that SES regresses to the mean in three generations — "from shirtsleeves to shirtsleeves in three generations." (Becker and Tomes 1986, p. 28) — while according to λ it takes close to ten generations. Although slower regression to the mean supports the selection mechanisms at the heart of evolutionary growth theories, we do not know if 10 generations is slow enough.

5 Selection and Growth

This section explicitly relates the parameters for reproductive inequality and inter-generational transmission to evolutionary growth theories. I focus on two eminent theories; the survival of the richest thesis (Clark 2007) and selection on quality (Galor and Moav 2002). After discussing these theories, I specify an overlapping generation model that I use to estimate the necessary conditions for the selection dynamics described by Clark (2007) and Galor and Moav (2002).

5.1 Evolutionary Growth Theory

In endogenous growth theories, "economic growth is an endogenous outcome of an economic system, not the result of forces that impinge from outside" (Romer 1994, p. 3). One family of theories, evolutionary growth, emphasizes the role of natural selection on traits complementary to the growth process. Galor and Moav postulate that:

> *"The evolutionary pressure during the Malthusian era gradually increased the representation of individuals whose characteristics were complementary to the growth process, triggering a positive feedback between technological progress and education that ultimately brought about the Industrial Revolution and the take-off from Malthusian epoch to sustained economic growth."* (Galor and Moav 2002, p. 1135)

Similarly, Clark and Hamilton (2006) find that in England "the rich seem to have been out-reproducing the poor" (28). Since the rich had more children, who were on average moving down the social hierarchy, the growth inducing *je ne sais quoi* of the rich spread to the rest of society.

> *"Thrift, prudence, negotiation and hard work were imbuing themselves into communities that had been spendthrift, violent, impulsive and leisure loving."* (Clark 2007, p. 180)

Both theories build on natural selection, albeit through somewhat different mechanisms. Galor and Moav's (2002) selection on quality models the canonical quantity-quality trade-off. Individuals can be of two types; *quality* individuals will allocate more resources to the quality (human capital or "endowment") of their offspring, while *quantity* individuals will have more offspring, allocating fewer resources per child. Although quantity individuals have an immediate reproductive advantage, in the long-run, quality lineages enjoy greater reproductive success due to higher incomes. High quality individuals (born to parents with a quality bias) generate higher income and have more resources for a larger number of offspring of higher quality (Galor and Moav 2002, p. 1140).

In survival of the richest (Clark 2007), there is no selection on a specific trait, but instead on wealth and all (potential) positive traits it is associated with. Here, given the positive association between SES and fertility, high SES individuals have greater reproductive success, out-producing their poorer compatriots and disseminating their traits down the socioeconomic ladder. Instead of the share of quality individuals increasing, here we expect the share of individuals with a high endowment to increase.

The key difference between the two formulations is that Clark (2007) describes selection across the socio-economic distribution, while Galor and Moav (2002) necessitates selection on a specific trait within any strata of the socio-economic distribution. It is unclear how these selection processes would behave at different levels of inter-generational transmission and reproductive inequality. Instead of probing the second stage – the link between natural selection and technological and/or cultural change – I investigate whether the selection mechanism is supported by demographic realities.

5.2 Model and Simulation

Model Setup. To formalize a simulation exercise, I specify a parsimonious overlapping generation model of inter-generational transmission and fertility choice in a static agricultural economy. Each generation, indexed by t, is alive for two periods. In period $t-1$ (childhood), individuals of generation t are born and inherit some endowment $E^i_{t,t-1}$ according to the coefficient of transmission λ and the random component e (i.e., socioeconomic luck):

$$E^i_{t,t-1} = a + \lambda E^i_{t-1,t-1} + e \tag{8}$$

Parents choose a binary investment in child quality $i^q_i \in \{0,1\}$. If they invest, augmented child endowment is $\gamma E^i_{t,t-1}$, where $\gamma \in [0,1]$ is an economy-wide scalar that describes the endowment-returns to investment in quality. This specification differs from Galor and Moav (2002), where endowment depends solely on parental investment and technological conditions. Here, I retain inter-generational transmission to focus on its effect on demographic dynamics.

Individuals born in the period $t-1$ enter the period t (adulthood). To keep the model tractable, I assume perfect assortative mating and abstract from describing a matching process.[27] During adulthood, individuals earn an income $I^i_{t,t}$ that is drawn from a constant income distribution based on their rank ($r^i_{t,t}$) in the population distribution of endowments. Income is assigned based on rank to account for stagnant average incomes (Malthusian economy), along-side a changing endowment distribution. $\varphi_t(\cdot)$ describes this generation dependent rank to income mapping.

$$I^i_{t,t} = \varphi_t(r^i_{t,t}) \tag{9}$$

During adulthood, individuals select their target fertility and whether to invest in the endowment of their children. Individuals have a utility function,

$$u^i_{t,t} = U(c_t, n_t, I_{t+1}) \tag{10}$$

that increases in current consumption (c_t), the number of children (n_t), and the future income of their children (I_{t+1}). I assume that consumption is constant across the population at some subsistence level $\overline{c_t}$. To introduce two distinct types of individuals – in accordance to the quality-quantity trade-off in Galor and Moav (2002) – I assume that there exists a unique value of the preference parameter for child income (ϕ_i) such that;

$$i^q_i = 1 \;\text{ if } \phi_i \geq \phi^* \;\text{ else } 0 \tag{11}$$

and couples either invest in the quality ("endowment") of their children, or do not.

The allocation of income to child quality and quantity is constrained by the budget constraint.

$$I^i_{t,t} - \overline{c_t} \geq n\,(p^n + i^q_i\, p^q) \tag{12}$$

[27] Since non-assortative mating reduces heritability it would reduce the parameter space for evolutionary growth theory. As such the conditions I delineate are necessarily lower-bounds for the true conditions.

where p^n denotes the cost of raising any child, and p^q denotes the additional cost of investing in child quality. Investment decisions are made for all children equally. Target fertility depends on whether individuals have a quality preference (i.e., $i_i^q = 1$) – all other individuals will only allocate income to the quantity of children. Thus, target fertility is given by:

$$n_{t,t}^{i*} = \frac{I_{t,t}^i - \overline{c_t}}{p^n + i_i^q \, p^q} \tag{13}$$

.

Simulation. This model can describe the selection processes at the heart of both models. In survival of the richest, the joint pressures of fertility differentials by income and inter-generational transmission of endowments lead to selection on higher endowment. Here, quality-quantity considerations have no bearing on the evolution of the economy. In selection on quality, this trade-off is central to the selection mechanism. Although individuals with a quality preference have a reproductive advantage in the short-run, the endowment (and thus income) advantage of lineages with a quality preference can result in their out-breeding the rest. I test both theories using simulations of the overlapping generation model. The simulation tests whether selection occurs given different parameter combinations. The only difference when testing the two theories is that the share of individuals with a quality preference (share^Q) in generation 0 is set to zero when testing survival of the richest and > 0 when testing SoQ.

To initialize the simulation, I create a population of size N, with endowment drawn from a normal distribution; $E_{i,0} \sim N(100, 40^2)$. Next, some share of the population is imbued with the quality preference $i^q = 1$. The quality preference increases endowment by a factor of $1 + \gamma$. Endowment determines income based on a rank-mapping to a log-normal distribution with a mean of 60 and a standard deviation of 15 in levels.[28] Perfect assortative mating is assumed. Since imperfect assortative mating reduces the inter-generational transmission of status, and it is unlikely that mating was perfectly assortative, this assumption increases the parameter space for evolutionary growth theory.

$$ExpectedFert_{i,t} = (1 - i_i^q \, k) \cdot \begin{cases} a \,+\, b\,(I_{10} - I_{50}) \,+\, e & \text{if} \quad I \leq I_{10} \\ a \,+\, b\,(I_i - I_{50}) \,+\, e & \text{if} \quad I_{10} < I < I_{90} \\ a \,+\, b\,(I_{90} - I_{50}) \,+\, e & \text{if} \quad I \geq I_{90} \end{cases} \tag{14}$$

Expected fertility follows a piecewise function that is parametrized to produce a specific fertility differential (B) between couples of the 10th (I_{10}) and 90th (I_{90}) percentiles of the income distribution and mean fertility (a) close to replacement (Equation 14).[29] Having a quality preference reduces expected fertility at any income by $k \cdot 100\%$. k is the fertility cost of investing in child quality.[30] To explore how selection behaves under varying degrees of randomness, a noise term

[28]The interpretation of the simulation results is not sensitive to initialization with alternative distributions.

[29]The slope (b) is a function of I_{10}, I_{90}, k and will produce B at the population level.

[30]Formally, $k^{-1} - 1$ is the proportion of the basic cost per child that parents with a quality preference pay on top to invest in quality, i.e., if $k = 0.5$ parents are paying 100% of a markup for child quality.

