Quantifying the Role of Firms in Intergenerational Mobility

Cauê Dobbin  
Georgetown

Tom Zohar  
CEMFI

Bringing Together Econometrics and Applied Microeconomics Workshop

September 23, 2023
What is the role of firms in the intergenerational mobility?

(1) Some firms pay more than others to similar workers → These firm pay premiums contribute to earnings inequality

AKM (1999); CHK (2013); Sorkin (2017, 2018); Card et al. (2018); Song et al. (2019)

(2) Richer children have privileged access to certain employers → Parental social networks influence the allocation of workers to firms

Corak and Piraino (2011); Kramarz and Skans (2014); Stinson and Wignall (2018); San (2020); Staiger (2021)

(1)+(2) Richer children work in better-paying firms → Contributing to the intergenerational persistence of earnings
What is the role of firms in the intergenerational mobility?

(1) Some firms pay more than others to similar workers

→ These firm pay premiums contribute to earnings inequality
  AKM (1999); CHK (2013); Sorkin (2017,2018); Card et al. (2018); Song et al. (2019)

(2) Richer children have privileged access to certain employers

→ Parental social networks influence the allocation of workers to firms
  Corak and Piraino (2011); Kramarz and Skans (2014); Stinson and Wignall (2018); San (2020); Staiger (2021)

(1)+(2) Richer children work in better-paying firms

→ Contributing to the intergenerational persistence of earnings
What is the role of firms in the intergenerational mobility?

(1) Some firms pay more than others to similar workers

→ These firm pay premiums contribute to earnings inequality
  AKM (1999); CHK (2013); Sorkin (2017, 2018); Card et al. (2018); Song et al. (2019)

(2) Richer children have privileged access to certain employers

→ Parental social networks influence the allocation of workers to firms
  Corak and Piraino (2011); Kramarz and Skans (2014); Stinson and Wignall (2018); San (2020); Staiger (2021)
What is the role of firms in the intergenerational mobility?

(1) Some firms pay more than others to similar workers

→ These *firm pay premiums* contribute to earnings inequality
  AKM (1999); CHK (2013); Sorkin (2017, 2018); Card et al. (2018); Song et al. (2019)

(2) Richer children have *privileged access to certain employers*

→ Parental social networks influence the allocation of workers to firms
  Corak and Piraino (2011); Kramarz and Skans (2014); Stinson and Wignall (2018); San (2020); Staiger (2021)

(1)+(2) Richer children work in better-paying firms

→ Contributing to the intergenerational persistence of earnings
Research question

How much does access to better-paying firms contribute to the intergenerational persistence of earnings?
Research question
How much does access to better-paying firms contribute to the intergenerational persistence of earnings?

Roadmap
1. 2-way fixed effect framework: \( \text{IGE} = \text{firm-IGE} + \text{individual-IGE} \)
Research question
How much does access to better-paying firms contribute to the intergenerational persistence of earnings?

Roadmap

1. 2-way fixed effect framework: \( IGE = \text{firm-IGE} + \text{individual-IGE} \)
   - \( \text{firm-IGE} = 22\% \text{ of the IGE} \)
Research question
How much does access to better-paying firms contribute to the intergenerational persistence of earnings?

Roadmap
1. 2-way fixed effect framework: $\text{IGE} = \text{firm-IGE} + \text{individual-IGE}$
   - $\text{firm-IGE} = 22\%$ of the IGE

2. Correlate firm/individual-IGE with observables
Research question
How much does access to better-paying firms contribute to the intergenerational persistence of earnings?

Roadmap

1. 2-way fixed effect framework: $\text{IGE} = \text{firm-IGE} + \text{individual-IGE}$
   - firm-IGE = 22% of the IGE

2. Correlate firm/individual-IGE with observables
   - Education $\rightarrow$ explains individual-IGE
   - Ethnicity, Neighborhoods $\rightarrow$ explains firm-IGE
Research question

How much does access to better-paying firms contribute to the intergenerational persistence of earnings?

Roadmap

1. 2-way fixed effect framework: \( \text{IGE} = \text{firm-IGE} + \text{individual-IGE} \)
   - \( \text{firm-IGE} = 22\% \) of the IGE

2. Correlate firm/individual-IGE with observables
   - Education \( \rightarrow \) explains individual-IGE
   - Ethnicity, Neighborhoods \( \rightarrow \) explains firm-IGE

3. Propose an econometric model to measure assortative matching
   - Allow for unobservable skill
Research question
How much does access to better-paying firms contribute to the intergenerational persistence of earnings?

Roadmap
1. 2-way fixed effect framework: $\text{IGE} = \text{firm-IGE} + \text{individual-IGE}$
   - $\text{firm-IGE} = 22\%$ of the IGE

2. Correlate firm/individual-IGE with observables
   - Education → explains individual-IGE
   - Ethnicity, Neighborhoods → explains firm-IGE

3. Propose an econometric model to measure assortative matching
   - Allow for unobservable skill
   - Only half of firm-IGE is due to skill-based sorting
1. Determinants of intergenerational mobility

HC (Becker and Tomes, 1979, 1986; Restuccia and Urrutia, 2004; Heckman and Mosso, 2014; Chetty et al., 2017; Bell et al., 2019; Lee and Seshadri, 2019; Acemoglu, 2022; Barrios-Fernandez et al., 2021; Hermo et al., 2021); nature vs nurture (Black et al., 2020); location (Chetty et al., 2016, 2018); social networks (Putnam, 2015; Chetty et al., 2022a,b).

- **Family networks and privileged access to employers**
  - Corak and Piraino, 2011; Kramarz and Skans, 2014; Stinson and Wignall, 2018; San, 2020; Staiger, 2021; Engzell and Wilmers, 2021
Literature

1. Determinants of intergenerational mobility
   HC (Becker and Tomes, 1979, 1986; Restuccia and Urrutia, 2004; Heckman and Mosso, 2014; Chetty et al., 2017; Bell et al., 2019; Lee and Seshadri, 2019; Acemoglu, 2022; Barrios-Fernandez et al., 2021; Hermo et al., 2021); nature vs nurture (Black et al., 2020); location (Chetty et al., 2016, 2018); social networks (Putnam, 2015; Chetty et al., 2022a,b).

   - Family networks and privileged access to employers
     Corak and Piraino, 2011; Kramarz and Skans, 2014; Stinson and Wignall, 2018; San, 2020; Staiger, 2021; Engzell and Wilmers, 2021

Contribution: Quantify contribution of firms to intergenerational mobility

2. Firms and earnings inequality
   Abowd et al. 1999; Card et al., 2013, 2016; Sorkin, 2018a; Card et al., 2018; Bloom et al., 2018; Song et al., 2019; Bonhomme et al., 2019, 2022; Kline et al., 2020

   - Firms, assortative matching, and racial inequality
     Gerard, Lagos, Severnini, & Card 2021

Contribution: Econometric framework to estimate assortative matching
Literature

1. Determinants of intergenerational mobility
   HC (Becker and Tomes, 1979, 1986; Restuccia and Urrutia, 2004; Heckman and Mosso, 2014; Chetty et al., 2017; Bell et al., 2019; Lee and Seshadri, 2019; Acemoglu, 2022; Barrios-Fernandez et al., 2021; Hermo et al., 2021); nature vs nurture (Black et al., 2020); location (Chetty et al., 2016, 2018); social networks (Putnam, 2015; Chetty et al., 2022a,b).
   - Family networks and privileged access to employers
     Corak and Piraino, 2011; Kramarz and Skans, 2014; Stinson and Wignall, 2018; San, 2020; Staiger, 2021; Engzell and Wilmers, 2021

   Contribution: Quantify contribution of firms to intergenerational mobility

2. Firms and earnings inequality
   Abowd et al. 1999; Card et al., 2013, 2016; Sorkin, 2018a; Card et al., 2018; Bloom et al., 2018; Song et al., 2019; Bonhomme et al., 2019, 2022; Kline et al., 2020
   - Firms, assortative matching, and racial inequality
     Gerard, Lagos, Severnini, & Card 2021
Literature

1. Determinants of intergenerational mobility

HC (Becker and Tomes, 1979, 1986; Restuccia and Urrutia, 2004; Heckman and Mosso, 2014; Chetty et al., 2017; Bell et al., 2019; Lee and Seshadri, 2019; Acemoglu, 2022; Barrios-Fernandez et al., 2021; Hermo et al., 2021); nature vs nurture (Black et al., 2020); location (Chetty et al., 2016, 2018); social networks (Putnam, 2015; Chetty et al., 2022a,b).

