Social Inequality of Opportunity

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THIS TALK IN ONE SLIDE

How much of inequality is inherited due to circumstances children never chose?

Family circumstances alone: **30–40%**

Adding the social world children grow up in: **40–50%**

. . . and **40–45%** of that unfair inequality runs through **housing and social circumstances**

EQUALITY OF OPPORTUNITY

- How much of our life outcomes is due to circumstances we cannot control?
- Inequality is justified only if it reflects choices for which individuals are responsible
- Inequalities due to circumstances are **unfair** and should be compensated (Roemer 1993, 1998; Roemer and Trannoy 2016)

The goal is to level the playing field

FROM RAWLS TO ROEMER

- **Rawls (Fair Equality of Opportunity):** people with the same talents and willingness should have the same life prospects — regardless of **social class, family, neighborhood, or community** (Rawls 1971)
  - A structural principle: society must neutralize the advantages of social background
  - Explicitly includes the social environment — not just the family
- **Roemer:** provides the empirical operationalization — partition factors into **circumstances** (beyond individual control) and **effort** (individual responsibility); measure and compensate for the former (Roemer 1993, 1998; Roemer and Trannoy 2016)
  - The IOp literature builds on this framework
  - But in practice has measured only a narrow set of family circumstances

⇒ **This paper returns to Rawls's broader vision**: social circumstances — the environment children grow up in — are circumstances too, and the IOp framework should measure them

IOP AS INHERITED INEQUALITY

- The traditional IGE focuses on a **single channel** — parental income — and estimates one summary statistic (IGE coefficient) (Solon 1992; Chetty et al. 2014)

- An emerging literature generalizes this by reframing IOp as **inherited inequality** (Brunori, Ferreira and Salas-Rojo 2024):
  - Shifts the question from "What is effort vs. circumstance?" to "How much do parental or early-life conditions predict adult outcomes?"
  - Focuses on the joint predictive power of all circumstances inherited before the age of consent

- In a society with full equality of opportunity, inherited circumstances should have **no predictive power** for adult outcomes

⇒ **This paper** expands the inherited-inequality view by including **social circumstances**: children inherit not only their family's resources but also their **position in a social network** — a position that is fully outside their control

FROM THEORY TO MEASUREMENT

- Most empirical applications adopt the **ex-ante** approach:
  - Focus on differences in expected outcomes *across* circumstance types
  - Before effort is exerted

$\Rightarrow$ IOp asks:

How much of inequality is explained by circumstances?

FROM INEQUALITY TO OPPORTUNITY

- Outcomes decompose into:

$$Y_i = \underbrace{m(C_i)}_{\text{opportunity set}} + e_i$$

where $m(C_i) = \mathbb{E}[Y_i \mid C_i]$ and e_i captures effort

- The counterfactual $Y_i^* = m(C_i)$ is the outcome individual i would achieve **due to circumstances alone**

$\Rightarrow$ IOp measures inequality in Y_i^*

IOp is about how circumstances map into expected outcomes

MEASURING IOP

- **Absolute IOp** — Gini applied to Y_i^*:

$$\text{IOp} = I(Y_i^*) = \tfrac{1}{2}\,\mathbb{E}\big(|m(C_i) - m(C_j)|\big)$$

  expected absolute difference in opportunities across all pairs

- **Relative IOp** — share of total inequality due to circumstances:

$$\text{Relative IOp} = \frac{I(Y_i^*)}{I(Y_i)}$$

- Two benchmarks:
  - $m(C_i) = \mathbb{E}(Y)$ for all $i \Rightarrow$ perfect EoO, IOp $= 0$
  - $m(C_i) = Y_i \Rightarrow$ circumstances fully determine outcomes, IOp $= I(Y)$

How much of total inequality is due to circumstances?

WHAT WE KNOW

Empirical findings

- **United States:** up to 43% of income inequality due to childhood circumstances (Hufe et al. 2017); IOp at least 68% higher than in Denmark (Mitnik, Helso and Bryant 2022); adding race raises relative IOp to nearly 58%
- **Europe (31 countries):** lowest IOp in Nordic countries, highest in Southern and Eastern Europe (Hufe, Kanbur and Peichl 2021; Brunori, Hufe and Mahler 2023)
- **Beyond income:** wealth IOp 62% in Germany, two-thirds driven by housing wealth (Graeber, Hilbert and König 2024)

Methodological progress

- ML reduces overfitting bias (Brunori et al. 2023; Escanciano and Terschuur 2022)
- Model uncertainty matters — ignoring it can overstate IOp (Bernardo, Durlauf, Kourtellos and Tan 2026)

Better methods — but the same limited set of circumstances

THE GAP

- **Social circumstances are entirely absent from IOp**
  - Children inherit not only family resources but also their **position in a social network**
  - Peer exposure, neighborhood norms, social learning — all outside the child's control, none measured in IOp
  - Even spatially rich studies use only census proxies (Hufe et al. 2025) — no direct measure of peer socioeconomic exposure

- **Housing circumstances are also absent**
  - Parental tenure, house value, housing costs, residential mobility are standard family background variables — yet excluded from IOp
  - Housing is the bridge: it determines *which* social environment the child enters

$\Rightarrow$ This paper fills both gaps — with **social circumstances as the primary contribution**

WHY DO SOCIAL CIRCUMSTANCES MATTER FOR IOP?

