# Direct and Cross-scheme effects in a Research and Development Subsidy Program

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SIMPATIC Conference
February 26-27 2015

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    2. Capital market imperfections

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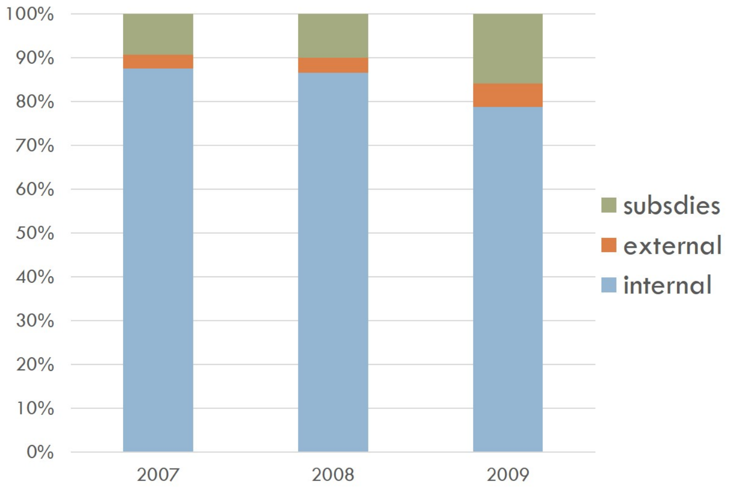
→ Firms rely on internal funds

# Financing Mix



## Innovation Policy

- If internal funds are limited: innovation projects may render unprofitable due to higher costs of capital
- From a society's point of view: sub-optimal investment in innovation

→ especially projects with high social returns and high levels of risk (Czarnitzki and Hottenrott 2011b)

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Previous research shows financing constraints for

- **research investments** rather than development (Czarnitzki, Hottenrott and Thorwarth 2011)
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...adds to the literature on the efficacy of R&D subsidies

- At which stage of the R&D process is it most effective?
- Is a policy with differentiated schemes for R and D more effective than a general one?
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## What we do

- Estimate impact of direct subsidies for R&D on private R&D investments (input additionality)
  - Distinguishing between R and D subsidies
    - Direct effects (within scheme)
    - Cross-scheme effects
  - → Measuring own and cross additionality
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## Research Setting

- Flanders: Regional Innovation Agency IWT distributes most R&D subsidies
- Different subsidy programs for R and D that differ wrt the share in total project costs to be borne
- About 40% for R, 15-25% for D
- Also mixed projects
- From 1997 to 2009, the Flemish government co-funded a total number of 2,872 projects in 1,868 different firms
- Annual R&D spending and control variables from the **OECD R&D survey**, accounting data from **Belfirst (BvD)**, patents from EPO data base

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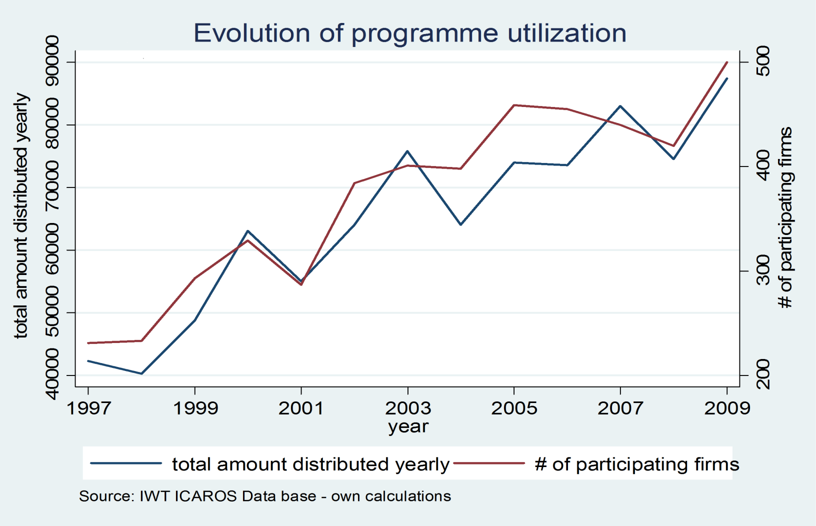
# How do R&D grants work?