- Family networks and privileged access to employers
  Corak and Piraino, 2011; Kramarz and Skans, 2014; Stinson and Wignall, 2018; San, 2020; Staiger, 2021; Engzell and Wilmers, 2021

**Contribution:** Quantify contribution of firms to intergenerational mobility

2. Firms and earnings inequality

Abowd et al. 1999; Card et al., 2013, 2016; Sorkin, 2018a; Card et al., 2018; Bloom et al., 2018; Song et al., 2019; Bonhomme et al., 2019, 2022; Kline et al., 2020

- Firms, assortative matching, and racial inequality
  Gerard, Lagos, Severnini, & Card 2021

**Contribution:** Econometric framework to estimate assortative matching
Outline

1. Decomposing Intergenerational Mobility
2. Mechanisms: Observables
3. Mechanisms: Assortative Matching
Outline

1 Decomposing Intergenerational Mobility

2 Mechanisms: Observables

3 Mechanisms: Assortative Matching
Data: Israeli National Insurance

The dataset

- Monthly level individual records of earnings
- Firms’ and workers’ identifiers
- Civil registry of all residents
  - Births, Deaths, Emigration
- Parent-child links
  - 95% match rate

Our sample

- Birth cohort: Children: 1965-1980
- Labor market outcomes: Children: 2010-2015 (30-50 years old)
- Fathers: 1986-1991 (78% between 30-50 years old)
Data: Israeli National Insurance

The dataset

- Monthly level individual records of earnings
- Firms’ and workers’ identifiers
- Civil registry of all residents
  - Births, Deaths, Emigration
- Parent-child links
  - 95% match rate

Our sample

- Birth cohort
  - Children: 1965-1980
- Labor market outcomes
  - Children: 2010-2015 (30-50 years old)
  - Fathers: 1986-1991 (78% between 30-50 years old)
Estimating firm earnings premium (AKM)

We impose a log-linear structure on earnings

\( \log Y_{it} = \alpha_i + \psi_{J_{it}} + x_{it}\beta_x + r_{it} \)

- \( \log Y_{it} \) - log-earnings of individual \( i \) at time \( t \)
- \( \alpha_i \) - worker fixed effects
- \( \psi_{J_{it}} \) - earnings premium of firm \( J_{it} \)
- \( x_{it} \) - time varying covariates: year fixed effects, age, and age squared
- \( r_{it} \) - error term
Individual- and Firm-IGE

Corr = 0.23

Slope = 0.20 (0.00)

Corr = 0.25

Slope = 0.06 (0.00)
Quantifying the Role of Firms in IGM

- Intergenerational Elasticity (IGE):
  \[
  \log Y_i = \beta^{IGE} \cdot \log Y_{f(i)} + \epsilon_i^{IGE}
  \]

- Regressing the AKM components on fathers’ earnings:
  \[
  \hat{\alpha}_i = \beta^\alpha \cdot \log Y_{f(i)} + \epsilon_i^\alpha
  \]
  \[
  \hat{\psi}_i = \beta^\psi \cdot \log Y_{f(i)} + \epsilon_i^\psi
  \]
Quantifying the Role of Firms in IGM

▷ Intergenerational Elasticity (IGE):
\[
\log Y_i = \beta^{IGE} \cdot \log Y_{f(i)} + \epsilon^{IGE}_i
\]

▷ Regressing the AKM components on fathers’ earnings:
\[
\hat{\alpha}_i = \beta^\alpha \cdot \log Y_{f(i)} + \epsilon^\alpha_i
\]
\[
\hat{\psi}_i = \beta^\psi \cdot \log Y_{f(i)} + \epsilon^\psi_i
\]

▷ We can decompose:
\[
\beta^{IGE} = \underbrace{\beta^\alpha}_{\text{individual-IGE}} + \underbrace{\beta^\psi}_{\text{firm-IGE}}
\]
22% of the IGE is Due to Access to Better Paying Firms

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log ( Y_i )</td>
<td></td>
<td>( \alpha_i )</td>
<td>( \bar{\psi}_i )</td>
</tr>
</tbody>
</table>

\[
\hat{\beta}_{IGE} = \hat{\beta}_{\alpha|Y_f} + \hat{\beta}_{\psi|Y_f}
\]

<table>
<thead>
<tr>
<th>( \log Y_{f(i)} )</th>
<th>0.253</th>
<th>0.197</th>
<th>0.056</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Share of IGE</th>
<th>1.00</th>
<th>0.78</th>
<th>0.22</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>595,493</th>
<th>595,493</th>
<th>595,493</th>
</tr>
</thead>
</table>
1 Decomposing Intergenerational Mobility

2 Mechanisms: Observables

3 Mechanisms: Assortative Matching
Behind the individual- and firm-IGE: Potential Channels

▷ Focus on factors that affect inequality and IGM: education, location, demographics
  Restuccia and Urrutia, 2004; Pekkarinen et al., 2009; Zimmerman, 2019; Chetty et al., 2014a, 2016; Chetty et al., 2020; Gerard, Lagos, Severini, & Card 2021

▷ Education is more strongly related to the individual-IGE
  ▷ Human capital?

▷ Demographics and location are more strongly related to the firm-IGE
  ▷ Local social networks/preferences/discrimination?
Outline

1 Decomposing Intergenerational Mobility

2 Mechanisms: Observables

3 Mechanisms: Assortative Matching
The Role of Assortative Matching (AM)

- The assortative matching channel
  - (1) High-SES children are more skilled
  - (2) More skilled workers sort into better-paying firms

(1) + (2) $\rightarrow$ High-SES children sort into better-paying firms
The Role of Assortative Matching (AM)

▷ The assortative matching channel

(1) High-SES children are more skilled

(2) More skilled workers sort into better-paying firms

(1) + (2) → High-SES children sort into better-paying firms

▷ How much of the firm-IGE is explained by assortative matching?

→ Do rich children work in better firms even compared to equally skilled poor children?
An Econometric Model of SES and Labor Market Outcomes

$$\text{SES} \rightarrow \text{(Human capital, Social capital)} \rightarrow (\alpha, \psi)$$
An Econometric Model of SES and Labor Market Outcomes

\[ \text{SES} \rightarrow (\text{Human capital, Social capital}) \rightarrow (\alpha, \psi) \]

Goals of the model

1. Formal definition of assortative matching
2. Propose alternative empirical strategies to estimate assortative matching
Econometric Model – Human (H) and Social (S) Capital

- Both $H$ and $S$ important within ($\alpha$) and across ($\psi$) firms:

$$\bar{\psi}_i = \theta_H^\psi \cdot H_i + \theta_S^\psi \cdot S_i + \eta_i^\psi$$

$$\alpha_i = \theta_H^\alpha \cdot H_i + \theta_S^\alpha \cdot S_i + \eta_i^\alpha$$

- $H, S$: Latent worker types
- $\theta$: Parameters
  - Determine how $H$ and $S$ affect labor market outcomes ($\alpha$ and $\psi$)
- $\eta$: Error term
  - Luck, measurement error
Decomposing the Firm-IGE

▷ (Unfeasible) regression of $H$ and $S$ on father earnings:

\[ H_i = \beta^H \cdot \log Y_{f(i)} + \epsilon_i^H \]
\[ S_i = \beta^S \cdot \log Y_{f(i)} + \epsilon_i^S \]
Decomposing the Firm-IGE

▷ (Unfeasible) regression of $H$ and $S$ on father earnings:

\[ H_i = \beta^H \cdot \log Y_{f(i)} + \epsilon^H_i \]
\[ S_i = \beta^S \cdot \log Y_{f(i)} + \epsilon^S_i \]

▷ Firm-IGE decomposed as:

\[ \hat{\beta}^\psi = \theta^H \cdot \beta^H + \theta^S \cdot \beta^S \]

\[ \text{assortative matching} \quad \text{SES-effect} \]
Decomposing the Firm-IGE

- (Unfeasible) regression of $H$ and $S$ on father earnings:
  
  $$
  H_i = \beta^H \cdot \log Y_{f(i)} + \epsilon_i^H \\
  S_i = \beta^S \cdot \log Y_{f(i)} + \epsilon_i^S
  $$

- Firm-IGE decomposed as:
  
  $$
  \beta^\psi = \theta_H \cdot \beta^H + \theta_S \cdot \beta^S
  $$

  - assortative matching
  - SES-effect

- Object of interest: assortative-matching share
  
  $$
  \overline{AM} \equiv \frac{\theta_H^\psi \cdot \beta^H}{\beta^\psi}
  $$
Estimating $\overline{AM}$: Roadmap

▷ Approach I: Controlled-firm IGE

  I.a Assume $\alpha = H \rightarrow$ estimate $\overline{AM}$
Estimating $\overline{AM}$: Roadmap

