Heterogeneous Peer Effects and Rank Concerns: Theory and Evidence

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Saturday 26th September, 2015
Introduction: Motivation

- Peers matter for student outcomes.
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- Linear-in-means model not appropriate model of ability peer effects in test scores (Sacerdote, 2014).
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We still do not know:
- How they work.
  - Learn from good classmates? Encouraged to keep up with them?
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We still do not know:
- How they work.
  - Learn from good classmates? Encouraged to keep up with them?
- Whether we can use existing evidence to improve classroom organization (Carrell, Sacerdote, West, 2013).
This paper:

1. Develops a model that has implications on the shape of peer effects
   - Mechanism of rank concerns
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   - Mechanism of rank concerns
2. Proposes a new way to identify heterogeneous and nonlinear peer effects
   - Estimates them among Chilean 8th graders
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1. Develops a model that has implications on the shape of peer effects
   - Mechanism of rank concerns

2. Proposes a new way to identify heterogeneous and nonlinear peer effects
   - Estimates them among Chilean 8th graders

3. Tests the theoretical predictions in a new empirical setting
   - Uses Chilean 2010 earthquake as a natural experiment
When PE are generated by Rank Concerns (RC), they operate through the entire distribution of ability, not just the mean.
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To capture heterogeneous effects of variance in the data, I need:
Introduction: Rank Concerns, Identification and Estimation

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- **Identification:** Exogenous variation in ability variance

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- **Estimation**: Econometric model that can detect heterogeneous impacts across ability distribution.
  - Use semi-parametric techniques
I find support for rank concerns.
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Implications:
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Implications:

For policy:

- New channel of operation of ability tracking
- Educators can exploit competition incentives when choosing classroom assignment rules
Introduction: Preview of Results

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  - For the estimation of peer effects: models that focus on the mean only
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Implications:

For policy:
- New channel of operation of ability tracking
- Educators can exploit competition incentives when choosing classroom assignment rules

For the estimation of peer effects: models that focus on the mean only
- Fail in out of sample predictions
- Fail to detect peer effects when they are present
I combine 4 waves of SIMCE (2005, 2007, 2009, 2011) to obtain two cohorts of students:
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Variables: 8th and 4th grade Math and Spanish test scores, household characteristics, teacher characteristics, classroom characteristics
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- Cohort PRE
- Cohort POST

Variables: 8th and 4th grade Math and Spanish test scores, household characteristics, teacher characteristics, classroom characteristics

Identifiers match students to classrooms, teachers and schools
Earthquake:

- February 27th 2010, Magnitude 8.8.
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- SIMCE 2011 sample collected 20-22 months after earthquake.
Data

Earthquake:

- February 27th 2010, Magnitude 8.8.
- SIMCE 2011 sample collected 20-22 months after earthquake.
- 80% of population affected. People affected differently.
Table: Estimated reconstruction costs by MSK-intensity (Adobe constructions worth USD 20,000)

<table>
<thead>
<tr>
<th>MSK Intensity</th>
<th>Expected cost (USD)</th>
<th>Expected cost (USD) over average household monthly income</th>
</tr>
</thead>
<tbody>
<tr>
<td>V</td>
<td>20</td>
<td>0.04</td>
</tr>
<tr>
<td>V $\frac{1}{2}$</td>
<td>120</td>
<td>0.26</td>
</tr>
<tr>
<td>VI</td>
<td>220</td>
<td>0.49</td>
</tr>
<tr>
<td>VI $\frac{1}{2}$</td>
<td>950</td>
<td>2.10</td>
</tr>
<tr>
<td>VII</td>
<td>1,680</td>
<td>3.72</td>
</tr>
<tr>
<td>VII $\frac{1}{2}$</td>
<td>4,210</td>
<td>9.32</td>
</tr>
<tr>
<td>VIII</td>
<td>6,740</td>
<td>14.92</td>
</tr>
<tr>
<td>VIII $\frac{1}{2}$</td>
<td>10,270</td>
<td>22.73</td>
</tr>
<tr>
<td>IX</td>
<td>13,800</td>
<td>30.54</td>
</tr>
</tbody>
</table>
Figure: Density of Seismic Intensity in my Sample of Students in Earthquake Regions
Earthquake reduced test scores by 0.05*** sd.
Data

- Earthquake reduced test scores by 0.05*** sd.
- House damage reduced test scores: $-0.016^{***}$ sd for every USD 100 in damages.
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- Earthquake reduced test scores by 0.05*** sd. [DD Reg. Table]
- House damage reduced test scores: $-0.016^{***}$ sd for every USD 100 in damages. [DD Reg Table]
- Damage reduces ability to study [Evidence 1 2 3]

Large differences in damages even between classmates
Average standard deviation in damages within classrooms USD 350 (sd USD 460), \sim 92\% average monthly income.

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Heterogeneous Peer Effects and Rank Concerns
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Identification idea:
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- Different classrooms have different damage distributions
Econometric Model

Identification idea:

- Different classrooms have different damage distributions
- Classrooms with different distributions of damages have different distributions of ability to study
Identification idea:

- Different classrooms have different damage distributions.
- Classrooms with different distributions of damages have different distributions of ability to study.
- This variation is free of typical confounding factors.
Preliminary Data Analysis

Heterogeneous Peer Effects and Rank Concerns
Model that allows for:

- Direct Peer Effects (DPE): student outcomes depend on classroom distribution of ability to study.
- Indirect Peer Effects (IPE): effect of observed classroom characteristics (e.g., teachers) depends on classroom composition.
- Correlated Effects (CE): effect of unobserved classroom characteristics depends on classroom composition.
- Heterogeneity: DPE, IPE, and CE vary by student’s ability to study.

