IWP
WORKING
PAPERS

10/2025
N° 7

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Tantalus Curse? Multigenerational Persistence of Welfare Dependency in Switzerland

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Abstract

We study the multigenerational transmission of welfare dependency using a new horizontal approach that exploits family links among siblings and cousins. Leveraging population-wide administrative data from Switzerland, we estimate how family background shapes the risk of welfare receipt across generations. In a three-generation framework, having a welfare-dependent sibling raises an individual's probability of welfare receipt by about 22 percentage points, while a cousin adds roughly 4 percentage points, indicating a steep decay in influence with generational distance. Welfare dependency shows a stronger nuclear family effect than income, consistent with greater persistence at the lower end of the status distribution. Yet the rate of decay across generations is similar for welfare and income, implying that this heterogeneity is confined to the first two generations.

Keywords: multigenerational social mobility, horizontal family lineages, welfare dependency
JEL Classification: I30, J62, J12

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1 Introduction

Intergenerational transmission at the lower end of the income distribution can be studied through the inheritability of welfare dependency. The persistence of welfare receipt across generations evokes the image of the Tantalus curse from Greek mythology—a fate that bound successive generations of the same family. In the myth, descendants were trapped by the circumstances of their birth, unable to escape inherited misfortune. This metaphor captures a central concern in public economics: when social and economic disadvantages are transmitted across generations, they signal a profound lack of equality of opportunity.

Recent research has documented substantial heterogeneity in the intergenerational transmission of economic outcomes across the socioeconomic spectrum, with persistence being particularly pronounced at the lower end of the distribution (Barone and Mocetti, 2021; Colagrossi et al., 2025; Lesner, 2018). These findings suggest that family background may act as a powerful constraint on upward mobility for individuals born into poverty.[1]

A key manifestation of such disadvantage is the intergenerational transmission of welfare dependency. Investigating the extent to which reliance on social assistance recurs within families provides a sharp and policy-relevant lens through which to study persistent disadvantage.

While the existing literature provides strong evidence of intergenerational persistence in social assistance between parents and children, those studies are limited to two-generation frameworks. In the United States, having a mother who received welfare benefits raises the probability that her daughter will also rely on welfare by at least 21 and up to 30 percentage points (Hartley et al., 2022; Page, 2004). In European settings, intergenerational correlations in welfare receipt range between 0.17 and 0.22 (Boschman et al., 2019;

[1] An extensive literature shows how childhood poverty can set in motion processes that perpetuate poverty and disadvantage into adulthood (Duncan et al., 2012; Vauhkonen et al., 2017).

De Haan and Schreiner, 2025a; Riphahn and Feichtmayer, 2024).[2] However, by restricting the analysis to a single vertical link, these studies may underestimate the broader reach of family background effects.

A growing body of research on income, education, and wealth mobility suggests that multigenerational influences—extending to grandparents and more distant relatives—can play a significant role in shaping long-term socioeconomic trajectories (Colagrossi et al., 2020b; Mare, 2011; Zeng and Xie, 2014). Grandparents, for example, may support their descendants through direct transfers, time investments, or bequests of advantageous traits. Ignoring these effects risks understating the persistence of inequality.[3] In a study spanning 15 generations of Swiss data, Häner and Schaltegger (2024) find significant effects of parents and grandparents, but not of great-grandparents or more distant relatives, suggesting no lasting dynastic effects on average socioeconomic status in Switzerland.

Capturing multigenerational dynamics poses substantial empirical challenges, as longitudinal data across several generations are rare. A further challenge with the "vertical" approach is that comparable socioeconomic information for more than two generations is difficult to obtain or not comparable between the generations, as e.g., welfare programs change over time. A common solution is the "horizontal" approach, which compares outcomes among siblings and cousins to take into account shared background effects beyond the nuclear family (Colagrossi et al., 2020a; Collado et al., 2022b). This captures not only vertical transmissions through shared parents or grandparents, but also broader, harder-to-measure family influences such as neighborhood conditions, school quality, and the transmission of cultural or social capital (Hällsten and Kolk, 2023; Solon, 1999).

While existing horizontal frameworks are useful for capturing broad patterns of kinship

[2] For more details on the welfare system and study design, see table A12 in Appendix A.

[3] An alternative approach argues that such patterns are better captured by latent factor models summarizing inherited family traits rather than explicitly modeling additional generational effects (Braun and Stuhler, 2018). However, our study contributes to the strand of literature that seeks to identify and estimate distinct generational influences.

resemblance, they lack the structure needed to disentangle the distinct layers of intergenerational influence that generate family similarities. For example, cousin correlations in these frameworks indicate that some force operates through the extended family, but they cannot reveal whether the transmission originates directly from grandparents or indirectly through parents, whose own traits were shaped by their upbringing. Similarly, sibling correlations conflate parental transmission with other circumstances that siblings share. To study how family influence decays across generations, we employ an outcomes-based framework that treats siblings as capturing the parental layer and cousins as capturing the additional grandparental layer. This structure allows us to juxtapose the two and trace how background similarity attenuates with generational distance, in the same spirit as in the existing vertical frameworks (for comparison to the existing approaches, see Appendix C).

This paper contributes to the literature on social mobility and welfare persistence in two main ways. First, we develop a new multigenerational framework based on horizontal family lineages. By jointly analyzing siblings and cousins, the framework recovers the overall influence of the extended family while separately identifying the marginal contributions of parents and grandparents. This design thus provides a broad "omnibus" measure of family background and, at the same time, isolates the additional influence that arises at different generational layers. In doing so, it complements and extends the traditional vertical parent–child perspective. Second, to our knowledge, this is the first study to quantify multigenerational family effects on social assistance dependency.

We exploit a uniquely rich administrative dataset for Switzerland that includes the full permanent resident population and records detailed welfare receipt histories. Importantly, the data allow us to link individuals across family ties and identify both siblings and cousins.