▷ Approach I: Controlled-firm IGE

  I.a Assume $\alpha = H \rightarrow$ estimate $\overline{AM}$

  I.b Assume $\alpha \approx H$ and Education $\approx H \rightarrow$ bound $\overline{AM}$
Estimating $\overline{AM}$: Roadmap

- **Approach I: Controlled-firm IGE**
  - I.a Assume $\alpha = H \rightarrow$ estimate $\overline{AM}$
  - I.b Assume $\alpha \approx H$ and $Education \approx H \rightarrow$ bound $\overline{AM}$

- **Approach II: Observable proxies**
  - II.a Assume $Education = H$ and $Demographics = S \rightarrow$ estimate $\overline{AM}$
Estimating $\overline{AM}$: Roadmap

▷ Approach I: Controlled-firm IGE

  I.a Assume $\alpha = H \rightarrow$ estimate $\overline{AM}$

  I.b Assume $\alpha \approx H$ and $Education \approx H \rightarrow$ bound $\overline{AM}$

▷ Approach II: Observable proxies

  II.a Assume $Education = H$ and $Demographics = S \rightarrow$ estimate $\overline{AM}$

  II.b Assume $Education \approx H$ and $Demographics \approx S \rightarrow$ bound $\overline{AM}$
Approach I: Individual FE ($\alpha$) as a Proxy for Skill

Firm-IGE:
\[
\log \hat{\psi}_i = \beta\psi \cdot \log Y_f(i) + \epsilon_i^\psi
\]

Controlled Firm-IGE:
\[
\log \hat{\psi}_i = \beta|\alpha\psi \cdot \log Y_f(i) + \beta\alpha \cdot \alpha_i + \epsilon_i^\psi|\alpha
\]

Assumptions:
A1 $\alpha_i$ is unaffected by social capital ($\theta\alpha S = 0$)
A2 $\alpha_i$ is estimated without measurement error ($\eta\alpha = 0$)
A3 Human and social capital are uncorrelated, conditional on fathers' earnings ($\epsilon H|Y_{fi} \perp \perp \epsilon S|Y_{fi}$)

Then:
Share explained by AM:
\[
1 - \beta|\alpha \beta^\psi| = 51%\]
Approach I: Individual FE (α) as a Proxy for Skill

Firm-IGE:
\[ \log \hat{\psi}_i = \beta^\psi \cdot \log Y_f(i) + \epsilon^\psi_i \]

Controlled Firm-IGE:
\[ \log \hat{\psi}_i = \beta^{\psi|\alpha} \cdot \log Y_f(i) + \beta^\alpha \cdot \alpha_i + \epsilon_i^{\psi|\alpha} \]

▷ Assumptions:

A1 \( \alpha_i \) is unaffected by social capital \( (\theta^\alpha_S = 0) \)

A2 \( \alpha_i \) is estimated without measurement error \( (\eta^\alpha = 0) \)

A3 Human and social capital are uncorrelated, conditional on fathers’ earnings
\( (\epsilon_i^H|Y_f \perp \perp \epsilon_i^S|Y_f) \)
Approach I: Individual FE (α) as a Proxy for Skill

Firm-IGE:
\[
\log \hat{\psi}_i = \beta \psi \cdot \log Y_f(i) + \epsilon_i^\psi
\]

Controlled Firm-IGE:
\[
\log \hat{\psi}_i = \beta |\psi| \alpha \cdot \log Y_f(i) + \beta \alpha \cdot \alpha_i + \epsilon_i^\psi |\alpha
\]

▶ Assumptions:

A1 \( \alpha_i \) is unaffected by social capital (\( \theta_S^\alpha = 0 \))

A2 \( \alpha_i \) is estimated without measurement error (\( \eta^\alpha = 0 \))

A3 Human and social capital are uncorrelated, conditional on fathers’ earnings
\( (\epsilon_i^H | Y_f \perp \epsilon_i^S | Y_f) \)

▶ Then:

Share explained by AM: \( 1 - \frac{\beta |\psi| \alpha}{\beta \psi} \)
Approach I: Individual FE (α) as a Proxy for Skill

Firm-IGE:
\[ \log \hat{\psi}_i = \beta^\psi \cdot \log Y_f(i) + \epsilon^\psi_i \]

Controlled Firm-IGE:
\[ \log \hat{\psi}_i = \beta^\psi|\alpha \cdot \log Y_f(i) + \beta^\alpha \cdot \alpha_i + \epsilon^\psi_i|\alpha \]

▷ Assumptions:

A1 \( \alpha_i \) is unaffected by social capital (\( \theta^\alpha_S = 0 \))

A2 \( \alpha_i \) is estimated without measurement error (\( \eta^\alpha = 0 \))

A3 Human and social capital are uncorrelated, conditional on fathers’ earnings (\( \epsilon^H_i|Y_f \perp \perp \epsilon^S_i|Y_f \))

▷ Then:

Share explained by AM: \( 1 - \frac{\beta^\psi|\alpha}{\beta^\psi} = 51\% \)
Relaxing A1: $\alpha_i$ is Unaffected by Social Capital

Instead: social capital is *relatively* more important during job search than for explaining within-firm earnings differences

\[
\left( \frac{\theta^\psi_S}{\theta^\psi_H} \geq \frac{\theta^\alpha_S}{\theta^\alpha_H} \right)
\]

▷ Stinson and Wignall (2018); San (2020); Staiger (2021).
Relaxing A1: $\alpha_i$ is Unaffected by Social Capital

Instead: social capital is *relatively* more important during job search than for explaining within-firm earnings differences

$$\left( \frac{\theta^\psi_S}{\theta^\psi_H} \geq \frac{\theta^\alpha_S}{\theta^\alpha_H} \right)$$

▷ Stinson and Wignall (2018); San (2020); Staiger (2021).

▷ Provides upper bound to $\bar{AM}$: since controlling for $\alpha$ includes (some) social capital
Relaxing Assumptions A2 and A3 (Bias in OLS)

▷ A2: \( \alpha_i \) is estimated without measurement error (\( \epsilon^\alpha_i = 0 \))

▷ A3: Human and social capital are uncorrelated, conditional on fathers’ earnings (\( \epsilon^H_i | Y_f \perp \perp \epsilon^S_i | Y_f \))
Relaxing Assumptions A2 and A3 (Bias in OLS)

▷ A2: $\alpha_i$ is estimated without measurement error ($\epsilon_{i}^{\alpha} = 0$)

▷ A3: Human and social capital are uncorrelated, conditional on fathers’ earnings ($\epsilon_{i}^{H|Y_f} \perp \perp \epsilon_{i}^{S|Y_f}$)

Solution – instrument $\alpha$ with workers’ educ ($Z_i$):

Second stage:
$$\overline{\psi_i} = \tilde{\beta}_{\alpha} \cdot \hat{\alpha} + \tilde{\beta}_{Y_f} \cdot \overline{\log Y_f(i)} + \tilde{\epsilon}_{i}^{\psi}$$

First stage:
$$\alpha_i = \beta_{Z} \cdot Z_i + \beta_{Y_f} \cdot \overline{\log Y_f(i)} + \epsilon_{i}^{\alpha},$$

Why not split-sample?
Added Assumptions for IV

- Inclusion restriction: education positively correlated with human capital
- Standard exclusion restriction: education uncorrelated with social capital
  - Not realistic: college networks valuable in the labor market
    [Zimmerman (2019), Michelman et al. (2022), Chetty et al. (2022)]

\[ AM \leq 1 - e^{\beta \psi Y_f \beta \psi} \]
Added Assumptions for IV

▷ Inclusion restriction: education positively correlated with human capital

▷ Standard exclusion restriction: education uncorrelated with social capital
  → Not realistic: college networks valuable in the labor market
      [Zimmerman (2019), Michelman et al. (2022), Chetty et al. (2022)]
  ▷ Instead we assume: education is not negatively correlated with social capital
  ▷ Violated if: worse social capital as a result of going to college
Added Assumptions for IV

▷ Inclusion restriction: education positively correlated with human capital

▷ Standard exclusion restriction: education uncorrelated with social capital
  → Not realistic: college networks valuable in the labor market
  [Zimmerman (2019), Michelman et al. (2022), Chetty et al. (2022)]
  ▷ Instead we assume: education is *not* negatively correlated with social capital
  ▷ Violated if: worse social capital as a result of going to college

▷ We get:

\[
\bar{AM} \leq 1 - \frac{\bar{\beta}_Y \psi}{\bar{\beta} \psi},
\]
Share explained by AM is at most 74% of the firm-IGE
Approach II: Observable proxies

Unfeasible regressions of $H$ and $S$ on father earnings:

\[ \begin{align*}
H_i &= \beta_H \cdot \log(Y_f(i)) + \epsilon_{H_i} \\
S_i &= \beta_S \cdot \log(Y_f(i)) + \epsilon_{S_i}
\end{align*} \quad (\text{Regression A})
\]

→ If we knew the parameters of Regression A, we could calculate $AM$.