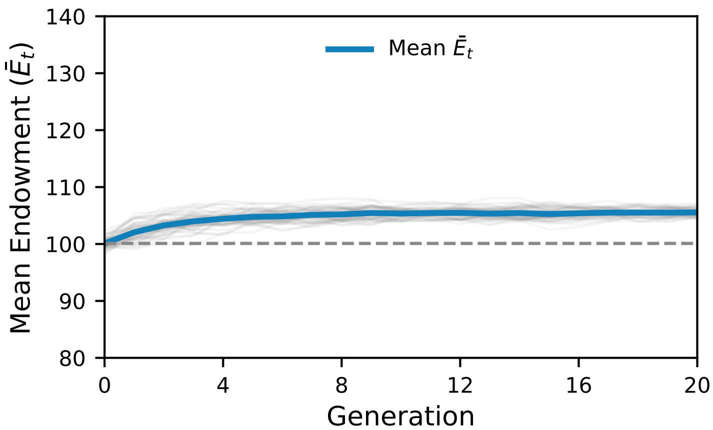

Figure 4: Survival of the Richest in Germany.
Notes: The figure plots the evolution over 20 generations of mean endowment across 50 iterations of the simulated OGM. Light grey lines correspond to individual simulations and the darker line corresponds to the average evolution across iterations. Parameters: $B = 1.47$, $H = 0.63$, $l = c = 0.5$.

that is scaled by a chance parameter $c \in \{0, 1\}$, such that $e \sim N(0, (c \cdot a)^2)$, is introduced.[31] Realized fertility is modeled as a Poisson draw, with the rate parameter determined by expected fertility.

$$E_{i,t} = exp(a \, + \, H \cdot E_{i,t-1} \, + \, v) \tag{15}$$

All offspring inherit endowment directly from their fathers according to the Equation 15. Again, to explore behavior under differing degrees of randomness, a noise term is introduced. This term is scaled by a luck parameter $c \in \{0, 1\}$ such that $v \sim N(0, (l \cdot \sigma)^2)$, where $\sigma = 40$ is the initial standard deviation of the endowment distribution. For children of quality preference parents, endowment increases by a factor of $1 + \gamma$. γ are the endowment (income) returns to investing in child quality. After they pass endowment onto the next generation $t + 1$, the current adult generation dies, and the offspring generation progresses to adulthood. This process repeats across a set number of generations. Thus, we can observe how selection pressures shape societal composition, both in terms of mean endowment and, when evaluating selection on quality, the share of the population with a quality preference.

5.3 Survival of the Richest

Germany. I first simulate the survival of the richest scenario using the parameters I estimated for Germany. The share with a quality preference (share^Q) is set to zero, and both noise scalars are 0.5. The fertility differential is 1.47, and the coefficient of transmission is 0.631. The outcome of interest is the generational mean endowment. If survival of the richest is taking place, then mean endowment will increase generation on generation. Figure 4 plots the evolution of mean

[31] Figure A1 plots expected fertility for individuals with and without a quality preference at $B = 2.0$, $k = 0.2$, and share$^Q = 0.2$.

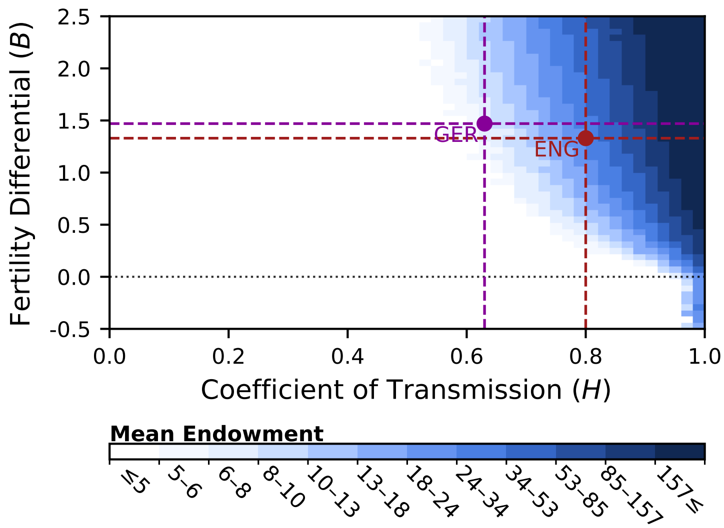

Figure 5: Parameter Space: Survival of the Richest

Notes: This figure plots the simulation outputs for 20 generations of the overlapping generation models across different parameter combinations. Each cell is based on the average outcome across 5 iterations of each combination. The colour of the cell correspond to the increase in mean endowment from generation 0 to generation 20.

endowment over 20 generations (approx. 500 years) across 50 iterations of the simulation. Although there is a slight increase in mean endowment, the selection pressures are insufficient for sustained drift. Even at a high coefficient of heritability – 0.63 – regression to the mean overpowers the selection pressure of the fertility differential. Here, higher reproductive success among the richest families does not lead to *survival of the richest.*

Parameter Space. To extrapolate beyond the German case, I simulate the overlapping generation model for different parameter combinations. The main parameters of interest are the fertility differential B and the coefficient of transmission H. I simulate combinations of H and B across different levels of noise. Socioeconomic luck l scales noise in the endowment process; if $l = 0$ endowment is entirely deterministic, at $l = 1$ the standard deviation of the noise term v is equal to the standard deviation of the initial endowment distribution. Fertility chance c scales noise in the fertility process. Since realized fertility is based on a Poisson draw, it is never fully deterministic; lower values of c correspond to less noise in expected fertility, while at $c = 1$ the noise term e has a standard deviation a. Each unique parameter combination is simulated across 20 generations and 5 iterations.

Figure 5 plots average outcomes for different values of B and H. Each cell summarizes the result of all simulations for that parameter combination, with the color corresponding to the average percentage change in mean endowment from generation 0 to generation 20. I.e., if we look at the German parameter combination, across all levels of noise and all iterations, the average increase in mean endowment was 5-6%. If we instead look at a set of parameters for England (B=1.33, H=0.8 (Clark and Cummins 2014; Clark and Cummins 2015)), we find that mean endowment

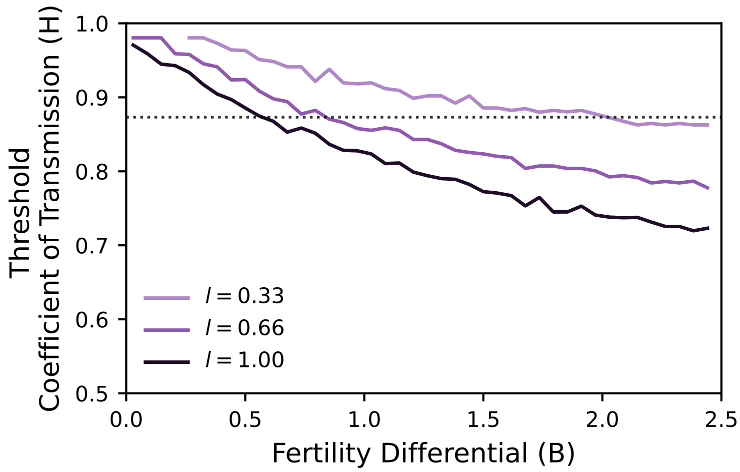

Figure 6: Threshold Condition for Survival of the Richest

Notes: This figure reports threshold values of H that produce a 50% increase in mean endowment across 20 generations. These figures are based on the simulations presented in Figure 6.

increased by around 20% on average.[32] While the German parameters do not enable survival of the richest, the English parameters induce some selection. Although Germany and England exhibit similar fertility differentials, the estimated coefficient of transmission for England is significantly higher, and regression to the mean is slower. Across the board, large and sustained increases in mean endowment occur if and only if this coefficient is large. If H is too low, regression to the mean overpowers the selection pressure of the fertility differentials. Concurrently, at larger fertility differentials, lower coefficients of heritability suffice to produce sustained drift in mean endowment. Determining whether the degree of selection in England is sufficient for the changes Clark (2007) described is up for debate and constitutes an interesting avenue for future research. Additionally, choosing a different set of parameters, such as the estimates for H presented by Zhu (2024), does not support the same level of selection.

The relevance of noise in the fertility and status inheritance process is summarized in Figure A2. The amount of noise in the fertility process (c) has no bearing on selection. Differences in the expected realized fertility at the group level (i.e., low or high endowment) suffice to induce selection regardless. Noise in the endowment process (l) increases the parameter space for survival of the richest considerably. Here, more noise interrupts regression to the mean, with the fertility differential amplifying positive shocks to endowment. The noise term is normally distributed and has a mean of zero. However, at the individual-level, the fertility differential increases fertility for individuals who experience a positive random endowment component (v), while it decreases fertility for those with a negative one. Thereafter, while neutral within any given generation, more noise increases selection on high endowment across generations. As a result, lower coefficients of transmission can sustain selection.