Mechanisms

- Local public finance and school quality (Bénabou 1996; Durlauf 1996)
- Peer interactions, role models, aspirations (Brock and Durlauf 2001)
- Identity and social norms (Akerlof and Kranton 2000)
- Social learning and belief formation (Bailey et al. 2018)

Empirical Evidence

(in the context of mobility)

- Sharp spatial gaps in upward mobility. Low-mobility areas share: segregation, inequality, weak schools, low civic capital, many single-parent households (Chetty, Hendren, Kline and Saez 2014)
- **Causal** childhood neighborhood exposure effects on adult earnings; $\sim$60% of tract-level mobility variation is causal, not sorting (Chetty, Hendren and Katz 2016; Chetty et al. 2026b; Katz 2026)
- Social capital geographically segregated and directly affects child outcomes (Chetty et al. 2022; Chetty and Hendren 2018)

(in the context of IOp)

- Neighborhood effects incorporated only via census proxies (Hufe et al. 2025)

KATZ (2026): NEIGHBORHOODS AND MISSING MARKETS

- **Causal exposure effects:** the longer the childhood spent in higher-opportunity neighborhoods, the better the adult outcomes; ∼60% of tract-level variation in upward mobility is causal, not sorting (Chetty, Hendren and Katz 2016; Chyn, Collinson and Sandler 2025; Chetty et al. 2026b)
- **Missing markets for opportunity** ⇒ residential segregation by parental SES is inefficiently high: families cannot borrow against children's future earnings; neighbor spillovers unpriced by housing markets; housing search frictions; restrictive land-use regulation
- **Social interactions are the mechanism:** HOPE VI gains for public-housing children driven by integration with higher-SES peers; economic connectedness predicts upward mobility (Chetty et al. 2022, 2026a)

⇒ **Complementary to this paper:** Katz identifies *causal* neighborhood effects; we quantify how much of *total inequality* is attributable to inherited social circumstances

HOUSING CIRCUMSTANCES

Housing has been largely absent from the set of circumstances in IOp.

Mechanisms (Ioannides and Ngai 2025)

- *Capital:* housing wealth → asset accumulation, collateral, intergenerational transfers
- *Consumption:* affordability and residential stability → disposable income, health, well-being
- *Location:* residential sorting → access to schools, peer networks, and amenities

Empirical evidence

- Graeber, Hilbert and König (2024): 62% of wealth inequality in Germany due to circumstances; housing wealth alone accounts for **two-thirds**
- Daysal et al. (2023): parental housing wealth explains 20–30% of child outcomes in Denmark

Housing is entirely a family circumstance — but through residential sorting, it determines which social environment the child enters and thus generates social circumstances

THIS PAPER

- Introduce **social circumstances** as a new category in the IOp framework: the socioeconomic characteristics of the families surrounding the child during childhood
- Incorporate **housing circumstances** as a family circumstance that has been overlooked — and that links family resources to social environments
- Estimate $m(C_i)$ flexibly using **Conditional Inference Forests**
- Decompose IOp across circumstance groups using **Shapley methods**

Inequality of opportunity is partly a social phenomenon

DATA

- **Panel Study of Income Dynamics (PSID)**
  - Nationally representative longitudinal survey, initiated 1968
  - Follows 18,000+ individuals from 5,000 U.S. families
  - Annual 1968–1997, biennial thereafter (latest wave: 2023)

- **Key feature:** we use the restricted **Geocode Match file** — family locations at the **U.S. Census Block level**
  - Publicly available PSID provides only regional data
  - Census Block precision enables distance measurement and construction of spatially weighted social circumstances

- **Sample:** link adult children to parents (biological and adoptive); first-born child only; birth cohorts 1968–1983; exclude Latino and SEO subsamples; final analysis sample: 789 children

The geocoded PSID is essential for constructing social circumstances

OUTCOMES IN ADULTHOOD

- Outcomes measured in **late thirties** (ages 35–40)
  - Stage of the life cycle where key economic outcomes have largely materialized

- **Four outcomes** covering income, wealth, and housing:

1. **Family income** — taxable income of head and partner (labor, assets, rentals, dividends)
2. **Housing wealth** — net home equity (house value minus mortgage)
3. **Net wealth** — all assets minus debts, excluding pensions
4. **Housing expenditure share** — total housing costs as a share of income (mortgage, rent, utilities, insurance, repairs, . . .)

CONSTRUCTING SOCIAL CIRCUMSTANCES 1/2

- Social circumstances capture the **socioeconomic characteristics of the families surrounding the child** during childhood

- For each child i, we construct **the social network circumstances** across **three childhood periods**, r =early (1–6), middle (7–12), late (13–18):

$$C_i^S(r) = \sum_{j \neq i} w_{ij}(r)\, C_{1,j}^F(r)$$

- We consider
  - **the social network income** as the weighted average parental income among families in the child's network
  - **the social network** housing value as the weighted average parental housing value among families in the child's network

CONSTRUCTING SOCIAL CIRCUMSTANCES 2/2

The weights determine each child's exposure to the broader socio-economic environment during childhood:

$$W = W_{\text{loc}}^{\text{50NN}} \times \left[W^{\text{Inc}} + W^{\text{Own}} + W^{\text{Edu}} + W^{\text{Occ}} \right]$$

- **Geographic:** 50 nearest neighbors by location
- **Socioeconomic:** similarity in income, homeownership, education, occupation (Kourtellos et al. 2025)
- **Spatial proximity** is a necessary condition for sustained social contact, whereas income, education, occupation, and homeownership operate as substitutable channels of homophily.