Table: Co-financed R&D projects in the Flemish innovation policy design 1997 -2009 (4,827 obs.)

| | mean | std. dev. | min | max |
|---|---|---|---|---|
| Projects per firm | 1.42 | 1.51 | 1 | 24 |
| Research grant (amt. yearly) | 32.65 | 172.98 | 0 | 6,360.93 |
| Development grant (amt. yearly) | 49.43 | 204.34 | 0 | 6,706.61 |
| Mixed grant (amt. yearly) | 90.35 | 382.03 | 0 | 7,526.76 |

Source: IWT ICAROS data base. Yearly amount in thousand Euros and at the project-year level.

# Flemish R&D policy



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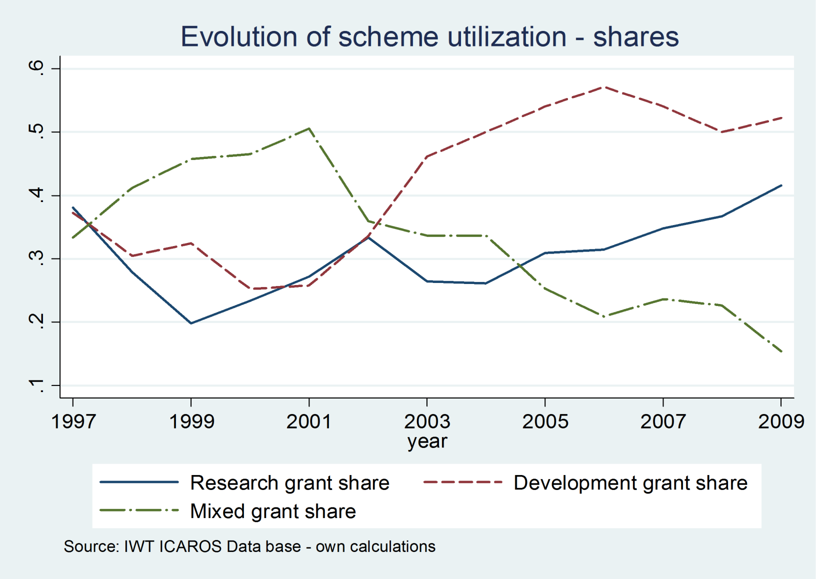

## Treatment Effects Analysis

**Evaluation problem**

What is the effect of a subsidy on firms own-financed R&D expenditure?

- Average treatment effect on the treated (ATT)

$$E(\alpha_{TT}) = E(Y^T|S=1) - E(Y^C|S=1) \qquad (1)$$

- $Y^C$ is the potential outcome that would have been realized if the treatment group ($S=1$) had not been treated
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$$E(Y^C|S=1) \neq E(Y^C|S=0) \tag{2}$$

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## Matching - CIA

- Conditional independence assumption (Rubin 1977)

$$Y^C \perp R | X = x \tag{3}$$

- Treatment and the outcome variables are statistically independent for firms with the same set of characteristics $X$

→ Nearest neighbor propensity score matching

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- Firm age, size, collaboration status, patent stock, past receipt of a subsidy (distinguishing between R scheme, D scheme and mixed scheme, EU and federal), qualifying as SME, being part of a group with a foreign parent, capital intensity, year, industry
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## Average Treatment Effect

- the ATT can be calculated as the mean difference in the outcome variable(s) of the matched samples

$$\hat{\alpha}_{TT} = \frac{1}{n^T}\left(\sum_i Y_i^T - \sum_i \hat{Y_i^C}\right) \tag{4}$$

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# Descriptives BEFORE the matching

| | No subs (3,549) | With subs (893) | t-test |
|---|---|---|---|
| | Mean | Mean | |
| **R&D_intensity_net** | 0.064 | 0.149 | $p < 0.000$ |
| **Development_intensity_net** | 0.031 | 0.058 | $p < 0.000$ |
| **Research_intensity_net** | 0.033 | 0.091 | $p < 0.000$ |
| R&D cooperation | 0.319 | 0.702 | $p < 0.000$ |
| Patent stock per employee | 0.017 | 0.047 | $p < 0.000$ |
| Past research grants | 0.042 | 0.152 | $p < 0.000$ |
| Past development grants | 0.060 | 0.163 | $p < 0.000$ |
| Past mixed grants | 0.032 | 0.226 | $p < 0.000$ |
| Foreign group | 0.225 | 0.243 | $p = 0.256$ |
| SME | 0.841 | 0.738 | $p < 0.000$ |
| Employees | 147.687 | 323.804 | $p < 0.000$ |
| Capital intensity | 41.295 | 39.451 | $p = 0.352$ |
| Age | 24.606 | 23.460 | $p = 0.146$ |