Our results reveal a rapid attenuation in the intergenerational transmission of welfare dependency across horizontal family links. In a three-generation framework, having a sibling who receives welfare increases an individual's probability of welfare receipt by approximately 22 percentage points. For cousins, the additional effect drops to around 4 percentage points, suggesting a sharp decline in familial influence with generational distance.

We complement our analysis by examining family background effects on income and educational attainment. Consistent with prior evidence, we find that the influence of the nuclear family is substantially stronger for welfare dependency than for income, confirming that intergenerational transmission is more pronounced at the lower end of the socioeconomic distribution. However, our multigenerational perspective reveals that this heterogeneity is largely confined to the first two generations: the decay in family influence across generations is strikingly similar for both welfare receipt and income. This suggests that while disadvantage is more acutely transmitted within the nuclear family for welfare outcomes, the long-run persistence of economic status may not differ substantially across the income distribution. In contrast, educational attainment exhibits a slower rate of decay, indicating a more durable transmission of family background effects across generations in the domain of education.

Together, our findings show that a horizontal multigenerational design can trace how family influences operate across distinct generational layers. This design not only captures unobserved background factors but also isolates the incremental contributions of parents and grandparents. Moreover, it provides a credible alternative to vertical approaches in settings where institutional changes in welfare programs make intergenerational comparisons of welfare dependency inherently difficult.

The remainder of the paper is organized as follows. Section 2 introduces the empirical framework, Section 3 the data, Section 4 the results, and Section 5 concludes.

2 Empirical approach

2.1 Two- and Multigenerational Models

The canonical framework for analyzing the intergenerational transmission of social status originates with Becker and Tomes (1986). In their model, status is transmitted through a linear autoregressive process of order one, AR(1):

$$y_t = \alpha + \beta_{t-1} \cdot y_{t-1} + \epsilon_t, \tag{1}$$

where y_t denotes the social status of generation t, y_{t-1} the status of the parental generation, and β_{t-1} captures the degree of intergenerational persistence.

In this framework, the total effect of family background originates exclusively from the parental generation and follows an AR(1) process. Accordingly, the correlation between grandparents and grandchildren equals β^2, and more generally the correlation across m generations equals β^m. This formulation implies that persistence decays at a geometric rate:

$$\beta_{t-x} = \beta_{t-1}^{x}, \quad \forall x > 1. \tag{2}$$

Recent evidence, however, suggests that this AR(1) specification may understate the importance of more distant ancestors. Several studies find significant grandparental effects on offspring outcomes even after conditioning on parental status (Colagrossi et al., 2020b; Mare, 2011; Zeng and Xie, 2014). In this case, persistence is better represented by a higher-order Markov process, such as an AR(2):

$$y_t = \alpha + \beta_{t-1} \cdot y_{t-1} + \beta_{t-2} \cdot y_{t-2} + \epsilon_t, \tag{3}$$

where β_{t-2} captures the additional effect of grandparents given the parental effect. More generally, AR(m) specifications allow for transmission channels that extend beyond the immediate parent–child link and thus provide a richer description of multigenerational mobility dynamics (Häner and Schaltegger, 2024).

2.2 A Multigenerational Horizontal Analysis

Corcoran et al. (1976) were among the first to highlight the value of sibling correlations for capturing unobserved family influences. From a horizontal perspective, correlations among relatives of the same generation reflect all factors jointly shared within the family environment.

Our multigenerational horizontal approach captures three broad channels of influence. First, it detects the influence of the parental and grandparental socioeconomic status. Second, our design incorporates the impact of parental and grandparental factors that are not easily measured directly—such as psychosocial mechanisms (e.g., aspirations, expectations, stigma). Third, it distinguishes between the parental and grandparental layers of family background. Siblings reflect what is shared through direct parental transmission, while cousins capture the additional influence of the extended family lineage that is not already absorbed by the parental effect (Collado et al., 2022a). Taken together, these correlations provide a broad "family effect" that encompasses multiple overlapping channels of influence rather than a single pathway.

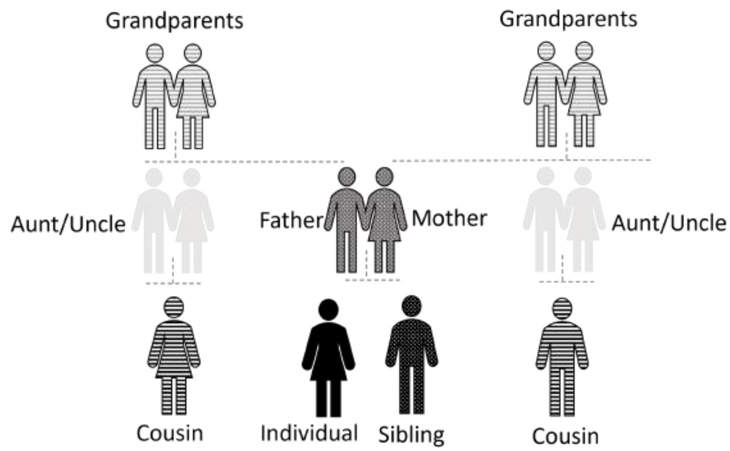
This perspective is particularly valuable for the study of welfare dependency. Unlike education or income, welfare systems evolve markedly over time in eligibility rules, benefit generosity, and social stigma. These institutional changes complicate vertical comparisons across generations, since parents and grandparents often confronted different program environments. The horizontal design, by contrast, measures how strongly welfare participation clusters within and across family lineages at a given point in time. In doing so, it provides a credible strategy to trace how family influence on welfare dependency decays across generations, even when the underlying programs are not directly comparable across generations.

Our approach integrates the horizontal perspective with the logic of higher-order persistence models. In our framework, siblings capture the parental layer and cousins the grandparental layer, making their joint consideration analogous to extending a parent–child model to an AR(2) specification. This approach goes beyond variance decompositions by describing how family influence attenuates with generational distance. In doing so, the horizontal design provides a structured way to quantify the incremental contribution of more distant ancestors and the rate at which background similarity diminishes across multiple generations.