CIRCUMSTANCES: THREE GROUPS

- **232 circumstances** organized into three groups, measured across three childhood periods: early (1–6), middle (7–12), late (13–18)

Group	Variables	Share
Baseline family circumstances	199	86%
Income, education, occupation, race, location		
Housing circumstances	27	11.5%
House value, costs, type, tenure, mobility		
Social circumstances	6	2.5%
Spatially weighted income & house value		

Note: social circumstances consist of only 6 variables but each is a spatially weighted average across up to 50 neighboring families, combining geographic proximity and socioeconomic similarity

FROM REGRESSION TO TREES TO FORESTS

- We estimate $m(C_i^F, C_i^S)$ — the opportunity function over **family and social circumstances** — using 232 childhood variables

- **Linear regression:** imposes linearity — misses nonlinearities and interactions among 232 circumstances

- **Regression tree:** partitions the circumstance space into discrete regions via recursive binary splits — conceptually aligned with IOp "types"
  - But a single tree is unstable (high variance)
  - And splits are chosen greedily — variable selection bias

- **Random Forest:** ensemble of trees on bootstrap samples with random predictor subsets — reduces variance
  - But split selection is still based on impurity, not statistical significance — variable selection bias remains

$\Rightarrow$ We use **Conditional Inference Forests** (C-Forest) (Hothorn, Hornik and Zeileis 2006)

FROM REGRESSION TREES TO FORESTS

- A **regression tree** $m_b(C)$ partitions the sample into M non-overlapping nodes by recursive binary splits; it predicts the node mean:

$$m_b(C_i) = \hat{\mu}_m = \frac{1}{N_m} \sum_{j \in \mathcal{S}_m} Y_j, \quad i \in \mathcal{S}_m$$

- Both **Random Forest** and **C-Forest** are **averages of trees**:

$$\hat{m}(C) = \frac{1}{B} \sum_{b=1}^{B} m_b(C)$$

- They differ in two ways:
  - **Resampling:** RF uses **bootstrap**; C-Forest uses **subsampling** (without replacement) (fraction 0.632) — recommended to avoid importance bias (Strobl et al. 2007)
  - **Split rule:** this is the main conceptual difference

RF asks: what split looks best? **C-Forest asks: what split is real?**

HOW SPLITS DIFFER: RF VS. C-FOREST

Random Forest (Breiman 2001)

- At each node $\mathcal{S}$, partition into left and right child nodes at cutpoint s on variable C_j:

$$\mathcal{S}_L(s) = \{i \in \mathcal{S} : C_{ji} \leq s\}$$

$$\mathcal{S}_R(s) = \{i \in \mathcal{S} : C_{ji} > s\}$$

- Find j and s minimising within-child RSS:

$$\min_{j,\,s} \sum_{i \in \mathcal{S}_L(s)} (Y_i - \bar{Y}_L)^2 + \sum_{i \in \mathcal{S}_R(s)} (Y_i - \bar{Y}_R)^2$$

where $\bar{Y}_L$, $\bar{Y}_R$ are child means

- Biased toward variables with many possible cutoffs (Hothorn, Hornik and Zeileis 2006; Strobl et al. 2007)

C-Forest (Hothorn, Hornik and Zeileis 2006)

- At each node $\mathcal{S}$, for each C_j test

$$H_0^j : \; Y \perp C_j \mid i \in \mathcal{S}$$

via permutation test; compute Bonferroni p_j

- Select $C^* = \arg\min_j p_j$; if $p^* > \alpha$ — stop; no split
- Split at s^* maximising the two-sample linear statistic within C^*
- Unbiased selection; stopping is built in

VARIABLE IMPORTANCE

- We report **conditional variable importance scores** (Strobl et al. 2008) to assess the contribution of each circumstance
- Standard importance: permute each variable globally, measure drop in predictive accuracy
- Problem: circumstances are correlated (e.g., parental income across three childhood periods)
  - Standard permutation underestimates importance of early childhood income, overestimates later periods
- **Conditional importance:** permute each variable *conditionally on correlated predictors*
  - Preserves the empirical dependence structure
  - Reflects the **unique** contribution of each circumstance beyond shared information

IOP INCREASES SUBSTANTIALLY

- **Baseline** (family background only): relative IOp **36%** for family income, 28% housing wealth, 31% net wealth
  - In line with Hufe et al. (2017) and Desai (2024): range 27%–43%
  - C-Forest estimates are about one third lower than Random Forest and half of LS — consistent with Brunori et al. (2023) and Bernardo et al. (2026)

