Managers and Productivity in the Public Sector

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The views expressed in this article are those of the author and do not involve the responsibility of the Istituto Nazionale di Previdenza Sociale.
Can The Public Sector Do More With Less?

- The public sector is a large share of modern economies
  - 18% of workers in OECD countries
  - 28% - 57% of government spending on GDP in OECD countries
Can The Public Sector Do More With Less?

- The public sector is a large share of modern economies
  - 18% of workers in OECD countries
  - 28% - 57% of gov. spending on GDP in OECD countries

- Growing literature on managers and managerial practices in the private sector, less is known about their impact in the public sector
  - limited tools (e.g. firing, promotions, incentive-pay schemes)
  - important role due to the lack of incentives for employees to perform
This Paper

- **Question**: Do managers in the public sector? How?

- **Data**: Administrative data from the Italian Social Security Agency

- **Main outcome**: Direct measure of $P$: output (claims processed) per worker

- **Strategy**: Exploit quasi-experimental manager rotation across offices

- **Bottom Line**:
  - Managers matter: ↑ managerial quality by $1\sigma \Rightarrow$ ↑ office $P$ by 10%
  - Main channel: old white-collar workers retire
  - Aggregate $P$ ↑ by 6.9% by optimally reallocating managers (lower bound)
Literature Review

- **Value of managers and managerial practices**

- **Bureaucrats/teachers matter for public service delivery**

- **Document dispersion productivity**

- **Movers Designs**
Institutional Background
Italian Social Security Agency

**Istituto Nazionale di Previdenza Sociale** (INPS) - since 1933

- Large centralized government agency (30,000 employees)
- HQ in Rome, ~100 main offices, ~400 smaller offices
- Each office has a manager and managers rotate across offices
- Each employee has a desktop, and they all work on the same software to review and approve/reject claims

**Ideal setting**: same rules for all offices, homog. product, no diff. in capital.
Manager Rotation

- Managers stationed in main offices (dirigenti) are rotated approximately every 5 years (anti-corruption law). Their 5-year tenure expires at a different point in times and there are limited opportunities to sort endogenously.

- Managers working at local branches (responsabili d’agenzia) rotate due to both plausibly exogenous reasons (e.g. retirement) and potentially endogenous choices (e.g. live close to home). Factors that limit endogenous sorting:
  - limited pool of applicants
  - lack of guideline ⇒ it depends on the HR officer
  - constraints

Overall, manager rotation is quite haphazard and subject to many constraints, which limits the concerns related to endogenous mobility.
Manager’s Duties

Managers are in charge of office operations and their main duty consists in operating the office as **efficiently** as possible.

What can they do?

- very limited scope in hiring/firing/moving workers against their will
- training
- contrast absenteeism
- authorize overtime
- reallocate tasks within the office
- might better motivate/monitor employee
- monitor production process and devise solutions (e.g. bottlenecks)
Data
Data

Office-level administrative quarterly data from INPS (2011-2017)

- 851 managers and 494 offices
- inputs: number of workers assigned to each team, absences, training, over-time
- output: number of claims processed weighted by their complexity
- composite ”quality” index (timeliness + error rate)


- trace careers (promotions, hiring, firing, transfers etc.)

These are administrative data recorded by INPS for internal monitoring purposes. These data are also used to pay wages (incentive pay).
Productivity Measure

\[ P_{it} = \frac{Y_{it}}{FTE_{it} \times 3} = \sum_{k=1}^{K} \frac{c_{k, it} \times w_{k, t}}{FTE_{it} \times 3} \]

- \( c_{k, it} \): \# claims of type \( k \) processed at time \( t \) by office \( i \)
- \( w_{k, t} \): weight of type \( k \) claim at time \( t \)
- \( FTE_{it} \): Full Time Equivalent Employment
- there are more than 1,000 products and hence weights
- it is analogous to the SMV (or SAM)

Intuitively, weights represent how many hours it should take on average to process each claim.
### Characteristics of Social Security Offices