Figure 1 illustrates the logic of our approach. Instead of relying on direct observations of parents and grandparents (cf. equation 3), we use the status of siblings and cousins: siblings share parents, while cousins share grandparents. This design generates a horizontal three-generational model. As emphasized by Collado et al. (2022b), the central advantage of horizontal information is that it recovers intergenerational links even when data on grandparents and grandchildren are missing. For example, if grandparents are unobserved but cousins can be observed at similar ages and in the same period, cousin resemblance identifies the strength of the grandparent–grandchild link.

We estimate the broader family effect with the following specification. Given the binary outcome, we employ a logit model:

Figure 1: Vertical versus horizontal multigenerational approach



Notes: The figure illustrates our multigenerational horizontal approach. Patterns indicate which vertical relationship is represented by the corresponding horizontal relatives: dots represent siblings (or parents), while stripes represent cousins (or grandparents). In this framework, siblings capture the parental layer and cousins the grandparental layer. Relatedness decays more steeply in the horizontal than in the vertical case: genetic similarity falls by 3/4 across horizontal links, compared with 1/2 across vertical links (Hällsten and Kolk, 2023).

$$y_j = \psi(\beta_0 + \beta_1 \cdot y_{s,j} + \beta_2 \cdot y_{c,j} + \epsilon_j), \tag{4}$$

where y_j denotes the status of the individual, $y_{s,j}$ the status of the sibling, and $y_{c,j}$ the status of the cousin.

3 Data

3.1 Institutional Background

In Switzerland, social security and social assistance form two interconnected pillars of the welfare state. Individuals who exhaust their social insurance entitlements or whose means-tested benefits are insufficient to meet basic needs may apply for social assistance, provided their income and assets fall below a legally defined threshold. Social assistance is a means-tested, last-resort program administered at the municipal level. Its objectives are twofold: (i) to secure a minimum standard of living and (ii) to promote reintegration into the labor market (FSO, 2022; FSIO, 2022).

Our analysis focuses on economic social assistance,[4] which constitutes the core safety net and applies to households at the very bottom of the income distribution (see Appendix B Figure A1 for further details on the Swiss social security and welfare system). We exclude other social security or means-tested benefits, as these vary across cantons.[5]

In 2022, 2.9% of Switzerland's permanent resident population received social assistance. The likelihood of receiving social assistance is particularly elevated among individuals in their mid-twenties to mid-forties, as well as among foreign nationals and those with low levels of education. Social assistance rates tend to be higher in urban areas and increase with the size of the municipality (FSO, 2025).

3.2 Administrative Dataset

Our analysis relies on a comprehensive administrative dataset constructed from multiple federal sources, linked via anonymized old-age insurance numbers provided by the Swiss Federal Social Insurance Office. The dataset covers approximately 11 million individuals. Sociodemographic variables as well as population and household statistics are available annually from 2010 to 2022, with the latter extending back to 1981 based on the decennial census and related registers. This structure enables us to observe socioeconomic outcomes from 2010 onward and reconstruct family linkages back to 1981, provided that at least one direct family member (e.g., child) was alive in 2010.

[4]This category includes four forms: regular support with a target agreement, one-time payments with a budget, one-time payments without a budget, and advance unemployment insurance.

[5]All cantons provide economic social assistance, but some also offer "social assistance in the broader sense," such as family allowances, unemployment allowances, or housing allowances (FSO, 2023a).

In addition to indicators such as welfare receipt and income, the dataset includes detailed family structures, allowing us to identify siblings and cousins. Compared to survey data, administrative records offer the advantage of full population coverage and are not subject to misreporting biases (Meyer et al., 2015). Our dataset therefore contains welfare dependency information for every permanent resident of Switzerland.

A limitation is the issue of non-take-up: some individuals who are eligible for social assistance do not claim benefits. A study from the canton of Bern estimates a non-take-up rate of about 25% (Hümbelin, 2019). Non-take-up arises partly from the stigma of welfare receipt and partly from legal rules requiring vertical family support when relatives exceed certain income or wealth thresholds (SKOS, 2021). Importantly, there is no evidence that non-take-up varies systematically across siblings or cousins, so our estimated correlations are unlikely to be biased.

3.3 Constructing Kinship Networks

We construct kinship networks in two steps. First, we identify nuclear families by linking parents and their children. Second, we extend these linkages by adding the parents' siblings (aunts and uncles) and their children, who constitute cousins. This procedure yields up to 20 possible cousin combinations across both paternal and maternal lines. In the final dataset, we retain only observations that share the same grandparents.

Unlike some previous studies, we do not restrict our analysis to patrilineal descent. In Switzerland, spouses are legally obliged to support one another financially, and in practice typically share welfare status. To account for this, we randomize lineage selection.

To avoid over-weighting from duplicate sibling-pair observations, we restrict the sample to unique sibling pairs. Cousin pairs, by contrast, are not necessarily unique, since the same cousin can appear in multiple sibling pairings within the extended family. To approximate the full set of possible pairings while keeping estimation tractable, we employ a Monte

Carlo sampling procedure: for each sibling pair, we randomly draw 100 admissible cousin pairings and conduct the analysis across these samples. Families of different sizes may therefore contribute a different number of cousin pairs, which in turn could affect the estimated correlation and potentially be correlated with family socioeconomic status, as noted by Hällsten (2014). In robustness (see Section 4.4), we therefore follow the spirit of this concern by restricting the sample to unique three-generation families, ensuring that each extended family contributes only once. The results remain stable, indicating that our findings are not mechanically driven by family size differences.

3.4 Multi-Year Prevalence of Social Assistance

Our primary outcome is a binary indicator equal to one if an individual received social assistance in any year between 2010 and 2022, and zero otherwise. We construct analogous measures for siblings and cousins. To facilitate comparability with the vertical intergenerational literature, we restrict the analysis to young adults. Specifically, we focus on individuals aged 20–33 during the observation period, corresponding to birth cohorts 1977–2002. This age range is consistent with prior studies on intergenerational welfare dependency, which typically examine recipients up to age 30 or 35.