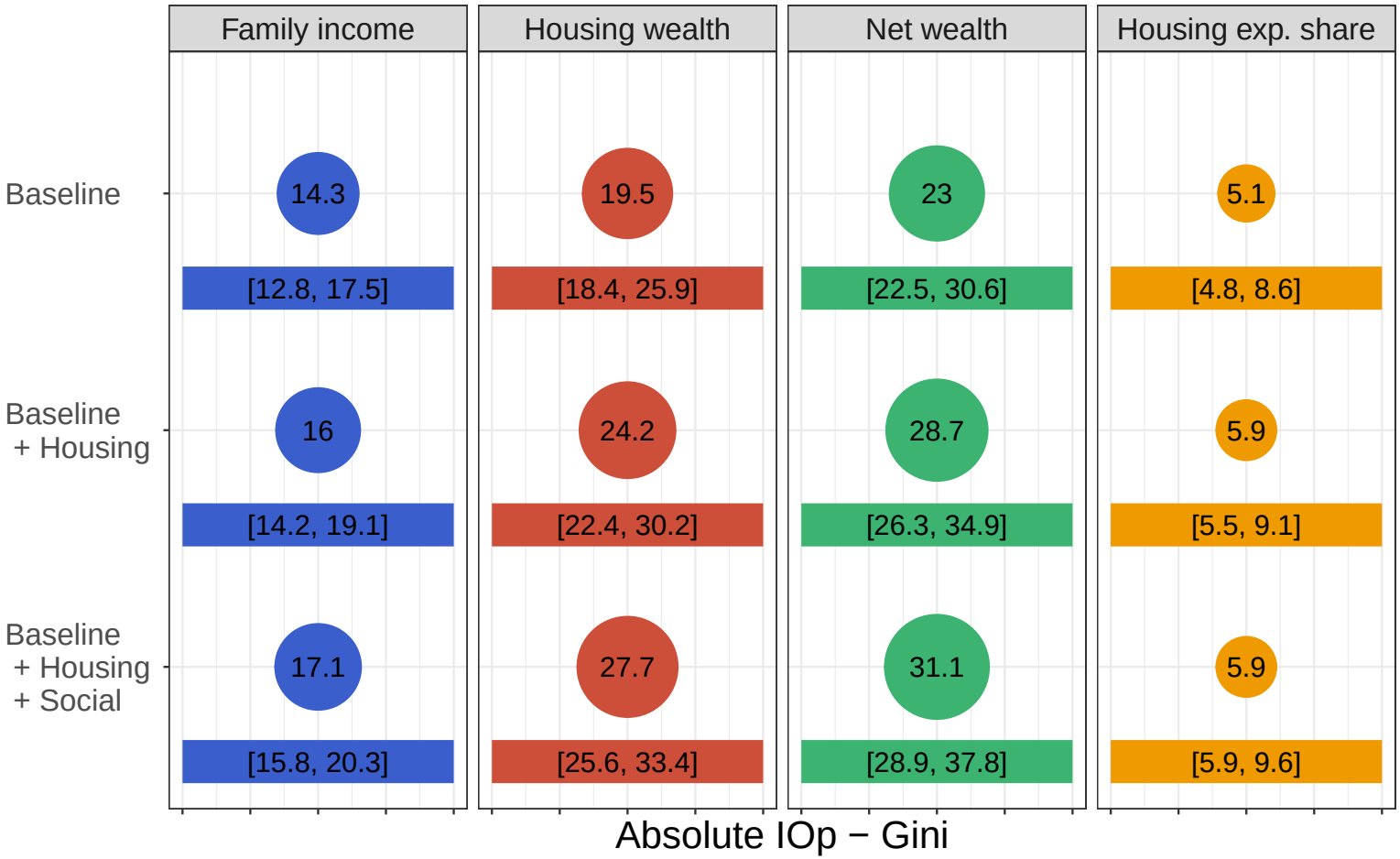
- Adding **housing circumstances**: rises to **40%** income, 35% housing wealth, 38% net wealth

- Adding **social circumstances**: reaches **43%** income, 40% housing wealth, 41% net wealth — 95% CI spans 40%–50%

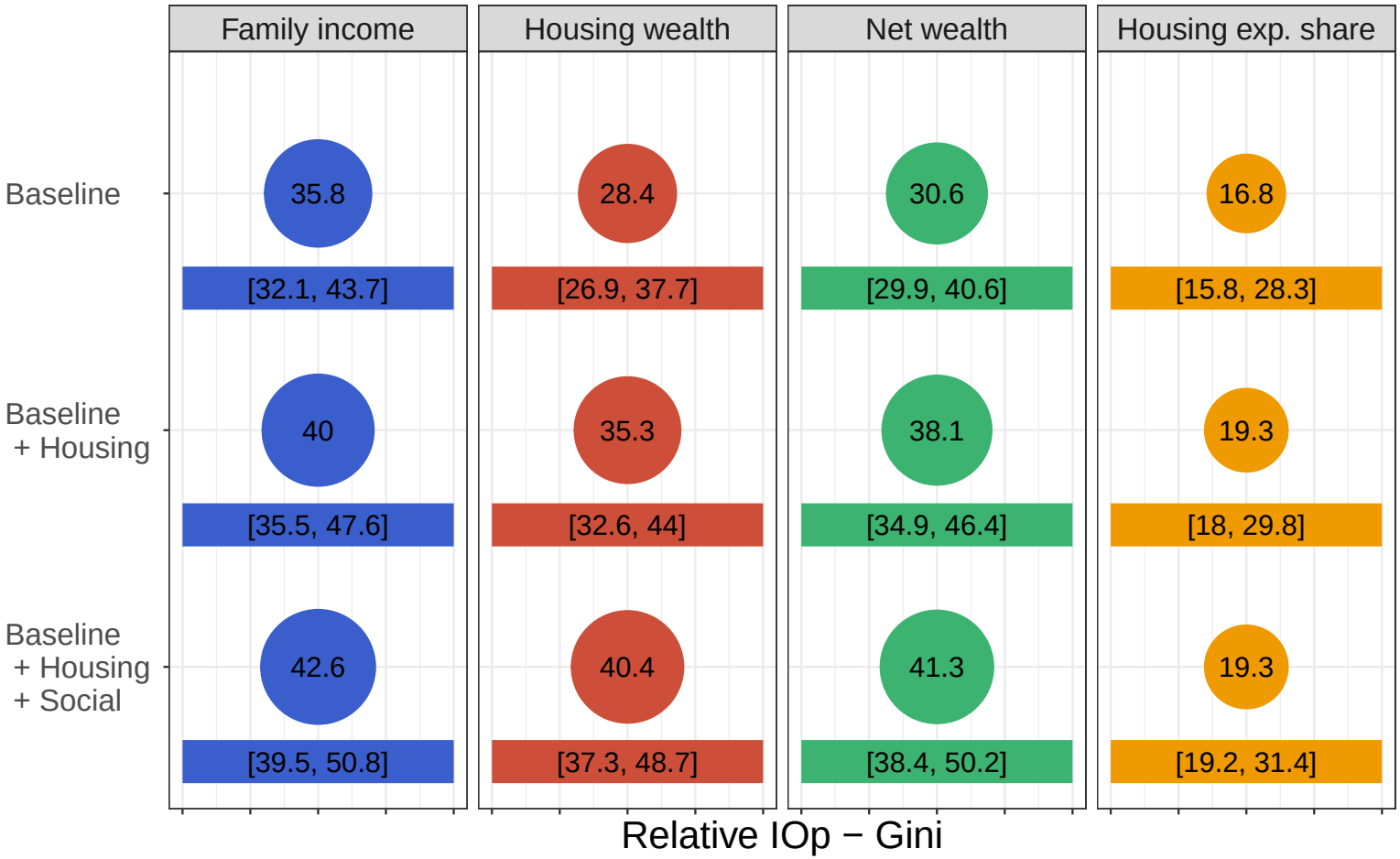
- **Housing expenditure share**: only 20% — inequality largely driven by shocks and personal choices rather than childhood circumstances