Across all parameter combinations, the average coefficient of heritability that produces growth

[32] B is based on the difference between the bottom and top wealth decile, as reported for England in Cummins (2020, Fig. 4.3).

in mean endowment greater than 2.5% per generation over 20 generations is 0.86.[33] This threshold value of H is decreasing in the fertility difference and noise in the endowment process (see Figure 6). Notably, the parameter space corresponds closely to the large coefficients of heritability estimated for England by Clark and Cummins (2014) and postulated as universal in Clark (2014). Overall, although not supported by the German parameters, the selection underpinnings of survival of the richest are feasible if the coefficient of transmission is exceptionally high.

5.4 Selection on Quality

Returns to and Cost of Quality. Investigating selection on quality requires additional parameters – namely, the endowment (income) return γ and the fertility cost k of child quality. These parameters describe the quantity-quality trade-off. The presence of this trade-off in historical settings and associated fertility control within-marriage is contested (e.g. Cinnirella et al. 2017; Clark and Cummins 2019). While I do not estimate the quality-quantity trade-off directly, the results in Appendix D suggest a limited role for fertility control within marriage, implying that k was likely small. A broad literature is concerned with the income returns to investment in quality (education), [34]. Although estimates of returns to education are not without controversy (Clark and Nielsen 2024), studies suggest that the returns to investing in child quality in the pre-Industrial period (i.e., via apprenticeship) were considerable (Wallis 2025). Anecdotally, it is difficult to justify why practices such as apprenticeship persisted for centuries if they did not produce some income returns. Hence, for pre-Industrial Germany, where I observe limited evidence for fertility control in marriage and investing in apprenticeships was a common practice (Klein 1936), I assume that income returns γ are greater than the fertility cost k. Still, since I am unable to estimate these parameters directly, I report results across different parameter combinations of γ and k.

Germany. If selection on quality is taking place, both the mean endowment and the share of the population with the quality preference (share^Q) will increase.[35] Figure 7 plots both outcomes across 20 generations and 50 iterations of the simulation for the parameters estimated in the German sample. When the returns in income to having a quality preference – i.e., parental investment in child quality – are larger than the fertility penalty couples incur due to the cost of "quality" children, the parameters for Germany support selection on quality. Like (Galor and Moav 2002), the model assumes that the preference for quality is perfectly heritable. Relaxing this assumption will produce different outcomes (see Figure 9). Nonetheless, based on the model assumptions, these findings suggest that the German demographic regime could have sustained the selection process underpinning Galor and Moav's (2002) selection on quality, while – at the estimated level of inter-generational transmission and reproductive inequality – the simulation does not produce Clark's (2007) survival of the richest.

[33] This threshold was chosen based on the articulation of the selection mechanism in Clark (2008, p. 189).

[34] e.g., Angrist and Krueger (1991), Duflo (2001), Oreopoulos (2006), McCrary and Royer (2011), Feigenbaum and Tan (2020), and Clark and Cummins (2020)

[35] I initiate the simulation with a quality share of 20%. While thresholds may vary, the pattern of results is consistent for other initial states (unreported).

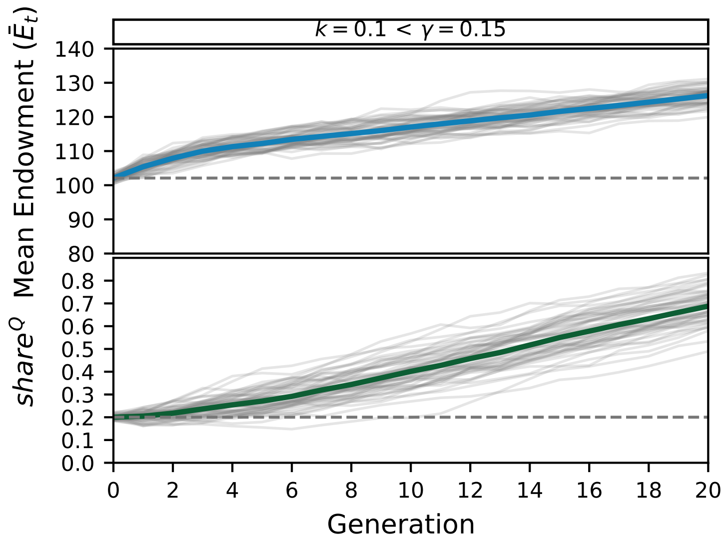

Figure 7: Selection on Quality in Germany

Notes: The figure plots the evolution over 20 generations of mean endowment (top panels) and quality share (bottom panels) across 50 iterations of the simulated OGM. Light grey lines correspond to individual simulations and the darker line corresponds to the average evolution across iterations. Parameters: $B = 1.47$, $H = 0.63$, $l = c = 0.5$.

Parameter Space. Selection on quality depends on a larger group of parameters. Figure 8 plots average outcomes – the increase in the share with a quality preference (left) and mean endowment (right) – over different values of luck l, chance c, income returns γ, and fertility cost k for each combination of B and H. Across all plots, the introduction of the quality preference increased the parameter space for substantial increases in mean endowment, as well as the magnitude of this increase. While survival of the richest depends on the coefficient of transmission (H), the viability of selection on quality depends on the fertility differential (B). Fertility differentials need to be sufficiently large such that the income returns that accrue to quality lineages materialize in a reproductive advantage.[36] The degree to which the increase in mean endowment in the right panel varies in the coefficient of transmission (H) is driven by survival of the richest dynamics instead of selection on quality.

Figure A3 unpacks these by the amount of noise in the fertility and endowment transmission process. Similar to survival of the richest, the amount of noise in the fertility process has no bearing on selection. Contrary to survival of the richest, where more noise in the endowment transmission process expanded the parameter space for selection, more noise contracts the parameter space for selection on quality. Less noise is associated with a larger parameter space along B and H for increases in share^Q and mean endowment. Although greater noise increases drift in mean ability, it weakens selection on quality since more noise in endowment counteracts the emergence of a bimodal distribution of endowment by preference for quality (see Figure A4). However, even when there is a lot of noise in the endowment process, the parameter space for selection on quality

[36]Notably, there is a U-shaped relationship between the fertility differential and the increase in the share with a quality preference. This is because quality preferences are initially equally distributed across the population. If the fertility differential is very large, it becomes more difficult for low-endowment quality lineages to out-reproduce high-endowment non-quality lineages.

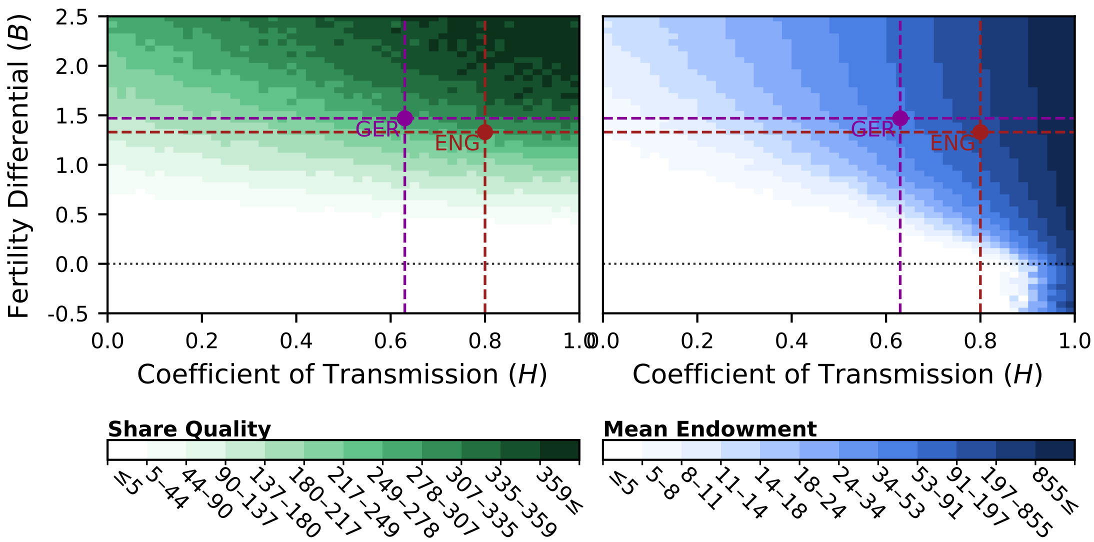

Figure 8: Parameter Space: Selection on Quality

Notes: This figure plots the simulation outputs for 20 generations of the overlapping generation models across different parameter combinations. Each cell is based on the average outcome across 5 iterations of each combination. The color of the cell correspond to the increase in mean endowment (left panel) or the increase in the population share with a quality preference (right panel) from generation 0 to generation 20.

remains larger than for survival of the richest.