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Full Sample</th>
<th>Main Offices</th>
<th>Local Branches</th>
</tr>
</thead>
<tbody>
<tr>
<td>Productivity</td>
<td>94.56</td>
<td>103.65</td>
<td>91.72</td>
</tr>
<tr>
<td>Output ($\times 1,000$)</td>
<td>10.24</td>
<td>29.18</td>
<td>4.33</td>
</tr>
<tr>
<td>FTE</td>
<td>39.95</td>
<td>115.39</td>
<td>16.41</td>
</tr>
<tr>
<td>Hours</td>
<td>31.66</td>
<td>91.76</td>
<td>12.91</td>
</tr>
<tr>
<td>Training</td>
<td>0.62</td>
<td>1.73</td>
<td>0.28</td>
</tr>
<tr>
<td>Overtime</td>
<td>0.70</td>
<td>2.10</td>
<td>0.26</td>
</tr>
<tr>
<td>Abs. Rate</td>
<td>0.21</td>
<td>0.21</td>
<td>0.21</td>
</tr>
<tr>
<td>Quality</td>
<td>100.37</td>
<td>101.03</td>
<td>100.16</td>
</tr>
<tr>
<td>Backlog ($\times 1,000$)</td>
<td>54.24</td>
<td>197.68</td>
<td>9.48</td>
</tr>
<tr>
<td>Office-quarters</td>
<td>13212</td>
<td>3142</td>
<td>10070</td>
</tr>
<tr>
<td>Managers</td>
<td>851</td>
<td>221</td>
<td>638</td>
</tr>
<tr>
<td>Offices</td>
<td>494</td>
<td>111</td>
<td>383</td>
</tr>
</tbody>
</table>

*Note:* The full sample includes all main offices and local branches, 2011q1-2017q2. All statistics are calculated across office-quarter observations.
Results

I. Do managers matter?

II. How do managers matter?

III. Counterfactual Exercises
Two-Way FE Model

Two-way fixed effects model:

\[ \ln(P)_{it} = \alpha_i + \tau_t + \theta_{m(i,t)} + u_{it} \]

- \( i \): office, \( t \): quarter
- \( \ln(P)_{it} = \ln \frac{Y_{it}}{FTE_{it}} \)
- \( \alpha_i \): office FE, \( \tau_t \): time FE, and \( \theta_{m(i,t)} \): manager FE

Exclude the quarter of the switch.

I can separately identify the office from the manager component thanks to manager rotation.
Two-Way FE Model

Identifying assumption:

Manager mobility is as-good-as random conditional on office and time fixed effects.

- sorting on $\alpha_i$ is not a threat
- sorting on $u_{it}$ is a violation of the identifying assumption

Threats to Identification:

- endogenous mobility. $\Delta M_i = \hat{\theta}_{\text{incoming}} - \hat{\theta}_{\text{outgoing}}$
- model misspecification
  - Mean Residuals
  - Log-Lin
  - Log-Lin Origin
No Sorting on the Error Component

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## Do Managers Matter?

Biased Corrected Variance-Covariance decomposition

<table>
<thead>
<tr>
<th>Var. Component</th>
<th>Var. Component</th>
<th>Sh. of Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var(Ln(P))</td>
<td>0.1106</td>
<td>100 %</td>
</tr>
<tr>
<td>Var(Manager)</td>
<td>0.0102</td>
<td>9.22%</td>
</tr>
<tr>
<td>Var(Office)</td>
<td>0.0319</td>
<td>28.84 %</td>
</tr>
<tr>
<td>Var(Time)</td>
<td>0.0408</td>
<td>36.89%</td>
</tr>
<tr>
<td>Cov(Manager, Office)</td>
<td>-0.0096</td>
<td>-8.68%</td>
</tr>
<tr>
<td>Cov(Time, Manag. + Office)</td>
<td>0.0015</td>
<td>1.39%</td>
</tr>
</tbody>
</table>

*Note:* The sample includes the largest connected set, 2011q1-2017q2.
Results

I. Do managers matter?

II. How do managers matter?

III. Counterfactual Exercises
What Makes for a Productive Manager?

The ideal specification

\[ y_{it} = \alpha_i + \sum_{k \neq 1} \left[ \pi_0^k D_{it}^k + \pi_1^k D_{it}^k \Delta M_i \right] + h_t (X_{it}) + \varepsilon_{it} \]  \hspace{1cm} (1)
What Makes for a Productive Manager?