Social and housing circumstances raise IOp by 5–12 percentage points

ESTIMATION RESULTS: ABSOLUTE IOP



ESTIMATION RESULTS: RELATIVE IOP



VARIABLE IMPORTANCE: WHAT PREDICTS EACH OUTCOME?

- **Family income:** parental income and house value (middle and late childhood) are the top predictors; social circumstances follow closely — just 6 of 232 variables but make up ∼**1/3 of root splits** across 200 trees

- **Housing wealth:** social circumstances are the **most frequent root splitters** — neighborhood house values and income dominate over parental house value; local housing market conditions are the strongest initial signal for long-run wealth accumulation

- **Net wealth:** time-varying baseline circumstances dominate root splits; social circumstances act as important complements; parental education more prominent than for income

- **Housing exp. share:** driven primarily by **location** (state fixed effects) — geographical residence while growing up matters most; parental income and social circumstances play a comparatively minor role

Social circumstances provide the strongest initial signal for housing wealth

TOP CIRCUMSTANCES FOR FAMILY INCOME

Circumstance	CVIS	95% CI	
Parental income (middle)	0.77	0.31	1.00
Parental house value (middle)	0.67	0.26	1.00
Parental income (late)	0.59	0.24	1.00
Parental house value (late)	0.55	0.19	1.00
Parental income (early)	0.44	0.14	0.95
Social circ.: Income (late)	0.40	0.13	0.79
Social circ.: House value (late)	0.38	0.09	0.92
Social circ.: Income (middle)	0.34	0.11	0.67
Parental house value (early)	0.34	0.09	0.70
Parental educ: College (late)	0.32	0.07	0.70

All 6 social circumstances (blue) appear in top 20.

TOP CIRCUMSTANCES FOR HOUSING WEALTH

Circumstance	CVIS	95% CI	
Parental house value (late)	0.65	0.20	1.00
Social circ.: House value (late)	0.60	0.19	1.00
Parental house value (middle)	0.57	0.19	1.00
Social circ.: Income (late)	0.52	0.17	1.00
Social circ.: House value (middle)	0.50	0.16	0.96
Parental income (early)	0.38	0.04	1.00
Parental income (middle)	0.38	0.05	0.99
Parental house value (early)	0.36	0.07	0.86
Social circ.: House value (early)	0.35	0.04	0.89
Social circ.: Income (middle)	0.32	0.09	0.64

Social circumstances are the top root splitters across 200 trees.

TOP CIRCUMSTANCES FOR NET WEALTH

Circumstance	CVIS	95% CI	
Parental house value (middle)	0.74	0.27	1.00
Parental house value (late)	0.66	0.21	1.00
Parental income (middle)	0.49	0.12	1.00
Non-housing wealth	0.44	0.05	1.00
Social circ.: House value (middle)	0.42	0.05	1.00
Parental house value (early)	0.40	0.10	0.98
Social circ.: Income (late)	0.39	0.10	0.89
Child birth year: 1970	0.38	-0.09	1.00
Parental income (early)	0.33	0.04	0.87
Social circ.: House value (late)	0.33	0.02	0.79

All 6 social circumstances appear in top 15.

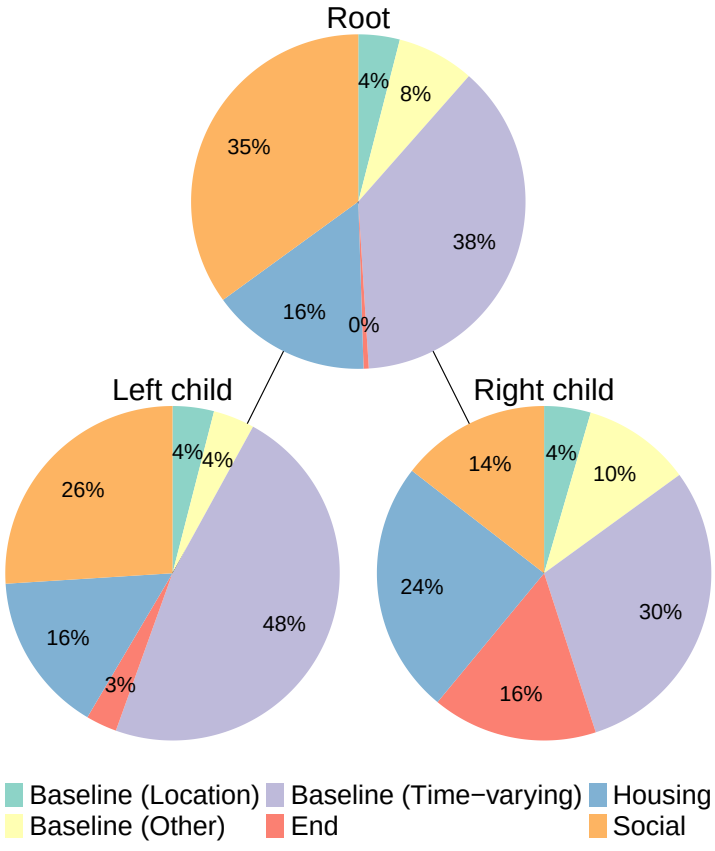
TOP CIRCUMSTANCES FOR HOUSING EXP. SHARE