More unfeasible regressions:

\[ \begin{align*}
H_i &= \beta_H \cdot \log(Y_f(i)) + \beta_H \cdot E \cdot \text{Educ}_i + \beta_H \cdot D \cdot \text{Demog}_i + \epsilon_{H_i} \\
S_i &= \beta_S \cdot \log(Y_f(i)) + \beta_S \cdot E \cdot \text{Educ}_i + \beta_S \cdot D \cdot \text{Demog}_i + \epsilon_{S_i}
\end{align*} \quad (\text{Regression B})
\]

→ If we knew the parameters of Regression B, we could:

1. Predict $b_H$ and $b_S$
2. Use $b_H$ and $b_S$ to estimate Regression A
3. Calculate $AM$.
Approach II: Observable proxies

▷ Unfeasible regressions of $H$ and $S$ on father earnings:

\[
H_i = \beta^H \cdot \log Y_{f(i)} + \epsilon^H_i \\
S_i = \beta^S \cdot \log Y_{f(i)} + \epsilon^S_i
\] (Regression A)

→ If we knew the parameters of Regression A, we could calculate $\overline{AM}$

More unfeasible regressions:

\[
H_i = \beta^H \cdot Y_{f(i)} \cdot \log Y_{f(i)} + \beta^H \cdot E_{educ} + \beta^H \cdot D_{demog} + \epsilon^H_i \\
S_i = \beta^S \cdot Y_{f(i)} \cdot \log Y_{f(i)} + \beta^S \cdot E_{educ} + \beta^S \cdot D_{demog} + \epsilon^S_i
\]

→ If we knew the parameters of Regression B, we could:

1. Predict $b^H$ and $b^S$
2. Use $b^H$ and $b^S$ to estimate Regression A
3. Calculate $\overline{AM}$

Restrictions on Regression B ⇒ Restrictions on $\overline{AM}$
Approach II: Observable proxies

- Unfeasible regressions of $H$ and $S$ on father earnings:

  \[ H_i = \beta^H \cdot \log Y_{f(i)} + \epsilon_i^H \quad \text{(Regression A)} \]
  \[ S_i = \beta^S \cdot \log Y_{f(i)} + \epsilon_i^S \]

  → If we knew the parameters of Regression A, we could calculate $\overline{AM}$

- More unfeasible regressions:

  \[ H_i = \beta^H_{Y_f} \cdot \log Y_{f(i)} + \beta^H_E \cdot Educ_i + \beta^H_D \cdot Demog_i + \epsilon_i^H \quad \text{(Regression B)} \]
  \[ S_i = \beta^S_{Y_f} \cdot \log Y_{f(i)} + \beta^S_E \cdot Educ_i + \beta^S_D \cdot Demog_i + \epsilon_i^S \]
Approach II: Observable proxies

▷ Unfeasible regressions of $H$ and $S$ on father earnings:

\[
H_i = \beta^H \cdot \log Y_{f(i)} + \epsilon^H_i
\]  \hspace{1cm} (Regression A)

\[
S_i = \beta^S \cdot \log Y_{f(i)} + \epsilon^S_i
\]

→ If we knew the parameters of Regression A, we could calculate $AM$

▷ More unfeasible regressions:

\[
H_i = \beta^H_{Y_f} \cdot \log Y_{f(i)} + \beta^H_E \cdot \text{Educ}_i + \beta^H_D \cdot \text{Demog}_i + \epsilon^H_i
\]  \hspace{1cm} (Regression B)

\[
S_i = \beta^S_{Y_f} \cdot \log Y_{f(i)} + \beta^S_E \cdot \text{Educ}_i + \beta^S_D \cdot \text{Demog}_i + \epsilon^S_i
\]

→ If we knew the parameters of Regression B, we could:

1. Predict $\hat{H}$ and $\hat{S}$
Approach II: Observable proxies

▷ Unfeasible regressions of $H$ and $S$ on father earnings:

\[
H_i = \beta^H \cdot \log Y_{f(i)} + \epsilon^H_i \\
S_i = \beta^S \cdot \log Y_{f(i)} + \epsilon^S_i
\]

(Regression A)

→ If we knew the parameters of Regression A, we could calculate $\overline{AM}$

▷ More unfeasible regressions:

\[
H_i = \beta^H_{Y_f} \cdot \log Y_{f(i)} + \beta^H_E \cdot \text{Educ}_i + \beta^H_D \cdot \text{Demog}_i + \epsilon^H_i \\
S_i = \beta^S_{Y_f} \cdot \log Y_{f(i)} + \beta^S_E \cdot \text{Educ}_i + \beta^S_D \cdot \text{Demog}_i + \epsilon^S_i
\]

(Regression B)

→ If we knew the parameters of Regression B, we could:

1. Predict $\hat{H}$ and $\hat{S}$
2. Use $\hat{H}$ and $\hat{S}$ to estimate Regression A
Approach II: Observable proxies

▷ Unfeasible regressions of $H$ and $S$ on father earnings:

\[ H_i = \beta^H \cdot \log Y_{f(i)} + \epsilon_i^H \]  \hspace{1cm} (Regression A)
\[ S_i = \beta^S \cdot \log Y_{f(i)} + \epsilon_i^S \]

→ If we knew the parameters of Regression A, we could calculate $\overline{AM}$

▷ More unfeasible regressions:

\[ H_i = \beta^H_{Y_f} \cdot \log Y_{f(i)} + \beta^H_E \cdot \text{Educ}_i + \beta^H_D \cdot \text{Demog}_i + \epsilon_i^H \]  \hspace{1cm} (Regression B)
\[ S_i = \beta^S_{Y_f} \cdot \log Y_{f(i)} + \beta^S_E \cdot \text{Educ}_i + \beta^S_D \cdot \text{Demog}_i + \epsilon_i^S \]

→ If we knew the parameters of Regression B, we could:

1. Predict $\hat{H}$ and $\hat{S}$
2. Use $\hat{H}$ and $\hat{S}$ to estimate Regression A
3. Calculate $\overline{AM}$
Approach II: Observable proxies

▷ Unfeasible regressions of $H$ and $S$ on father earnings:

\[
H_i = \beta^H \cdot \log Y_{f(i)} + \epsilon_i^H \\
S_i = \beta^S \cdot \log Y_{f(i)} + \epsilon_i^S
\]

(Regression A)

→ If we knew the parameters of Regression A, we could calculate $\overline{AM}$

▷ More unfeasible regressions:

\[
H_i = \beta^H \cdot \log Y_{f(i)} + \beta^H \cdot Educ_i + \beta^H \cdot Demog_i + \epsilon_i^H \\
S_i = \beta^S \cdot \log Y_{f(i)} + \beta^S \cdot Educ_i + \beta^S \cdot Demog_i + \epsilon_i^S
\]

(Regression B)

→ If we knew the parameters of Regression B, we could:

1. Predict $\hat{H}$ and $\hat{S}$
2. Use $\hat{H}$ and $\hat{S}$ to estimate Regression A
3. Calculate $\overline{AM}$

▷ Restrictions on Regression B $\Rightarrow$ Restrictions on $\overline{AM}$
Bounding the parameters of Regression B

\[ \begin{align*}
H_i &= \beta^H_{Y_f} \cdot \log Y_{f(i)} + \beta^H_E \cdot Educ_i + \beta^H_D \cdot Demog_i + \epsilon^H_i \\
S_i &= \beta^S_{Y_f} \cdot \log Y_{f(i)} + \beta^S_E \cdot Educ_i + \beta^S_D \cdot Demog_i + \epsilon^S_i
\end{align*} \quad \text{(Regression B)} \]
Bounding the parameters of Regression B

\[ H_i = \beta^H_{Y_f} \cdot \log Y_{f(i)} + \beta^H_E \cdot \text{Educ}_i + \beta^H_D \cdot \text{Demog}_i + \epsilon^H_i \]  

\[ S_i = \beta^S_{Y_f} \cdot \log Y_{f(i)} + \beta^S_E \cdot \text{Educ}_i + \beta^S_D \cdot \text{Demog}_i + \epsilon^S_i \]  