Make assumptions that allow me to separately identify DPE from IPE and CE.
Econometric Model

Model that allows for:

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Econometric Model

Achievement production function with peer effects:

\[ y_{il} = e(c_i; G_l(c)) + u(c_i, z_l, F_l(x_i)) + \nu_{il} \]

\[ E(\nu_{il}|c_i, l) \neq 0. \]

- \( y_{il} \): test score of student \( i \) in classroom \( l \).
Econometric Model

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- \( y_{il} \): test score of student \( i \) in classroom \( l \).
- \( c_i \): student’s type, cost of effort (scalar).
  \( c_i = \alpha_1 x_i \)
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Econometric Model

Achievement production function with peer effects:

\[ y_{il} = e(c_i; G_i(c)) + u(c_i, z_l, F_l(x_i)) + \nu_{il} \quad \text{with} \quad E(\nu_{il}|c_i, l) \neq 0. \]

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IPE: \( u(c_i, z_l, F_l(x_i)) \) effect of classroom characteristics depends on peer composition \( F_l(x_i) \)

CE: \( E(\nu_{il}|c_i, l) = \psi(c_i, z_l, F_l(x_i)) \)
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- CE: \( E(\nu_{il}|c_i, l) = \psi(c_i, z_l, F_l(x_i)) \)
- Goal: estimate effect of \( \text{Var}_l(c) \) on \( e_l(\cdot) \), net of effects on \( u_l(\cdot) \) and \( \psi_l(\cdot) \).
Econometric Model

Achievement production function with peer effects:

\[ y_{il} = e(c_i; G_l(c)) + u(c_i, z_l, F_l(x_i)) + v_{il} \quad E(v_{il}|c_i, l) \neq 0. \]

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- Goal: estimate effect of \( \text{Var}_l(c) \) on \( e_l(\cdot) \), net of effects on \( u_l(\cdot) \) and \( \psi_l(\cdot) \).
- Problem: when \( \text{Var}_l(c) \) changes, \( \text{Var}_l(x) \) changes
Solution:
- Find a determinant of $c_i$ that is not in $x_i$. Its classroom variance will affect $Var_l(c)$, but not $Var_l(x_i)$ and, therefore, not $u_l(\cdot)$ nor $\psi_l(\cdot)$.
Econometric Model

Solution:

- Find a determinant of $c_i$ that is not in $x_i$. Its classroom variance will affect $\text{Var}_I(c)$, but not $\text{Var}_I(x_i)$ and, therefore, not $u_I(\cdot)$ nor $\psi_I(\cdot)$

$$c_i = \begin{cases} 
\alpha_1 x_i, & \text{if } i \in \text{pre-earthquake cohort.} \\
\alpha_1 x_i + \alpha_2 E_i + \alpha_3 E_i x_i, & \text{if } i \in \text{post-earthquake cohort.}
\end{cases}$$
Econometric Model

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- In the post-earthquake cohort, classrooms with different $\sigma^2_{EI}$, have different $Var_l(c) \Rightarrow \text{DPE}$
Econometric Model

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- In the post-earthquake cohort, classrooms with different $\sigma_{EI}^2$, have different $Var_I(c) \Rightarrow DPE$

- Exclusion restriction: IPE and CE depend on variance of $x_i$, but not on variance of $E_i$
Econometric Model

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- Reasonable restriction?
Econometric Model

What is identifiable?


Normalize one element of $\alpha$ and jointly estimate $\alpha$ and $m_l(\cdot)$, $\forall l$.

Algorithm $\hat{\alpha}^2 > 0$. 

Table Michela M. Tincani UCL and IFS Heterogeneous Peer Effects and Rank Concerns
Econometric Model

What is identifiable?

\[ y_{il} = e(c_i; G_I(c)) + u_l(c_i) + \psi_l(c_i) + \epsilon_{il} \]
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y_{il} = e(c_i; G_l(c)) + u_l(c_i) + \psi_l(c_i) + \epsilon_{il} \\
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\[
= e_l(c_i) + u_l(c_i) + \psi_l(c_i) + \epsilon_{il}
\]

\[
= m_l(c_i) + \epsilon_{il}
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- Normalize one element of \( \alpha \) and jointly estimate \( \alpha \) and \( m_l(\cdot) \), \( \forall l \).
- \( \hat{\alpha}_2 > 0 \).
Econometric Model

Example of estimated $m$ functions in two classrooms:

Very good fit.
Can’t directly check whether $u_l(\cdot)$ and $\psi_l(\cdot)$ vary with $\sigma^2_{E_l}$
Econometric Model

- Can’t directly check whether $u_i(\cdot)$ and $\psi_i(\cdot)$ vary with $\sigma_{Ei}^2$
- Check correlation between $\sigma_{Ei}^2$ and:

```
  observed classroom characteristics
  student characteristics
  observed teacher effectiveness

There is a correlation, but it is the same for pre- and post-earthquake cohorts. Therefore:

- $u_i(\cdot)$ and $\psi_i(\cdot)$ vary with $\sigma_{Ei}^2$, but only because of geographic dispersion
  Can account for this by differencing out geographic effect
```
Econometric Model

- Can’t directly check whether $u_l(\cdot)$ and $\psi_l(\cdot)$ vary with $\sigma_{El}^2$
- Check correlation between $\sigma_{El}^2$ and:
  - observed classroom characteristics
  - student characteristics
  - observed teacher effectiveness
Can’t directly check whether \( u_l(\cdot) \) and \( \psi_l(\cdot) \) vary with \( \sigma^2_{EL} \)

Check correlation between \( \sigma^2_{EL} \) and:
- observed classroom characteristics
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Econometric Model

- Can’t directly check whether $u_l(\cdot)$ and $\psi_l(\cdot)$ vary with $\sigma^2_{EI}$
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There is a correlation, but it is the same for pre- and post-earthquake cohorts. Therefore:
- $u_i(\cdot)$ and $\psi_i(\cdot)$ vary with $\sigma^2_{EI}$, but only because of geographic dispersion
- Can account for this by differencing out geographic dispersion effect
Two identical pre- \((l, l')\) and two post-earthquake \((s, s')\) classrooms except for \(\sigma_E^2\).
Two identical pre- \((l, l')\) and two post-earthquake \((s, s')\) classrooms except for \(\sigma_E^2\).
Econometric Model: Differencing Out Location Effects

$\Delta m^{\text{post}}_{ss}(c)$

$\Delta m^{\text{post}}_{c_{II}}(c)$

$\Delta m^{\text{pre}}_{c_{III}}(c)$

$\Delta m^{\text{post}}(c) - \Delta m^{\text{pre}}(c)$
I make the correct comparisons between pre- and post-earthquake students. Quantile DD (Athey and Imbens (ECMTA, 2006)) not applicable.
I estimate over 1,500 $m(\cdot)$ functions in each cohort:

\[ \hat{m}_{\text{pre}}(\hat{c}) \quad \hat{m}_{\text{post}}(\hat{c}) \]

Subject to the same treatment intensities $\Delta \sigma^2_{\text{Ell}} = \Delta \sigma^2_{\text{Ess}}$. 