Circumstance	CVIS	95% CI	
Lived in State: OR (early)	0.45	-0.10	1.00
Lived in State: OR (late)	0.42	-0.07	1.00
Lived in State: OR (middle)	0.38	-0.14	1.00
Parents married (late)	0.37	0.01	0.99
Family head grew up in Northeast	0.33	0.04	0.83
House type: Apartment (middle)	0.32	-0.11	1.00
Rooms/person (late)	0.32	0.01	1.00
Parental housing cost share (middle)	0.31	0.04	0.85
Lived in State: TN (early)	0.30	0.00	0.91
Social circ.: House value (early)	0.29	0.04	0.78

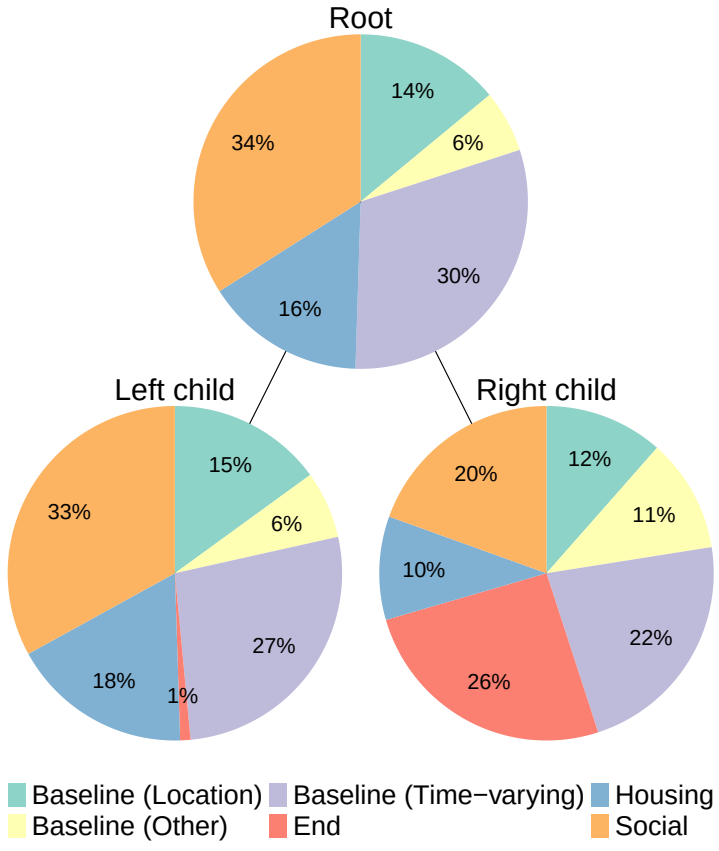
Location (state) dominates; social play a smaller role.