▷ Observed: Joint distribution of \((\alpha, \psi, \log Y_f, \text{Educ}, \text{Demog})\)
- Not enough because \((\alpha, \psi) \neq (H, S)\)
Bounding the parameters of Regression B

\[ H_i = \beta^H_{Y_f} \cdot \log Y_{f(i)} + \beta^H_E \cdot \text{Educ}_i + \beta^H_D \cdot \text{Demog}_i + \epsilon^H_i \]  
\[ S_i = \beta^S_{Y_f} \cdot \log Y_{f(i)} + \beta^S_E \cdot \text{Educ}_i + \beta^S_D \cdot \text{Demog}_i + \epsilon^S_i \]  

- Observed: Joint distribution of \((\alpha, \psi, \log Y_f, \text{Educ}, \text{Demog})\)
  - Not enough because \((\alpha, \psi) \neq (H, S)\)

- Assumptions:
  Baseline: \( \beta^H_D = 0 \) and \( \beta^S_E = 0 \)
Bounding the parameters of Regression B

\[ H_i = \beta^H_{Y_f} \cdot \log Y_{f(i)} + \beta^H_E \cdot Educ_i + \beta^H_D \cdot Demog_i + \epsilon^H_i \]  
\[ S_i = \beta^S_{Y_f} \cdot \log Y_{f(i)} + \beta^S_E \cdot Educ_i + \beta^S_D \cdot Demog_i + \epsilon^S_i \]  

▷ Observed: Joint distribution of \((\alpha, \psi, \log Y_f, Educ, Demog)\)
  - Not enough because \((\alpha, \psi) \neq (H, S)\)

▷ Assumptions:

Baseline: \( \beta^H_D = 0 \) and \( \beta^S_E = 0 \)

Bounds I: \( 0 \leq \beta^H_D \leq \beta^S_D \) and \( \beta^S_E = 0 \)
Bounding the parameters of Regression B

\[ H_i = \beta_{Yf}^H \cdot \log Y_{f(i)} + \beta_{E}^H \cdot Educi + \beta_{D}^H \cdot Demogi + \epsilon_i^H \]

\[ S_i = \beta_{Yf}^S \cdot \log Y_{f(i)} + \beta_{E}^S \cdot Educi + \beta_{D}^S \cdot Demogi + \epsilon_i^S \]

▷ Observed: Joint distribution of \((\alpha, \psi, \log Y_f, Educ, Demog)\)
  - Not enough because \((\alpha, \psi) \neq (H, S)\)

▷ Assumptions:

Baseline: \(\beta_{D}^H = 0\) and \(\beta_{E}^S = 0\)

Bounds I: \(0 \leq \beta_{D}^H \leq \beta_{D}^S\) and \(\beta_{E}^S = 0\)

Bounds II: \(0 \leq \beta_{D}^H \leq \beta_{D}^S\) and \(\beta_{E}^S \geq 0\)
Observable Proxies Approach: Different Assumptions, Similar Result

Total effect of firms

Method

OLS (Controlled Firm-IGE)
2SLS
Baseline
Bounds I
Bounds II (Observable Proxies)

Robustness
Observable Proxies Approach: The AM is at most 53% of the firm-IGE.
Conclusion
Conclusion

- Wealthier children work in better-paying firms (firm-IGE)
  - Firm-IGE = 22% of the IGE

- Transmission of social status goes beyond productivity and skills
- Labor market segregation contributes to inter-generational mobility
- Expanding access to high-paying firms is key to improve mobility
Conclusion

- Wealthier children work in better-paying firms (firm-IGE)
  - Firm-IGE = 22% of the IGE
  - Education → explains individual-IGE
  - Ethnicity, Neighborhoods → explains firm-IGE
Conclusion

Wealthier children work in better-paying firms (firm-IGE)

- Firm-IGE = 22% of the IGE
- Education → explains individual-IGE
- Ethnicity, Neighborhoods → explains firm-IGE
- Around half of firm-IGE due to skill-based sorting
Conclusion

▷ Wealthier children work in better-paying firms (firm-IGE)
  - Firm-IGE = 22% of the IGE
  - Education → explains individual-IGE
  - Ethnicity, Neighborhoods → explains firm-IGE
  - Around half of firm-IGE due to skill-based sorting

▷ Implications
  - Transmission of social status goes beyond productivity and skills
  - Labor market segregation contributes to inter-generational mobility
  - Expanding access to high-paying firms is key to improve mobility
THE END!
Appendix
<table>
<thead>
<tr>
<th>Demographic Groups (%)</th>
<th>Full Sample</th>
<th>IGM Sample</th>
<th>IGM-AKM Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arab</td>
<td>20.1</td>
<td>14.9</td>
<td>13.8</td>
</tr>
<tr>
<td>Ashkenaz</td>
<td>21.2</td>
<td>22.3</td>
<td>22.7</td>
</tr>
<tr>
<td>Ethiopian</td>
<td>0.3</td>
<td>0.3</td>
<td>0.5</td>
</tr>
<tr>
<td>Sepharadic</td>
<td>35.9</td>
<td>39.9</td>
<td>39.8</td>
</tr>
<tr>
<td>Ultra-Orthodox Jew</td>
<td>5.0</td>
<td>3.3</td>
<td>3.6</td>
</tr>
<tr>
<td>USSR</td>
<td>4.7</td>
<td>4.9</td>
<td>5.3</td>
</tr>
<tr>
<td>Missing</td>
<td>12.7</td>
<td>14.4</td>
<td>14.3</td>
</tr>
<tr>
<td>College Educated (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>39.3</td>
<td>49.6</td>
<td>52.5</td>
</tr>
<tr>
<td>Earnings</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean of log-earnings</td>
<td>11.59</td>
<td>11.67</td>
<td></td>
</tr>
<tr>
<td>Mean of father's log-earnings</td>
<td>10.70</td>
<td>10.74</td>
<td></td>
</tr>
</tbody>
</table>
Most fathers observed between 30 and 50 years old
Persistence is driven by fathers’ earnings

\[ \text{rank}(\text{family earnings}) = \beta \cdot \text{rank}(\text{child earnings}) \]

<table>
<thead>
<tr>
<th>Family Earnings Measure</th>
<th>Household</th>
<th>Father</th>
<th>Mother</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>.23</td>
<td>.246</td>
<td>.093</td>
</tr>
<tr>
<td></td>
<td>(.003)</td>
<td>(.003)</td>
<td>(.003)</td>
</tr>
<tr>
<td>Obs</td>
<td>156555</td>
<td>156555</td>
<td>156555</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>.049</td>
<td>.055</td>
<td>.008</td>
</tr>
</tbody>
</table>
The log-linear structure implies:

$$\mathbb{E}[\Delta w_{i,t} - \Delta X_{i,t} \cdot \beta] = \mathbb{E}[\Delta \psi_{J[i,t]}].$$

Taking it to the data:

The diagram shows a linear relationship between change in earnings (ΔY) and change in firm premiums (Δψ). The slope is given as 0.86 (0.00).
### Correlation between firm premiums in different samples

<table>
<thead>
<tr>
<th></th>
<th>Full</th>
<th>IGM</th>
<th>Random (Full)</th>
<th>Random (IGM) (IGM)</th>
<th>Low-SES</th>
<th>High-SES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IGM</td>
<td>0.86</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random (Full)</td>
<td>0.89</td>
<td>0.76</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random (IGM)</td>
<td>0.80</td>
<td>0.91</td>
<td>0.74</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low-SES</td>
<td>0.77</td>
<td>0.89</td>
<td>0.71</td>
<td>0.80</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>High-SES</td>
<td>0.82</td>
<td>0.93</td>
<td>0.77</td>
<td>0.86</td>
<td>0.70</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Variance Decomposition

\[ \text{Var}( \log Y_{it} ) = \underbrace{\text{Var}(\alpha_i)}_{\text{individual comp.}} + \underbrace{\text{Var}(\psi_{J(i,t)})}_{\text{firm comp.}} + \underbrace{2 \cdot \text{Cov}(\alpha_i, \psi_{J(i,t)})}_{\text{sorting}} \]

\[ + \underbrace{\text{Var}(x_{it}'\beta^x)}_{\text{covariates and residual}} + 2 \cdot \text{Cov}(x_{it}'\beta^x, \alpha_i + \psi_{J(i,t)}) + \underbrace{\text{Var}(r_{i,t})}_{\text{covariates and residual}} \]
Variance Decomposition

\[
\text{Var}(\log Y_{it}) = \underbrace{\text{Var}(\alpha_i)}_{\text{individual comp.}} + \underbrace{\text{Var}(\psi_{J(i,t)})}_{\text{firm comp.}} + 2 \cdot \underbrace{\text{Cov}(\alpha_i, \psi_{J(i,t)})}_{\text{sorting}} + \underbrace{\text{Var}(x_{it}'\beta^x) + 2 \cdot \text{Cov}(x_{it}'\beta^x, \alpha_i + \psi_{J(i,t)}) + \text{Var}(r_{i,t})}_{\text{covariates and residual}}
\]