The ideal specification

\[ y_{it} = \alpha_i + \sum_{k \neq 1} \left[ \pi_0^k D_{it}^k + \pi_1^k D_{it}^k \Delta M_i^k \right] + h_t(X_{it}) + \varepsilon_{it} \]  

(1)

\( \Delta M_i \) is unobservable \((\Rightarrow)\) estimate it using the two-way FE model.
What Makes for a Productive Manager?

The ideal specification

\[ y_{it} = \alpha_i + \sum_{k \neq 1} \left[ \pi_0^k D_{it}^k + \pi_1^k D_{it}^k \Delta M_i \right] + h_t(X_{it}) + \epsilon_{it} \] (1)

\( \Delta M_i \) is unobservable \( \Rightarrow \) estimate it using the two-way FE model

**Spurious correlation** between \( y_{it} \) and \( \Delta M_i \) \( \Rightarrow \) estimate \( \hat{\Delta M}_{i,k}^L \) using a leave-out procedure purges \( \pi_{1,k}^i \) from the spurious correlation

\[ \Delta y_i^k = \pi_0^k + \pi_1^k \hat{\Delta M}_{i,k}^L + \Gamma^k X_i + \Delta \epsilon_i^k \] (2)
Decomposition
We have learnt that it takes some time for a "productive" manager to increase productivity of the office she moves to.

But what do "productive" managers actually do?

I decompose the impact of managers on productivity into its effect on

- Output (reduced form)
- FTE (reduced form)
1%↑ in \( P \) (induced by a change in leadership) \( \Rightarrow \) ↑ \( Y \) by 0.25% (at \( k=6 \))
Decomposition: FTE

\[ \text{Ln}(\text{FTE}) \]

1\%↑ in \( P \) (induced by a change in leadership) \( \Rightarrow \) ↓ \( \text{FTE} \) by 0.75\% (at \( k=6 \))
Mechanisms
Mechanisms: Retirement

A(Cum. Retirement)

Quarter

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Results

I. Do managers matter?

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Counterfactual Exercises

Four Policies

1. reallocate existing managers to offices: 6.9% ↑ in $P$ (lower bound).

2. fire the bottom 20% of managers and replace them with the median manager: 3% ↑ in $P$

3. fire the bottom 20% of managers and replace them with the median manager AND reallocate them: 7.4% ↑ in $P$ (lower bound).

4. randomly assign managers ($i=1000$): 2% ↑ in $P$
Conclusion
Conclusion

- I study the impact of public sector managers on office productivity.

- Managers have a quantitatively meaningful impact on productivity: $\uparrow$ managerial talent by $1\sigma \Rightarrow \uparrow$ office P by 10%. This effect is mainly driven by the exit of older workers (retirement) and time reallocation within the office.

- By optimally reallocating managers aggregate $P \uparrow$ by 6.9%.

- These results suggest that there may be large social returns to carefully modeling public sector productivity and the impacts of managerial talent.

- They imply that governments should design policies aimed at hiring, retaining and properly allocating managerial talent.
Thank you!
Motivation

![Employment Public Sector/Total Employment graph]

Government Spending / GDP

Source: OECD, 2015.
## Stylized Facts

<table>
<thead>
<tr>
<th>Productivity Measure</th>
<th>Within-Industry Productivity Moment</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: My Measure</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor productivity:</td>
<td>Median</td>
<td>4.524</td>
</tr>
<tr>
<td>log(weighted claims/employee)</td>
<td>IQ range</td>
<td>0.426</td>
</tr>
<tr>
<td></td>
<td>90-10 percentile range</td>
<td>0.860</td>
</tr>
<tr>
<td></td>
<td>95-5 percentile range</td>
<td>1.161</td>
</tr>
<tr>
<td></td>
<td>St. deviation</td>
<td>0.366</td>
</tr>
</tbody>
</table>

| **Panel B: Syverson (2004)** | | |
| Labor productivity: | Median | 3.174 |
| log(value added/employee) | IQ range | 0.662 |
| | 90-10 percentile range | 1.417 |
| | 95-5 percentile range | 2.014 |

*Note*: Panel A reports the same statistics calculated over the full sample (2011q1-2017q2). Panel B is taken from Table 1 of Syverson (2004).
Stylized Facts

![Histogram of Ln(Productivity)](image)

1st to 99th percentile.