AGGREGATED DECISION TREE SPLITS

(A) Family income



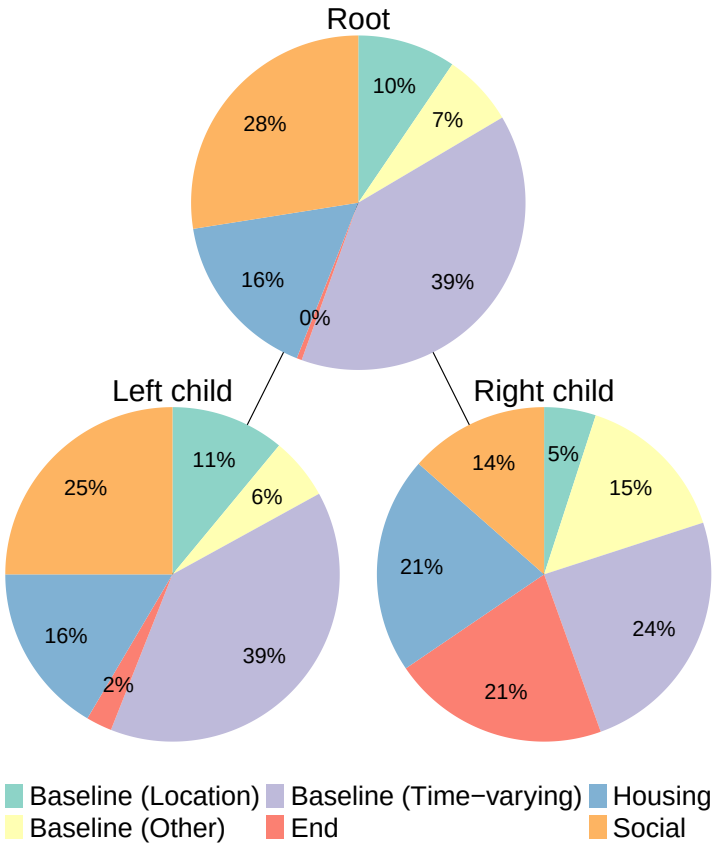
(B) Housing wealth



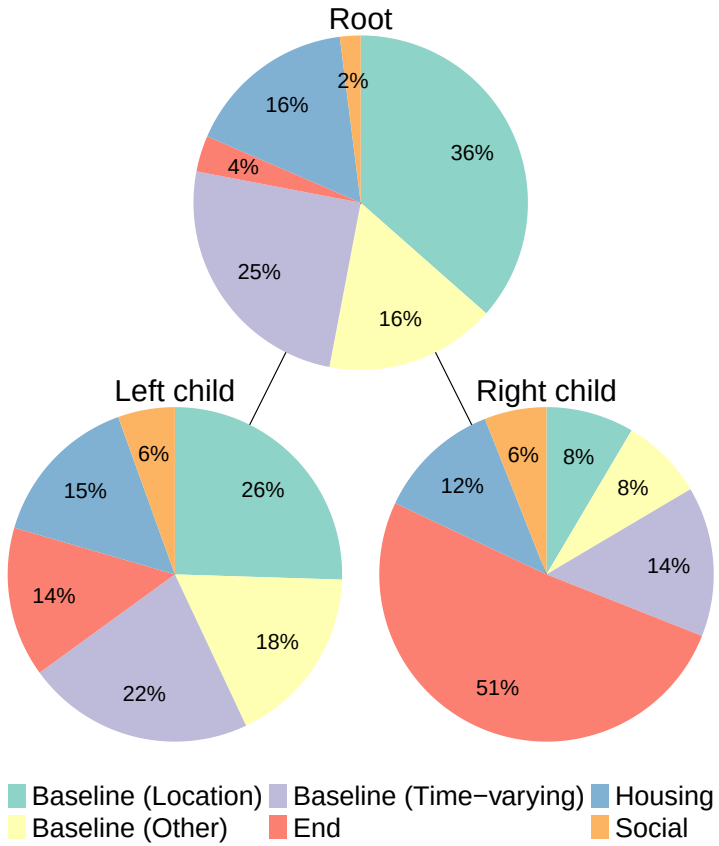
Share of first three splits in 200 trees by circumstance group. Housing and social circumstances appear prominently among the earliest and most informative splits.

AGGREGATED DECISION TREE SPLITS

(C) Net wealth



(D) Housing exp. share



SHAPLEY DECOMPOSITION OF IOP

- Shapley decomposition: each group's average marginal contribution across all coalitions — a fair attribution when groups overlap
- Attribute total IOp to **five circumstance groups**
  - Time-varying baseline, other baseline, location, housing, social
- For each subset S of groups, estimate IOp using only those groups:

$$v(S) = I\big(\hat{m}_S(C_S)\big)$$

- Shapley contribution of group k:

$$\phi_k = \sum_{S \subseteq N \setminus \{k\}} \frac{|S|!\,(K - |S| - 1)!}{K!} \big[v(S \cup \{k\}) - v(S)\big]$$

- 5 groups $\Rightarrow 2^5 = 32$ coalitions to evaluate
- By construction: $\sum_{k=1}^{K} \phi_k = I\big(\hat{m}(C)\big)$

SHAPLEY DECOMPOSITION OF IOP (% OF GINI INDEX)

Circumstances	Family income	Housing wealth	Net wealth	Housing exp. share
Baseline				
Time-varying	38.7	24.7	30.4	23.6
Other	7.0	9.2	9.2	15.1
Location	9.3	21.2	16.4	34.6
Housing	**25.6**	**21.7**	**23.3**	**19.3**
Social	**19.4**	**23.3**	**20.7**	**7.3**

- **Housing + social** together explain **40–45%** of IOp for income and wealth outcomes
- Social circumstances alone account for ∼**20%** despite comprising only 6 of 232 variables

WHY DO SOCIAL CIRCUMSTANCES MATTER FOR HOUSING WEALTH?

- **Direct intergenerational channel** (transfers, down-payment assistance, parental borrowing capacity) only **partially explains** IOp in housing wealth
- **Social learning channel:** exposure to networks experiencing rapid house price growth raises optimism about future prices and the propensity to invest in housing — childhood social circumstances shape adult beliefs and investment behavior (Bailey et al. 2018)
- **Social integration channel:** interactions with higher-SES peers causally improve children's long-run outcomes — the mechanism behind HOPE VI gains and economic connectedness (Chetty et al. 2022, 2026a; Katz 2026)
- **Institutional channel:** redlining and differential mortgage access created long-lasting geographic disparities in neighborhood wealth; pre-GFC credit expansion and foreclosures amplified them (Aaronson et al. 2021; Fishback et al. 2024)

Social circumstances operate through beliefs, networks, and historically shaped credit environments

ROBUSTNESS EXERCISES

Results are robust to:

1. **Debiasing** (Escanciano and Terschuur 2022) — corrects for regularization bias introduced by the C-Forest first step; debiased relative IOp reaches **51%** for family income and **46–47%** for wealth outcomes, uniformly above the baseline

2. **Transformation Trees** (Brunori, Ferreira and Salas-Rojo 2024) — ex-post approach based on full conditional distributions; types identified by housing and social circumstances

3. **Childhood windows sequentially** (Desai 2024) — early childhood circumstances alone already explain one third of IOp; adding later periods raises estimates by $\sim$8 percentage points