Whether quality lineages enjoy a reproductive advantage depends on the returns (γ) to and cost (k) of quality. Figure A5 holds luck and chance constant at 0.5 while letting γ and k vary. To induce selection on quality, the *fertility* returns to quality – which are a function of the *income* returns and the fertility differential – need to be greater than the fertility cost. This is one of two central conditions for selection on quality. The left panel of Figure 9 plots this threshold conditions. The color of each cell corresponds to the lowest magnitude of the income returns ($\gamma \in (0, 0.5)$) that enables a 50% increase in the population share with a quality preference (i.e., 20 $\rightarrow$ 30%). In gray cells, no iteration of the simulation produced sufficient selection on quality. At a given fertility cost, selection becomes possible if the fertility differential is larger (increases along the y-axis) or if the income returns increase (darker cell color).

The second condition concerns the heritability of the quality preference. As discussed, prior simulations assume that the preference for quality is perfectly heritable. Weakening this assumption reveals a similar pattern to Figure 5; whereas survival of the richest depends on the heritability of the endowments, selection on quality depends on the heritability of the quality preference. The right panel of Figure 9 plots this threshold condition under a constant coefficient of transmission. If the coefficient of heritability is too low, selection on quality cannot take place. Prior to this, a lower-bound selection on quality is possible if the fertility differential is larger, or if the income returns to quality are bigger. Overall, although the parameter space along H and B is larger for selection on quality, the mechanism depends on a larger set of conditions. Selection on quality is possible if; (C1) *the fertility returns – the fertility differential and the income returns to quality – are*

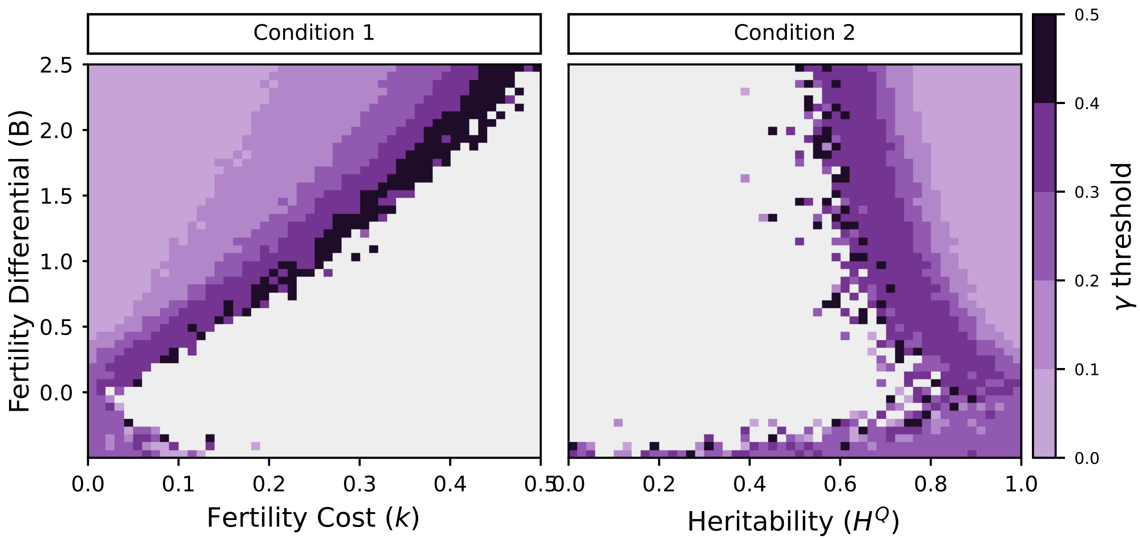

Figure 9: Conditions for Selection on Quality

Notes: This figure plots threshold conditions that produce a 50% increase in the quality share (share^Q) over 20 generations. Each plot corresponds to one condition. The color of the cells corresponds to the lowest income returns to quality (γ) that precipitate a 50% increase. The parameter combinations in grey cells never produce a 50% increase at $\gamma \leq 0.5$. The left plot illustrates condition 1; the fertility returns to quality (fertility differential on the y-axis, and the income returns as the color) that enable selection on quality at a given different fertility costs to quality (k, x-axis). These values are based on simulations with $H = 0.6$, $H^Q = 1$, $c = l = 0.5$. The right plot illustrates condition 2; the fertility differential and income returns necessary to induce selection at a given heritability of the quality preference (H^Q, x-axis). These values are based on simulations with $H = 0.6$, $k = 0.10$, $c = l = 0.5$.

larger than the fertility cost of investing in quality, and if (C2) *the preference for investing in quality is strongly heritable.*

5.5 Summary

Monte-carlo simulations of a simple overlapping generation model help explore the parameter space that induces the selection mechanisms described by Clark (2007) and Galor and Moav (2002). Based on my estimates, survival of the richest was not viable under the German demographic regime, while selection on quality could occur if the returns to investing in quality (i.e., via apprenticeship) were greater than the associated fertility cost. Anecdotal evidence and the absence of significant deliberate fertility control within marriage serve to support these assumptions.

Based on several 100,000 iterations of the simulation across different parameters, I am able to describe some general conditions for the selection mechanisms. The main condition for Clark's (2007) is an exceptionally high coefficient of transmission. Latent socioeconomic status needs to be heritable according to a coefficient of more than 0.8. This condition concurs with Clark's (2014) estimates of social mobility. The parameter space – along B and H is significantly larger for selection under Galor and Moav (2002). However, this is partially because other conditions are more important. Selection is possible if the combination of the fertility differential and the income returns to quality imbues quality lineages with a reproductive advantage that is greater than the fertility cost of investing in child quality. This condition was likely met in early-modern Europe where (1) fertility differentials were large, (2) returns to quality are sizable, and (3) there is limited fertility control within marriage. The second condition is that the preference for quality is heritable. The degree to which educational attainment and economic preferences, more generally, are heritable is subject to debate (e.g. Kettlewell et al. 2025; Silventoinen et al. 2020). Still, what we know about inter-generational correlations of educational attainment (e.g. Feigenbaum 2018) suggests that this condition may have been met. Educational attainment is colored by genetic and *extragenetic* factors that are inherited from prior generations.

Overall, in both theories, the inter-generational transmission of the growth-inducing trait(s) is a central condition. This was likely a weaker condition when thinking about investment in education instead of a catch-all set of positive traits associated with wealth, that needed to persist even when the descendants were no longer wealthy (Bowles 2007). The viability of transmission and the nature of selection, i.e., within any SES group (for quality) or across the entire distribution (for the richest), determine the viability of evolutionary growth theories.

Conclusion

This paper is the first to estimate reproductive inequality and the inter-generational transmission of SES for pre-industrial Germany. I find that high SES couples had between 1 and 2 additional surviving children. This gradient is driven by differences in gross fertility and specifically variation in the age at marriage for women. Whether these fertility differentials create selection pressure depends on the inter-generational transmission of SES. I use a ratio estimator (Stuhler 2012) to identify the unattenuated coefficient of inter-generational transmission. In the full sample, the coefficient of transmission is equal to 0.63. This is the first estimate of inter-generational transmission for pre-industrial Germany (1675-1850). While substantively higher than implied by simple inter-generational correlations, the coefficient is much smaller than 0.80 as proposed by Clark (2014). Notably, estimates for Germany from the 20th century – also around 0.60 – lead to the same conclusion (Braun and Stuhler 2018).

I simulate overlapping generation models to test whether the German demographic regime could have sustained the selection processes underpinning evolutionary growth theories. I show that the German demographic regime could not sustain *survival of the richest*. I find that the story for *selection on quality* is more complex; if the income returns were greater than the fertility cost of investing in child quality, selection pressure on quality preferences emerges. I generalize these results across different parameter combinations. The selection mechanism underpinning survival of the richest is contingent on exceptionally high heritability of SES. Across simulations, the threshold coefficient of transmission that produces a 50% increase in mean endowment over 20 generations is 0.87. In terms of fertility differentials and status transmission, the parameter space for selection on quality is larger. However, selection depends on a greater number of conditions. Chiefly, the income returns to quality and the fertility differential need to be large enough to offset the fertility cost of investing in quality. If this condition is met and preferences for quality are strongly heritable, lineages with a quality preference enjoy a reproductive advantage.

This is the first paper to simulate threshold conditions for the selection processes underpinning evolutionary growth theories. In doing so, it demonstrates that a natural selection story of modern economic growth is contingent on strong conditions. Even the coefficient of transmission of 0.70 Clark and Cummins (2014) estimate for England falls below the average threshold of 0.87. Similarly, selection on quality in Galor and Moav's (2002) depends on high returns to investing in child quality. Although the conditions for selection on quality are less strong, more applied historical work is needed to probe their validity.

