The EU ETS's time-varying impact on Competitiveness and Investments: Evidence from Dutch Manufacturing

Konstantin Sommer Leon Bremer

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University of Amsterdam
Economics & Business

VU University Amsterdam

Motivation

EU Emissions trading system (ETS)

- EU's main climate policy tool
- World's oldest and largest carbon trading system

Policy (side) effects

- Competitiveness loss and leakage? (Pollution haven hypothesis)
- Investment impulse?

Effect identification

- Firms within the ETS can be very different to each other
- Effect is likely dynamic and dependent on regulation stringency
- Heterogeneities matter for identification

Research Question(s)

Study effect of ETS on regulated firms':

- Employment
- Profitability
- Investment behavior

→ Differentiate the effects for different groups of firms, in different phases

Background info ETS

- Introduced in 2005, revised three times (08,13,21)
  $\rightarrow$ New firms got regulated each phase
- Caps total amount of emissions (about 45% of EU emissions)
- Based on certificates, each corresponding to one tonne of CO2eq
- Each year, firms have to hand in as many certificates as they emitted
- Certificates can be traded, establishing a carbon price

ETS prices

Regulated firms - Identification part

Not all firms regulated. Regulation on plant/installation level. Covered if:

- Exceeding fuel combustion capacity threshold, or
- Incorporate certain processes (NACE sectors C17,19,23,24), or
- Exceeding sector-specific output or input thresholds

Some of these regulations get adjusted (extended) between phases
$\rightarrow$ Use the fact that some firms remain unregulated for identification

Number of firms

Literature

Competitiveness

- No negative effects on productivity and employment; little evidence for leakage (Marin et al. (2018), Wagner and Petrick (2014), Löschel et al. (2019), and Jaraite-Kažukauske & Di Maria (2016), Dechezleprêtre et al. (2019), Klemetsen et al. (2020), Colmer et al. (2022), Hintermann et al. (2020))

→ Verde (2020): no overall evidence of losses in competitiveness

Investments

- Increase in green patenting (Calel & Dechezleprêtre, 2016), and in targeted investments (Colmer et al., 2022)

→ Teixidó et al. (2019): evidence on technological change sparse

Outline and main conclusions

Heterogeneity

- Firms starting in different phases differ substantially
- Treatment stringency varies substantially over time

Estimation

- Two-way FE model (TWFE)
- Flexible DiD method, Callaway & Sant'Anna (2021) (CSA)

Effects on competitiveness and investment

- Some sign of reduction in employment for earlier regulated firms
- Effect heterogeneous over time and by cohort

Data

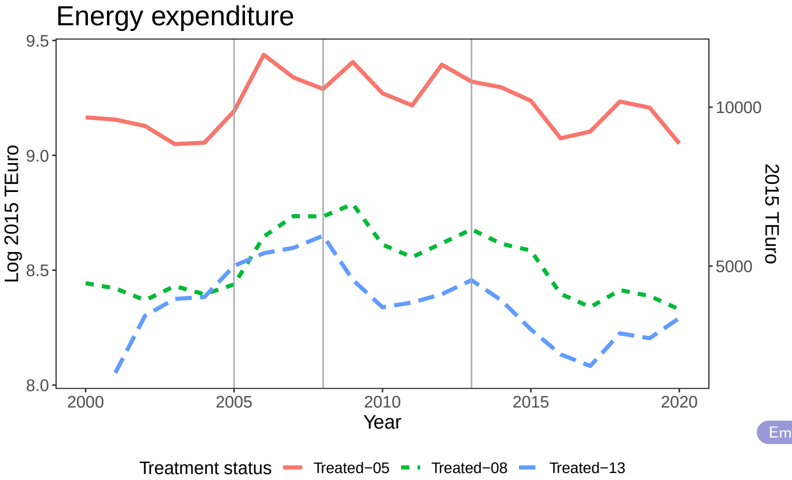
Combining 2 data sources:

1. EU ETS transaction log - Plant level
    - Link to account holder, corresponding to chamber of commerce (KvK)
2. Statistics Netherlands (CBS) - (Manufacturing) Firm level
    - Administrative data
    - Merged based on KvK number