\[ 124 = \frac{h}{\text{day}} \times \text{days/month} \times \text{presence rate} = 7 \times 22 \times 0.81 \]
Productivity Measure

There are more than 1,000 products and hence weights:

- 10p-90p: 0.03-1.03
- min-max: 0.01-6.5

Examples:

<table>
<thead>
<tr>
<th>Claim</th>
<th>Basic</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Old Age Pension</td>
<td>Y</td>
<td>0.52</td>
</tr>
<tr>
<td>Unemployment Benefit</td>
<td>Y</td>
<td>0.45</td>
</tr>
<tr>
<td>Sick Leave</td>
<td>Y</td>
<td>0.44</td>
</tr>
<tr>
<td>Maternity Leave</td>
<td>Y</td>
<td>0.66</td>
</tr>
<tr>
<td>Overdue Pension Benefits</td>
<td>Y</td>
<td>0.1</td>
</tr>
<tr>
<td>Evaluating House Mortgage</td>
<td>N</td>
<td>6</td>
</tr>
</tbody>
</table>
Conceptual Framework

Office production function

\[ Y_{it} = A_{it} K_{it}^a (e_{it} L_{it})^b M_{it}^{1-a-b}, \]

- \(Y_{it}\): homogeneous product
- \(A_{it} = \tilde{A}_i v_{it}\): TFP
- \(e_{it} = m_{it}^\lambda\): effort as a f. of managerial talent per worker
- \(L_{it} = h(L_1, L_2, \ldots, L_\ell)\): labor aggregate
- \(K_{it} = k_t \times L_{it}\): physical capital
- \(k_t\): physical capital per worker
- \(M_{it}\): managerial talent
Conceptual Framework

Given these assumptions, output per worker \( P_{it} \) becomes

\[
P_{it} = \frac{Y_{it}}{L_{it}} = A_{it} k_t^a m_{it}^{\lambda b} m_{it}^{1-a-b},
\]

Managers can

- have a direct impact on \( Y_{it} \) (e.g., by reassigning tasks and solving bottlenecks)
- affect office size (i.e., \( L_{it} \)), worker composition (i.e., mix of \( L_1, L_1, \ldots, L_\ell \)), and workers’ effort (i.e., \( e_{it} \))

Then

\[
\ln P_{it} = \left[ \ln \tilde{A}_i \right] + [a \ln k_t] + [(1 - a - b(1 - \lambda)) \ln m_{it}] + \ln v_{it}
\]

I approximate this with a combination of office, time, and manager effects.
Incentive-Pay Scheme

Bonuses are a complicated function of office performance ($P$ and quality), which is evaluated relative to (i) production targets, (ii) previous year achievements, and (iii) national average.

**Managers in Main Offices**
- 56% performance of the office
- 14% performance of the geographical region
- 30% boss’ evaluation

**Managers in Local Branches**
- office performance + boost/penalty (performance region)

**Clerks**
- performance of the region
## Characteristics of Social Security Offices

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Main Offices</th>
<th>Local Branches</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand ($\times 1,000$)</td>
<td>68.02</td>
<td>220.55</td>
<td>20.42</td>
</tr>
<tr>
<td>Hires</td>
<td>0.06</td>
<td>0.18</td>
<td>0.02</td>
</tr>
<tr>
<td>Separations</td>
<td>0.50</td>
<td>1.53</td>
<td>0.17</td>
</tr>
<tr>
<td>Fires</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Inbound Transfers</td>
<td>0.87</td>
<td>2.64</td>
<td>0.32</td>
</tr>
<tr>
<td>Outbound Transfers</td>
<td>0.41</td>
<td>0.98</td>
<td>0.23</td>
</tr>
<tr>
<td>Retirement</td>
<td>0.31</td>
<td>0.97</td>
<td>0.10</td>
</tr>
<tr>
<td>Divorce</td>
<td>0.87</td>
<td>0.88</td>
<td>0.87</td>
</tr>
<tr>
<td>Blood donations</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>Office-quarters</td>
<td>13212</td>
<td>3142</td>
<td>10070</td>
</tr>
<tr>
<td>Managers</td>
<td>851</td>
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<td>638</td>
</tr>
<tr>
<td>Offices</td>
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<td>111</td>
<td>383</td>
</tr>
</tbody>
</table>

