American Inequality and Social Mobility Viewed Through a Danish Prism

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Inequality and Social Mobility
Figure 1: Intergenerational Mobility and Inequality: The “Gatsby Curve”

\[
\ln Y_1 = \alpha + \beta \ln Y_0 + \varepsilon
\]

Income of child \(\ln Y_1\) = \(\alpha + \beta \ln Y_0 + \varepsilon\)
Income of parent or parents \(\ln Y_0\)

\(\beta \uparrow\), Mobility \(\downarrow\)

Source: Corak (2016), “Inequality from Generation to Generation: The United States in Comparison”.
“The American Dream is now spoken with a Scandinavian accent.”

Unlike in the U.S., Recent Danish Cohorts Are Doing More or Less The Same as Their Parents
Figure 2: Absolute Mobility: Probability Children Do Better Than Parents by Cohort, U.S. – Pre-Tax and Transfer

Source: Chetty et al. (2017)
Figure 3: Absolute Mobility: Probability Children Do Better Than Parents) by Cohort: U.S – Pre-Tax and Transfer

Source: Chetty et al. (2017)
Figure 4: Absolute Mobility: Probability Children Do Better Than Parents) by Cohort: Denmark – Pre-Tax and Transfer

Source: Own calculations based on data from Statistics Denmark
What Can Be Learned from Denmark About Reducing Inequality and Promoting Social Mobility?
Specifically, Should America Emulate the Scandinavian Model?
Denmark is a Laboratory for Understanding the Sources of Inequality and Social Mobility

- Reducing inequality and promoting social mobility is a central focus of the modern Danish welfare state.
- Many traditional explanations of inequality and social mobility do not hold in Denmark.
- Suggest a fresh look at the origins of inequality and social mobility.
- Equality in services offered is mandated.
- Health care; teachers paid the same everywhere; free daycare; free college.
- Greater social cohesion (witness U.S. versus Danish response to COVID-19).
- Post tax and transfers, income inequality is low and income mobility is high.
- Not due to superior production of human capital.
- Educational mobility is remarkably similar in the U.S. and Denmark.
- There are substantial skill and education gaps across families by background.
Advantages from Denmark’s universal access to services are reaped relatively more by the affluent rather than by the disadvantaged (Matthew Effects) who don’t often know or find it more difficult to use these services.

We find strong evidence of sorting of families by parental income and education.

“Power of place” is a consequence of family sorting and family influence.

Families purposefully choose neighborhoods and timing of moves.

Not random (in contrast to influential claims otherwise).

Sorting in Denmark is comparable to that in the U.S.

This sorting affects estimated IGEs.

IGE ↓ average family income ↑; more affluent places have lower IGEs but higher $\alpha$.

Sorting ⇒ strong family income gradients on child outcomes.

Sorting by teachers into more advantaged districts.

Despite equal wages across neighborhoods, payment to teachers is in quality of students taught.
Our Argument

1 A central premise of the welfare state (since the writings of Max Weber) is the equality of access — in Denmark this is mandated by law, yet equal access by the state does not imply equal use of public services.

   1 Equality in the law does not imply equality in use of services.
   2 “Matthew effects” (to those who have, more is given) play a powerful role.

      i Parents reinforce (or substitute) for public services delivered.
      ii Pick neighborhoods that offer better public services.
      iii Enforce delivery of services.

3 Karlson and Landersø show how effective targeting can be: the move to universal access (rather than focus on disadvantage) increased the education IGE.

2 Denmark has a free housing market, as do most economies—sorting is large and increasing.
3 Sorting by parental income and resources plays a powerful role in the U.S. and Denmark.
4 The choice of the neighborhood of residence to raise children has a powerful role in explaining intergenerational inequality, which has been ignored in much recent work.
5 The IGE regression $\ln Y_1 = \alpha + \beta \ln Y_0 + \varepsilon$ has focused on $\beta$ across countries.
6 Yet, when we look at neighborhoods within countries $n \in N$,

$$Y_{1n} = \alpha_n + \beta_n \ln Y_{0n} + \varepsilon_n$$

7 Child outcomes depend on $(\alpha_n, \beta_n)$ pair, not just $\beta_n$.
8 $\alpha_n$ is initial condition associated with $n$.
9 Parents purposefully select neighborhoods when children are very young often well before schooling begins (not random with regards to age of child).
Access to register data enables us to investigate appropriate measures of lifetime well-being for measuring family influence.