- Firm defined by CBS, bundle of KvKs

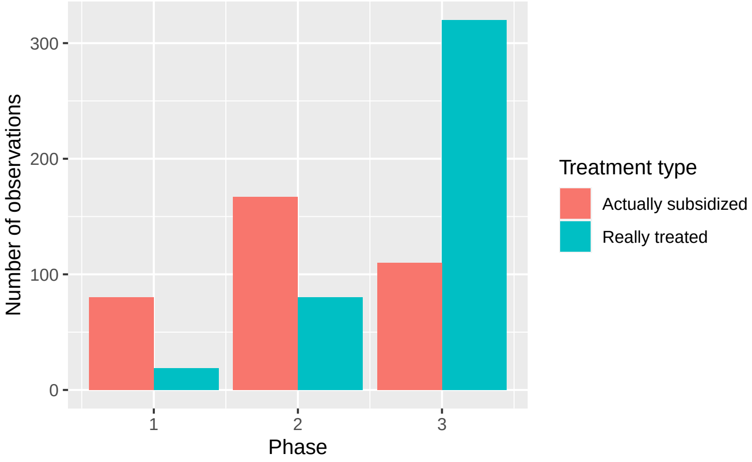
→ "Loss" of firms from merging, balancing panel, and enforcing common support leaves us with 118 treated firms; 2000-2020.

Heterogeneity between treated firms - Energy expenditure



Employment

Stringency: Emissions —free allowances



ETS prices

Key challenges and approach

Control group

- Problem: ETS firms are significantly different to non ETS firms
- TWFE: Matching
- CSA: Propensity scores and outcome regression adjustment

Heterogeneity assumptions

- Homogenous treatment effect for which firms?
- We estimate cohort-phase effects

DiD example Skip TWFE

TWFE - Estimation

Start by matching treated to control firms Details

Effects by treatment phase

$$y_{it} = \sum_{c \in C} \sum_{p \in P} ETS_i^c \times P_t^p \times \mathbb{1}\{p \geq c\} \alpha^{c,p} + \Gamma_{i,t} + \varepsilon_{i,t} \tag{1}$$

- y_{it}, employment, profit margin, or investment ratio for firm i in year t
- ETS_i^c, dummy is one if firm in cohort c. Cohort defined by first year in treatment.
- P_t^p dummy is one if year in phase p
- Run without controls. Year and/or firm FEs in Γ.

CSA - Estimation

Effects by cohort and year

$$\widehat{ATT}_{ct} = \frac{1}{N}\sum_{i\in\mathcal{I}}\Big[\hat{w}_{i,c}^{treat}(y_{it} - y_{i,b} - \hat{m}_{i,c,t}(X_i, \hat{\lambda}_{c,t})) - \hat{w}_{i,c}^{cont}(y_{it} - y_{i,b} - \hat{m}_{i,c,t}(X_i, \hat{\lambda}_{c,t}))\Big] \quad (2)$$

- y_{it}, employment, profit margin, or investment for firm i in year t
- X_i Pre-treatment controls
- $\hat{w}_{i,c}^{treat} - \hat{w}_{i,c}^{cont}$ adjusts for the probability of being treated (inverse probability weighting) Details
- $\hat{\lambda}$ from reg $y_{it} - y_{ib} = X_i\lambda + \varepsilon_i$ (outcome regression on non-treated units)

CSA details CSA results

CSA - Aggregations

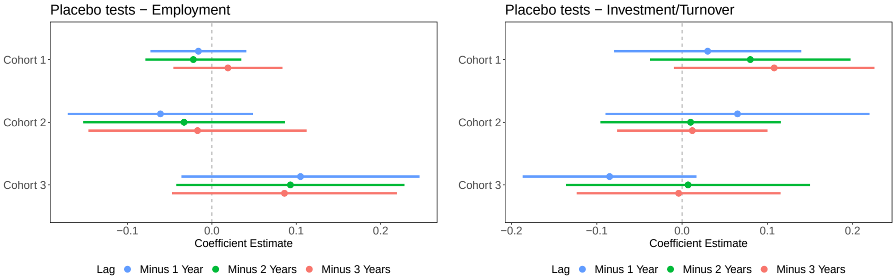
Aggregate the individual ATTs:

$$\hat{\theta} = \sum_{t=2005}^{2019} \sum_{c \in \{2005,2008,2013\}} \hat{w}(ct)\, \widehat{ATT}_{ct} \qquad (3)$$