# Descriptives BEFORE the matching

| | 'R' (N=245) | 'D' (N=400) | t-test |
|---|---|---|---|
| | Mean | Mean | |
| **R&D_intensity_net** | 0.176 | 0.147 | $p = 0.162$ |
| **Development_intensity_net** | 0.086 | 0.050 | $p < 0.000$ |
| **Research_intensity_net** | 0.089 | 0.097 | $p = 0.568$ |
| R&D cooperation | 0.686 | 0.650 | $p = 0.192$ |
| Patent stock per employee | 0.054 | 0.035 | $p = 0.048$ |
| Past research grants | 0.261 | 0.135 | $p < 0.000$ |
| Past development grants | 0.180 | 0.260 | $p = 0.116$ |
| Past mixed grants | 0.212 | 0.200 | $p = 0.370$ |
| Foreign group | 0.196 | 0.195 | $p = 0.744$ |
| SME | 0.808 | 0.770 | $p = 0.531$ |
| Employees | 259.959 | 290.134 | $p = 0.782$ |
| Capital intensity | 36.359 | 38.946 | $p = 0.600$ |
| Age | 21.657 | 22.985 | $p = 0.870$ |

# AFTER the matching

Table: Outcome Variables

| | *R&D* | *R* | *D* |
|---|---|---|---|
| Treatment | | | |
| Any subs | 0.062*** | 0.045*** | 0.017*** |
| Research subs | 0.070*** | 0.031** | 0.038*** |
| | | (I) | (II) |
| Development subs | 0.069*** | 0.055*** | 0.014* |
| | | (III) | (IV) |

Note: All covariates balances after the matching.

# AFTER the matching

Table: Results by Period

| Treatment | Outcome variables | | |
|---|---|---|---|
| | **R&D** | **R** | **D** |
| **2000-2005** | | | |
| Any subsidy | 0.044*** | 0.030*** | 0.014 |
| **2005-2009** | | | |
| Any subsidy | 0.078*** | 0.058*** | 0.020** |
| T-test on ATT difference | | | |
| $Pr(T < t)$ | 0.0422** | 0.0276** | 0.310 |

# Dose Response Function (DRF)

Based on the Generalized Propensity Score (Hirano and Imbens 2004)

$$GPS = r(T, X) \tag{5}$$

we can estimate the DRF

$$\varphi[E(Y_i | T_i, GPS_i)] = \psi(T_i, GPS_i, \alpha) \tag{6}$$

$$= \alpha_0 + \alpha_1 \cdot T_i + \alpha_2 \cdot T_i^2 + \alpha_3 \cdot GPS_i + \alpha_4 \cdot GPS_i^2 + \alpha_5 \cdot T_i \cdot GPS_i \tag{7}$$

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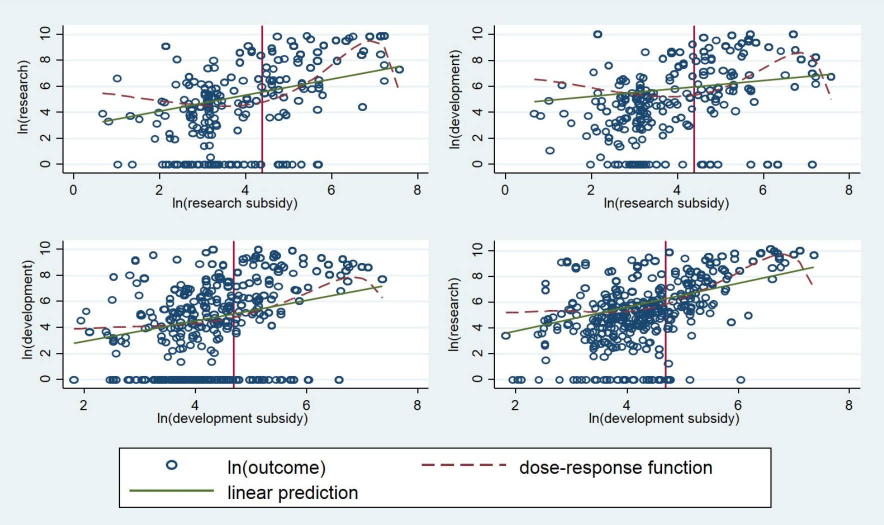
- log-log model $\rightarrow$ estimation of elasticities