1. Which income concept? Does it matter?
2. Consumption?
3. Average income around age 35 (as traditionally used?)
4. Lifetime resources (value function)? (valuing uncertainty; leisure; accounting for credit constraints)
5. PDV (discounted family income)?

PDV is best predictor of child outcomes.

IGE based on PDV (after tax and transfers) is very high (much higher than traditional measures).
### Denmark Spends Generously on Public Education

Figure 5: Expenditure on educational institutions as a percentage of GDP, by source of funding and level of education

<table>
<thead>
<tr>
<th></th>
<th>Pre-primary</th>
<th>Prim., secon., and post-secon.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Public ¹</td>
<td>Priv. ²</td>
</tr>
<tr>
<td>Denmark</td>
<td>1.30</td>
<td>0.11</td>
</tr>
<tr>
<td>U.S.</td>
<td>0.33</td>
<td>0.14</td>
</tr>
</tbody>
</table>

**Note:** Table shows public, private, and total expenditures on education as percentages of GDP in 2013 for Denmark and the U.S.

¹: Including public subsidies to households attributable for educational institutions, tuition and fees (U.S.), and direct expenditure on educational institutions.

²: Net of public subsidies attributable for educational institutions.

**Source:** OECD: Education at a glance 2014.
Figure 6: Daycare and Preschool Use

(a) Trend in pre-school participation, age 4, U.S.

(b) Trend in pre-school participation, age 4, Denmark

Source: Figure 4 Landersø and Heckman (2018).
School expenditures much more equal geographically in Denmark than in the U.S.:

Figure 7: Gross expenditures per student, public schools, deviation from mean
**Pre-K expenditures much more equal geographically in Denmark than in the U.S.**

**Figure 8:** Expenditures per child, state pre-K / municipal daycares, deviation from mean

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*Image of a graph showing the distribution of expenditures per child in Denmark and the U.S.*

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*Text continues...*
Educational Mobility
In Terms of IGE in Education, Denmark Not Better Than U.S. Despite its Generous Welfare State

Figure 9: Intergenerational Educational Mobility and Inequality

High School Completion
U.S.

US: Belley and Lochner (2007)

High School Completion
Denmark

Denmark: Landersø and Heckman (2017)
Relationships Between Child Education and Parental Income *Stronger* in Denmark Than U.S.
**Figure 10:** Local Intergenerational Elasticities between children’s education and parental log gross income including transfers, absolute income weights, Denmark and the U.S.

(a) High school completion, Denmark

(b) High school completion, U.S.

*Source:* Figure 7 Landersø and Heckman (2018).
Figure 11: Local Intergenerational Elasticities between children’s education and parental log gross income including transfers, absolute income weights, Denmark and the U.S.

(d) College completion, Denmark

(e) College completion, U.S.

Source: Figure 7 Landersø and Heckman (2018).
Substantial Gaps in Life Outcomes Across Children With Mothers With Different Education Levels
Gaps by Mother’s Education

Figure 12: U.S. CNLSY

Age: 0 yrs

Outcome: Birth weight

Unit: Ounces

- Green: College educated
- Red: High school
- Blue: Less than high school

Age: 3–5 yrs

Outcome: Sociability Score

Unit: Rating
Figure 13: U.S. CNLSY, Cont.

- Green: College educated
- Red: High school
- Blue: Less than high school

**Outcome:**
- PIAT Reading Comprehension Score
- No criminal conviction
- Years of schooling
- Wage Earnings

**Unit:**
- Test score
- Fraction
- Years
- Thousands of 2010 U.S. Dollars
Danish Counterparts
Birth weight

Not admitted to neonatal ward

- Green: College educated
- Red: High school
- Blue: Less than high school

Figure 14: Years of Schooling

3-5 yo.  
Assessed skills

8-14 yo.  
Test scores, reading

25 yo.  
No crime conviction

30 yo.  
Years of Schooling

40 yo.  
Income

- Green: College educated
- Red: High school
- Blue: Less than high school

Note: Figure shows average outcomes by mother’s highest completed education. In the figures with three levels, mother’s education is defined as: BLUE, only compulsory schooling; RED, high school; GREEN, college.
**Note:** Figure shows average outcomes by mother’s highest completed education. In the figures with three levels, mother’s education is defined as: BLUE, only compulsory schooling; RED, high school; GREEN, college.
Figure 15: Equally aged peers’ language test scores, by mother’s education