- Per cohort-phase combination

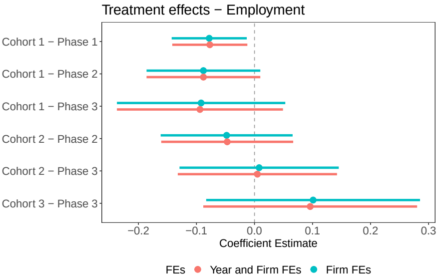
Aggregations

Parallel trends

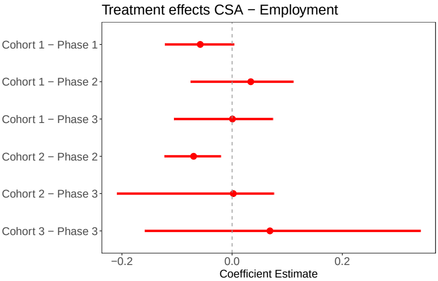


In CSA setting: Pre-trends tests do not reject for our three dependent variables. Matching Results

Employment



(c) TWFE

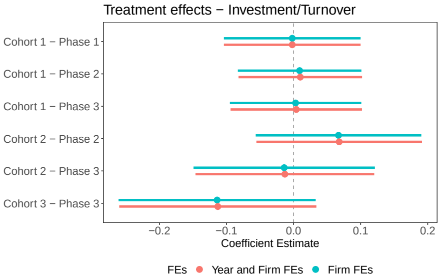


(d) CSA

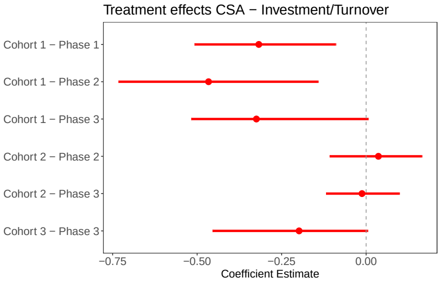
Profitability

Disaggregated

Investment margin



(e) TWFE



(f) CSA

Disaggregated

Conclusion

Effects of regulation

- Noticeable differences between treatment cohorts
- Reduction of employment in earliest phase
  - Might be because of early adjustments
  - Phase 2 firms react similar
- Negative effect on investments of phase 1 firms, might indicate a reduction in EU activity
- Shows that most affected firms (cohort 1) show strongest response
- Results for last cohort very unstable
- Some differences between estimators

Different Matching | Different cohort 2 assumption | Never treated

Thank you

Thank you for your attendance!
We are happy for any kind of feedback or discussion:

k.h.l.sommer2@uva.nl —— https://kosommer.github.io/
l.bremer@vu.nl —— https://leonbremer.nl/

References

- Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200-230.
- Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The review of economic studies*, 64(4), 605-654.
- Marin, G., Marino, M., & Pellegrin, C. (2018). The impact of the European Emission Trading Scheme on multiple measures of economic performance. *Environmental and Resource Economics*, 71(2), 551-582.
- Sant'Anna, P. H., & Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics*, 219(1), 101-122.