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Heterogeneous Peer Effects and Rank Concerns
I estimate over 1,500 $m(\cdot)$ functions in each cohort:

\[ \hat{m}_{pre}(\hat{c}) \quad \hat{m}_{post}(\hat{c}) \]

I must find all possible pairs of pairs of classrooms that are:

Identical except for seismic intensity variance $\sigma^2_{E}$, i.e. find mean-preserving spreads of ability distribution. Subject to the same treatment intensities $\Delta\sigma^2_E$. 

Michela M. Tincani UCL and IFS

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I estimate over 1,500 $m(\cdot)$ functions in each cohort:

\[
\hat{m}_{\text{pre}}(\hat{c}) \quad \text{and} \quad \hat{m}_{\text{post}}(\hat{c})
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I must find all possible pairs of pairs of classrooms that are:

- Identical except for seismic intensity variance $\sigma^2_E$, i.e. find mean-preserving spreads of ability distribution.
- Subject to the same treatment intensities $\Delta \sigma^2_{Ell'} = \Delta \sigma^2_{Ess'}$. 

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Heterogeneous Peer Effects and Rank Concerns
Perform all possible pair-wise comparisons, classroom with larger variance is the treated one.
Perform all possible pair-wise comparisons, classroom with larger variance is the treated one.

With $n$ classrooms, $\frac{1}{2} \binom{n}{2} = \frac{1}{2} \frac{n(n-1)}{2}$ comparisons.
Perform all possible pair-wise comparisons, classroom with larger variance is the treated one.

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- Weight for quadruplet: $\omega_{ll's's'}$.  

**Additional smoothness assumptions**
Estimator of $\Delta e_{ss'}(c)$ at $c$ is $\gamma_{OLS}$ in:

$$\left(\widehat{\Delta m}_{ss'}^{post} - \widehat{\Delta m}_{ll'}^{pre}\right) = \omega_{ll'ss'} \gamma + \xi_{ll'ss'}$$

with $E[\xi_{ll'ss'}] = 0$. 
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with $E[\xi ll'ss'] = 0$.

$$\gamma = \Delta e(c) = \frac{\sum_{l=1}^{N_{\text{pre}}-1} \sum_{l'=l+1}^{N_{\text{pre}}} \sum_{s=1}^{N_{\text{post}}-1} \sum_{s'=s+1}^{N_{\text{post}}} \omega ll'ss' (\Delta m_{ss'}^{\text{post}} - \Delta m_{ll'}^{\text{pre}})}{\sum_{l=1}^{N_{\text{pre}}-1} \sum_{l'=l+1}^{N_{\text{pre}}} \sum_{s=1}^{N_{\text{post}}-1} \sum_{s'=s+1}^{N_{\text{post}}} \omega ll'ss'}. $$
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with $E[\xi_{ll'ss'}] = 0$.

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Estimate $\gamma$ over a grid of values for $c$ with parallel processing.
Empirical Results

Estimated $\Delta e_{ss'}(c)$ for Math test scores. One-sided 90 percent confidence interval reported:
Estimated $\Delta e_{ss'}(c)$ for Spanish test scores. One-sided 90 percent confidence interval reported.
Empirical Results

What mechanism of social interactions can generate these patterns?
Model builds on model of conspicuous consumption in Hopkins and Kornienko (AER, 2004).
Theoretical Model

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Assumptions:

1. Achievement is produced through costly effort $q(e_i; c_i)$.

Details

2. Students are heterogeneous in terms of cost of effort $c_i \sim G(c_i)$.

3. There are technological spill-overs working through means of peer ability (peer costs of effort).

4. Utility is increasing in own achievement.

5. Utility is increasing in own rank in terms of achievement.


5: novel
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Additional references:
- Michela M. Tincani UCL and IFS

Heterogeneous Peer Effects and Rank Concerns
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Achievement production with technological spill-overs:

\[ y_{ii} = a(\mu_i)e_l(c_i) + u(\mu_l) \]
Theoretical Model

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\[ y_{ii} = a(\mu_l)e_l(c_i) + u(\mu_l) \]

- \( e_i = e_l(c_i) \) = effort of student \( i \) in class \( l \).
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- \( e_i = e_l(c_i) \): effort of student \( i \) in class \( l \).
- \( a(\mu_l) \): productivity of effort, depends on mean \( c \).
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- \( e_i = e_i(c_i) \) = effort of student \( i \) in class \( l \).
- \( a(\mu_i) \): productivity of effort, depends on mean \( c \).
- \( u(\mu_i) \): effect of classroom characteristics, including of mean \( c \).
Utility has two components:

- Ut. from achievement: $V(y_{il}, q(e_i; c_i))$ with $V_1 > 0$, $V_2 < 0$, $V_{11} = 0$, $V_{22} = 0$ and $V_{12} \leq 0$. 

- Ut. from rank: $S(F_{Y_l}(\cdot), y_{il}) = F_{Y_l}(y_{il}) + \phi$ with $\phi \geq 0$, where $F_{Y_l}(\cdot)$ is cdf of $y$ in class $l$. 

Overall utility $U(\cdot) = V(\cdot) \ast S(\cdot)$.

- $\phi = 0$: aversion to low rank (evidence: Kuziemko et al. QJE, 2014).
- $\phi > 0$: minimum-guaranteed level of utility.
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[Michela M. Tincani, UCL and IFS] Heterogeneous Peer Effects and Rank Concerns
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Theoretical Model

- Students max utility w.r.t. effort.
- A (symmetric) strategy is a mapping from type $c_i$ to effort $e_i$: $e_i(c_i)$. 
Theoretical Model

- Students max utility w.r.t. effort.
- A (symmetric) strategy is a mapping from type $c_i$ to effort $e_i$: $e_l(c_i)$.
- From F.O.C., the larger the density around one’s type, $g(c_i)$, the larger the marginal utility of effort.
Theoretical Model

Theorem (Existence and Uniqueness)

*There is a unique symmetric Nash Equilibrium. Eqm strategy \( e(c) \) is strictly decreasing in type \( c \).*
Theoretical Model

**Theorem (Existence and Uniqueness)**

*There is a unique symmetric Nash Equilibrium. Eqm strategy \( e(c) \) is strictly decreasing in type \( c \).*