<table>
<thead>
<tr>
<th>Variance components:</th>
<th>AKM Sample</th>
<th>IGM-AKM Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual component ( \text{Var}(\alpha) )</td>
<td>0.78</td>
<td>0.70</td>
</tr>
<tr>
<td>Firm component ( \text{Var}(\psi) )</td>
<td>0.11</td>
<td>0.10</td>
</tr>
<tr>
<td>Sorting ( \text{Cov}(\alpha, \psi) )</td>
<td>0.16</td>
<td>0.19</td>
</tr>
<tr>
<td>Covariates and residual</td>
<td>-0.05</td>
<td>0.01</td>
</tr>
</tbody>
</table>
Estimating Intergenerational Elasticity of Earnings (IGE)

Child’s earnings (taking out age effects):

\[ \log \tilde{Y}_{it} \equiv \alpha_i + \psi_{J(i,t)} + r_{i,t}. \]
Estimating Intergenerational Elasticity of Earnings (IGE)

Child’s earnings (taking out age effects):

\[ \log \tilde{Y}_{it} \equiv \alpha_i + \psi_{J(i,t)} + r_{i,t}. \]

Parent’s earnings (since can’t est. AKM for them):

\[ \log Y_{it} = \begin{cases} x_{it}' \beta^x + \log \tilde{Y}_{it}, \quad \text{covariates} \\ \text{residual} \end{cases} \]
Estimating Intergenerational Elasticity of Earnings (IGE)

Child’s earnings (taking out age effects):

\[ \log \tilde{Y}_{it} \equiv \alpha_i + \psi_{J(i,t)} + r_{i,t}. \]

Parent’s earnings (since can’t est. AKM for them):

\[
\log Y_{it} = \underbrace{x_{it}' \beta_x} + \underbrace{\log \tilde{Y}_{it}},
\]

Average net earnings:

\[
\log Y_i \equiv \frac{1}{N_i} \sum_{t \in \mathcal{T}_i} \log \tilde{Y}_{it}
\]

IGE:

\[
\log Y_i = \beta_0^{IGE} + \beta^{IGE} \cdot \log Y_f(i) + \epsilon_i^{IGE}
\]
Decomposing the IGE: Proof

\[ \log Y_i \equiv \frac{1}{N_i} \sum_{t \in \mathcal{T}_i} \log \tilde{Y}_{it} \]

\[ = \frac{1}{N_i} \sum_{t \in \mathcal{T}_i} \left\{ \alpha_i + \psi_{J(i,t)} + r_{i,t} \right\} \]

\[ = \frac{1}{N_i} \sum_{t \in \mathcal{T}_i} \alpha_i + \frac{1}{N_i} \sum_{t \in \mathcal{T}_i} \psi_{J(i,t)} + \frac{1}{N_i} \sum_{t \in \mathcal{T}_i} r_{i,t} \]

\[ = \alpha_i + \bar{\psi}_i + 0 \]

\[ = \alpha_i + \bar{\psi}_i. \]
Decomposing the IGE: Proof

\[
\beta^{IGE} = \frac{\text{Cov} \left( \log Y_i, \log Y_{f(i)} \right)}{\text{Var} \left( \log Y_{f(i)} \right)}
\]

\[
= \frac{\text{Cov} \left( \alpha_i + \psi_i, \log Y_{f(i)} \right)}{\text{Var} \left( \log Y_{f(i)} \right)}
\]

\[
= \frac{\text{Cov} \left( \alpha_i, \log Y_{f(i)} \right)}{\text{Var} \left( \log Y_{f(i)} \right)} + \frac{\text{Cov} \left( \psi_i, \log Y_{f(i)} \right)}{\text{Var} \left( \log Y_{f(i)} \right)}
\]

\[
= \beta^\alpha|Y_f + \beta^\psi|Y_f
\]
Rank-Rank IGM

Source: Israeli National Insurance
Individual and Firm IGM (Ranks)

Correlation = 0.24

Correlation = 0.27
Decomposing the Role of Assortative Matching in IGM

Consider 3 regressions:

1. Firm premiums on father's earnings:
   \[ \hat{\psi}_i = \beta_{\psi} \cdot \log Y_{f(i)} + \epsilon_{\psi} \]

Using these cross-elasticities to decompose the role of firms:

\[ \beta_{\psi} = \beta_{\psi\alpha} \cdot \beta_{\alpha} Y_{f} |_{\{z\}} + \beta_{\psi Y_{f}} |_{\{z\}} \]
Decomposing the Role of Assortative Matching in IGM

Consider 3 regressions:

1. Firm premiums on father's earnings:

\[ \hat{\psi}_i = \beta_\psi \cdot \log Y_{f(i)} + \epsilon_\psi_i \]

2. Worker FE on father's income:

\[ \hat{\alpha}_i = \beta_\alpha \cdot \log Y_{f(i)} + \epsilon_\alpha_i \]
Decomposing the Role of Assortative Matching in IGM

▷ Consider 3 regressions:

1. Firm premiums on father’s earnings:

\[
\hat{\psi}_i = \beta^\psi \cdot \log Y_f(i) + \epsilon^\psi_i
\]

2. Worker FE on father’s income:

\[
\hat{\alpha}_i = \beta^\alpha \cdot \log Y_f(i) + \epsilon^\alpha_i
\]

3. Firm premium on worker FE and father’s earnings (cross-elasticities):

\[
\hat{\psi}_i = \beta^\psi \cdot \alpha_i + \beta^\psi \cdot \log Y_f(i) + \eta^\psi_i
\]
Decomposing the Role of Assortative Matching in IGM

Consider 3 regressions:

1. Firm premiums on father's earnings:
   \[ \hat{\psi}_i = \beta^\psi \cdot \log Y_f(i) + e^\psi_i \]

2. Worker FE on father's income:
   \[ \hat{\alpha}_i = \beta^\alpha \cdot \log Y_f(i) + e^\alpha_i \]

3. Firm premium on worker FE and fathers earnings (cross-elasticites):
   \[ \hat{\psi}_i = \beta^\psi \cdot \alpha_i + \beta^\psi \cdot \log Y_f(i) + \eta^\psi_i \]

Using these cross-elasticities to decompose the role of firms:

\[ \beta^\psi = \underbrace{\beta^\alpha \cdot \beta^\psi_{Y_f}}_{\text{Assortative Matching}} + \underbrace{\beta^\psi_{Y_f}}_{\text{SES}} \]
## Firm earnings premium and father’s earnings

**Dependent variable: Firm earnings premium ($\bar{\bar{Y}}_i$)**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log Y_{f(i)}$</td>
<td>0.056</td>
<td>0.027</td>
<td>0.014</td>
<td>0.014</td>
<td>0.011</td>
<td>0.015</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Control</th>
<th>Instrument</th>
<th>Quality Measure</th>
<th>$\alpha$</th>
<th>Has Higher Ed</th>
<th>$\alpha$</th>
<th>Higher Ed Quality</th>
<th>Father Inc</th>
<th>$\alpha$</th>
<th>Higher Ed Quality</th>
<th>Own Inc</th>
<th>$\alpha$</th>
<th>Higher Ed Quality</th>
<th>Share Stable Job</th>
<th>$\alpha$</th>
<th>Higher Ed Quality</th>
<th>Higher Ed Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-stat</td>
<td>775,977</td>
<td>1,098,853</td>
<td>1,109,100</td>
<td>700,612</td>
<td>174,159</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>595,493</td>
<td>595,493</td>
<td>595,493</td>
<td>595,493</td>
<td>595,493</td>
<td>595,493</td>
<td>595,493</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Assortative matching – Robustness

\[ \beta_\psi = \beta_H^\psi \cdot \beta_H + \beta_S^\psi \cdot \beta_S \]

- assortative matching
- SES-effect

Total effect of firms

<table>
<thead>
<tr>
<th>Instrumental Variable</th>
<th>Assortative Matching (% of IGE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Has Higher Ed</td>
<td>16.5</td>
</tr>
<tr>
<td>Higher Ed Father’s Income</td>
<td>17.2</td>
</tr>
<tr>
<td>Higher Ed Quality By Own Income</td>
<td>18.0</td>
</tr>
<tr>
<td>Higher Ed Quality Share Stable Job</td>
<td>17.3</td>
</tr>
<tr>
<td>Higher Ed Type</td>
<td>18.5</td>
</tr>
</tbody>
</table>
## Assortative matching