# Dose Response Function



# Heterogeneity in Treatment Effects

$$\alpha_i^{TT} = (Y_i - \widehat{Y}_i^c)$$

| Treatment | R grant | | D grant | |
|---|---|---|---|---|
| **Dep. Var.** | $\alpha_i$ **research** | $\alpha_i$ **develop** | $\alpha_i$ **develop** | $\alpha_i$ **research** |
| amount (annualized) | 0.030* | 0.003 | -0.008 | -0.002 |
| | -0.015 | -0.011 | -0.011 | -0.019 |
| young | -0.046 | -0.005 | 0.033 | -0.039 |
| | -0.074 | -0.069 | -0.028 | -0.034 |
| small | 0.017 | -0.01 | -0.014 | 0.034 |
| | -0.038 | -0.027 | -0.011 | -0.027 |
| young X small | 0.017 | 0.223*** | -0.047 | 0.039 |
| | -0.098 | -0.079 | -0.053 | -0.087 |
| medium | 0.069** | 0.028 | 0.011 | 0.060** |
| | -0.034 | -0.027 | -0.014 | -0.024 |
| N | 198 | | 319 | |
| Joint sign. of industries | 1.84** | 1.12 | 0.98 | 1.96** |
| Overall significance | 2.42*** | 3.59*** | 1.44** | 1.95** |

## Conclusions

- Additionality on NET investment: neither total nor partial crowding out
- Disentangling R and D matters:
  - Own effects: R grants > D grants (additionality)
- Cross effects:
  - R similar effects on both components
  - D higher impact on R
- Minimum efficient grant size
- Little heterogeneity, but cross effects highest for young and small firms

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- Targeted schemes increase overall R&D in the economy
- Firms may still shift grant money to activities that are most constrained

## Further research

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- Incorporating access to external funding in the analysis

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- Estimate the impact of such policy on unsupported firms

**Thank you for letting me get to this slide!**

## Appendices

Table: Industry Distribution

| Industry | NACE (rev. 2008) | Description | N |
|---|---|---|---|
| 1 | 10, 11, 12 | Food and Tobacco | 365 |
| 2 | 13, 14, 15 | Textiles, Clothing and Leather | 261 |
| 3 | 16, 31 | Wood and Furniture | 113 |
| 4 | 17, 18 | Paper | 104 |
| 5 | 19, 20 | Chemicals | 330 |
| 6 | 21 | Pharmaceuticals | 81 |
| 7 | 22 | Rubber and Plastic | 201 |
| 8 | 24, 25, 33 | Metal | 329 |
| 9 | 27, 28 | Machines and Equipment | 579 |
| 10 | 26 | ICT | 247 |
| 11 | 29, 30 | Transport | 114 |
| 12 | 41 | Building and Construction | 92 |
| 13 | 1, 5, 23, 37, 35, 32 | Miscellaneous Industries | 280 |
| 14 | 45, 46, 47, 49, 55, 58 | Commerce and Transport | 291 |
| 15 | 59, 64, 68, 69, 71 - 79 | Other Services | 607 |
| 16 | 61, 62 | Software Development and Communications | 448 |
| | | | 4,442 |

# Appendices

Table: Firm Size Distribution

| | Size class definition | | Frequency | % |
|---|---|---|---|---|
| 1 | $< 20$ empl. | Tiny | 1,26 | 28.37 |
| 2 | $\geq 20$ & $< 50$ | Small | 1,053 | 23.71 |
| 3 | $\geq 50$ & $< 100$ | Medium small | 610 | 13.73 |
| 4 | $\geq 100$ & $< 250$ | Medium | 720 | 16.21 |
| 5 | $\geq 250$ | Large | 799 | 17.99 |
| | | | 4,442 | 100.00 |