3.5 Descriptive Statistics

Table 1 reports descriptive statistics for the main variables. We observe approximately 558,000 sibling pairs and 542,000 cousin pairs. These correspond to about 232,000 unique nuclear families (distinct parents) and roughly 124,000 extended families (shared grandparents). The average birth year of both siblings and cousins is 1991. Women represent a slightly larger share among siblings than among cousins. Welfare dependency amounts to about 4 percent among siblings and cousins.

Table 1: Descriptive statistics

Sample: Three Generations

	Siblings	Cousins
number of unique observations	558,256	541,724
number of unique families [a]	231,845	123,761
average year of birth (sd)	1991 (6.39)	1991 (6.60)
share of welfare dependents	0.040	0.038
share of females	0.52	0.51

[a]Unique Parents (siblings) or Grandparents (1^{st} cousins).
Notes: This table presents descriptive statistics for the updated three-generational sample.

4 Results

4.1 The Influence of Relatives beyond the Nuclear Family

To justify higher-order Markov models, we first test whether the intergenerational transmission of welfare dependency follows a simple AR(1) process. In the canonical Becker and Tomes (1986) framework, persistence decays geometrically: each additional generational step multiplies the persistence parameter, so that more distant relatives contain no independent information. Under this stylized, one-line AR(1) model, the cousin correlation should equal the *square* of the sibling correlation. In other words, cousins are one step farther removed along the same vertical line, so the correlation compounds multiplicatively. If the observed cousin correlation exceeds this squared sibling benchmark, AR(1) is rejected.

Two clarifications are important. First, the "square rule" holds only under the stylized unilinear AR(1) assumption of a single parental line. In reality, transmission is bilinear (through both mother and father), and cousins typically share only one line. This makes the *true* AR(1) cousin benchmark weakly lower than the squared sibling correlation. Thus, using the square rule as a benchmark is conservative: if actual cousin correlations exceed even this level, the evidence against AR(1) is particularly strong.

Table 2 shows that the observed cousin correlation (y–y_c: Actual) exceeds the squared sibling benchmark (y–y_c: Predicted = $(y$–$y_s)^2$) by 0.013, or about 25 percent in relative terms. Since the squared sibling correlation already represents a conservative upper bound under AR(1), this finding implies that persistence decays more slowly than predicted by a pure AR(1) process. The excess cousin similarity may reflect an additional grandparental component (an AR(2)-like process). This implies a departure from the AR(1) benchmark. Thus, cousins carry independent information about status transmission, supporting the use of multigenerational frameworks beyond the nuclear family.

Table 2: Correlation coefficients to compare to AR(1) process

	Probability of Welfare Dependency
$y - y_s$	0.228^{***}
	(0.001)
$y - y_c$: Predicted	0.052^{***}
	(1e-06)
$y - y_c$: Actual	0.065^{***}
	(0.002)
Δ Actual–Predicted	0.013

Notes: The table compares the measured cousin correlation coefficient to the one predicted by the AR(1) process. Row $y - y_s$ indicates the sibling coefficient and the corresponding standard error in parentheses. Row $y - y_c$: Actual corresponds to the regression coefficient when the individual is regressed on the cousins' status. $y - y_c$: Predicted shows the predicted value according to the AR(1) process (square of the sibling coefficient), where status persistence decays at a geometric rate. Finally, Δ Actual–Predicted shows the absolute difference between the predicted and the actual $y - y_c$ slope; the commented row expresses the difference as a percent. Standard errors are clustered at the family level. Corresponding logit estimates are reported in Appendix Tables A6 and A7 .

4.2 Multigenerational Analysis

We next examine the family effect on welfare dependency and its attenuation across generations using the horizontal approach with siblings' and cousins' welfare status. As outlined in Section 3.3, we implement a Monte Carlo procedure, estimating the model 100 times on random subsamples of cousin-pairings.[6]

Table 3 presents the logit coefficients and the corresponding average marginal effects (AME). The sibling coefficient implies that having a welfare-dependent sibling raises the probability of welfare receipt by about 22 percentage points. The cousin coefficient indicates an additional increase of roughly 4 percentage points. In odds-ratio terms, individuals with a welfare-dependent sibling are more than ten times as likely to be welfare recipients as those without.[7] The relative influence of cousins compared to siblings is about one-fifth.[8]

These results reveal a steep attenuation of family influence across generations. Several

[6] Point estimates and standard errors are obtained by averaging across iterations.
[7] exp(2.36)
[8] 0.04/0.20

mechanisms may contribute to this pattern. First, both observed and unobserved family characteristics—such as parental resources, expectations, or stigma—are more directly shared among siblings. Second, contextual family influences like neighborhood quality are more similar within sibling pairs than among cousins. Third, genetic relatedness declines from 50% among siblings to 12.5% among cousins. Together, these factors help explain the strong sibling correlation and the substantially smaller cousin effect.

Overall, the results indicate that the nuclear family exerts a dominant influence on welfare dependency, while additional effects from more distant relatives are modest, suggesting a rapid attenuation of family effects across generations.

Table 3: Logit Coefficients and Average Marginal Effects (AME)

	Probability of Welfare Dependency	
(Intercept)	-3.513 (0.01)***	
Sibling dependency	2.36 (0.03)***	0.216 (0.004)***
Cousin dependency	0.85 (0.04)***	0.042 (0.002)***
Observations	447,804	447,804

*p<0.1; **p<0.05; ***p<0.01
Notes: The table above presents the results of the median coefficents of 100 iterations. For all models, cluster-robust standard errors at the family level (grandparents) are reported in parentheses.

4.3 Extension to Other Status Indicators

Because horizontal decay has not previously been studied, direct benchmarks are unavailable. While welfare dependency captures outcomes at the very bottom of the income distribution, extending the analysis to income and education for the full population enables us to compare overall mobility with welfare mobility. This broader perspective situates our findings on welfare dependency within the wider context of social mobility and allows us to assess whether disadvantage at the bottom differs fundamentally from patterns observed across the entire socioeconomic distribution.