<table>
<thead>
<tr>
<th></th>
<th>Dep. Var.: Firm Earnings Premium</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>log(Father’s Earnings)</td>
<td>0.064</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td>Individual Earnings FE</td>
<td>0.135</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td># Obs</td>
<td>184,431</td>
</tr>
</tbody>
</table>
Why Not Split-Sample Instrument?

\[
\log Y_{i,t} = \alpha_i + \psi_{J(i,t)} + x_{it}'\beta_x + r_{i,t},
\]

- **Individual component**: \(\alpha_i\)
- **Firm component**: \(\psi_{J(i,t)}\)
- **Covariates**: \(x_{it}'\beta_x\)
- **Error term**: \(r_{i,t}\)

\[
r_{i,t} = \eta_{iJ(i,t)}^M + \zeta_{it} + \eta_{it}^T.
\]

- **Matching component** – \(\eta_{ij}^M\):
  - constant across time, mean zero across workers and firms
- **Idiosyncratic shocks** – \(\eta_{it}^T, \eta_{it}^P\)
- **Permanent worker-level shock** – \(\zeta_{it}^P\):
  \[
  \zeta_{it}^P = \zeta_{i,t-1}^P + \eta_{it}^P
  \]
Split Sample Instrument for Firm Premiums

\[ y_{it} = \beta_0^{y|\psi} + \beta^{y|\psi} \cdot \psi_{J(i,t)} + \epsilon_{it}^{y|\psi}, \]

- Problem - attenuation bias: we use estimated firm premiums (since they are unobserved)
Split Sample Instrument for Firm Premiums

\[ y_{it} = \beta^y_0 + \beta^y \cdot \psi_{J(i,t)} + \epsilon_{it} \]

▷ Problem - attenuation bias: we use estimated firm premiums (since they are unobserved)

▷ Solution: split sample, and 2SLS using \( \psi_{J(i,t)} \) of each regression
  ▷ Measurement error is uncorrelated in both sample
  ▷ All the elements of the error term are uncorrelated across workers, and are estimated using different workers

Second stage:
\[ y_{it} = \beta^y_0 + \beta^y \cdot \widehat{\psi}^1_{J(i,t)} + \epsilon_{it}^1 \]

First stage:
\[ \widehat{\psi}^1_{J(i,t)} = \beta^\psi_0^1 \cdot \psi^2 + \beta^\psi^1 \cdot \widehat{\psi}^2_{J(i,t)} + \epsilon_{it}^1 \]
\[(No) \text{ Instrument for Individual Effect}\]

\[y_i = \beta^y_{0|\alpha} + \beta^y_{\alpha|\alpha} \cdot \alpha_i + \epsilon^y_{\alpha|\alpha},\]

- Same problem - attenuation bias: we use estimated individual effect (since they are unobserved)
- Cannot split the sample by worker – no \(\alpha\)'s estimated in both samples
(No) Instrument for Individual Effect

\[ y_i = \beta_0^{y|\alpha} + \beta^{y|\alpha} \cdot \alpha_i + e_i^{y|\alpha}, \]

- Same problem - attenuation bias: we use *estimated* individual effect (since they are unobserved)
- Cannot split the sample by worker – no \( \alpha \)'s estimated in both samples
- Split sample by years? No, measurement error will be correlated
  - Matching component (same workers and firms in the two samples)
  - Permanent shock (same workers in the two samples)
(No) Instrument for Individual Effect

\[ y_i = \beta_{0y|\alpha} + \beta_{y|\alpha} \cdot \alpha_i + \epsilon_{y|\alpha}, \]

▷ Same problem - attenuation bias: we use estimated individual effect (since they are unobserved)

▷ Cannot split the sample by worker – no \( \alpha \)'s estimated in both samples

▷ Split sample by years? No, measurement error will be correlated
  ▷ Matching component (same workers and firms in the two samples)
  ▷ Permanent shock (same workers in the two samples)

▷ Split sample by firm? No, permanent shock still correlated (same workers in two samples)
No relationship b/t search time and parental income
Correlates of future firm

- Sample: movers
- Current firm predicts future firm
- Father's earnings predicts future firm, after controlling for current firm

<table>
<thead>
<tr>
<th>Dependent Variable: $\psi_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>$\psi_0$</td>
</tr>
<tr>
<td>$q$</td>
</tr>
</tbody>
</table>

Observations: 157,852

$R^2$: 0.319, 0.038, 0.327

Note: *p<0.1; **p<0.05; ***p<0.01
Correlates of change in earnings premium

<table>
<thead>
<tr>
<th></th>
<th>Model: Only Pref</th>
<th>Model: Only Pref</th>
<th>Model</th>
<th>Model</th>
<th>Model</th>
<th>Data</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \psi &gt; 0$</td>
<td>$\Delta \psi$</td>
<td>$\Delta \psi &gt; 0$</td>
<td>$\Delta \psi$</td>
<td>$\Delta \psi &gt; 0$</td>
<td>$\Delta \psi$</td>
<td>$\Delta \psi$</td>
<td></td>
</tr>
<tr>
<td>$\psi_0$</td>
<td>$-1.395^{***}$</td>
<td>$-0.979^{***}$</td>
<td>$-1.369^{***}$</td>
<td>$-0.976^{***}$</td>
<td>$-0.524^{***}$</td>
<td>$-0.431^{***}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.005)</td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>$q$</td>
<td>$-0.013^{***}$</td>
<td>$-0.009^{***}$</td>
<td>0.153***</td>
<td>0.114***</td>
<td>0.136***</td>
<td>0.078***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.501***</td>
<td>0.007***</td>
<td>0.522***</td>
<td>0.007***</td>
<td>0.566***</td>
<td>0.029***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.0003)</td>
<td>(0.001)</td>
<td>(0.0003)</td>
<td>(0.001)</td>
<td>(0.0005)</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.320</td>
<td>0.488</td>
<td>0.311</td>
<td>0.486</td>
<td>0.056</td>
<td>0.198</td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
Inequality & Ethnicity in Israel

- Israel is one of the most unequal countries in the OECD, second only to the United States in terms of disposable income inequality.

- This high inequality is commonly attributed to the SES disadvantages and high unemployment rates experienced by two segregated communities:
  - Israeli-Arab
  - Ultra-Orthodox Jews
IGE by Demog. & Educ.

![Graph 1: Log(earnings) vs. Log(father's earnings) for Higher Ed and No Higher Ed groups.]

![Graph 2: Log(earnings) vs. Log(father's earnings) for Secular Jews, Ultra-Orthodox Jews, and Israeli-Arabs groups.]

firm-IGE
Firm-IGE by Educ. & Demog.
Individual-IGE by Educ. & Demog.

- **Graph 1:**
  - Title: Individual Component ($\alpha$)
  - X-axis: Log (father's earnings)
  - Y-axis: Individual Component ($\alpha$)
  - Legend:
    - Higher Ed
    - No Higher Ed

- **Graph 2:**
  - Title: Individual Component ($\alpha$)
  - X-axis: Log (father's earnings)
  - Y-axis: Individual Component ($\alpha$)
  - Legend:
    - Secular Jew
    - Israeli-Arab
    - Ultra-Orthodox Jew
The Importance of Segregation

▷ Location:
  ▷ High-SES individuals tend to live around other high-SES individuals  
  ▷ Neighbors of high-SES individuals work in better-paying firms  

▷ Demographic groups:
  ▷ Israeli-Arabs and Ultra-Orthodox Jews work in lower earnings-premium firms than secular Jews  
  ▷ High segregation between these two demographic groups and secular-Jews
Firm earnings premium and father’s earnings

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log Y_{f(i)}$</td>
<td>0.056</td>
<td>0.029</td>
<td>0.032</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
</tbody>
</table>

Control Settlement FE Demographic Group FE

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>595,493</td>
<td>571,896</td>
<td>595,493</td>
</tr>
</tbody>
</table>
Distribution of Neighbors’ SES by Own SES Background

![Heatmap showing the distribution of Neighbors' Father's Earnings Quartile by Own Father's Earnings Quartile]

- **Share within Location**: 20, 24, 28, 32
- **Values**:
  - Q1: 31.9, 27, 22.3, 18.6
  - Q2: 26.5, 25.9, 23.7, 21.9
  - Q3: 22.5, 24.4, 26.5, 27.1
  - Q4: 19.1, 22.8, 27.4, 32.4

**Legend**: Darker colors indicate higher percentages.
Richer Children’s Neighbors’ Earn High Firm Premiums

![Bar chart showing firm premiums by father income quartile]