References

- Calel, R., & Dechezleprêtre, A. (2016). Environmental policy and directed technological change: evidence from the European carbon market. *Review of economics and statistics*, 98(1), 173-191.
- Dechezleprêtre, A., Gennaioli, C., Martin, R., Muûls, M., & Stoerk, T. (2021). Searching for carbon leaks in multinational companies. *Journal of Environmental Economics and Management*, 102601.
- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254-277.
- Jaraite-Kažukauske, J., & Di Maria, C. (2016). Did the EU ETS make a difference? An empirical assessment using Lithuanian firm-level data. *The Energy Journal*, 37(1).
- Klemetsen, M. E., Rosendahl, K. E., & Jakobsen, A. L. (2016). The impacts of the EU ETS on Norwegian plants' environmental and economic performance. *Statistics Norway, Research Department, (No. 833). Discussion Papers.*

References

- Löschel, A., Lutz, B. J., & Managi, S. (2019). The impacts of the EU ETS on efficiency and economic performance–An empirical analyses for German manufacturing firms. *Resource and Energy Economics*, 56, 71-95.
- Petrick, S., & Wagner, U. J. (2014). The impact of carbon trading on industry: Evidence from German manufacturing firms. Available at SSRN 2389800.
- Teixidó, J., Verde, S. F., & Nicolli, F. (2019). The impact of the EU Emissions Trading System on low-carbon technological change: The empirical evidence. *Ecological Economics*, 164, 106347.
- Verde, S. F. (2020). The impact of the EU emissions trading system on competitiveness and carbon leakage: the econometric evidence. *Journal of economic surveys*, 34(2), 320-343.
- Wagner, U. J., Muûls, M., Martin, R., & Colmer, J. (2014, June). The causal effects of the European Union Emissions Trading Scheme: evidence from French manufacturing plants. *In Fifth World Congress of Environmental and Resources Economists*, Istanbul, Turkey.

ETS allowances

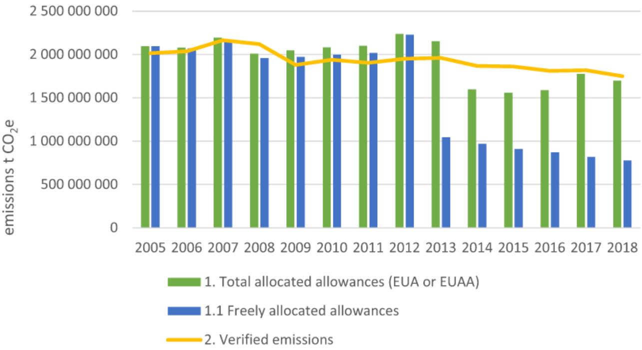


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Figure: ETS allowances and their allocation

Source: European Court of Auditors

ETS price path

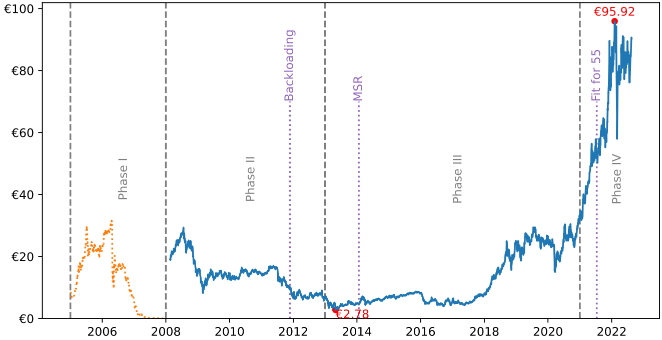
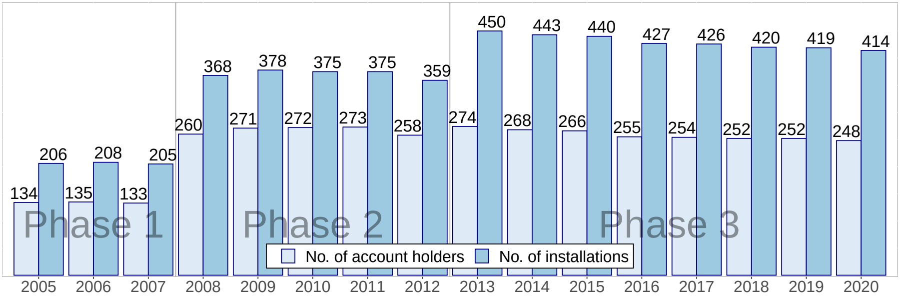


Figure: ETS price development. Differentiated by phases.