Educational attainment is captured through years of schooling, consistent with established practice (Anderson et al., 2024; Braun and Stuhler, 2018).[9] For income, we follow the standard approach in the literature (e.g., Chetty et al., 2014), measuring children's earnings at ages 30–33.[10] Our outcome is long-run logged real income, expressed in 2022 Swiss francs and adjusted for inflation.[11]

Results are presented in Table 4. In the income model, a 100% increase in sibling income is associated with a 10.3% increase in own income, while the additional cousin effect is only 2.1%. Thus, cousin income predicts less than one-fifth of the sibling effect, indicating a steep attenuation of income spillovers across kinship lines.

Compared to the welfare analysis, these results highlight an important asymmetry. The nuclear family effect is substantially stronger for welfare dependency than for income, confirming that intergenerational transmission is more pronounced at the lower end of the status distribution. However, this heterogeneity does not persist across generations: the

[9]For education, we use the Structural Survey (SE), which has been conducted annually since 2010 and samples about 200,000 individuals per year under mandatory participation rules. Across 12 waves, the SE covers 2.9 million unique individuals. Although not all family members appear in the survey, the data provide rich information on educational attainment and other socio-demographics. We translate reported degrees into years of schooling using standard federal classifications.

[10]The core sample covers individuals born between 1977 and 2002.

[11]To smooth transitory fluctuations, we average earnings over four years. We include the full distribution, retaining zero earners (assigned a value of CHF 1 to permit log transformation).

decay from siblings to cousins is strikingly similar for both welfare and income.

By contrast, education exhibits a slower rate of decay. One additional year of a sibling's schooling raises own attainment by 0.31 years, while a cousin's schooling adds 0.11 years—about one-third of the sibling effect.

Overall, cousin effects across all three outcomes—welfare, income, and education—are modest, suggesting high multigenerational mobility in Switzerland in multiple status indicators.

Table 4: Mean Estimates for Income and Education

	Income (log)		*Education (years)*	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
Intercept	9.450***	(0.034)	8.155***	(0.451)
Sibling outcome	0.103***	(0.002)	0.306***	(0.025)
Cousin outcome	0.021***	(0.002)	0.114***	(0.024)
Observations	190,927		1,461	

·p<0.1; *p<0.05; **p<0.01; ***p<0.001

Notes: The table reports mean coefficients from 100 iterations. Cluster-robust standard errors at the family level (grandparents) are in parentheses.

4.4 Alternative model specifications

Our baseline specification abstracts from potential moderating factors such as gender, cohort spacing, and geographic location. Since these dimensions may confound family similarity estimates, we subject our results to a series of robustness checks, reported in Table 5, with additional details in the Appendix (see Appendix Tables A8 to A11). In addition, we estimate a parent-child model to facilitate comparison to other countries.

Robustness and Heterogeneity Analyses

In the full sample, the potential age gap between siblings and cousins can be as large as 27 years, reflecting the full range of birth cohorts (1975–2002). Large gaps may bias cousin correlations upward if cross-cohort differences inflate within-family similarity, or downward if closer cohorts capture stronger shared environments (Collado et al., 2022b; Hällsten and Kolk, 2023). The average spacing is three and half years for siblings and almost six years for cousins. Restricting the sample to dyads with a maximum age difference of three years yields virtually identical estimates, ruling out systematic bias from cohort spacing.

To assess the role of local context, we limit the sample to families whose members all reside in the same canton. This restriction leaves sibling correlations essentially unchanged and cousin correlations entirely unaffected. These findings are consistent with evidence that geographic clustering explains little residual variation in intergenerational resemblance once parental background is controlled for (Chetty et al., 2014; Solon, 1999; Björklund and Jäntti, 2011).

As a further robustness check, we address the potential overweighting of large extended families. Instead of applying weighting schemes to cousin pairs as proposed by Björklund et al. (2009) and discussed in Hällsten (2014), we retain only one observation per extended family with unique grandparents. The results remain stable, confirming that our findings are not driven by the size distribution of cousin clusters.

Finally, we examine heterogeneity by gender. Table 5 shows that sisters exhibit a modestly lower probability of welfare receipt than brothers, in line with documented gender gaps in intergenerational income and educational attainment (Björklund and Jäntti, 2020; Black and Devereux, 2010; Collado et al., 2022b). For cousins, by contrast, we find no systematic gender differences. This pattern aligns with Hällsten (2014), who report negligible gender variation in cousin correlations across cognitive and educational outcomes, though Hällsten and Kolk (2023) document somewhat stronger male cousin correlations in education. Overall, our evidence suggests that welfare dependency does not display meaningful gender-specific heterogeneity in cousin linkages.

Table 5: Robustness and Heterogeneity analyses

	Probability of Welfare Dependency	
	Sibling correlation	Cousin correlation
Baseline estimates:	0.216***	0.042***
	(0.001)	(0.002)
R1: Max 3 yrs age difference	0.219***	0.042***
	(0.001)	(0.002)
R2: Same canton	0.2***	0.042***
	(0.001)	(0.002)
R3: Unique Grandparents	0.222***	0.041***
	(0.005)	(0.003)
R4: Only females	0.213***	0.044***
	(0.002)	(0.004)
R5: Only males	0.229***	0.039***
	(0.004)	(0.003)

Notes: The table above presents the robustness and heterogeneity analyses for both the sibling and the cousin correlation. The baseline model corresponds to the average marginal effects depicted in column 2 of Table 3. R1 restricts the sample to siblings and cousins with a maximum age difference of three years. R2 restricts the sample to siblings and cousins residing in the same canton. R3 retains only one observation per extended family with unique grandparents to avoid overweighting large cousin clusters R4 examines sisters and female cousins, while R5 focuses on brothers and male cousins.