Both theories rely on the heritability of certain expressed traits – endowments in the case of Clark (2007) and the preference for quality in Galor and Moav (2002). It is unlikely that social preferences and attitudes were ever as heritable as, for example, height. Further, heritability never exists in isolation; instead, it is shaped by environmental factors, and the same holds for social preferences and attitudes (Feldman et al. 2000). The heritability of height falls during periods of nutritional stress that produce stunting (Silventoinen 2003).[37] Behavioral traits and their inter-generational transmission are overdetermined in a complex system of genetic, extragenetic, and epigenetic processes, most of which depend on and interact with the environment (Lala and Feldman 2024). This raises the question of how much of the observed inter-generational persistence is the consequence of direct genetic transmission, how much is the product of being born into the same environment as one's parents, and how this squares with the natural selection story of economic growth. When evolutionary growth theory accounts for the multiple pathways of transmission, and acknowledges the co-evolution of genes, culture, and environment, it offers an appealing explanation for growth (i.e. Galor 2022). Mechanisms of genetic transmission are similar across populations, while extragenetic transmission varies significantly across different cultural and institutional environments. Societies that fostered the inter-generational transmission of human capital (i.e., a preference for quality) – via extragenetic pathways – likely enjoyed a growth advantage. Further causal empirical work is needed to identify this link between selection and growth outcomes.

[37]Across the social sciences, a substantial body of literature stresses the relevance of environmental factors (e.g. Cole 2019; Chetty et al. 2016).

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A Additional Tables and Figures

Table A1: Correlation Matrix: LLM-Based vs. Hand-Coded Status Measure

	LLM-based			Hand-coded	
	Social Class	Classes (C&H, 2007)	HISCAM	Classes (C&H, 2007)	HISCAM
Social Class	1.0000				
Classes (C&H, 2007)	0.7018	1.0000			
HISCAM	0.6017	0.8486	1.0000		
Classes (C&H, 2007)	0.7276	0.8344	0.6476	1.0000	
HISCAM	0.6692	0.7177	0.7461	0.8288	1.0000

Table A2: Robustness to other SES Measures

	Gross Fertility				
	(1)	(2)	(3)	(4)	(5)
Observation:	low	high	average		
Classification:	LLM	LLM	manual	LLM	manual
ln(HISCAM)	1.031***	1.317***	1.839***		
	(0.194)	(0.192)	(0.228)		
Rank 2 (Smallholders)				0.183	0.406**
				(0.174)	(0.144)
Rank 3 (Workers)				0.341**	0.574***
				(0.144)	(0.131)
Rank 4 (Craftsmen)				0.288	0.598***
				(0.213)	(0.157)
Rank 5 (Traders/Clerks)				0.918***	0.436
				(0.269)	(0.573)
Rank 6 (Professionals/Academics)				1.033***	0.969***
				(0.170)	(0.129)
Rank 7 (Gentry/Officers)				-0.053	1.074***
				(0.311)	(0.279)
Mean DV	5.143	5.143	5.131	5.139	5.139
Observations	5294	5294	5348	5068	5109
Parishes (clusters)	16	16	16	16	16
R^2	0.032	0.037	0.036	0.041	0.035

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Top 5 Occupations by Social Class

Social Class	**Occupation (German)**	**Occupation (English)**	**Frequency**
Lower	Viehhirt	Cattle herder	10
	Schweinehirt	Swineherd	13
	Nachtwächter	Night watchman	14
	Knecht	Farmhand / servant	28
	Tagelöhner	Day laborer	241
Lower-Middle	Hirt	Herdsman	44
	Leinweber	Linen weaver	98
	Soldat	Soldier	100
	Schäfer	Shepherd	160
	Köhler	Charcoal burner	163
Upper-Middle	Schmied	Blacksmith	116
	Schuhmachermeister	Master shoemaker	132
	Schneidermeister	Master tailor	146
	Schuhmacher	Shoemaker / cobbler	225
	Kirchenaeltester	Church elder	340
Upper	Schulmeister	Schoolmaster	35
	Schultheiss	Mayor / reeve	43
	Zimmermeister	Master carpenter	45
	Gerichtsschöffe	Judge / juror	47
	Lehrer	Teacher	64

Table A4: Alternative Estimators

	Gross Fertility	Mortality	Net Fertlity
	(1) PPML	(2) Logit	(3) PPML
ln(HISCAM)	0.246***	-0.188*	0.300***
	(0.040)	(0.102)	(0.048)
Observations	5325	27700	5325
Parishes (clusters)	16	16	16

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: All models include parish and marriage-decade fixed effects. Standard errors are clustered at the parish level.

Table A5: Reproductive Inequality with Clustered Errors at the Priest Level.

	Gross Fertility		$1(\text{AgeDeath} \leq 15)$		Net Fertility	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(HISCAM)	1.335***		-0.039**		1.140***	
	(0.210)		(0.016)		(0.164)	
Lower-middle)		0.518***		0.009		0.325**
		(0.177)		(0.018)		(0.133)
Upper-middle		0.900***		0.007		0.594***
		(0.168)		(0.015)		(0.117)
Upper		1.165***		0.000		0.823***
		(0.199)		(0.017)		(0.153)
Mean DV	5.144	5.136	0.298	0.298	3.594	3.587
Observations	5325	5561	27700	28874	5325	5561
Parishes	16	16	16	16	16	16
Priests (Parish × Decade)	275	275	275	275	275	275
R^2	0.035	0.036	0.008	0.007	0.034	0.033

Robust clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table reports OLS estimates for the association between SES and demographic outcomes. In columns (1), (3), and (5) the exposure variable is ln(HISCAM) – logged continuous occupational status – and in all other columns SES is operationalised as discrete status categories, with "lower class" being the reference category. The outcome variable in columns (1) and (2) is gross fertility measured at the couple level. Columns (3) and (4) are estimated at the birth level and the outcome variable is a indicator variable equal to one if the child died prior to turning 15. Here status is measured using father's status. Columns (5) and (6) present estimates for net fertility, gross fertility minus adjusted under-15 mortality, and are estimated at the couple level. All regressions include parish and marriage/birth decade fixed effects.