**Theorem (Comparative Statics)**

*The effect of increasing the variance of \( c \) is heterogeneous across individuals, and it depends on type of preferences for rank \((\phi = 0 \text{ or } \phi > 0)\).*
Theoretical Model: Comparative Statics

(a) $\phi > 0$, no aversion to a low rank

(b) $\phi = 0$, aversion to a low rank
Theoretical Model: Intuition

- $G_B$ (Larger Variance)
- $G_A$ (Smaller Variance)
- Ratio $[1 - G_A(c) + \phi] /[1 - G_B(c) + \phi]$

Density vs. Type c

- Low c
- Middle c
- High c

Michela M. Tincani UCL and IFS
Heterogeneous Peer Effects and Rank Concerns
I estimated:

- type $\hat{c}_i$.
- $\hat{m}_l(\hat{c}_i) = e_l(\hat{c}_i) + u_l(\hat{c}_i) + \psi_l(\hat{c}_i)$.

Result: Do not reject monotonicity of $\hat{m}_l(\hat{c}_i)$ in all classrooms (Chetverikov (2013)).
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- $\hat{m}_I(\hat{c}_i) = e_I(\hat{c}_i) + u_I(\hat{c}_i) + \psi_I(\hat{c}_i)$.
- I can test monotonicity of $\hat{m}_I(\hat{c}_i)$:

If $u_I(\hat{c}_i) + \psi_I(\hat{c}_i)$ constant, then $\hat{m}_I(\hat{c}_i)$ decreasing $\Rightarrow$ $e_I(\hat{c}_i)$ decreasing.

If $u_I(\hat{c}_i) + \psi_I(\hat{c}_i)$ not constant, then $\hat{m}_I(\hat{c}_i)$ decreasing $\Rightarrow$ not true that $e_I(\cdot)$ and $u_I(\cdot) + \psi_I(\cdot)$ both increasing.

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**Result:** Do not reject monotonicity of \( \hat{m}_l(\hat{c}_i) \) in all classrooms (Chetverikov (2013)).
I do not reject comparative statics result.
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Support for no aversion to low rank ($\phi > 0$).
I do not reject comparative statics result.

Support for no aversion to low rank $(\phi > 0)$. Back to theoretical predictions Back to empirical results

Difference between Math and Spanish explained by different strengths of preference for rank.
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Support for no aversion to low rank \((\phi > 0)\).

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⇒ **Out of sample prediction**: Tracking students by ability ↑ incentive for all to exert more effort.
Teachers adjust their focus of instruction depending on variance in damages.

Social cognitive learning (Bandura 1986, Schunk 1996), i.e. learning from similar classmates. Cannot explain why high-ability Spanish students do worse when there are more high-ability students.

Endogenous sub-group formation, i.e. PE working through mean and students choose similar peers as friends. Cannot explain why low-ability students do better when there are more low-ability students.

Technological spill-over working through the variance? Different patterns of heterogeneity across subjects hard to rationalize with current knowledge.
Alternative Mechanisms

1. Teachers adjust their focus of instruction depending on variance in damages.
   - No evidence supporting this.
   - Must assume Math and Spanish teachers react differently.

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Michela M. Tincani UCL and IFS
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**For policy:**
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- **For the estimation of peer effects:** under RC, PE work through entire distribution of ability, not just mean.
  - Could explain why standard models estimate larger peer effects for risky behaviors and crime than for test scores (Sacerdote, *ARE*, 2014).
  - Standard models may fail in out of sample predictions.
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  - There is an interaction between classroom assignment rules and academic competition. It can be exploited by policymaker.
  - New channel of operation of ability tracking: easier to compete amongst equals.

- **For the estimation of peer effects:** under RC, PE work through entire distribution of ability, not just mean.
  - Could explain why standard models estimate larger peer effects for risky behaviors and crime than for test scores (Sacerdote, ARE, 2014).
  - Standard models may fail in out of sample predictions.
  - Standard models may fail to detect peer effects when they are present.
Directions for future research

Currently, two separate strands of experimental research in education: interventions on classroom composition, interventions on incentives to compete (affirmative action, merit fellowships). Consider both variations together, potential complementarities.
Directions for future research

- Currently, two separate strands of experimental research in education: interventions on classroom composition, interventions on incentives to compete (affirmative action, merit fellowships). Consider both variations together, potential complementarities.

- Working with Ministry of Education in Chile to randomize expansion of aa program (PACE), estimate effect across schools that do and do not implement ability tracking.
Handmade sign in Cauquenes, Chile, February 2, 2012. Translation: “Reconstruction is like God. Everyone knows it exists, but nobody has seen it.” (Photo courtesy of Michael Dear)
### Diff-in-diff evaluation of earthquake impact on test scores.

<table>
<thead>
<tr>
<th></th>
<th>Spanish</th>
<th>Mathematics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spanish test score</td>
<td>0.645***</td>
<td>0.645***</td>
</tr>
<tr>
<td>in fourth grade</td>
<td>(0.00167)</td>
<td>(0.00159)</td>
</tr>
<tr>
<td>Math test score</td>
<td></td>
<td></td>
</tr>
<tr>
<td>in fourth grade</td>
<td>0.645***</td>
<td>(0.00159)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Father's education (yrs)</td>
<td>0.00885***</td>
<td>0.00715***</td>
</tr>
<tr>
<td></td>
<td>(0.000538)</td>
<td>(0.000497)</td>
</tr>
<tr>
<td>Female</td>
<td>0.124***</td>
<td>-0.104***</td>
</tr>
<tr>
<td></td>
<td>(0.00290)</td>
<td>(0.00268)</td>
</tr>
<tr>
<td>Household lives</td>
<td>0.0566*</td>
<td>0.0395+</td>
</tr>
<tr>
<td>in earthquake region (E)</td>
<td>(0.0247)</td>
<td>(0.0229)</td>
</tr>
<tr>
<td>Cohort 2007-2011,</td>
<td>0.0548***</td>
<td>0.0429***</td>
</tr>
<tr>
<td>affected by earthquake (P)</td>
<td>(0.00580)</td>
<td>(0.00535)</td>
</tr>
<tr>
<td>P*E</td>
<td>-0.0492***</td>
<td>-0.0509***</td>
</tr>
<tr>
<td></td>
<td>(0.00667)</td>
<td>(0.00616)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.333***</td>
<td>-0.185***</td>
</tr>
<tr>
<td></td>
<td>(0.0200)</td>
<td>(0.0185)</td>
</tr>
<tr>
<td>School Fixed Effects</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Observations</td>
<td>233892</td>
<td>235170</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Other included regressors: mother’s education, household income.
Appendix

- drop 5,988 evacuees and 803 schools receiving them.
Public school students represent a little less than the 50% poorest student population.