Data source: FactSet Background Stringency

Number of regulated plants and accounts in Netherlands



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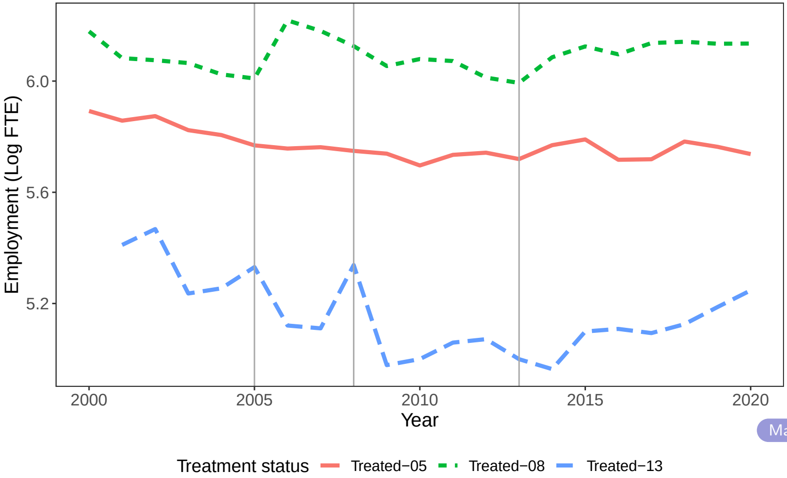
Employment



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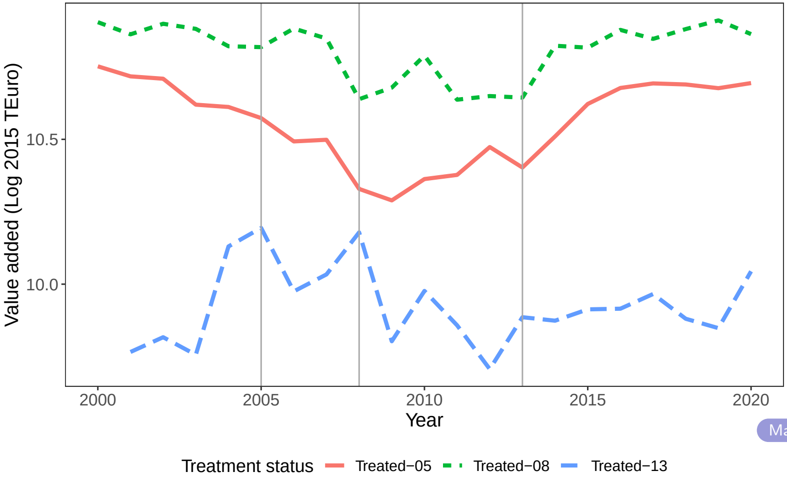
Value added



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Staggered DiD: A Three-Group Example

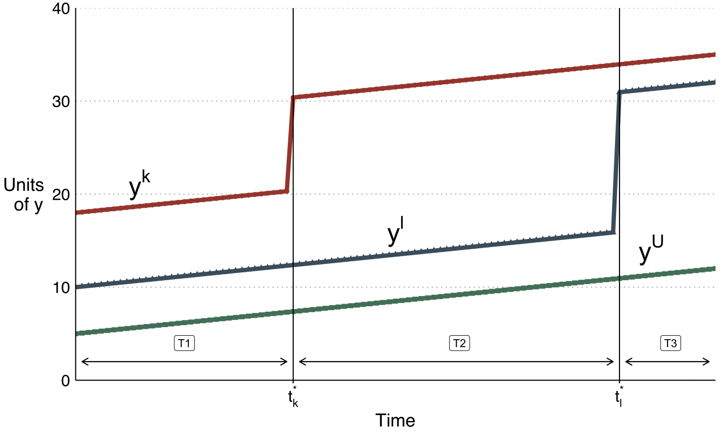

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Figure: Source: Goodman-Bacon (2021)

TWFE - Matching

Match ETS firms to firms that are never regulated, based on pre-treatment values of:

- Energy costs
- Employment
- Turnover
- Wage bill
- 2-digit sector code (exact)