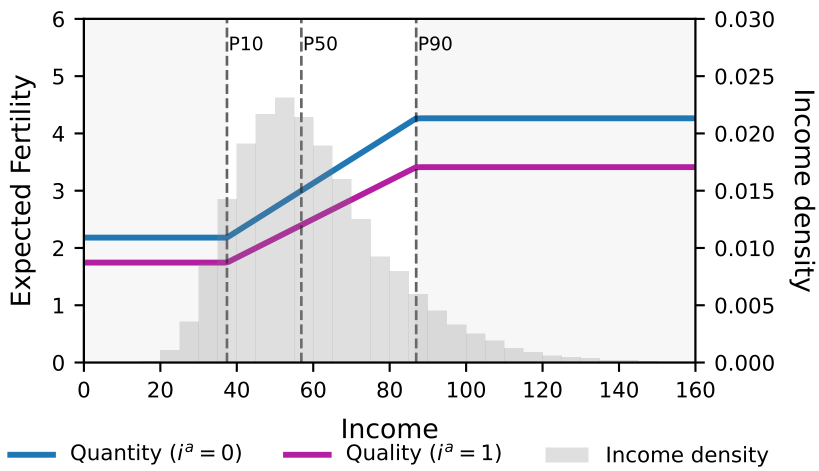

Figure A1: Simulated Fertility

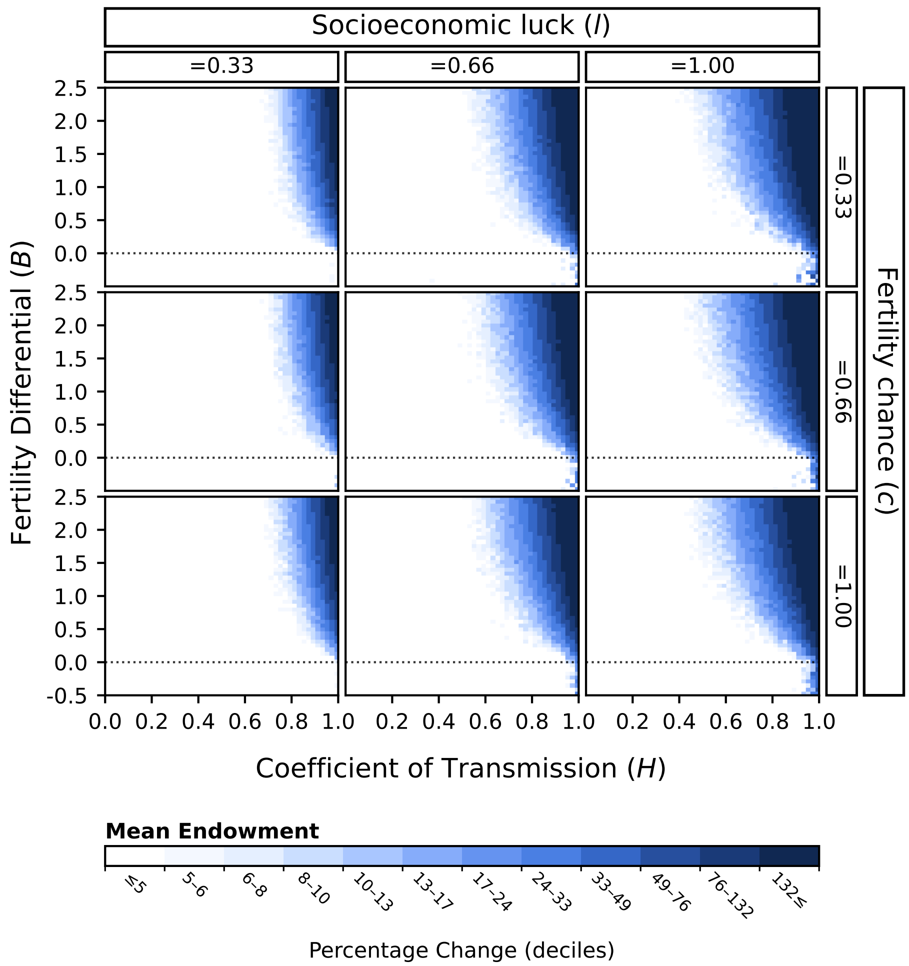

Figure A2: Survival of the Richest and Noise

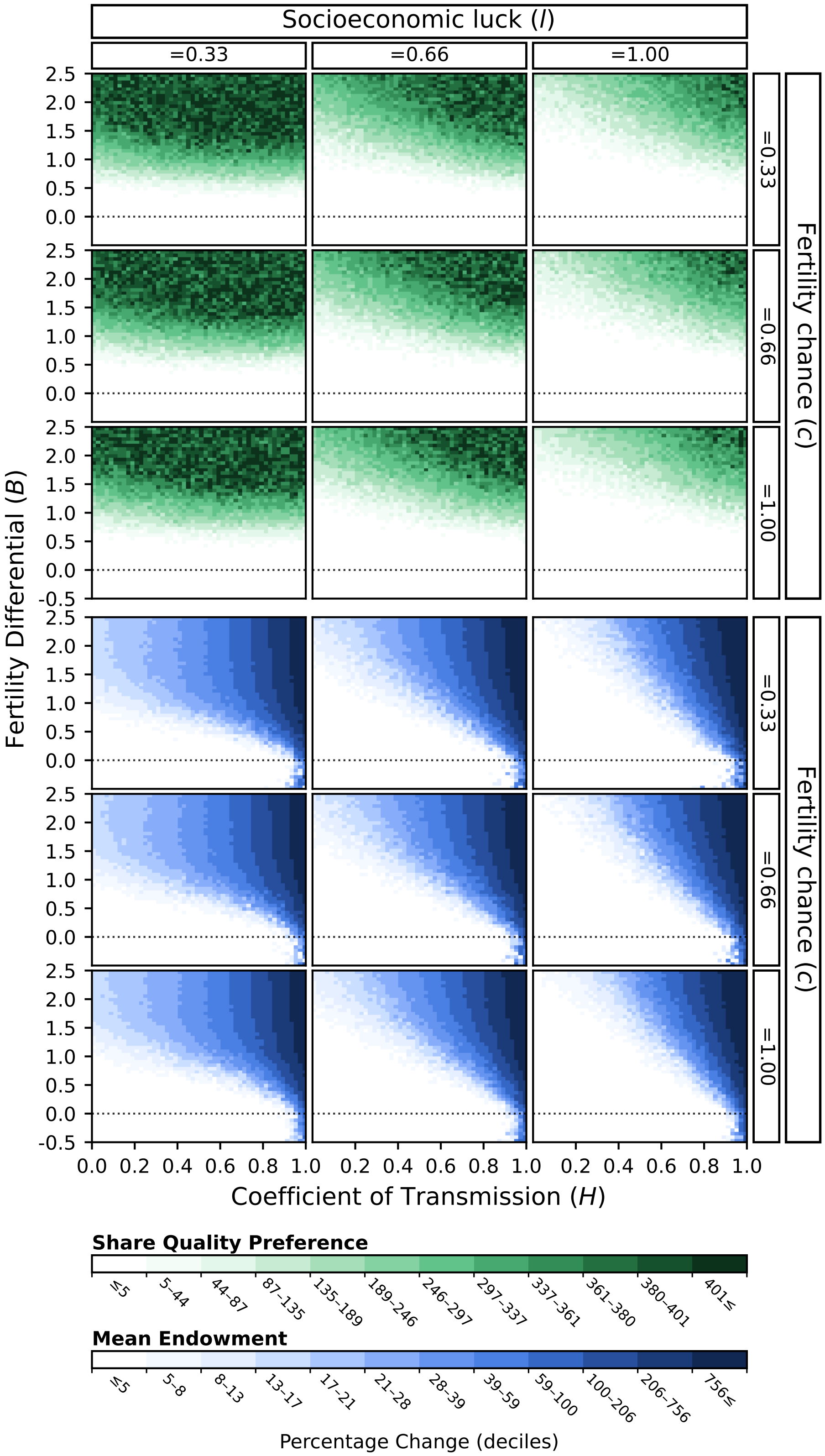

Figure A3: Selection on Quality and Noise

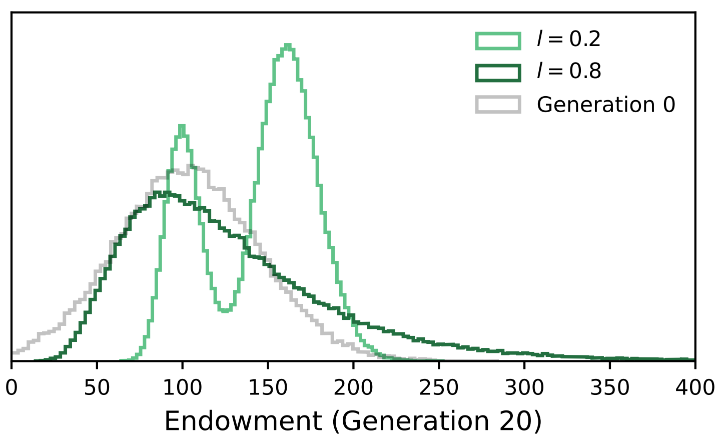

Figure A4: Noise and the emergence of a bimodal endowment distribution

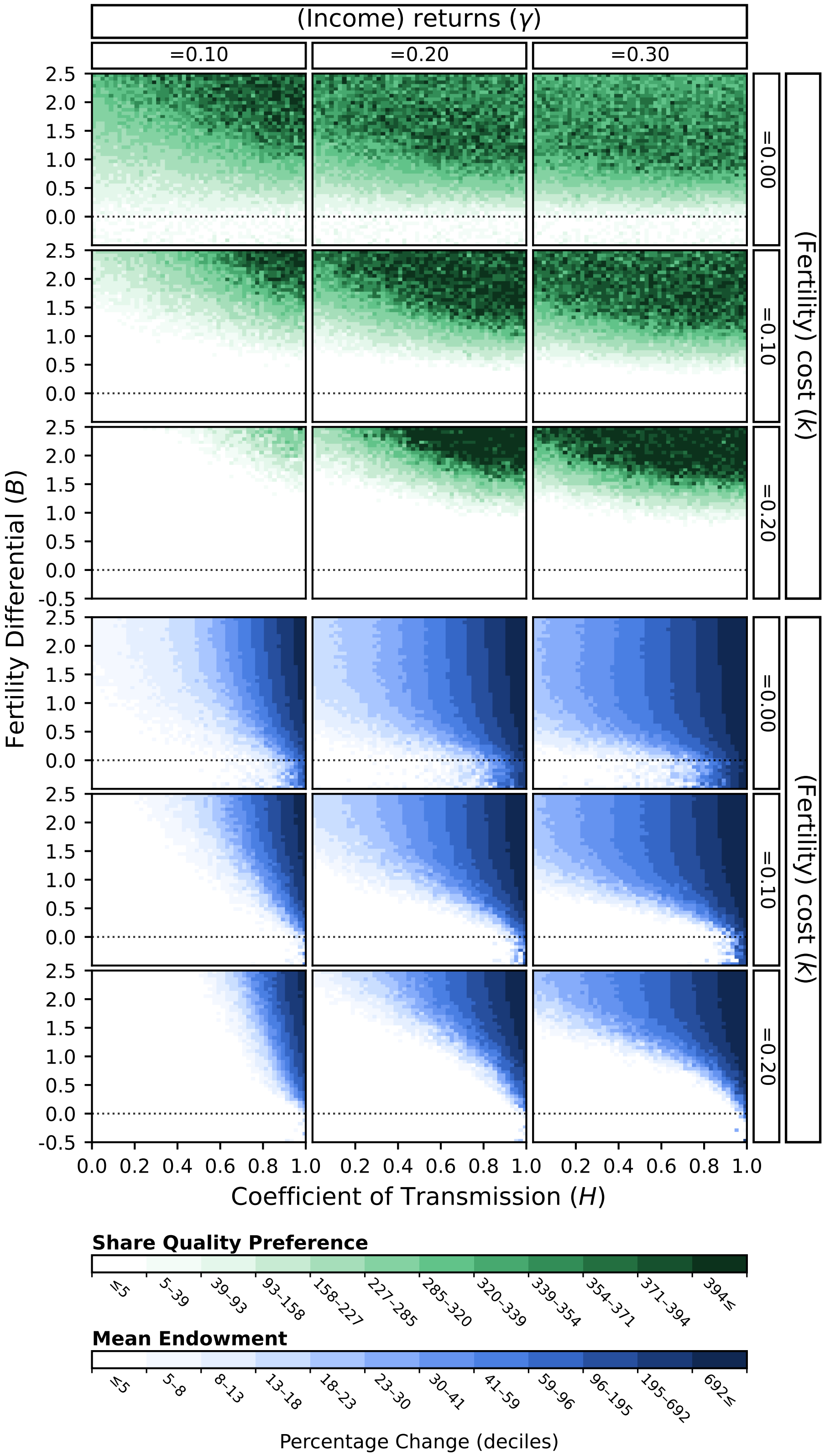

Figure A5: Selection on Quality and quantity-quality tradeoff.