Vertical Approach

In addition to the horizontal analysis, we also conduct a two-generational vertical analysis of mobility using the same dataset. This specification focuses on the mother–child link in welfare dependency and facilitates direct comparison with evidence from other countries. We restrict the analysis to two generations because grandparents are observed only after retirement age, when individuals are no longer eligible for social assistance but instead covered by separate insurance and means-tested programs for the elderly. Any measure of grandparental "welfare dependency" would therefore not be comparable to that of parents or children and would introduce systematic incomparability. Table 6 reports the results, including logit coefficients and corresponding average marginal effects.

Drawing on prior evidence that parental welfare receipt during adolescence is particularly predictive for intergenerational transmission (Beaulieu et al., 2005; Edmark and Hanspers, 2015), we use the welfare status of the mother when the child was aged 15–18 as the explanatory variable. The estimates indicate that children exposed to maternal welfare receipt in this period are 24 percentage points more likely to experience welfare dependency themselves compared to children whose mothers were not dependent. Put differently, they are about 17 times more likely to rely on welfare later in life[12].

Our results are at the upper bound of recent estimates for Sweden, Norway, and Germany, and remain somewhat below those reported for the United States (Boschman et al., 2019; De Haan and Schreiner, 2025b; Feichtmayer and Riphahn, 2021; Hartley et al., 2022; Page, 2004). Given the considerable institutional heterogeneity in welfare regimes across countries, however, these cross-country comparisons must be interpreted with caution (see Table A12 for details).

[12] exp(2.85)

Table 6: Means Logit Regression Results and AME for vertical analysis

	Probability of welfare dependency individuals at least 22 years old	
	(1) Logit estimates	(2) AME
Mother dependent at child age 15–18	2.85***	0.24***
	(0.012)	(0.003)
Constant	−3.90***	
	(0.019)	
Observations	394,374	

*p<0.1; **p<0.05; ***p<0.01
Notes: The table above presents the results of the vertical analysis investigating the effect of mothers' welfare dependency on children's dependency. Column 1 shows the regression output and column 2 the corresponding average marginal effect. Cluster-robust standard errors at the family level are reported in parentheses.

5 Conclusion

This paper examines the role of family background in welfare dependency using a novel multigenerational design. We contribute to the literature in two main ways. First, we develop a horizontal framework that jointly analyzes siblings and cousins. This approach captures the overall influence of the extended family while separately identifying the marginal contributions of parents and grandparents, thereby providing a broad "omnibus" measure of family background that complements the traditional vertical parent–child perspective. Second, to our knowledge, this is the first study to quantify multigenerational family effects on social assistance dependency.

Our results reveal a sharp attenuation of family influence across kinship lines. Having a welfare-dependent sibling increases the probability of welfare receipt by about 20 percentage points, whereas having a welfare-dependent cousin raises it by only 4 percentage points. This rapid decay implies that welfare dependency does not extend across generations in a manner consistent with the enduring "Tantalus curse". Instead, the influence of family background diminishes quickly with generational distance.

Comparable patterns emerge for income. While the sibling effect on welfare is stronger than on income—consistent with greater persistence at the bottom of the distribution—the decay from siblings to cousins is nearly identical across both outcomes. This indicates that heterogeneity between welfare and income is largely confined to the nuclear family: disadvantage is more acutely transmitted within the first generation for welfare, but over longer generational distances the persistence of economic status appears not to differ substantially between welfare and income. Education, by contrast, displays a slower attenuation, indicating more durable multigenerational transmission. Across all three domains, cousin effects remain modest, suggesting relatively high multigenerational mobility in Switzerland.

Beyond these findings, our study highlights the value of horizontal designs for analyzing the decay of multigenerational persistence. Future research should extend this framework to investigate the mechanisms underlying sibling and cousin correlations and to compare horizontal persistence across institutional settings. Applying this approach to other countries would shed light on whether the Swiss case reflects broader patterns or unique features of its institutional context. More broadly, our results underscore that while family background matters strongly within the nuclear family, extended family effects are modest, suggesting that concerns about entrenched welfare dependence across multiple generations may be overstated.

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Appendix

A Additional Tables

Table A1: Descriptive Statistics – Mean from Iterations (N = 100)

Variable	**Siblings**	**Cousins**
Mean of unique pairs	447,805	391,458
Mean of unique families[a]	231,845	124,780
Average year of birth	1990.38	1990.73
Mean share of welfare dependents	0.0391	0.0370
Mean share of females[b]	0.49	0.49

[a] Unique parents (siblings) or grandparents (1st cousins).
[b] Converted from numeric sex coding where 1 = male, 2 = female.
Notes: Descriptive statistics are averages over 100 iterations.

Table A2: Vertical Sample: Descriptive Statistics

Child's characteristics as an adult (age 22)	
Share of welfare recipients	0.034
Share of females	0.49
Mother's characteristics at child's age 16	
Share of welfare recipients	0.049
Year of birth (sd)	1967 (5.03)

Notes: Descriptive statistics for the intergenerational (vertical) sample.

Table A3: Descriptive Statistics — Three Generations: Education and Income

	Education		**Income**	
	Siblings	Cousins	Siblings	Cousins
Number of unique individuals	2,691	1,799	239,727	251,773
Number of unique families[a]	1,307	1,289	106,946	63,410
Average year of birth (sd)	1985 (3.49)	1985 (3.70)	1986 (4.07)	1986 (4.29)
Average years of education (sd)	14.00 (2.46)	14.00 (2.53)	—	—
Average income age 30–33 (sd)	—	—	68,297 (37,690)	68,233 (39,122)
Share of females	0.49	0.49	0.54	0.49

[a] Unique parents (siblings) or grandparents (1st cousins).
Notes: Descriptive statistics for the three-generational sample, grouped by education and income for siblings and cousins.

Table A4: Descriptive Statistics – Mean from Iterations for Education (N = 100)

	Siblings	**Cousins**
Mean of unique pairs	1,461.00	1,397.42
Mean of unique families[a]	1,307.00	1,221.96
Average year of birth	1984.83	1985.05
Mean years of education	14.07198	14.09470
Mean share of females[b]	0.51	0.50

[a] Unique parents (siblings) or grandparents (1st cousins).
[b] Converted from numeric sex coding where 1 = male, 2 = female.
Notes: All values represent averages taken over these 100 iterations for the education sample.