60% poorest Chilean population lives in adobe constructions (6.1%) or unreinforced masonries (51.9%)

very similar earthquake resistance (Astroza et al. 2012)
Table: Effect of seismic intensity on test scores

<table>
<thead>
<tr>
<th></th>
<th>Math</th>
<th>Spanish</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged test score</td>
<td>0.635***</td>
<td>0.656***</td>
</tr>
<tr>
<td></td>
<td>(0.0023)</td>
<td>(0.0025)</td>
</tr>
<tr>
<td>Household lives in earthquake region (E)</td>
<td>0.275*</td>
<td>0.0699</td>
</tr>
<tr>
<td></td>
<td>(0.125)</td>
<td>(0.133)</td>
</tr>
<tr>
<td>Cohort 2007-2011, post-earthquake (P)</td>
<td>0.0496***</td>
<td>0.0522***</td>
</tr>
<tr>
<td></td>
<td>(0.0074)</td>
<td>(0.0080)</td>
</tr>
<tr>
<td>(1-P)*Earthquake Intensity $\theta_{pre}$</td>
<td>-0.0279</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0202)</td>
<td>(0.0214)</td>
</tr>
<tr>
<td>P*Earthquake Intensity $\theta_{post}$</td>
<td>-0.0326</td>
<td>-0.0058</td>
</tr>
<tr>
<td></td>
<td>(0.0202)</td>
<td>(0.0214)</td>
</tr>
<tr>
<td>Effect of Earthquake Intensity $\theta_{post} - \theta_{pre}$</td>
<td>-0.0046**</td>
<td>-0.0060***</td>
</tr>
<tr>
<td></td>
<td>(0.0014)</td>
<td>(0.0015)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.369***</td>
<td>-0.428***</td>
</tr>
<tr>
<td></td>
<td>(0.0289)</td>
<td>(0.0310)</td>
</tr>
<tr>
<td>Observations</td>
<td>97,658</td>
<td>97,057</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

$+ p < 0.10$, $* p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Included regressors: household income, mother’s and father’s education, student gender, school fixed effects.
**Table**: Probit regression, marginal probability estimates reported. Dependent variables: being at top or bottom third of the distribution of elicited cost of effort

<table>
<thead>
<tr>
<th></th>
<th>top 33 percent</th>
<th>bottom 33 percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mother’s education</td>
<td>.0007012</td>
<td>.0020148*</td>
</tr>
<tr>
<td></td>
<td>(.0007415)</td>
<td>(.0008893)</td>
</tr>
<tr>
<td>Father’s education</td>
<td>-.0007132</td>
<td>.0013843</td>
</tr>
<tr>
<td></td>
<td>(.0007134)</td>
<td>(.0008544)</td>
</tr>
<tr>
<td>Household income</td>
<td>$1.76e−08^+$</td>
<td>$−2.32e−08^+$</td>
</tr>
<tr>
<td></td>
<td>(1.02e-08)</td>
<td>(1.23e-08)</td>
</tr>
<tr>
<td>Math test score t-1</td>
<td>−.0549353***</td>
<td>.1004088***</td>
</tr>
<tr>
<td></td>
<td>(.0019868)</td>
<td>(.0023838)</td>
</tr>
<tr>
<td>Seismic intensity</td>
<td>.0128674***</td>
<td>−.0105234***</td>
</tr>
<tr>
<td>at student’s home</td>
<td>(.0022842)</td>
<td>(.002741)</td>
</tr>
<tr>
<td>Observations</td>
<td>46059</td>
<td>46059</td>
</tr>
<tr>
<td>Standard errors in parentheses</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$+ p &lt; 0.10$, $^{<em>} p &lt; 0.05$, $^{<strong>} p &lt; 0.01$, $^{</strong></em>} p &lt; 0.001$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Interaction between seismic intensity and homework load. Dependent variable Math test score in the 8<sup>th</sup> grade.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seismic Intensity</td>
<td>0.0119</td>
<td>0.0110</td>
<td>0.0116</td>
</tr>
<tr>
<td>$\theta$</td>
<td>(0.0076)</td>
<td>(0.0077)</td>
<td>(0.0079)</td>
</tr>
<tr>
<td>Seismic Intensity* $\theta$</td>
<td>-0.0055</td>
<td>-0.0055</td>
<td>-0.0069</td>
</tr>
<tr>
<td>High homework load $\theta^{int}$</td>
<td>(0.0033)</td>
<td>(0.0033)</td>
<td>(0.0052)</td>
</tr>
<tr>
<td>Additional Impact $\theta^{int} - \theta$</td>
<td>-0.0174*</td>
<td>-0.0165+</td>
<td>-0.0184+</td>
</tr>
<tr>
<td></td>
<td>(0.0088)</td>
<td>(0.0089)</td>
<td>(0.0106)</td>
</tr>
<tr>
<td>Class size</td>
<td>0.0119***</td>
<td>0.0120***</td>
<td>0.0120***</td>
</tr>
<tr>
<td></td>
<td>(0.0017)</td>
<td>(0.0017)</td>
<td>(0.0017)</td>
</tr>
<tr>
<td>Math teacher</td>
<td>0.0008</td>
<td>0.0008</td>
<td>0.0008</td>
</tr>
<tr>
<td>experience</td>
<td>(0.0007)</td>
<td>(0.0007)</td>
<td>(0.0007)</td>
</tr>
<tr>
<td>High homework workload in Math class</td>
<td>0.0088</td>
<td>0.0088</td>
<td>0.0088</td>
</tr>
<tr>
<td></td>
<td>(0.0261)</td>
<td>(0.0261)</td>
<td>(0.0261)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.316***</td>
<td>-0.679***</td>
<td>-0.683***</td>
</tr>
<tr>
<td></td>
<td>(0.0342)</td>
<td>(0.0622)</td>
<td>(0.0636)</td>
</tr>
<tr>
<td>Observations</td>
<td>47196</td>
<td>46394</td>
<td>46394</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
$+ p < 0.10$, $* p < 0.05$, $** p < 0.01$, $*** p < 0.001$

Other regressors: lagged Math test score, household income, father's education, mother's education, student gender
1 Normalize to -1 the coefficient on lagged test score.