B Migration

Migration induced censoring of life histories constitutes another source of bias. As discussed in section 2, only non-migrants and in-migrants prior to marriage are included in the sample. This restriction can become problematic through two related, albeit distinct routes. First, if the demographic behavior of the uncensored subset of the population is not representative of the general population, the results are subject to selection bias. Second, if migration is a function of both the exposure and outcome e.g., if celibacy and low status are associated with greater rates of emigration this introduces collider bias since the inclusion restrictions condition the sample on migration.[38]

To circumvent the imperceptibility of out-migrant outcomes, de la Croix et al. (2019) suggest looking at the differences between in-migrants and non-migrants. This test is contingent on the assumption that the unobserved out-migrants (who immigrate to a similar nearby parish) are the same group as the observed in-migrants (who emigrated from such a parish). In the Wittgenstein reconstitution, where short-distance migrants are observed as non-migrants, this appears unlikely. However, a comparison between the two groups still yields some insights. Estimating the primary specification for in- and non-migrants reveals that the status gradient does vary strongly (see Table A6). The results are insignificant among in-migrants. One potential explanation is that in-migrants – particularly in this sample where migration occurs over longer distances – are more socially mobile and therefore less affected by property relations that shape age at marriage among non migrants. I interpret all results with the caveat that they apply to non-migrants or those who only migrated between neighboring parishes.

Table A6: Migration Status

	Non-Migrants	In-Migrants (Both/Either)
	(1)	(2)
$\ln$(HISCAM)	1.275***	0.730
	(0.224)	(0.711)
Mean DV	5.289	4.416
Observations	4443	880
Parishes (clusters)	16	14
R^2	0.043	0.044

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: All regressions include parish and marriage-decade fixed effects. Standard errors are clustered at the parish level. For non-migrants the birth of both spouses is observed in the core parishes, for in-migrants the birth of at least on spouse is not observed.

To evaluate whether collider bias affects my results, I would need to test whether migration is a function of SES and demographic outcomes. Although demographic outcomes are unobservable for out-migrants, I can compare SES across in-, none-, and out-migrants after marriage. The average status for out-migrants is lower than that of in- and non-migrants. I run individual level linear probability models to estimate the effect of a fathers occupational status on the choice to

[38] For a fuller discussion of collider bias, see Schneider (2020).

emigrate.[39] I find that the children of high-SES parents were less likely to emigrate (see Table A7). This relationship between SES and migration would bias the results if migration decisions are also affected by the demographic outcome in question. Turning to the aforementioned example of celibacy, if rates of out-migration are greater among celibate women – i.e., to migrate to an urban center with a larger marriage market – the results reported in Table A8 likely underestimate rates of celibacy among women with lower SES since these are *a priori* more likely to be part of the excluded group. For such an association to drive results, the demographic outcomes would have to be a central driver of the migration decisions. Since it is impossible to verify whether the outcome affects migration, all results presented in section 3 are interpreted under the identifying assumption of no such association. This assumption is more likely to hold for some results than for others. While celibacy may be associated with greater rates of out-migration, the same does not necessarily apply to fertility or childlessness.

Table A7: Migration Decision

	$1\{Migrated\}$ (1)
ln(HISCAM)	-0.048**
	(0.018)
Mean DV	0.382
Observations	27,394
Parishes (clusters)	16
R^2	0.184

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: Unit of analysis are all births. Dependent variable equals one if the child migrated. Migration is assumed if no demographic events after birth are observed. All regressions include parish and marriage-decade fixed effects. Standard errors are clustered at the parish level.

C Extensive Margin of Fertility

Baudin et al. (2015) decompose group level fertility into an intensive and extensive margin. The intensive margin corresponds to the number of surviving children per reproductive unit (couple). The extensive margin is determined by the share of all potential reproductive units that do not have children, namely couples that remain childless and individuals that remain celibate.

To study childlessness, I regress a binary indicator for childlessness $1\{\text{Childless}_i\}$ on ln(HISCAM) in a linear probability model; the coefficient is insignificant and economically small (Column (1), Table A8). The probability of remaining childless, conditional on marriage, is 0.045 irrespective of SES. Remaining childless was likely driven by biological chance and infertility instead of socio-economic factors. To study celibacy, I look at the life histories of all surviving children born in Wittgenstein. To ensure that celibacy is not biased upwards for more geographically mobile groups, only individuals whose burial is recorded in Wittgenstein are included. I regress an indicator

[39] I operationalize emigration as an indicator variable equal to one if there is no death record, or the death record is not from a core parish of the reconstitution.

Table A8: Mechanism I: Extensive Margin of Fertility

	$1\{\text{Childless}\}$	$1\{\text{Celibate}\}$	
	(1)	(2) Male	(3) Female
ln(HISCAM)	0.004	-0.013	-0.013
	(0.016)	(0.041)	(0.026)
Mean DV	0.045	0.259	0.171
Observations	2805	4687	5013
Parishes (clusters)	16	14	15
R^2	0.027	0.140	0.080

Robust clustered standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table reports OLS estimates for the association between SES and the extensive margin of fertility. The exposure variable is ln(HISCAM) – logged continuous occupational status. In column (1) I investigate childlessness, and the outcome variable is a indicator variable equal to one if a couple remained childless. Here I use the status of the husbands father as exposure. The sample is restricted to complete marriages – where both spouses survive to 50 – and did not migrate. In columns (2) and (3) I investigate celibacy separately for men and women at the level of all births (with observed burial). The outcome is a indicator variable equal to one if no marriage is observed. Fathers status is used as the exposure. All regressions include parish and marriage/birth decade fixed effects.

variable equal to one if I do not observe a marriage $1\{\text{NoMarriage}_i\}$ on father's ln(HISCAM).[40] For both men and women, there is no evidence of a SES gradient in celibacy (Column (2) & (3), Table A8). The average rate of celibacy for men is significantly higher than for women (0.259 vs 0.171). This could be a manifestation of the dynamics described by Guinnane and Ogilvie (2013), whereby certain groups of men were excluded from the marriage market, although these groups do not overlap with my measure of SES. Alternatively, these rates could reflect differing propensities to out-migrate. While celibate men stayed in the parental household, women who did not succeed in the local marriage market were sent abroad to seek out better prospects.[41]

In Wittgenstein, the extensive margin of fertility did not vary with SES. Instead, reproductive inequality was manifest only along the intensive margin. As evident in Table 3, all the action came from gross fertility, with the probability of under-15 mortality constant in status. To better understand the relationship between SES and gross fertility, I now turn to its inner workings.

D Intensive Margin of Fertility

The intensive margin of gross fertility is a function of when reproductive behavior begins (*starting*), when reproductive behavior ceases (*stopping*), and how frequently births occur within this period (*spacing*). I assume that reproductive behavior begins upon marriage and operationalize starting at the mother's age at marriage. Stopping is simply measured by the mothers age at last birth. Measuring deliberate spacing is complicated since it is subject to a plethora of non-volitional factors

[40] Occupation was normally recorded at marriage or at offsprings baptisms. Ergo, celibate men were much less likely to have recorded occupations. The sample of men who have a recorded occupation regardless is thus highly selected on more notable occupations (that were recorded at death).

[41] Since I can only identify celibacy for individuals who did not migrate, I cannot test this empirically. Across the entire sample, men were significantly more likely to out-migrate. However, it is difficult to pinpoint how this interacted with marriage markets.