**Note**: The full sample includes all main offices and local branches, 2011q1-2017q2. All statistics are calculated across office-quarter observations.
## Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Balanced Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td># Managers</td>
<td>851</td>
<td>601</td>
</tr>
<tr>
<td># Offices</td>
<td>494</td>
<td>282</td>
</tr>
<tr>
<td># Managers &gt;1 Office</td>
<td>207</td>
<td>184</td>
</tr>
<tr>
<td># Offices &gt;1 Manager</td>
<td>404</td>
<td>282</td>
</tr>
<tr>
<td># Connected Sets</td>
<td>276</td>
<td>143</td>
</tr>
<tr>
<td># Events</td>
<td>635</td>
<td>318</td>
</tr>
<tr>
<td># Events in Main Offices</td>
<td>226</td>
<td>80</td>
</tr>
<tr>
<td># Events in Local Branches</td>
<td>409</td>
<td>238</td>
</tr>
</tbody>
</table>

*Note: Column 1 reports the summary statistics computed over the full sample (2011q1-2017q2, N=13,212). Column 2 reports the same statistics over the balanced-analysis sample (2011q1-2017q2, N=8165).*
## Manager Rotation by Macro-Region

<table>
<thead>
<tr>
<th>Region</th>
<th>N Switches</th>
<th>N Offices</th>
<th>Switches/Office</th>
</tr>
</thead>
<tbody>
<tr>
<td>North-East</td>
<td>115</td>
<td>91</td>
<td>1.3</td>
</tr>
<tr>
<td>North-West</td>
<td>183</td>
<td>130</td>
<td>1.4</td>
</tr>
<tr>
<td>Center</td>
<td>122</td>
<td>102</td>
<td>1.2</td>
</tr>
<tr>
<td>South</td>
<td>164</td>
<td>123</td>
<td>1.3</td>
</tr>
<tr>
<td>Islands</td>
<td>99</td>
<td>68</td>
<td>1.5</td>
</tr>
</tbody>
</table>

*Note: Full sample, 2011q1-2017q2.*
Summary Statistics

N Switches per Office

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Do Managers Matter?

\[ \ln P_{it} = \alpha_i + \tau_t + u_{it} \]  

(2)

\[ \ln P_{it} = \alpha_i + \tau_t + \theta_{m(i,t)} + u_{it} \]  

(3)

<table>
<thead>
<tr>
<th></th>
<th>(1) (\text{Ln(P)})</th>
<th>(2) (\text{Ln(P)})</th>
<th>(3) (\text{Ln(P)})</th>
<th>(4) (\text{Ln(P3)})</th>
<th>(5) (\text{Ln(P)})</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>12278</td>
<td>12278</td>
<td>12278</td>
<td>12278</td>
<td>12278</td>
</tr>
<tr>
<td>R sq.</td>
<td>0.345</td>
<td>0.573</td>
<td>0.631</td>
<td>0.605</td>
<td>0.633</td>
</tr>
<tr>
<td>Adj. R sq.</td>
<td>0.343</td>
<td>0.554</td>
<td>0.595</td>
<td>0.575</td>
<td>0.596</td>
</tr>
<tr>
<td>Time FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Office FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Manager FE</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Manag-by-Office FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Pvalue</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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AKM Assumptions

AKM-style model in matrix notation:

\[ \ln(P) = D\alpha + G\theta + u_{it} \]  

(4)

I follow CHK (2013) and specify the following error structure:

\[ u_{it} = \eta_{i,m} + \zeta_{it} + \epsilon_{it} \]

Identifying assumptions:

\[ E[d_i'u] = 0 \forall i \]

\[ E[g_m'u] = 0 \forall i \]
Mean Residuals
Non Parametric Evidence

Slope .21 (SE .101)
Manager Fixed Effects

Deviations of Manager FE from connected set average

2011–2017
Normalization: One Connected Set

\[ y_{it} = \alpha_i + \theta_{m(i,t)} + u_{it} \]

Omit one manager and do not omit any office FE (no constant)

\[ \hat{\theta}_j = \theta_j - \theta^0 \]
Normalization: Two Connected Sets

\[ \hat{\theta}^1_j = \theta^1_j - \theta^{01} \quad \hat{\theta}^2_j = \theta^2_j - \theta^{02} \]