Source: Own calculations based on data from Tryg Fonden and Statistics Denmark.
Why Do These Gaps Arise?
Greater Income Mobility is Largely Due to the Highly Progressive Danish Tax-Transfer System Not Because of a Better Production of Child Skills
Figure 16: Differences in income mobility (IGEs) between the U.S. and Denmark: $\ln Y_i^C = \alpha + \beta^{IGE} \ln Y_i^P + \varepsilon_i$ for different income definitions

Note: Child income on parents’ income for cohorts of 1973-75. 
Source: Landersø and Heckman (2017).
Figure 17: U.S.-Denmark differences in income mobility across parents’ income:

\[
\min_{\alpha[\ln(Y^P_0)], \beta[\ln(Y^P_0)]} \sum_{i=1}^{N} K_{h\lambda}(Y^P_0, Y^P_i) \cdot \{\ln(Y^C_i) - \alpha[\ln(Y^P_0)] - \beta^{IGE}[\ln(Y^P_0)]\ln(Y^P_i)\}^2
\]

By market income, IGE is only higher in U.S. for affluent families.

\[\text{Note: Child income on parents’ income for cohorts of 1973-75. Source: Landersø and Heckman (2017).}\]
Figure 18: U.S.-Denmark differences in income mobility across parents’ income:

\[
\min_{\alpha[\ln(Y_0^P)], \beta[\ln(Y_0^P)]} \sum_{i=1}^{N} K_h^{\lambda}(Y_0^P, Y_i^P) \cdot \left\{ \ln(Y_i^C) - \alpha[\ln(Y_0^P)] - \beta^{IGE}[\ln(Y_0^P)]\ln(Y_i^P) \right\}^2
\]

By post transfer income, IGE differences emerge at low levels too.

Lower Income Inequality and Social Mobility Not Skills-Based
Tax and Transfer System Based Equality
Summarizing

Figure 19: U.S.-Denmark differences in Income and Education IGEs

**Income IGE**

**College attendance IGE**

*Source:* Tables 1 and 4 Landersø and Heckman.
Sorting by Income and Education: Endogenous Neighborhoods
Outcomes by family background in Denmark suggest that something else besides public expenditure is at work and strongly so, despite near equality of public expenditure.

Equalizing expenditure is not enough to reduce gaps.
Evidence on the early emergence of gaps leaves open the question of what aspects of families are responsible for producing these gaps.

The evidence from a large body of research demonstrates an important role for investments and family and community environments in determining adult capacities above and beyond the role of genes.

Home investments matter.

But the choice of neighborhoods: peers and public goods also matters.

The element of family choice of neighborhoods has been neglected in recent literature that ignores such choices and treats neighborhoods as randomly assigned.
American Neighborhood Effects Have Been Heavily Featured in the Press (e.g., Atlas of Opportunity)
Figure 20: The Great Gatsby Curve, within the U.S.

Source: Chetty et al. (2014).

Note: $\bar{r}_{25}$ is the relative mobility in rank at the 25th percentile.
Effective upward mobility of children born 1971–1976 (parental income measured as 9-year averages during child generations; childhood; children’s income measured at ages 35–37,...,40–42 depending on cohort). Figure shows a scatter plot of “absolute upward mobility” (defined as the expected child rank at parents’ 25th percentile, where ranks are defined in terms of gross income excluding transfers in full population) across municipality-specific Gini coefficients. 15 bins of 6.67% of municipalities.
Sorting and Segregation
• Segregation: How similar are families who live in the same neighborhood?
  • Can be measured in many different ways
  • Different dimensions of segregation: native / immigrant (binary), education (discrete), income (continuous).
  • Different definitions of areas

• Measure of segregation in income in neighborhoods: Theil (1972), Reardon and Bishoff (2011), can be used to form a scale from 0-1:
  • 0 is no income segregation, 1 is full income segregation
  • 0: All income percentiles equally represented in all neighborhoods.
  • 1: Each neighborhood consists of families from same part of income distribution.
In the U.S., Sorting is High at Both Ends of the Income Distribution and Sorting Increasing
Figure 22: Income Segregation Patterns in the U.S.
Figure 23: Income segregation by gross income excl. transfers across primary school Catchment Areas by year, Denmark
Figure 24: Strong Socioeconomic Gradients in Neighborhood Quality in Educational Attainment in Denmark

(A) High school completion and college attendance rates across average gross income of school peers’ parents

(B) High school completion and college attendance rates across average highest grade completed of school peers’ parents
Danish Family Environments Fundamentally Unequal Across the Income Distribution