Table A5: Descriptive Statistics – Mean from Iterations for Income (N = 100)

	Siblings	**Cousins**
Mean of unique pairs	190,927.00	166,995.50
Mean of unique families[a]	106,946.00	62,846.25
Average year of birth	1985.36	1985.73
Average income	67,800.15	68,206.49
Mean share of females[b]	0.48	0.48

[a] Unique parents (siblings) or grandparents (1^{st} cousins).
[b] Converted from numeric sex coding where 1 = male, 2 = female.
Notes: Averages over 100 iterations for the income sample.

Table A6: AR (1) Empty Model: Logit Coefficients and Average Marginal Effects (AME)

	Dependent Variable: Probability of Welfare Dependency	
	Logit	**AME**
Sibling dependency	2.41 (0.02)***	0.228 (0.001)***
(Intercept)	-3.47 (0.01)***	
Observations: 447,805		

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Notes: Logit coefficients with cluster-robust standard errors at the family level (parents) in parentheses. The second column shows the average marginal effects (AME) for the corresponding model.

Table A7: AR (1): Logit Coefficients and Average Marginal Effects (AME)

	Dependent Variable: Probability of Welfare Dependency	
	Logit	**AME**
Cousin dependency	1.09 (0.04)***	0.065 (0.002)***
(Intercept)	-3.27 (0.01)***	
Observations: 447,805		

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Notes: Logit coefficients with cluster-robust standard errors at the family level (grandparents) in parentheses. The second column shows the average marginal effects (AME) for the corresponding model.

Table A8: *Sensitivity Check I — Age Difference*

	Dependent Variable: Probability of Welfare Dependency	
	Logit	**AME**
Sibling dependency	2.48 (0.03)***	0.219 (0.001)***
Cousin dependency	0.92 (0.05)***	0.042 (0.002)***
(Intercept)	-3.64 (0.02)***	
Observations: 223,776		

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Notes: Cluster-robust standard errors at the family (grandparents) level in parentheses. The second column shows the average marginal effects (AME) for the corresponding model.

Table A9: *Sensitivity Check II — Same Canton*

	Dependent Variable: Probability of Welfare Dependency	
	Logit	**AME**
Sibling dependency	2.46 (0.04)***	0.200 (0.001)***
Cousin dependency	0.98 (0.06)***	0.042 (0.002)***
(Intercept)	-3.73 (0.02)***	
Observations: 262,349		

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Notes: Cluster-robust standard errors at the family (grandparents) level in parentheses. The second column shows the average marginal effects (AME) for the corresponding model.

Table A10: *Sensitivity Check III — Unique Grandparents*

	Dependent Variable: Probability of Welfare Dependency	
Term	**Logit**	**AME**
Sibling dependency	2.32 (0.04)***	0.222 (0.004)***
Cousin dependency	0.79 (0.05)***	0.041 (0.003)***
(Intercept)	-3.43 (0.02)***	
Observations: 128,279		

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Notes: Standard errors are robust to heteroskedasticity. The second column shows the average marginal effects (AME) for the corresponding model.

Table A11: *Sensitivity Check IV — Correlations by Gender*

	Dependent Variable: Probability of Welfare Dependency			
	Female Sample		**Male Sample**	
	Logit	**AME**	**Logit**	**AME**
Sibling dependency	2.36 (0.05)***	0.213 (0.002)***	2.51 (0.05)***	0.229 (0.004)***
Cousin dependency	0.89 (0.07)***	0.044 (0.004)***	0.85 (0.07)***	0.039 (0.003)***
(Intercept)	-3.53 (0.02)***		-3.61 (0.02)***	
Observations:	94,666		102,984	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Notes: Cluster-robust standard errors at the family (grandparents) level in parentheses. The second and fourth columns show the average marginal effects (AME) for the corresponding model.

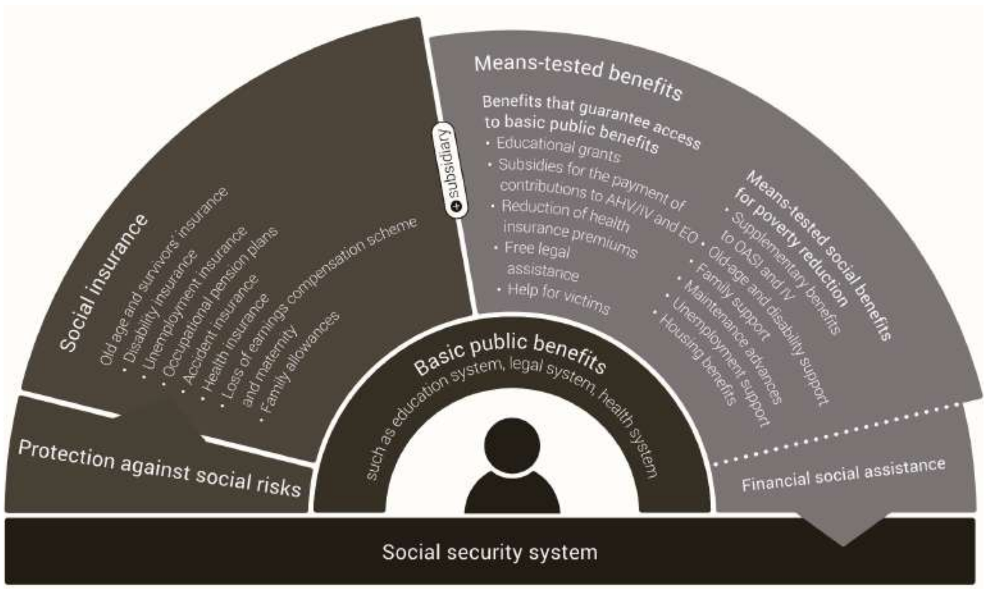
Table A12: Comparison of Welfare Systems and Study Designs