If manager \( j \) and \( j' \) belong to the same CS, then

\[ \hat{\Delta M} = \hat{\theta}_j - \hat{\theta}_{j'} = \theta_j - \theta_{j'} \]
Mechanisms: Covariate Index

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Mechanisms: Covariate Index

Pred Ln(P)

-4   -2   0   2   4   6
Quarter

Office+Time FE + Age + Gender + Hour Allocation

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Mechanisms: Covariate Index

Pred Ln(P)

Quarter

Office+Time FE + Age
+ Gender + Hour Allocation

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Mechanisms: Covariate Index

Observables explain 56% of the increase in P (14% demog. vs 86% allocation)
As robustness check, I follow CFR (2014)

- Estimate the manager VA using data outside manager-office spell (leave-out-mean)
- Regress $\Delta \ln P$ on $\hat{\Delta M}$

This procedure allows me to construct a VA measure only for managers who work in at least two different offices, which drastically reduces the number of events.
Leave-Office-Out Estimates of Managerial Talent

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Leave-Office-Out Estimates of Managerial Talent

![Graph showing Ln(P) vs Quarter]

- Ln(P) values range from approximately -4 to 1.5.
- The X-axis represents Quarters ranging from -4 to 6.
- The graph indicates fluctuations in Ln(P) over time, with peaks and troughs.

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Leave-Office-Out Estimates of Managerial Talent

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Ln(FTE)

Quarter

back
back to Presentation

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Leave-Office-Out Estimates of Managerial Talent

Procedure (CFR I (2014))

- \( \ln P_{it} = \alpha_i + \tau_t + \theta_{m(i,t)} + \eta_{it} \)

- generate "residuals" \( \ln P_{it}^* = \ln P_{it} - \alpha_i - \tau_t \)

- construct the leave out mean of these "residuals" as

\[
\overline{\ln P_{m,-i}} = \frac{\sum_{j\neq i} \sum_t \ln P_{jt}^* 1(M_{jt} = m)}{\sum_{j\neq i} \sum_t 1(M_{jt} = m)}
\]

- shrink \( \overline{\ln P_{m,-i}} \) toward the grand mean
Treatment Intensity

Delta M

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Shrinkage Procedure

Shrinkage procedure

\[ \mu_j^* = \left( \frac{\hat{\sigma}_m^2}{\hat{\sigma}_m^2 + \hat{SE}(\hat{\mu}_j)^2} \right) \hat{\mu}_j + \left( 1 - \frac{\hat{\sigma}_m^2}{\hat{\sigma}_m^2 + \hat{SE}(\hat{\mu}_j)^2} \right) \bar{y} \]

- \( \mu_j^* \): shrunk estimate for manager \( j \)
- \( \hat{\mu}_j \): estimate of the manager effect
- \( \hat{\sigma}_m^2 \): variance of the true manager effect
- \( \hat{SE}(\hat{\mu}_j)^2 \): variance of the estimated manager effect
- \( \bar{y} \): grand mean.
Shrunk Estimates of Managerial Talent

10% ↑ in managerial talent (i.e., $\Delta \hat{M}_i = 0.1$ ) $\Rightarrow$ 8%↑ in $P$ (at $k=6$)
Shrunk Estimates of Managerial Talent

\[ \text{Ln}(Y) \]

10% ↑ in managerial talent (i.e., \( \Delta M_i^L = 0.1 \)) \( \Rightarrow \) 2.8% ↑ in Y (at k=6)
Shrunk Estimates of Managerial Talent

\[ \text{Ln(FTE)} \]

10% ↑ in managerial talent (i.e., \( \Delta M_i^L = 0.1 \)) \( \Rightarrow \) 5.2% ↓ in FTE (at k=6)
### Workers’ Composition