Figure 25: Fraction of mothers smoke during pregnancy by household wage earnings year prior to childbirth
Sorting of Teacher Quality Across Neighborhoods
Figure 26: Teachers’ hourly wage distribution and high school GPA

Source: Gensowski et al. (2020).
• Consider how teachers sort. All teachers more or less paid the same.
• ⇒ non-price allocation mechanism at work ⇒ sorting by student quality
• Sorting is a non-price mechanism. Best teachers sorted to best neighborhoods.
• Parents (through school boards) also have say on hires.
Figure 27: Parents’ years of schoolings by average teacher quality in schools

Source: Gensowski et al. (2020).
Figure 28: Average teacher quality in schools and parent’s education, by housing values

Source: Gensowski et al. (2020).
Another Role for Parental Influence: Parents Also May Reinforce School Quality or Substitute Away From It
1. “Equal” access downstream but not equal skill formation upstream:
   • More advantaged children enter schools with greater skill
   • Two (stylized) potential barriers for education: parental costs and parental skills.
   • Denmark eliminates costs but retains importance of parental skills
   • Implicitly favors investments of children of high skilled parents.
2. How do parents respond to public investments?
   • Do they adjust their own investments?
   • Reinforcement or substitution?

3. Parents maximizing child skills by own investments at home and sorting into better institutions will choose inputs such that:

\[
\text{MRTS (home, institutions)} = \frac{\text{slope of education production function}}{\text{slope of home production function}}
\]

• The role of i) family inputs, ii) institutions, and iii) sorting possibilities are closely linked.
• Gensowski and Landersø show that parents on net substitute their inputs in the presence of better quality schools.
Public Policy Shift (Karlson and Landersø, 2020)
• A strong disconnect between the expansion of the welfare state from the 1960s onwards, and when educational mobility peaked in Denmark.

  • Denmark saw massive expansion of education in the bottom from 1940s - mid 1960s cohorts ⇒ high mobility. Lower tail expansion driven by those from low-resource families.
  • Expansion in college and university from cohorts born during the 1970s onward ⇒ lower mobility. Upper tail expansion driven by those from affluent families.
Figure 29: Correlation between upward educational mobility and parents’ education, back to 1910

- Policy targeted downward disadvantaged
- Growth of Universality

Legend:
- Education IGE, register data
- Survey data
- Correlation, upward mobility and parents education, register data
- Survey data
\[ y^C = \alpha + \beta^{IGE} y^P + u \]

\( \beta \uparrow, \text{Mobility} \downarrow \)

Compulsory School Reforms Increased Educational Mobility

Universality: Helps Children From Better Family Backgrounds Relatively More
Targeting Disadvantaged Children Yields Highest Benefits

- Elango et al. (2016): Early Childhood Interventions most effective for disadvantaged.
- Dustmann et al. (2017) study an expansion of childcare in Germany and find similar results.
- Walters (2018) shows similar evidence for choice of charter schools.
New Evidence on Neighborhood Effects
Estimating Neighborhood-level Mobility

- Estimate neighborhood-specific intercepts and slopes (with no controls)

\[ y_{in}^c = \alpha_n + \beta_{nIGE} y_{in}^p + u_{in} \]

using market income (labor earnings and capital income), before transfers and taxes, of children and parents.
• Let $n \in \mathcal{N}$ index neighborhoods: Danish parishes
  • Parishes are administrative units from the Church of Denmark
  • On average, home to 2,500 residents (comparable to a small U.S. Census tract or small zip code area)
• For much of the presentation, assign children to the parish they spent the longest time during childhood (ages 0-17)
  • However social, neighborhood mobility estimates are robust when accounting for exposures to different neighborhoods during childhood
• Let $y_{in}^c$: log of long-run average income between ages 30-45; $y_{in}^p$ is log of child’s family when they are 0-17
• Main measure of income: market income (labor earnings and capital income). We use alternative measures from register data: before or after transfers and taxes
• We also use PDV of disposable income
Sample construction for empirical analysis:

<table>
<thead>
<tr>
<th>Analysis</th>
<th>Neighborhood</th>
<th>Permanent Inc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source</td>
<td>Danish registers</td>
<td>registers/survey</td>
</tr>
<tr>
<td>Sample</td>
<td>birth cohorts 1973/83</td>
<td>birth cohorts 1981/82</td>
</tr>
<tr>
<td>Years</td>
<td>1980-2018</td>
<td>1980-2018</td>
</tr>
<tr>
<td>Unit</td>
<td>family</td>
<td>father/family</td>
</tr>
<tr>
<td>Age: -Child</td>
<td>30 onward (up to 45)</td>
<td>30-35</td>
</tr>
<tr>
<td></td>
<td>-Parent 0-17 of child</td>
<td>0-17 of child</td>
</tr>
</tbody>
</table>
Figure 30: Empirical Distribution of $\hat{\beta}_{n}^{IGE}$ of Market Income
Redistribution Greatly Reduces $\hat{\beta}_{n}^{IGE}$ and its Variability Across Neighborhoods
Figure 31: Empirical Distribution of $\hat{\beta}_{n}^{IGE}$ (parishes), by Income Measure Used
• Variation in $\hat{\beta}^{IGE}_n$ appears to increase for more granular neighborhoods.
• Fewer families at smaller neighborhood units.
• Greater sampling error?

Focus on:
• Parishes are neighborhood unit; Like zip codes.
• Market income before transfers and taxes as measure or child and parent income

Note: results that follow are qualitatively similar across alternative income measures
Lots of Sampling Error: Variance of Estimated $\beta_n$

\[
\text{Var}(\hat{\beta}_n^{\text{IGE}}) = \mathbb{E} \left[ \hat{\sigma}^2(\hat{\beta}_n^{\text{IGE}}) \right] + \text{Var} (\beta_n^{\text{IGE}})
\]

- 65\% of the variation in $\alpha_n$, $\beta_n^{\text{IGE}}$ is due to sampling error
- Even for statistically significant estimates, 60\% of variance among $n$ is due to sampling error
- Consistent with Mogstad et al. (2020)
Contribution of the Neighborhoods to Inequality in Child Income as Adult

Variance decomposition between vs. within neighborhoods (accounting for sampling error)

\[ \text{Var} \left( y_{in}^c \right) = \text{Var} \left( \bar{y}_n^c \right) + \mathbb{E} \left[ \text{Var} \left( y_{in}^c \mid i \text{ lives in } n \right) \right] \]

between nbhd. 10%  \hspace{1cm}  \text{within nbhd. 90%}
Association between \((\alpha_n, \beta_{n}^{IGE})\) and Neighborhood Characteristics

\[
\hat{\beta}_{n}^{IGE} = \gamma_0 + \gamma_1 Z_n + u_n
\]

- \(Z_n\): mean parent income, mean mother education, mean parent crime, Gini coefficient of parent income, school quality, etc.
- \(Z_n\) is standardized across neighborhoods to help compare effects across characteristics.
Figure 32: $\hat{\alpha}_n$ Increases in Neighborhood Mean Parent Income

Neighborhood Intercept Estimates vs. Mean Parent Income (thousands)

Slope Estimate: 0.024 (0.005)
Figure 33: $\hat{\beta}_{IGE}^n$ Decreases in Neighborhood Mean Parent Income

Neighborhood IGE Estimates vs. Mean Parent Income (thousands)

Slope Estimate: $-0.002 (0.000)$
More Advantaged Families associated with Lower Neighborhood IGEs

Figure 34: Slope coefficient estimates of regression of $\hat{\beta}_n^{IGE}$ on $Z_n$

<table>
<thead>
<tr>
<th>S.D. of Neighborhood Characteristic</th>
<th>Point Estimate (with 95% C.I.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean School Quality</td>
<td></td>
</tr>
<tr>
<td>Prop. Intact Families</td>
<td></td>
</tr>
<tr>
<td>Mean Parent Assets</td>
<td></td>
</tr>
<tr>
<td>Prop. Farmers</td>
<td></td>
</tr>
<tr>
<td>Mean Yrs. Schooling, Mother</td>
<td></td>
</tr>
<tr>
<td>Mean Parent Income</td>
<td></td>
</tr>
<tr>
<td>Gini Coefficient, Parent Income</td>
<td></td>
</tr>
<tr>
<td>Prop. Muslim Immigrants</td>
<td></td>
</tr>
<tr>
<td>Prop. Parents Hospitalized</td>
<td></td>
</tr>
<tr>
<td>Prop. Parents Committed Crime</td>
<td></td>
</tr>
</tbody>
</table>
Figure 35: Local Linear Fit of $\hat{\beta}_{IGE}^n$ against $\bar{Y}_p^n$ vs. Population Local Linear IGE

$\hat{\beta}_{IGE}^n$ decreases as mean parent income increases — similar to the nonlinear IGE for the population.
More Advantaged Families associated with Higher Neighborhood Intercepts