Table A9: Mechanism II: Starting, Spacing, and Stopping

	Age at Marriage	Age at Last Birth	Birth Interval
	(1)	(2)	(3)
ln(HISCAM)	-4.754***	0.058	-2.914***
	(0.351)	(0.340)	(0.821)
Mean DV	25.646	39.088	32.840
Observations	5325	3194	22375
Parishes (clusters)	16	16	16
R^2	0.055	0.027	0.012

Robust clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: Table reports OLS estimates of the association between socioeconomic status (SES) and components of the intensive margin of fertility: starting, spacing, and stopping. Columns (1) and (2) use couples as the unit of analysis. Column (1) models mothers age at marriage. Column (2) models mothers age at last birth, restricting the sample to complete marriages where both spouses survived to age 50. Column (3) uses births as the unit of analysis and includes all births at parity greater than one. The dependent variable is the interval (in months) to the prior birth. Parity is controlled for, as intervals tend to lengthen with parity. The exposure variable is the husbands status measured by ln(HISCAM). All regressions include parish and marriage-decade fixed effects.

(e.g., infant feeding practices) (Knodel 1987). However, since I am interested in the mechanical mediators of gross fertility, I measure spacing irrespective of whether it is the product of deliberate fertility control using birth intervals.

Table A9 reports the results of this exercise. The coefficient in column (1) reveals a strong and significant negative association between ln(HISCAM) and Mother's age at marriage. In couples of the top SES decile, women married $4.754 \times \ln(80/40) = 3.295$ years earlier.[42] Turning to column (2), there is no association between age at last birth and SES. Irrespective of SES, reproductive behavior ceased around 39 years of age for women. This pattern for starting and stopping replicates for men, albeit in a less pronounced manner. For spacing, the coefficient for ln(HISCAM) in column (3) is statistically significant at the 95 % level. High-SES couples have $2.914 \times \ln(80/40) = 2.020$ months shorter birth intervals on average.

Table A10: Starting and Stopping for Men

	Age at Marriage	Age at Last Birth
	(1)	(2)
ln(HISCAM)	-2.687***	2.111***
	(0.646)	(0.690)
Mean DV	29.144	42.561
Observations	5325	3194
Parishes (clusters)	16	16
R^2	0.025	0.044

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: All regressions include parish and marriage-decade fixed effects. Standard errors are clustered at the parish level.

[42] These class differences in female age at marriage concur with earlier findings for Germany based on the parish of Belm (Schlumbohm 1992). However, while Schlumbohn looks only at differences between land-rich and landless peasants, the detailed occupational data of the Wittgenstein reconstitution enables evaluation of the relationship between status and demographic outcomes in a more granular manner.

These results clash with Knodels (1987) finding that deliberate spacing cannot be identified in pre-industrial Germany. However, non-deliberate birth spacing can emerge mechanically in historical populations. Variation in non-volitional factors affecting birth intervals – i.e., different breastfeeding practices or nutritional effects during periods of economic stress (Jaadla et al. 2020; Thiehoff 2015) – could explain the significant coefficient in column (3). Dribe and Scalone (2010) use the same data as Knodel (1987) to argue for the presence of deliberate fertility adjustments via spacing during such periods of economic stress. They cite the rapid response to price shocks as evidence that this adjustment was the product of deliberate spacing instead of hardship induced sub-fecundity. Since they find that lower SES couples responded to these price shocks more strongly, this offers another explanation for the association between SES and spacing. Nonetheless, mechanical explanations, such as the peculiarities of local labor markets, offer a stronger candidate explanation. Lower SES men often traveled to neighboring principalities to seek out work, taking leave for several months on end (Klein 1936). These periods of absence mechanically increase birth intervals for low SES couples, offering an appealing explanation for the association between spacing and SES. Such labor migration was common across Germany and would increase in times of economic hardship as work became scarcer. As such, the variation in spacing may be attributable to the specific economic conditions of the area.

To check whether starting and spacing account for the entirety of the association between SES and gross fertility, I include them as controls when regressing ln(HISCAM) on gross fertility. The coefficient for ln(HISCAM) is insignificant and close to zero. This implies that there is no direct effect of SES on gross fertility. Instead, SES is only associated with gross fertility via starting and spacing. To further understand the relative contributions of the two mechanisms, I conduct a simple decomposition exercise. I regress mother's age at marriage on gross fertility to obtain β_{start}, and the average birth interval on gross fertility to obtain β_{space}. The product of the coefficient in Table A11 column (2) and β_{start} captures the indirect effect of SES on fertility via starting δ_{start}. The product of the coefficient in column (3) and β_{space} describes the indirect effect via spacing δ_{space}. The total effect of SES on gross fertility $\delta = \delta_{start} + \delta_{space}$ is $1.243 = 1.036 + 0.207$. The share of the total effect mediated by starting is $1.036/1.243 = 0.83$.

Table A11: Mechanism and Decomposition

	Gross Fertility			Age at Marriage	Birth Interval
	(1)	(2)	(3)	(4)	(5)
Age at Marriage	-0.203***	-0.218***			
	(0.004)	(0.003)			
Average Birth Interval	-0.047***		-0.051***		
	(0.003)		(0.004)		
ln(HISCAM)	0.034			-4.754***	-4.061***
	(0.176)			(0.351)	(0.862)
Mean DV	5.821	5.175	5.867	25.646	35.537
Observations	4640	10323	8978	5325	4640
Parishes (clusters)	16	16	16	16	16
R^2	0.295	0.209	0.127	0.055	0.033

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: All regressions include parish and marriage-decade fixed effects. Standard errors are clustered at the parish level.

The dominance of age at marriage over other mechanisms is consistent with evidence from other European contexts (Wrigley et al. 1997; Clark and Cummins 2015; Cummins 2020). One explanation for the strong association between age at marriage and SES is the start-up costs of marriage and childrearing. Neo-locality – the practice of forming an independent household instead of staying in the parental household – common to western Europe, significantly increased the cost of marriage. As such, lower-SES men had to earn and save for longer before marrying (Tilly and Tilly 1971).

E Multi-generational Transmission

I estimate elasticities of status across one ($G4 - G3$), two ($G4 - G2$) and three ($G4 - G1$) generations.

$$\ln(\text{HISCAM}_{i,G4}) = \alpha + \beta_{-m} \ln(\text{HISCAM}i, G4 - m) + \pi_{t,G4} + \epsilon_{i,G4} \tag{A1}$$

Additionally, I estimate an AR(3) model that regresses the SES of three prior generations on G4. In the absence of measurement error, this model estimates the effect of fathers (G2) conditional on direct grandfather (G3) and great-grandfather (G4) effects. Throughout, SES is measured using HISCAM. In the baseline specification, when individuals have multiple status observations, I use a random draw. In later specifications, to test the identifying assumption and account for measurement error, SES is averaged across available occupations. To account for time-variation in average SES, half-century fixed-effects $\pi_{t,G4}$ are included. All standard errors are clustered at the parish level.

Columns (1), (3), and (5) of Table A12 report baseline estimates for multi-generational elasticities. Across the board, the multi-generational effect is larger than the predicted effect based on an AR(1) transmission mechanism. Concordantly, the AR(3) model in column (7) implies that the grandfather effects persist – both in statistical and economic significance – when we condition on the direct father effect. However, as discussed in subsection 4.1, assigning a structural interpretation to these associations is rife with problems. As such, these coefficients do not necessarily imply a direct grandfather effect (Ward et al. 2025). Comparing estimates to ones that partially correct for measurement error – see columns (2), (4), (6), and (8) – suggests spurious multi-generational effects. Although using average SES is only a partial remedy, it suffices to increase the magnitude of β_{-1} by 22 %, while reducing excess persistence by 73 pp for the grandfather (β_{-2}), and 147 pp for the great-grandfather effect (β_{-3}). Similarly, in the AR(3) model, the measurement error correction reduces the relative magnitude of the grandfather by 17 pp. In the absence of multiple independent SES measurements per observation, I am unable to fully account for measurement error. Thus, it is impossible to conclude whether the significant grandfather effects are statistical artifacts. Still, given this pattern and existing evidence on multi-generational mobility, it appears likely that the remaining effect is driven by measurement error. All subsequent analyzes are conducted under the identifying assumption of no structural grandfather effect.

Table A12: Multi-generational Elasticities of SES

	$\ln(\text{HISCAM}_{i,G4})$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(\text{HISCAM}_{i,G3})$	0.247***	0.301***					0.212***	0.270***
	(0.016)	(0.023)					(0.026)	(0.031)
$\ln(\text{HISCAM}_{i,G2})$			0.173***	0.191***			0.125***	0.113***
			(0.024)	(0.027)			(0.024)	(0.029)
$\ln(\text{HISCAM}_{i,G1})$					0.055***	0.060***	-0.013	-0.013
					(0.009)	(0.010)	(0.013)	(0.018)
Predicted Effect			0.061	0.090	0.015	0.027		
Excess Persistence (%)			184	111	266	119		
Observations	5066	5066	3237	3237	2332	2332	1887	1887
R^2	0.158	0.177	0.132	0.133	0.070	0.070	0.161	0.170

Notes: Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.