Paper	**USA (Page, 2004; Hartley et al., 2022)**	**Germany (Riphahn & Feichtmayer, 2024)**	**Netherlands (Boschman et al., 2019)**	**Norway (de Haan & Schreiner, 2025)**
System type & key program studied	Means-tested, state-fragmented safety net; studies focus on AFDC/TANF, SNAP, SSI, and General Assistance.	Social insurance plus means-tested assistance; studies cover Sozialhilfe & Arbeitslosenhilfe (pre-2005) and ALG II/Sozialgeld (post-2005).	Universalistic system with strong social insurance; studies examine bijstand (social assistance) and unemployment insurance.	Nordic universalistic model; studies focus on Disability Insurance and Social Assistance (SFA).
Eligibility rules	Income thresholds (AFDC/TANF) with historical restrictions for two-parent cases; SNAP/SSI are means-tested.	UB II is means-tested for households with a member able to work ≥15 hrs/week; adults ≥25 may claim individually; non-employable members receive Sozialgeld; Sozialhilfe is reserved for those unable to work in households without an employable member.	Means-tested; no strict time limits; municipal administration of social assistance.	DI requires medically assessed reduced work capacity; SA/SFA is last-resort, means-tested aid administered locally.
Level of decentralization	States set TANF parameters and generosity.	Federal framework; implemented via local job centers; limited regional variation.	National framework with strong municipal implementation.	National framework; SA delivered by municipalities (NAV offices).
Study outcome	Intergenerational participation in AFDC/TANF and broader safety net.	Intergenerational transmission of ALG II receipt.	Intergenerational persistence and mechanisms of benefit receipt.	Intergenerational transmission in DI and SA.
Data used	PSID linked over decades; administrative linkages for reform timing.	SOEP panel data; methods tied to German admin/household sources.	Linked Dutch administrative registers (parents–children).	Linked Norwegian administrative registers (Statistics Norway).
Coefficient reported in Section 1	OLS: Page (2004) = 0.302 (pre-reform AFDC) & 0.372 with mother's participation (age 14–16); Hartley et al. (2022) = 0.210 (pre-reform AFDC) & 0.300 (AFDC/TANF, SNAP, SSI with mother's participation, age 12–18).	ALG II receipt (0/1): 0.187.	Social assistance: 0.17 (mother), 0.14 (father).	Social Assistance receipt (OLS): 0.223.

Notes: PRWORA = Personal Responsibility and Work Opportunity Reconciliation Act (1996). AFDC = Aid to Families with Dependent Children. TANF = Temporary Assistance for Needy Families. SNAP = Supplemental Nutrition Assistance Program (Food Stamps). SSI = Supplemental Security Income. ALG = *Arbeitslosengeld* (ALG I = insurance benefit; ALG II = means-tested unemployment benefit, also called UB II/Hartz IV). UB II = Unemployment Benefit II (post-2005); Sozialgeld = benefit for non-employable household members under ALG II. Sozialhilfe = social assistance (last resort). Bijstand = Dutch social assistance. DI = Disability Insurance. SA = Social Assistance. SFA = Social (Financial) Assistance; in Norway, *økonomisk sosialhjelp*. NAV = Norwegian Labour and Welfare Administration.

B Additional Figures

Figure A1: Welfare System in Switzerland



Notes: The figure illustrates the structure of Switzerland's social security system (FSO, 2023b). It shows that various social insurance schemes (e.g., old-age and survivors' insurance, disability insurance, unemployment insurance, accident insurance) and other means-tested social benefits serve as the first line of protection against social risks. Financial/Economic social assistance, shown on the far right of the figure, functions as the *final safety net*.

C Variance Decomposition vs. AR(2) Outcomes Framework

Variance–components models decompose resemblance into lineage (σ_G^2) and nuclear family (σ_F^2) shares but, by construction, attribute all cross–relative similarity to unobserved random effects and thus cannot deliver an independent parental influence. In this setting, the cousin correlation is

$$\rho_{cous} \;=\; \frac{\sigma_G^2}{\sigma_G^2 + \sigma_F^2 + \sigma_E^2},$$

while the sibling correlation is

$$\rho_{sib} \;=\; \frac{\sigma_G^2 + \sigma_F^2}{\sigma_G^2 + \sigma_F^2 + \sigma_E^2}.$$

The difference,

$$\rho_{sib} - \rho_{cous} \;=\; \frac{\sigma_F^2}{\sigma_G^2 + \sigma_F^2 + \sigma_E^2},$$

isolates the incremental nuclear family variance share.

However, these quantities do not correspond to independent effects of the parental and grandparental generations. The reason is that the variance–components framework treats resemblance across relatives as arising from unobserved random effects, not from explicit transmission mechanisms. In particular, ρ_{cous} captures the proportion of variance explained by a lineage component σ_G^2, but it does not distinguish between whether this similarity is generated by direct grandparental influences on grandchildren or by correlated parental behaviors that are themselves shaped by grandparents. Put differently, variance decomposition partitions statistical covariance into layers of kinship but does not map those layers one-to-one into generational transmission parameters. Identifying independent effects of parents and grandparents therefore requires an outcomes framework where their influence enters explicitly, analogous to an AR(2) process with both parent and grandparent outcomes as regressors.

To identify such pathways, we adopt an *outcomes framework* that parallels an AR(2) process from the vertical literature. Specifically, we estimate

$$y_{i,p,g} \;=\; \alpha \;+\; \beta_1\,\mathrm{sibling}_{p,g} \;+\; \beta_2\,\mathrm{cousin}_g \;+\; e_{i,p,g},$$

where i indexes the child, p the nuclear family, and g the lineage. Here, $\mathrm{sibling}_{p,g}$ captures the *nuclear channel* (analogous to the parent-to child link), while cousin_g captures the *grandparental channel* (analogous to the grandparent-to-grandchild link). In this way, β_1 and β_2 are interpreted analogously to an AR(2) persistence parameter: parents exert an additional effect beyond what is transmitted from the grandparental line, while cousins serve as the empirical window into the grandparental component.