Figure 36: Slope coefficient estimates of regression of $\hat{\alpha}_{IGE}^n$ on $Z_n$

Landersø & Heckman
Purposive Choice of Neighborhood to Raise Children by Education of Mother
Family move to new parish, by time to/from birth of first-born:

![Graph showing the fraction of families moving to a new parish by time to/from birth of the first child, with different lines representing educational levels: less than high school, high school, college, and university.]
Obviously Family Moves Not Random
The Assumption of Random Moves is a Key Identifying Assumption in Recent Work on Neighborhood Effects
Move to new parish, by time to/from birth of first-born: conditional on move during first-born’s childhood

Landersø & Heckman
Move to new parish, by time to/from birth of second-born: conditional on move during first-born’s childhood

- Less than high school
- High school
- College
- University

Landersø & Heckman
Danish Prism
Quality of Neighborhood for Child Rearing Improves With Education of the Mother
Average household level market income in parish of residence, by time to/from birth of first-born

![Graph showing average household income by educational level and time from birth of first child.](image)

Legend:
- Less than high school
- High school
- College
- University

Landersø & Heckman

Danish Prism
Summary of Location Choice

1. Most moves made by young parents prior to the start of school.
2. First-born children experience moves more often than second- and third-borns.
3. Highly educated mothers make fewer moves after arrival of children with large positive changes in neighborhood quality.
4. Gaps in neighborhood quality remain large and persist during adolescence.
Sorting Can Create Artificial Neighborhood Effects if Parental Income Not Well Measured
Census-Based U.S. Data Analyses Do Not Measure Family Income During Childhood Very Well Heckman (2018)
Example
• Take an underlying data generating process

\[ y^c = \alpha + \beta y^p + \epsilon \]
\[ y^p = \gamma_0 + \gamma_1 E^p + u^p \]

• $E^p$ is education of parent
Income measured with mean zero classical measurement error

\[ \hat{y}^p = y^p + \epsilon_p \]
• Assume individuals sort on neighborhoods indexed 1:10.
• We can do this through choosing cutoffs for each neighborhood:

\[
\begin{align*}
C_1 & \leq E_1 < C_2 \\
C_2 & \leq E_2 < C_3 \\
& \quad \vdots \\
C_K & \leq E_K < C_{K+1}
\end{align*}
\]
What happens when we regress:

\[ \mathbf{y}^c = \alpha_0 + \beta_0 \hat{\mathbf{y}}^p + \delta_n + \epsilon_0 \]  

when \( \delta_n = 0 \)?
Figure 37: Kernel Density of the Neighborhood Effects, $\delta_n$, for Different Amounts of Measurement Error, $\epsilon_p$

Includes the kernel densities for $\delta_n$ over multiple simulations for different amounts of measurement error in the proxy for parental income, $\hat{y}^p$. 
Figure 38: Probability of finding Neighborhood Effects Even Though None Exist, As a Function of Measurement Error

This shows the probability of finding neighborhood effects as $\delta_n$ by increasing amounts of measurement error $\text{Var}(\epsilon_p)$. $\text{Var}(U_p) = .419$ is chosen from regression estimated using empirical counterparts.
Figure 39: Probability of finding Neighborhood Effects Even Though None Exist, As a Function of $u_p$
Intergenerational Transmission of Utility
Toward Lifetime Measures of IGE
IGE of Value Functions
• The traditional literature on the IGE focuses on matching the income of father to that of son over certain windows of age.
• It sometimes matches income of child’s family income with family income of parent.
• We construct lifetime measures (both on individuals and on families).
• Compute IGEs of value functions and other approximations of value functions.
• Investment in child skills is the outcome of a lifetime investment strategy by parents which we model.
• Today: Report first installment of our project of parental lifetime wealth (value function) on child:
  (i) Age of marriage and cohabitation
  (ii) Onset of fertility
  (iii) Timing and spacing of births
  (iv) Divorce
Conventional measures

- Wage income
- Disposable income
- Income (with and without) tax/transfers
- Consumption (with and without equivalence scale)

Lifetime measures

- Human wealth (the value of human capital)
- Expected PDV of disposable income
- Permanent inc. (annuitized value of lifetime resources)
Consumption

• Impute total household expenditures from the relationship between Danish Expenditure Survey and Danish register data
• Compute equivalence scale consumption by adjusting imputed consumption for household composition
• Alternatively, consumption can be imputed using accounting identity by only using registers (Browning et. al. (2003)).
• This, however, likely leads to attenuation bias in consumption IGE due to measurement errors (Bruze (2018))
Human Wealth Measure