2 Initial guess $\alpha^{(0)}$.

3 Form $c_i^{(0)}$ $\forall i$: $c_i^{(0)} = \alpha_1^{(0)} x_i + \alpha_2^{(0)} P_iE_i + \alpha_3^{(0)} P_iE_i x_i$

4 Estimate $E(y_i|c, l; \alpha)$ $\forall l$ by Nadaraya-Watson kernel regression with weights $w_i$ (Ichimura 1993):

$$\hat{m}_l(c; \alpha) = \frac{\sum_{i \in l} w_i K \left( \frac{c_i - c}{h} \right) y_i}{\sum_{i \in l} w_i K \left( \frac{c_i - c}{h} \right)}$$

w/ standard normal Kernel and optimal bandwidth $h = 1.06 \hat{\sigma}_c n^{-1/5}$

5 Sum of squared residuals in each $l$ at current guess:
$$SSR_l(\alpha) = \sum_{i \in l} w_i (y_i - \hat{m}_l(c_i; \alpha))^2.$$

6 Update guess for $\alpha$ using Generating Set Search algorithm (HOPSPACK)

7 Repeat steps 1-6 until convergence to minimizer of $\sum_l SSR_l(\alpha)$
Parameter Estimates (bootstrapped standard errors in parentheses)

<table>
<thead>
<tr>
<th>Coefficient on</th>
<th>Math</th>
<th>Spanish</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parental Education</td>
<td>$-0.01162^{***}$</td>
<td>$-0.0212^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0052)</td>
<td>(0.0045)</td>
</tr>
<tr>
<td>High Income Dummy</td>
<td>$-0.0560^{***}$</td>
<td>$-0.0356^{**}$</td>
</tr>
<tr>
<td></td>
<td>(0.0162)</td>
<td>(0.0175)</td>
</tr>
<tr>
<td>Female</td>
<td>$0.1290^{***}$</td>
<td>$-0.2303^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0195)</td>
<td>(0.0350)</td>
</tr>
<tr>
<td>Seismic Intensity</td>
<td>0.0326</td>
<td>0.0946</td>
</tr>
<tr>
<td></td>
<td>(0.0596)</td>
<td>(0.1438)</td>
</tr>
<tr>
<td>Seismic Intensity*High Income</td>
<td>$-0.0004^{***}$</td>
<td>$-0.0004$</td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
<td>(0.0027)</td>
</tr>
<tr>
<td>Seismic Intensity*Female</td>
<td>$-0.0031$</td>
<td>0.0550*</td>
</tr>
<tr>
<td></td>
<td>(0.0288)</td>
<td>(0.0334)</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
### Mathematics and Spanish Models: Pre-Earthquake Cohort

<table>
<thead>
<tr>
<th></th>
<th>Mathematics Actual</th>
<th>Mathematics Model</th>
<th>Spanish Actual</th>
<th>Spanish Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Overall</strong></td>
<td>-0.185</td>
<td>-0.189</td>
<td>-0.121</td>
<td>-0.123</td>
</tr>
<tr>
<td><strong>Female</strong></td>
<td>-0.304</td>
<td>-0.283</td>
<td>-0.050</td>
<td>-0.063</td>
</tr>
<tr>
<td><strong>Male</strong></td>
<td>-0.058</td>
<td>-0.089</td>
<td>-0.196</td>
<td>-0.186</td>
</tr>
<tr>
<td><strong>Female</strong> (Urban)</td>
<td>-0.300</td>
<td>-0.279</td>
<td>-0.052</td>
<td>-0.064</td>
</tr>
<tr>
<td><strong>Female</strong> (Rural)</td>
<td>-0.322</td>
<td>-0.302</td>
<td>-0.043</td>
<td>-0.056</td>
</tr>
<tr>
<td><strong>Male</strong> (Urban)</td>
<td>-0.035</td>
<td>-0.066</td>
<td>-0.180</td>
<td>-0.172</td>
</tr>
<tr>
<td><strong>Male</strong> (Rural)</td>
<td>-0.159</td>
<td>-0.188</td>
<td>-0.262</td>
<td>-0.249</td>
</tr>
<tr>
<td><strong>Female</strong> (Lower Income)</td>
<td>-0.414</td>
<td>-0.387</td>
<td>-0.148</td>
<td>-0.155</td>
</tr>
<tr>
<td><strong>Female</strong> (Higher Income)</td>
<td>-0.130</td>
<td>-0.120</td>
<td>0.104</td>
<td>0.083</td>
</tr>
<tr>
<td><strong>Male</strong> (Lower Income)</td>
<td>-0.222</td>
<td>-0.246</td>
<td>-0.348</td>
<td>-0.328</td>
</tr>
<tr>
<td><strong>Male</strong> (Higher Income)</td>
<td>0.155</td>
<td>0.116</td>
<td>0.001</td>
<td>0.003</td>
</tr>
</tbody>
</table>

### Mathematics and Spanish Models: Post-Earthquake Cohort

<table>
<thead>
<tr>
<th></th>
<th>Mathematics Actual</th>
<th>Mathematics Model</th>
<th>Spanish Actual</th>
<th>Spanish Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Overall</strong></td>
<td>-0.222</td>
<td>-0.228</td>
<td>-0.153</td>
<td>-0.156</td>
</tr>
<tr>
<td><strong>Female</strong></td>
<td>-0.307</td>
<td>-0.292</td>
<td>-0.058</td>
<td>-0.078</td>
</tr>
<tr>
<td><strong>Male</strong></td>
<td>-0.132</td>
<td>-0.159</td>
<td>-0.254</td>
<td>-0.239</td>
</tr>
<tr>
<td><strong>Female</strong> (Urban)</td>
<td>-0.302</td>
<td>-0.287</td>
<td>-0.071</td>
<td>-0.086</td>
</tr>
<tr>
<td><strong>Female</strong> (Rural)</td>
<td>-0.329</td>
<td>-0.315</td>
<td>0.001</td>
<td>0.039</td>
</tr>
<tr>
<td><strong>Male</strong> (Urban)</td>
<td>-0.120</td>
<td>-0.148</td>
<td>-0.257</td>
<td>-0.246</td>
</tr>
<tr>
<td><strong>Male</strong> (Rural)</td>
<td>-0.180</td>
<td>-0.205</td>
<td>-0.242</td>
<td>-0.209</td>
</tr>
<tr>
<td><strong>Female</strong> (Lower Income)</td>
<td>-0.414</td>
<td>-0.388</td>
<td>-0.146</td>
<td>-0.160</td>
</tr>
<tr>
<td><strong>Female</strong> (Higher Income)</td>
<td>-0.151</td>
<td>-0.151</td>
<td>0.071</td>
<td>0.042</td>
</tr>
</tbody>
</table>
Pre-Earthquake Cohort, dependent variables Spanish and Math test scores in eighth grade