4. **Tuning parameters** `alpha` and `mtry` — 5-fold cross-validation confirms stability of IOp estimates

DEBIASED IOP ESTIMATES

Outcome	Debiased estimate and SE		Baseline and 95% CI	
	Abs. IOp	Rel. IOp	Abs. IOp	Rel. IOp
Family income	0.205	0.511	0.171	0.426
	(0.022)	(0.058)	[0.158, 0.203]	[0.395, 0.508]
Housing wealth	0.318	0.464	0.277	0.404
	(0.043)	(0.063)	[0.256, 0.334]	[0.373, 0.487]
Net wealth	0.355	0.472	0.311	0.413
	(0.058)	(0.077)	[0.289, 0.378]	[0.384, 0.502]
Housing exp. share	0.058	0.191	0.059	0.193
	(0.015)	(0.051)	[0.059, 0.096]	[0.192, 0.314]

- Debiased estimates are **uniformly higher** than the C-Forest baseline
- Relative IOp reaches **51%** for family income and **46–47%** for wealth outcomes after debiasing

TRANSFORMATION TREES: BEYOND THE MEAN

- **Transformation Trees** (Hothorn and Zeileis 2021; Brunori, Ferreira and Salas-Rojo 2024) adopt the **stronger** criterion:

$$F(Y \mid C = c) = F(Y) \quad \forall\, c$$

- A **single tree**: at each node the algorithm fits a transformation model:

$$h(y) = a(y)'\vartheta, \quad \hat{\vartheta}_{\mathcal{S}} = \arg\max_{\vartheta} \sum_{i \in \mathcal{S}} \ell_i(\vartheta)$$

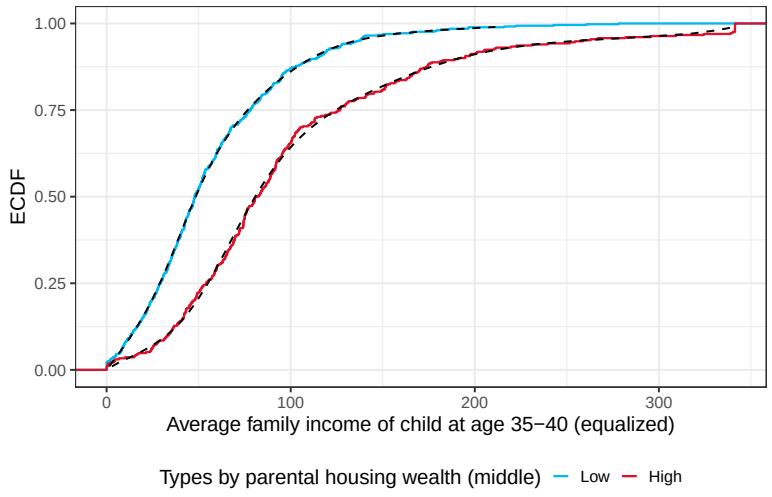
  where $a(y)$ is a Bernstein polynomial basis of order M, encoding the full conditional CDF of Y in node $\mathcal{S}$

- A split on circumstance C_j occurs if the score contributions $s_i(\hat{\vartheta}_{\mathcal{S}}) = \partial \ell_i / \partial \vartheta$ vary **systematically with** C_j — i.e. if the fitted distribution parameters are not stable across values of C_j
  - Analogous to the permutation test in C-Forest, but applied to the **full distribution**, not just the mean

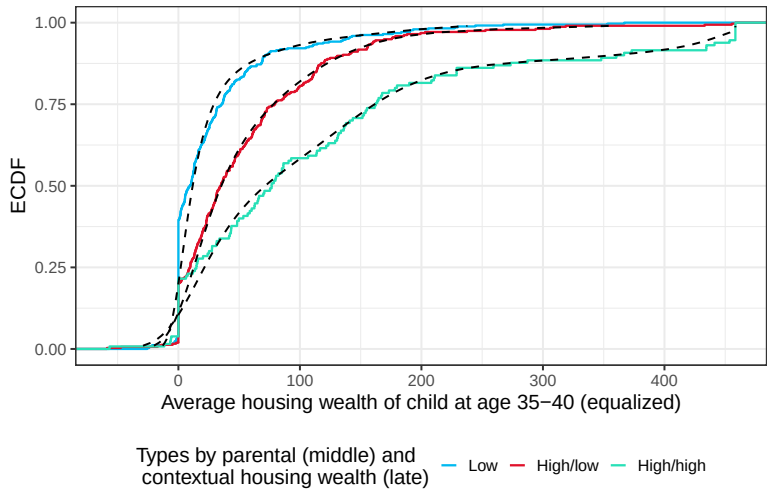
- Types with identical means but different dispersion are treated as having **unequal opportunity**

RESULTS FROM TRANSFORMATION TREES: ECDF

Family income



Housing wealth



Types based on housing and social circumstances; confirming that social and housing circumstances generate distinct opportunity distributions

CONCLUSION

- We extend the IOp framework by incorporating **housing and social circumstances**
- **Key findings:**
  - Relative IOp rises from 30–40% to 40–50% across family income, housing wealth, and net wealth
  - Housing and social circumstances together explain **40–45% of IOp itself**
  - Social circumstances account for ∼20% of IOp despite representing only 2.5% of the circumstance set
- Our IOp accounting complements the causal neighborhood effects literature (Katz 2026): the social environments children inherit are both **measurable circumstances** and **actionable policy margins**
- **Inequality is not only transmitted through families — social structure and spatial sorting matter too**