<table>
<thead>
<tr>
<th>$k$</th>
<th>A(Retirement)</th>
<th>A(Hires)</th>
<th>A(Fires)</th>
<th>A(Inbound T)</th>
<th>A(Outbound T)</th>
</tr>
</thead>
<tbody>
<tr>
<td>-4</td>
<td>0.044</td>
<td>0.178</td>
<td>0.003</td>
<td>0.077</td>
<td>-0.055</td>
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<tr>
<td></td>
<td>(0.125)</td>
<td>(0.110)</td>
<td>(0.004)</td>
<td>(0.106)</td>
<td>(0.144)</td>
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<tr>
<td>-3</td>
<td>-0.037</td>
<td>0.093</td>
<td>0.002</td>
<td>0.027</td>
<td>-0.108</td>
</tr>
<tr>
<td></td>
<td>(0.089)</td>
<td>(0.090)</td>
<td>(0.004)</td>
<td>(0.085)</td>
<td>(0.131)</td>
</tr>
<tr>
<td>-2</td>
<td>-0.048</td>
<td>0.034</td>
<td>0.003</td>
<td>0.031</td>
<td>-0.090</td>
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<tr>
<td></td>
<td>(0.059)</td>
<td>(0.073)</td>
<td>(0.004)</td>
<td>(0.074)</td>
<td>(0.112)</td>
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<tr>
<td>0</td>
<td>0.299</td>
<td>0.024</td>
<td>-0.008</td>
<td>0.000</td>
<td>-0.043</td>
</tr>
<tr>
<td></td>
<td>(0.087)</td>
<td>(0.018)</td>
<td>(0.010)</td>
<td>(0.154)</td>
<td>(0.053)</td>
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<td>1</td>
<td>0.401</td>
<td>0.027</td>
<td>-0.056</td>
<td>-0.098</td>
<td>-0.019</td>
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<tr>
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<td>(0.102)</td>
<td>(0.033)</td>
<td>(0.031)</td>
<td>(0.158)</td>
<td>(0.066)</td>
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<tr>
<td>2</td>
<td>0.380</td>
<td>0.024</td>
<td>-0.049</td>
<td>-0.274</td>
<td>-0.167</td>
</tr>
<tr>
<td></td>
<td>(0.108)</td>
<td>(0.033)</td>
<td>(0.040)</td>
<td>(0.167)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>3</td>
<td>0.396</td>
<td>0.006</td>
<td>-0.063</td>
<td>-0.405</td>
<td>-0.245</td>
</tr>
<tr>
<td></td>
<td>(0.119)</td>
<td>(0.038)</td>
<td>(0.045)</td>
<td>(0.169)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>4</td>
<td>0.458</td>
<td>-0.015</td>
<td>-0.040</td>
<td>-0.454</td>
<td>-0.243</td>
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<tr>
<td></td>
<td>(0.121)</td>
<td>(0.039)</td>
<td>(0.038)</td>
<td>(0.166)</td>
<td>(0.124)</td>
</tr>
<tr>
<td>5</td>
<td>0.422</td>
<td>0.005</td>
<td>-0.061</td>
<td>-0.471</td>
<td>-0.303</td>
</tr>
<tr>
<td></td>
<td>(0.123)</td>
<td>(0.039)</td>
<td>(0.041)</td>
<td>(0.170)</td>
<td>(0.124)</td>
</tr>
<tr>
<td>6</td>
<td>0.376</td>
<td>-0.077</td>
<td>-0.059</td>
<td>-0.581</td>
<td>-0.402</td>
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<tr>
<td></td>
<td>(0.132)</td>
<td>(0.056)</td>
<td>(0.042)</td>
<td>(0.180)</td>
<td>(0.135)</td>
</tr>
</tbody>
</table>

| N   | 318 | 318 | 318 | 318 | 318 |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Mean  | 0.415 | 0.038 | 0.019 | 0.900 | 0.374 |
Mechanisms: Abs. Rate

Abs. Rate

Quarter

-4 -2 0 2 4 6

-0.15 -0.1 -0.05 0 0.05

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Mechanisms: Hours
Mechanisms: Wage Bill

Wage Bill = 1 × hours + (1 + 30%) × Overtime

Ln(Wage Bill, OT 30%)
Mechanisms: Over-Time

A(Overtime)

Quarter

back
Mechanisms: Hiring

A(Cum. Hires)
Mechanisms: Firing

A(Cum. Fires)

Quarter

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Mechanisms: Covariate Index

My covariate index includes the following regressors

- **demographic characteristics of the office**
  - share of employees in each of the 10 deciles of the age distribution, average office age, fraction female
  - (linear and quadratic term + two-way interactions with time FE and main office time)

- **time allocation**
  - ln FTE, asinh(absences), asinh(over-time), asinh(training)
  - (linear and quadratic term + two-way interactions with time FE and main office time)