The Value of an Individual’s Human Capital (Huggett and Kaplan, 2016):

- Human wealth (HW) $\theta_j$ measures the asset value of human capital at age $j$:

  \[
  \theta_j \equiv E \left[ \sum_{k=j+1}^{J} m_{j,k} d_k \right]
  \]  

  (2)

  where $m_{j,k}$ is the stochastic discount factor and $d_k$ dividends at age $k$

- Dividends $d_k$ include earnings and the value of leisure
• Derived from a thought experiment
• Maximize lifetime utility accounting for consumption and labor supply (value of leisure)
• Prices and asset rate of returns are external parameters facing agents
• $\theta_j$ is the monetary equivalent value of lifetime program: how much a person would be willing to pay (or sell) for his/her lifetime program.
Human Wealth and Economic Well-being:

- Human wealth captures impacts of:
  - Credit constraints: For borrowing constrained agents, the value tends to be lower.
    - Future earnings are valued less by individuals who cannot access them in advance.
  - Income uncertainty: Risk aversion and uncertainty reduce lifetime utility.
- Closer link to economic decisions than per period realized income (or average over a few periods)
Permanent Income
Annuitized Human Wealth and Financial Wealth Discounted Value of Income

- Present Discounted Value (PDV) of disposable income is similar to HW.
- Instead of stochastic discount factor use a risk-free rate to discount future income.
Figure 40: Log-Log IGE Estimates

- Child measured at individual, parents at both individual (father) and family level averaged over ages 0-17 of child
Figure 41: Education Outcomes of Child by Measures of Parental Resources

<table>
<thead>
<tr>
<th>Unit of Parental Measures</th>
<th>Father</th>
<th></th>
<th></th>
<th></th>
<th>Family</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>R Square</td>
<td>Coefficient</td>
<td>R Square</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wage Income</td>
<td>0.27***</td>
<td>0.014</td>
<td>0.81***</td>
<td>0.005</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dispos. Income</td>
<td>1.16***</td>
<td>0.042</td>
<td>2.73***</td>
<td>0.080</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inc. w/ Trans.</td>
<td>1.75***</td>
<td>0.074</td>
<td>2.74***</td>
<td>0.102</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inc. w/o Trans.</td>
<td>1.00***</td>
<td>0.065</td>
<td>1.64***</td>
<td>0.110</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH. Cons.</td>
<td>3.76***</td>
<td>0.090</td>
<td>4.27***</td>
<td>0.098</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH. Cons. (EQ)</td>
<td>2.91***</td>
<td>0.036</td>
<td>4.14***</td>
<td>0.061</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Human Wealth</td>
<td>2.74***</td>
<td>0.070</td>
<td>3.21***</td>
<td>0.078</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected PDV</td>
<td>3.05***</td>
<td>0.099</td>
<td>3.88***</td>
<td>0.112</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Permanent Inc. (annuit. HW+assets)</td>
<td>2.48***</td>
<td>0.082</td>
<td>3.35***</td>
<td>0.106</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Permanent Inc. (annuit. PDV+assets)</td>
<td>2.96***</td>
<td>0.116</td>
<td>4.06***</td>
<td>0.143</td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Note: Sample is restricted to native Danes of 1981-82 birth cohorts and their parents. The slope coefficient reported in this table is estimated as follows: \( \text{edu}_i^c = \alpha + \beta \cdot \log(\bar{y}_i) \) where \( \text{edu}_i^c \) denotes the child's years of schooling, and \( \bar{y}_i \) denotes the average of father (family) measure when the child was 0 to 17 years old.

Standard errors are reported in parentheses.

* \( p < .1 \), ** \( p < .05 \), *** \( p < .01 \).
### Figure 42: Expected PDV of Child by Measures of Parental Resources