Matching 1:5, with replacement based on Mahalanobis distance, too far matches are dropped.
86 treated, 183 untreated, about 4000 total observations

Matching details

- Measure Mahalanobis distance:
  $d(A,B) = \sqrt{(x_A^T - \mu^T)S^{-1}(x_B^C - \mu^C)}$
- Chose 5 closest neighbours
- Filter out any matched values that are 80% percent larger or smaller than the treated unit's values
- Do for each treatment group

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Problems with TWFE

Recent literature has pointed out problems with TWFE in staggered DiD settings for:

- Heterogeneity over treatment groups
- Heterogeneity over treatment time

We thus also rely on more flexible recent methodology developed by Callaway & Sant'Anna (2021) (CSA)

Main

CSA - Idea

Estimate :

$$\widehat{ATT}_{t,g} = \frac{1}{N_g} \sum_{i:G_i=g} [y_{i,t} - y_{i,b}] - \frac{1}{N_{\mathcal{G}}} \sum_{i:G_i \in \mathcal{G}} [y_{i,t} - y_{i,b}] \tag{4}$$

- g: the treatment group/cohort, e.g. the start of the treatment (2005,2008,2013)
- G_i: indicating the first year of treatment for a firm
- b: the group-specific base year
- $\mathcal{G}$: the set of control firms

→ Thus estimate treatment effect by cohort and for each year into treatment

CSA - Covariate conditioning

Inverse probability weighting

- Estimate propensity scores (probability to be treated)
- Re-weight control observations based on propensity scores

Outcome regression adjustment

- Estimate $\hat{\lambda}$ in $y_{it} - y_{ib} = \lambda X_{ib} + \varepsilon_i$, for untreated
- Predict $\hat{m}_{i,t}(X_i, \hat{\lambda}_{t,g}) = \widehat{y_{it} - y_{ib}}$, for treated
- Use this instead of difference in control outcomes

$\rightarrow$ Combine both for "double-robustness" (Sant'Anna et al.(2020))

CSA - Estimation

Effects by cohort and year

$$\widehat{ATT}_{t,g} = \frac{1}{N}\sum_{i\in\mathcal{I}}[\underbrace{(\hat{w}_{i,g}^{treat} - \hat{w}_{i,g}^{cont})}_{\text{Inv. prob.}}(y_{it} - y_{i,b} - \underbrace{\hat{m}_{i,t,g}(X_i, \hat{\lambda}_{t,g})}_{\text{Outc. reg.}})] \quad (5)$$

- N the amount of all firms, $\mathcal{I}$ the set of all firms
- X_i Pre-treatment controls (whereby pre-treatment is group-specific).
- $\hat{w}_{i,g}^{treat} - \hat{w}_{i,g}^{cont}$ adjusts for the probability of being treated (inverse probability weighting) Details
- $\hat{m}_{i,g}(X, \hat{\lambda}_{t,g})$, adjustment from outcome regression.

CSA - Estimation

$$\hat{w}_{i,g}^{treat} = \frac{G_{i,g}}{\frac{1}{N}\sum_i G_{i,g}} \tag{6}$$

$$\hat{w}_{i,g}^{cont} = C_{i,g} \frac{\frac{p_{i,g}(X_i,\hat{pi}_g)}{1-p_{i,g}(X_i,\hat{pi}_g)}}{\frac{1}{N}\sum_i \frac{p_{i,g}(X_i,\hat{pi}_g)}{1-p_{i,g}(X_i,\hat{pi}_g)}} \tag{7}$$

Main

CSA - Estimation

Standard errors:

- Bootstrapped

Testing for pre-trends:

- Wald test on pre-treatment estimates

Table: Weights used in the different aggregations.