- **other**
  - office and time FE
Mechanisms

Ln(Backlog)

Quarter
Gaming

\[ \ln P_{it} = \mu_i + \nu_t + \sum_{\nu} \tilde{V} \beta^k D^k_{it} + \sum_{\nu} \tilde{V} \delta^k D^k_{it} \times \Delta M_i + u_{it} \]
Gaming

\[
\ln P_{it} = \mu_i + \nu_t + \sum_{k=-V}^{\bar{V}} \beta_k D_{it}^k + \sum_{k=-V}^{\bar{V}} \delta_k D_{it}^k \times \Delta M_i + u_{it}
\]
Gaming

Categories:

1. Insurance and pensions
2. Subsidies to the poor
3. Services to contributors
4. Social and medical services
5. Specialized products
6. Archives and data management
7. Administrative cross-checks
8. Checks on benefits
9. Appeals
Placebo Test: Demand

Ln(Demand)

Quarter

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On-the-Job Learning

Do managers learn on the job?

- relax the assumption that ability is a time-invariant characteristic of managers
- I cannot accurately measure experience for managers in main offices ⇒ focus on local branches
- I can not study the early years (exper ≥ 5 ∀ m)

\[
\ln(P)_{it} = \mu_i + \nu_t + \theta_{m(i)} + \sum_j \beta_j Q_{ji} + \beta_6 1(\text{exper} > 12) + \epsilon_{it}
\]

\(Q_{ji}\) is the j-th quintile of the experience distribution to the left of 12
On-the-Job Learning
Quartiles of $\Delta M_i^L$

\[ \Delta y_{it}^k = \beta_0^k + \sum_{v=2}^{4} \beta_v^k \times Q_{iv} + \Delta \tau + \psi^k \Delta X_{it} + \Delta \epsilon_{it}^k. \] (5)
Quartiles of $\Delta M_i^L$

<table>
<thead>
<tr>
<th>Quart</th>
<th>Q2 − Q1</th>
<th>Q3 − Q1</th>
<th>Q4 − Q1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln(Y)</td>
<td>−.3 −.1 .1 .3</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>−4 −2 0 2 4 6</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Quartiles of $\Delta M_i^L$

<table>
<thead>
<tr>
<th>Ln(FTE)</th>
<th>Quarter</th>
<th>Q2 − Q1</th>
<th>Q3 − Q1</th>
<th>Q4 − Q1</th>
</tr>
</thead>
<tbody>
<tr>
<td>−3</td>
<td>−4</td>
<td>−2</td>
<td>0</td>
<td>2</td>
</tr>
</tbody>
</table>

Legend:
- Q2 − Q1
- Q3 − Q1
- Q4 − Q1

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Simulations

The diagram shows simulated data with event times on the x-axis and values on the y-axis. The data is labeled with different symbols and lines for different correlation values: rho = -0.1, rho = -0.4, and rho = -0.8. The legend indicates the types of errors: 'iid errors' and specific rho values.
Heterogeneous Treatment Effects

Are better managers more effective in smaller offices?

$$\Delta \ln P_{it}^k = \pi_0^k + \pi_1^k \Delta M_i^L + \pi_1^{kH} \Delta M_i^L \times H_i + \Delta \tau_t + \psi^k \Delta X_{it}^k + \Delta \epsilon_{it}^k$$ (6)

where $H_i$ is a pre-determined characteristic of office $i$. 
Heterogeneous Treatment Effects

![Graph showing heterogeneous treatment effects](image)

- **Ln(P)**
  - X-axis: Quarter
  - Y-axis: Ln(P)
  - Data points marked with "North – South"

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Heterogeneous Treatment Effects

Ln(P)

Quarter

High SC − Low SC

SC: Newspapers

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Heterogeneous Treatment Effects

SC: Blood Donations

Ln(P)

Quarter
High SC – Low SC

SC: Blood Donations
Heterogeneous Treatment Effects

![Graph showing the relationship between Ln(P) and Quarter, with points indicating High P - Low P.](image)
Heterogeneous Treatment Effects

Quarter
High FTE − Low FTE
Ln(P)
Heterogeneous Treatment Effects

\[ \text{Ln}(P) \]

-4  -2  0  2  4  6

Quarter

Main office – Local Branches

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