- **Q1**: Neighborhood Average: 0.04, Own: 0.03
- **Q2**: Neighborhood Average: 0.05, Own: 0.045
- **Q3**: Neighborhood Average: 0.06, Own: 0.055
- **Q4**: Neighborhood Average: 0.10, Own: 0.10

Legend:
- **Blue**: Neighborhood Average
- **Orange**: Own

The chart illustrates that as father income quartile increases, the firm premium also increases, with richer neighbors earning higher premiums compared to their own income levels.
Population Density of Log Father’s Earnings

- Secular Jews
- Ultra-Orthodox Jews
- Israeli-Arabs
### Firm earnings premium and father’s earnings

<table>
<thead>
<tr>
<th>Dependent variable: Firm earnings premium ($\psi_i$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>$logY_f(i)$</td>
</tr>
<tr>
<td>(0.000)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Control</th>
<th>$\alpha$</th>
<th>Instrument</th>
<th>$\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Has Higher Ed</td>
<td>775,977</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>F-stat</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>595,493</td>
<td>595,493</td>
</tr>
</tbody>
</table>

Robust to other instruments accounting for differences in education quality
## Firm earnings premium and father’s earnings

### Dependent variable: Firm earnings premium ($\psi_i$)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\log Y_f(i))</td>
<td>0.056</td>
<td>0.017</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Control</th>
<th>Instrument</th>
<th>(\alpha)</th>
<th>Has Higher Ed</th>
<th>F-stat</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(\alpha)</td>
<td>Has Higher Ed</td>
<td>775,977</td>
<td>595,493</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>595,493</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>595,493</td>
</tr>
</tbody>
</table>

- Robust to other instruments accounting for differences in education quality
1. Separating four states: stable job, temporary job, self-employed, and non-employed
   ▶ Focus on rank-rank rather than IGE (deal with non-employment)
   ▶ Non-employment is important for IGM, yet excluded from measurement

2. Suggest a method to correct IGM measures
Define Employment States

- Stable job: worked at least 5 months, and earned 2 months of min wage in a year

- Temporary job: working in a non-stable job

- Self-employed: reported in tax records
Define Employment States

- Stable job: worked at least 5 months, and earned 2 months of min wage in a year
- Temporary job: working in a non-stable job
- Self-employed: reported in tax records
- Non-employed: receiving unemployment insurance, or with zero/unreported earnings
IGM in % Months Employed by Employment Type

![Graph showing IGM in % Months Employed by Employment Type](image-url)
Define Employment States

▷ Stable job: worked at least 5 months, and earned 2 months of min wage a year

▷ Temporary job: working in a non-stable job

▷ Self-employed: reported in tax records

▷ Non-employed: receiving unemployment insurance, or with zero/unreported earnings
  ▷ Never in stable job
  ▷ Always non-employed
IGM in % Non-Employed Type

![Graph showing the share of workers by father's earnings' rank, with two lines representing 'Never in Stable Job' and 'Always Non-Employed'. The x-axis represents father's earnings' rank from 0.00 to 1.00, and the y-axis represents the share of workers from 0.00 to 0.40. The legend indicates blue triangles for 'Never in Stable Job' and orange dots for 'Always Non-Employed'.]
Takeaways

▷ Job stability plays an important part in IGM measurement

▷ Kids from low-income families are more likely to be non-employed and less likely to be in a stable job

▷ These differences are driven by the differences in labor force participation
Next Step - Correct the Measure

1. Impute rank zero for non-employed
   ▷ Can only do in rank-rank, not IGE
   ▷ What about transfers and informal employment?
Next Step - Correct the Measure

1. Impute rank zero for non-employed
   ▶ Can only do in rank-rank, not IGE
   ▶ What about transfers and informal employment?

2. Compliment with survey data
   ▶ Measure employment level within a bin: zipcode X gender X ethnicity
   ▶ Compare the measure from tax vs survey data
   ▶ Impute other income sources (transfers and informal)
Relaxing Assumptions

- If the individual is observed in the admin data (i.e. formal), she doesn't work in the informal sector
  - Use information from survey data: \( \text{Pr(formal and informal \mid bin)} \)
Relaxing Assumptions

▷ If the individual is observed in the admin data (i.e. formal), she doesn’t work in the informal sector

▷ Use information from survey data: Pr(formal and informal | bin)

▷ Within a bin (zipcode X gender X ethnicity): the share of individuals working informally is constant across parental earnings level

▷ This could be relaxed by using the existing nonemp-IGM relationship within a bin in the admin data

▷ Alternative assumption on the relationship between informal income and parental earnings within the bin
Education Explains More of the Individual-IGE

**Education**

- Graph showing individual component ($\alpha$) against log(father's earnings) for education.
  - Two categories: Higher Ed and No Higher Ed.

**Demographics**

- Graph showing individual component ($\alpha$) against log(father's earnings) for demographic groups.
  - Groups include Secular Jew, Israeli-Arab, and Ultra-Orth Jew.

Back
Demographics Explains More of the Firm-IGE

**Education**

Firm premium ($\psi$) vs. log(father's earnings)

- **Education**
  - Higher Ed
  - No Higher Ed

**Demographics**

Firm premium ($\psi$) vs. log(father's earnings)

- **Demographic Group**
  - Secular Jew
  - Israeli-Arab
  - Ultra-Orth Jew
Secular Jews and Higher Ed Children Earn More Regardless of SES

Education

Demographics

\[ \text{log(earnings)} \]

\[ \text{log(father's earnings)} \]

- Higher Ed
- No Higher Ed

- Secular Jews
- Arab
- Ultra-Orthodox Jews
Share of Intergenerational Elasticities Explained by Observables

\[
\log \text{Outcome}_i = \beta^O \cdot \log Y_{f(i)} + \epsilon_i^O
\]

\[
\log \text{Outcome}_i = \beta^{O|X} \cdot \log Y_{f(i)} + \gamma X + \epsilon_i^{O|X}
\]

Share explained by \(X\): \(1 - \frac{\beta^{O|X}}{\beta^O}\)

- \(\text{Outcome}_i\): outcome of interest
  - \(\alpha_i, \psi_i\)

- \(X_i\): explanatory variable
  - Education, Demographics
Firm-IGE is Related Mostly to Demog. & Neighborhoods

![Bar Chart]

- **Education**
  - Firm-IGE: 0.30
  - Individual-IGE: 0.40

- **Demographics**
- **Comm. Zone**
- **Neighborhood**

**Explanatory Variables**
- **Share of IGE Explained**

[@Page] {44 / 47}
Firm-IGE is Related Mostly to Demog. & Neighborhoods

The diagram shows the share of IGE explained by different explanatory variables. The explanatory variables include Education, Demographics, Comm. Zone, and Neighborhood. The bar chart compares Firm-IGE and Individual-IGE, with Firm-IGE generally showing higher shares of IGE explained.
Firm-IGE is Related Mostly to Demog. & Neighborhoods

[Bar chart showing the share of IGE explained by education, demographics, community zone, and neighborhood. The chart compares Firm-IGE and Individual-IGE.]
Firm-IGE is Related Mostly to Demog. & Neighborhoods

The bar chart illustrates the share of IGE explained by different explanatory variables. The variables include Education, Demographics, Commercial Zone, and Neighborhood. The chart compares the share explained by Firm-IGE and Individual-IGE.
Firm Segregation: % of Secular Jewish Co-workers by Parental Inc.
Firm Segregation: % of Secular Jewish Co-workers by Demog. Groups
Firm Segregation: % of Orthodox Co-workers by Demog. Groups
Share of Demographic-IGE Explained by Observables

\[
\log Dem_i = \beta^O \cdot \log Y_{f(i)} + \epsilon_i^O
\]

\[
\log Dem_i = \beta^{O|X} \cdot \log Y_{f(i)} + \gamma X + \epsilon_i^{O|X}
\]

Share explained by \(X\): \(1 - \frac{\beta^{O|X}}{\beta^O}\)

- \(Dem_i\): share of secular-Jews in the same firm as individual \(i\)
- \(X_i\): explanatory variable
  - Education, Demographics, Neighborhoods
Demog. Explains Most of the Firm- and Dem-IGE

Explanatory Variables

- Education
- Demographics
- Neighborhood
- Neighborhood Demographics

Share of IGE explained

- Firm-IGE
- Dem-IGE
Demog. Explains Most of the Firm- and Dem-IGE
Demog. Explains Most of the Firm- and Dem-IGE

![Graph showing the share of IGE explained by different explanatory variables.](image)
Demog. Explains Most of the Firm- and Dem-IGE

![Charts showing the share of IGE explained by different explanatory variables. The variable 'Education' explains the least, while 'Demographics' and 'Neighborhood Demographics' explain more, with 'Neighborhood' explaining the most.]