Aggregation	$w(t, g)$
Cohort Phase	$\mathbb{1}(g = \tilde{g})\mathbb{1}(t \in \tilde{p})P(t \mid g = \tilde{g} \cap t \in \tilde{p})$
Dynamic	$\mathbb{1}(g + e \leq 2019)\mathbb{1}(t - g = e)P(G = g \mid G + e \leq 2019)$
Group	$\mathbb{1}(t \geq g)\mathbb{1}(g = \tilde{g})/(2019 - g - 1)$
Calendar	$\mathbb{1}(t \leq g)\mathbb{1}(t = \tilde{t})P(G = g \mid G \leq t)$

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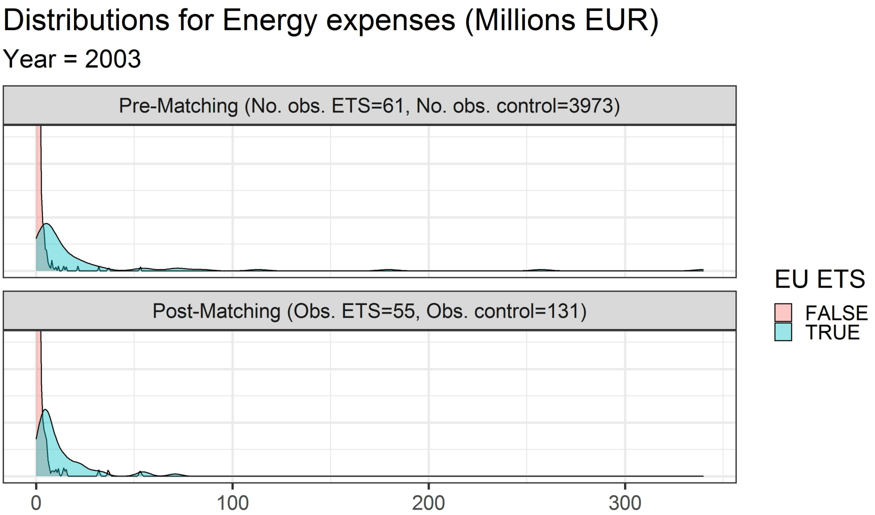
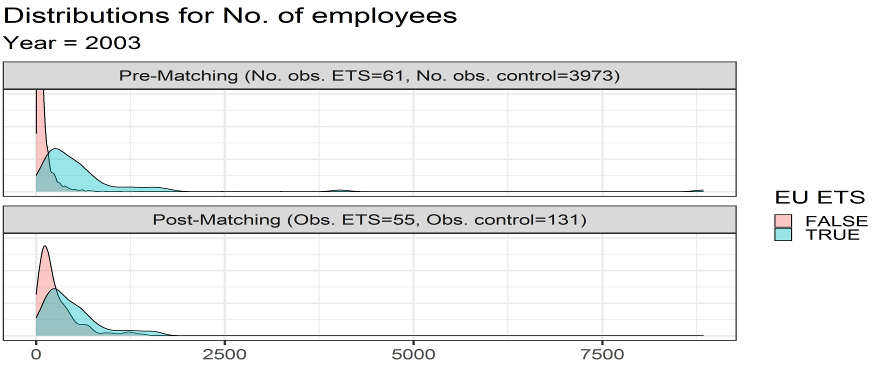
TWFE - Matching Energy first cohort