<table>
<thead>
<tr>
<th></th>
<th>(1) Spanish</th>
<th>(2) Math</th>
</tr>
</thead>
<tbody>
<tr>
<td>Own Intensity</td>
<td>0.0149</td>
<td>0.0146</td>
</tr>
<tr>
<td>(0.0129)</td>
<td>(0.0120)</td>
<td></td>
</tr>
<tr>
<td>Classroom Intensity Mean</td>
<td>0.00943</td>
<td>0.0580</td>
</tr>
<tr>
<td>(0.0688)</td>
<td>(0.0648)</td>
<td></td>
</tr>
<tr>
<td>Classroom Intensity Variance</td>
<td>0.223+</td>
<td>0.319**</td>
</tr>
<tr>
<td>(0.128)</td>
<td>(0.120)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.472</td>
<td>-0.681+</td>
</tr>
<tr>
<td>(0.425)</td>
<td>(0.400)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>35175</td>
<td>35302</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Only municipal schools are in the estimation sample.
Other included regressors: lagged test score, household income, father’s education, mother’s education, student gender, school fixed effects.
## Difference-in-differences evaluation of the effect of seismic intensity mean and variance on classroom composition

<table>
<thead>
<tr>
<th></th>
<th>(1) Mean Spanish Lagged Test Score</th>
<th>(2) Mean Math Lagged Test Score</th>
<th>(3) Mean hh income (CLP)</th>
<th>(4) Mean father’s education (yrs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1-P)*Classroom Intensity Mean, $\theta_{\mu}^{\text{pre}}$</td>
<td>0.0388*** (0.00598)</td>
<td>0.0522*** (0.00618)</td>
<td>2086.0 (1581.7)</td>
<td>-0.216*** (0.0247)</td>
</tr>
<tr>
<td>P*Classroom Intensity Mean, $\theta_{\mu}^{\text{post}}$</td>
<td>0.0334*** (0.00599)</td>
<td>0.0532*** (0.00619)</td>
<td>-306.2 (1572.6)</td>
<td>-0.218*** (0.0245)</td>
</tr>
<tr>
<td>Effect of Classroom Intensity Mean, $\theta_{\mu}^{\text{post}} - \theta_{\mu}^{\text{pre}}$</td>
<td>-0.0054516+ (0.0030045)</td>
<td>0.0009108 (0.0031042)</td>
<td>-2392.183** (787.414)</td>
<td>-0.0020608 (0.0122813)</td>
</tr>
<tr>
<td>(1-P)*Classroom Intensity Variance, $\theta_{\sigma^2}^{\text{pre}}$</td>
<td>-0.0373 (0.119)</td>
<td>-0.0306 (0.123)</td>
<td>8081.1 (31829.6)</td>
<td>-1.526** (0.496)</td>
</tr>
<tr>
<td>P*Classroom Intensity Variance, $\theta_{\sigma^2}^{\text{post}}$</td>
<td>0.174* (0.0842)</td>
<td>0.0601 (0.0871)</td>
<td>2292.5 (22021.0)</td>
<td>-0.827* (0.343)</td>
</tr>
<tr>
<td>Effect of Classroom Intensity Variance, $\theta_{\sigma^2}^{\text{post}} - \theta_{\sigma^2}^{\text{pre}}$</td>
<td>0.210873 (0.1456232)</td>
<td>0.0907525 (0.1505045)</td>
<td>-5788.624 (38715.2)</td>
<td>0.6992537 (0.6033702)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.122*** (0.0108)</td>
<td>-0.135*** (0.0111)</td>
<td>234675.0*** (2861.5)</td>
<td>9.342*** (0.0446)</td>
</tr>
<tr>
<td>Observations</td>
<td>10477</td>
<td>10480</td>
<td>10086</td>
<td>10077</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
$+ p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Included regressors: earthquake region dummy, cohort dummy.
Appendix