<table>
<thead>
<tr>
<th>Unit of Parental Measures</th>
<th>Father</th>
<th>Family</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>R Square</td>
</tr>
<tr>
<td>Wage Income</td>
<td>0.02***</td>
<td>0.010</td>
</tr>
<tr>
<td>Dispos. Income</td>
<td>0.12***</td>
<td>0.035</td>
</tr>
<tr>
<td>Inc. w/ Trans.</td>
<td>0.20***</td>
<td>0.070</td>
</tr>
<tr>
<td>Inc. w/o Trans.</td>
<td>0.11***</td>
<td>0.060</td>
</tr>
<tr>
<td>HH. Cons.</td>
<td>0.42***</td>
<td>0.082</td>
</tr>
<tr>
<td>HH. Cons. (EQ)</td>
<td>0.32***</td>
<td>0.032</td>
</tr>
<tr>
<td>Human Wealth</td>
<td>0.30***</td>
<td>0.063</td>
</tr>
<tr>
<td>Expected PDV</td>
<td>0.33***</td>
<td>0.084</td>
</tr>
<tr>
<td>Permanent Inc. (annuit. HW+assets)</td>
<td>0.27***</td>
<td>0.071</td>
</tr>
<tr>
<td>Permanent Inc. (annuit. PDV+assets)</td>
<td>0.31***</td>
<td>0.097</td>
</tr>
</tbody>
</table>

Note: Sample is restricted to native Danes of 1981-82 birth cohorts and their parents. The slope coefficient reported in this table is estimated as follows: \( \log(\overline{PDV}_c) = \alpha + \beta \log(\overline{y}_f) \) where \( \overline{PDV}_c \) denotes the child’s expected PDV of disp. income, and \( \overline{y}_f \) denotes the average of father (family) measure when the child was 0 to 17 years old. Family outcomes are the sum of mother’s and father’s outcome. Standard errors are reported in parentheses.

* \( p < .1 \), ** \( p < .05 \), *** \( p < .01 \)
Figure 43: Distribution of IGE Estimates across Neighborhoods

Source: Registers and survey data from Denmark.

Landersø & Heckman

Danish Prism
Figure 44: Distribution of Intercept Estimates across Neighborhoods

Source: Registers and survey data from Denmark.

Landersø & Heckman

Danish Prism
Figure 45: Theil’s T Index Decomposition Across Neighborhoods

Source: Registers and survey data from Denmark.
Figure 46: Segregation by Source of Income

Source: Registers and survey data from Denmark.
Summary of Value Function IGEs

- Measures of lifetime resources show a stronger link across generations than traditional measures:
  - PDV/HW/PI IGE estimates range from 0.38 to 0.47 for family and 0.32-0.35 for father
  - Conventional IGE estimates range from 0.16 to 0.33 for family and 0.06-0.21 for father

- Compared to measures at father’s income, family resources better predict child outcomes.

- Lifetime resources have a closer connection to economic decisions (e.g. investments in children) than resources averaged over a short panel.

- Lifetime measures of IGE paint a different picture of income mobility in Denmark: mobility is significantly lower than previously thought.
Summary

• Denmark is widely perceived to be a Garden of Eden by many politicians, public figures, and “informed” citizens around the world.

• Danish policies have been widely advocated.
Our previous work (SJE, 2018) examined Danish policy and evidence.

(a) For Denmark: less inequality and greater social mobility, in terms of income.
(b) Equality in earnings and IGE in earnings is a consequence of tax and transfer policy.
(c) This equalizes income and at the same time reduces the incentives of children to acquire skills.
(d) This equality is not a result of education and skills policies.
(e) They are generous and offered equally to all:
   (i) Universal pre-K
   (ii) Equal pay and financial resources for all schools everywhere
   (iii) Extensive job training and retraining associated with its carrot-and-stick policy for unemployment insurance
   (iv) Universal health care
   (v) Free college
   (vi) Generous work leaves for parents with newly-born children.
(f) However, welfare state policies distort incentives to acquire skills (see SJE, 2018).

(g) Gaps in skills and lifetime outcomes (e.g., earnings, health, and crime) of children of the less educated and the more educated mothers about the same for the U.S. and Denmark, both quantitatively and qualitatively.
• We find strong evidence of sorting of families on income and education

• Advantages from universal access to services are reaped relatively more by the affluent rather than by the disadvantaged (Matthew Effects)

• “Power of place” is due to family sorting
  • Family choice of neighborhoods
  • Timing of choices not random (in contrast to influential claims otherwise)
  • Sorting patterns comparable to U.S.
  • IGE ↓ Family income ↑; More affluent places have lower IGEs
  • The sorting shows up most strongly in initial conditions
  • Sorting \(\implies\) Strong family income gradients on child outcomes
• Sorting by teachers into more advantaged districts
• Despite equal wages for teachers; payment is in quality of students taught.
• Neighborhood effects large through parental choices, not some intrinsic property of an address.
• A life cycle – human wealth approach to measuring family influence.

• Long-term measures of family income (value functions) much more predictive of child outcomes than currently used measures.

• IGEs higher for life cycle measures of family resources than traditional sources.