Difference-in-differences evaluation of the effect of seismic intensity mean and variance on teacher characteristics
(Spanish teachers, similar results for Math teachers)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Class size</td>
<td>Permanent contract</td>
<td>Experience</td>
<td>Spanish Teacher Postgrad degree</td>
</tr>
<tr>
<td>(1-P)*Classroom Intensity</td>
<td>-0.278*</td>
<td>-0.0058</td>
<td>-0.121</td>
<td>0.0297</td>
</tr>
<tr>
<td>Mean, $\theta_{\mu}^{pre}$</td>
<td>(0.150)</td>
<td>(0.0188)</td>
<td>(0.207)</td>
<td>(0.0187)</td>
</tr>
<tr>
<td>P*Classroom Intensity</td>
<td>-0.324*</td>
<td>-0.0309*</td>
<td>-0.105</td>
<td>0.0094</td>
</tr>
<tr>
<td>Mean, $\theta_{\mu}^{post}$</td>
<td>(0.150)</td>
<td>(0.0186)</td>
<td>(0.204)</td>
<td>(0.0185)</td>
</tr>
<tr>
<td>Effect of Classroom Intensity</td>
<td>-0.0457</td>
<td>-0.0252**</td>
<td>0.0162</td>
<td>-0.0203*</td>
</tr>
<tr>
<td>Mean, $\theta_{\mu}^{post} - \theta_{\mu}^{pre}$</td>
<td>(0.0749)</td>
<td>(0.0095)</td>
<td>(0.1065)</td>
<td>(0.0094)</td>
</tr>
<tr>
<td>(1-P)*Classroom Intensity</td>
<td>-7.374*</td>
<td>-0.240</td>
<td>-5.653</td>
<td>0.585</td>
</tr>
<tr>
<td>Variance, $\theta_{\sigma^2}^{pre}$</td>
<td>(2.936)</td>
<td>(0.374)</td>
<td>(4.121)</td>
<td>(0.400)</td>
</tr>
<tr>
<td>P*Classroom Intensity</td>
<td>-9.218***</td>
<td>0.0429</td>
<td>1.255</td>
<td>-0.105</td>
</tr>
<tr>
<td>Variance, $\theta_{\sigma^2}^{post}$</td>
<td>(2.095)</td>
<td>(0.275)</td>
<td>(2.867)</td>
<td>(0.266)</td>
</tr>
<tr>
<td>Effect of Classroom Intensity</td>
<td>-1.8437</td>
<td>0.2832</td>
<td>6.9077</td>
<td>-0.69014</td>
</tr>
<tr>
<td>Variance, $\theta_{\sigma^2}^{post} - \theta_{\sigma^2}^{pre}$</td>
<td>(3.6082)</td>
<td>(0.4645)</td>
<td>(5.0200)</td>
<td>(0.4807)</td>
</tr>
<tr>
<td>Constant</td>
<td>25.60***</td>
<td>0.139**</td>
<td>22.38***</td>
<td>-0.146**</td>
</tr>
<tr>
<td></td>
<td>(0.381)</td>
<td>(0.0487)</td>
<td>(0.563)</td>
<td>(0.0485)</td>
</tr>
<tr>
<td>Observations</td>
<td>10339</td>
<td>9128</td>
<td>8358</td>
<td>9128</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Included regressors: earthquake region dummy, cohort dummy.
\[ \omega_{ll'ss'} = d_{ll'ss'} \frac{1}{h_{\Delta \sigma}} k \left( \frac{\Delta \sigma^2_{E_{ll'}} - \Delta \sigma^2_{E_{ss'}}}{h} \right) \prod_{tt' \in \{ll', ss', sl\}} \frac{1}{k} \left( \frac{Z_t - Z_{t'}}{h} \right) \]
Appendix: additional smoothness assumptions

Two additional sets of assumptions (technical)
Appendix: additional smoothness assumptions

Two additional sets of assumptions (technical)

- Must be innocuous to control for mean, variance, skewness and kurtosis of $F_i(x_i)$ when controlling for $F_i(x_i)$.
Appendix: additional smoothness assumptions

Two additional sets of assumptions (technical)

- Must be innocuous to control for mean, variance, skewness and kurtosis of $F_i(x_i)$ when controlling for $F_i(x_i)$.
- Matched classrooms are very similar, not identical $\Rightarrow$ DPE, IPE and CE must vary smoothly with classroom characteristics.
## Appendix


<table>
<thead>
<tr>
<th></th>
<th>(1) Math</th>
<th>(2) Spanish</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1-P)*Classroom Intensity Mean</td>
<td>0.0753 (0.102)</td>
<td>-0.193+ (0.111)</td>
</tr>
<tr>
<td>P*Classroom Intensity Mean</td>
<td>0.0676 (0.102)</td>
<td>-0.191+ (0.111)</td>
</tr>
<tr>
<td>Effect of Intensity Mean</td>
<td>-0.0076943 (0.0158669)</td>
<td>0.0020984 (0.0169411)</td>
</tr>
<tr>
<td>(1-P)*Classroom Intensity Variance</td>
<td>-0.113 (0.101)</td>
<td>0.238* (0.108)</td>
</tr>
<tr>
<td>P*Classroom Intensity Variance</td>
<td>-0.0243 (0.0633)</td>
<td>-0.0171 (0.0719)</td>
</tr>
<tr>
<td>Effect of Intensity Variance</td>
<td>0.0885604 (0.1149763)</td>
<td>-0.2549768* (0.124782)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.675 (0.449)</td>
<td>0.331 (0.484)</td>
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<tr>
<td>Observations</td>
<td>83295</td>
<td>81307</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Other included regressors: household income, seismic intensity at home interacted with cohort dummy, father's education, mother's education, student gender, teacher gender, teacher experience, class size, Math and Spanish lagged test scores, dummies for earthquake region and cohort.
Students differ in terms of cost of effort:

- Very broadly defined: psychological, financial, time cost.
- Cost of effort $q(e_i; c_i)$: increasing and convex in effort $e_i$, increasing in type $c_i$, cross-derivative $\geq 0$.
- Type is distributed in the classroom according to cdf $G(\cdot)$ on $[c, \bar{c}]$ with mean $\mu_c$

(Identical model implications if students differ in terms of productivity of effort.)
The larger the density around one’s type, $g(c_i)$, the larger the marginal utility of effort.

The smaller the fraction of students with a higher cost $(1 - G(c_i))$, the larger the marginal utility of effort. Effect stronger when $\phi = 0$ (aversion to low rank).

\[
V_1 \underbrace{a(\mu)}_{\text{mg. increase in achiev.}} + \frac{V(y, q)}{1 - G(c(e_i)) + \phi} \underbrace{g(c(e_i))(-c'(e_i))}_{\text{mg. increase in rank}} = -V_2 \frac{\partial q}{\partial e}
\]
## Appendix

Difference-in-differences evaluation of the effect of the seismic intensity mean and variance on coverage of the Spanish curriculum

<table>
<thead>
<tr>
<th></th>
<th>% of Spanish curriculum covered</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1-P)*Classroom Intensity Mean</td>
<td>-0.00149 (0.00248)</td>
</tr>
<tr>
<td>P*Classroom Intensity Mean</td>
<td>-0.00110 (0.00246)</td>
</tr>
<tr>
<td>Effect of Earthquake Intensity Mean</td>
<td>0.0003955 (0.0013076)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>% of Spanish curriculum covered</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1-P)*Classroom Intensity Variance</td>
<td>0.0192 (0.0574)</td>
</tr>
<tr>
<td>P*Classroom Intensity Variance</td>
<td>0.0415 (0.0346)</td>
</tr>
<tr>
<td>Effect of Earthquake Intensity Variance</td>
<td>0.0222701 (0.0670429)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.661*** (0.00874)</td>
</tr>
</tbody>
</table>

Observations 6438

Other included regressors: Spanish teacher characteristics (tenure at school, type of contract, possession of postgraduate degree, gender), class size, mean and variance of lagged test scores in Spanish, teacher experience, dummies for earthquake region and cohort.

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$