TWFE - Matching Employment first cohort



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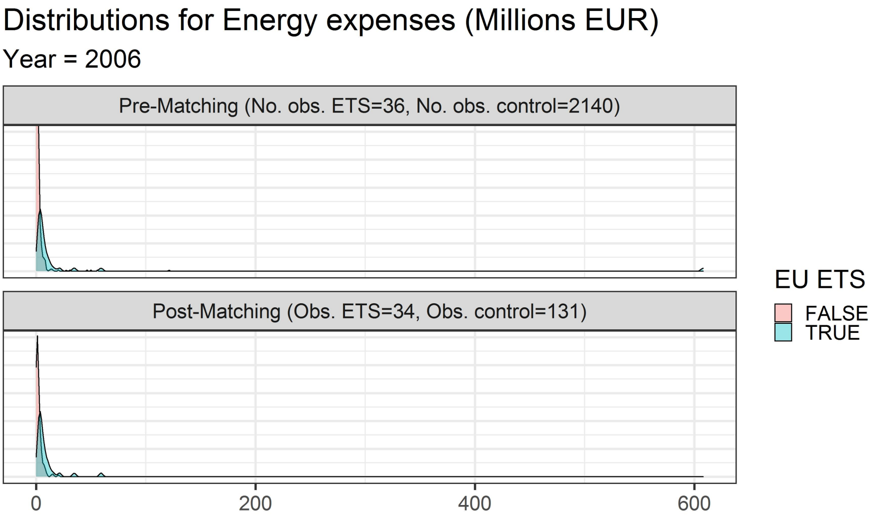
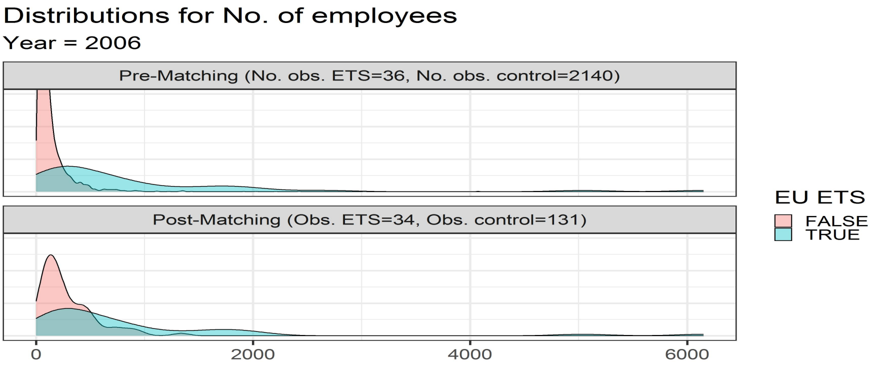
TWFE - Matching Energy second cohort



TWFE - Matching Employment second cohort



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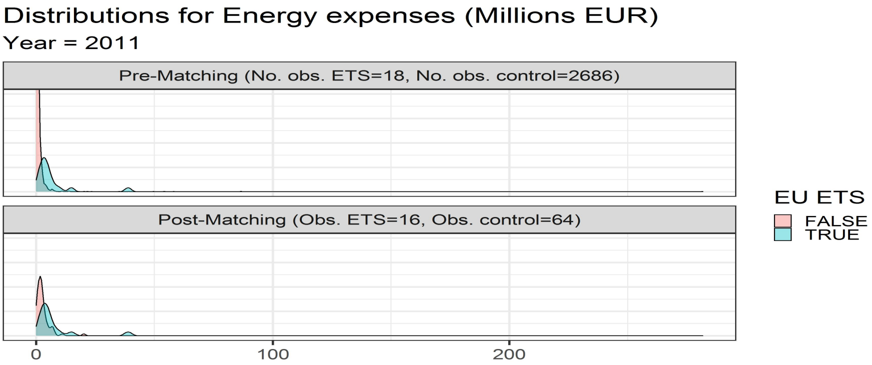
TWFE - Matching Energy third cohort



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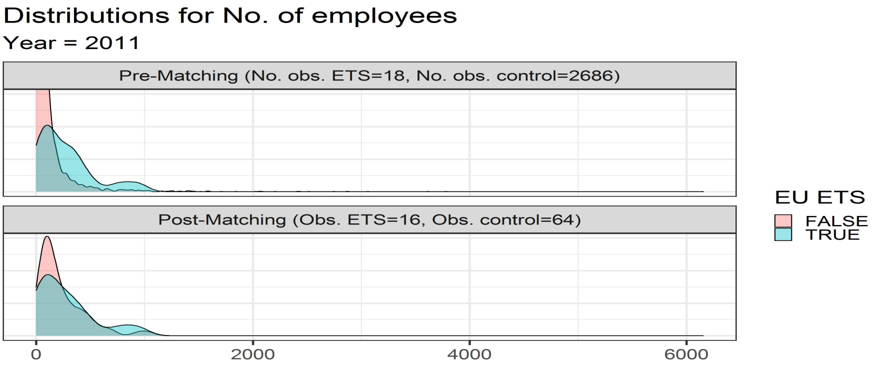
TWFE - Matching Employment third cohort



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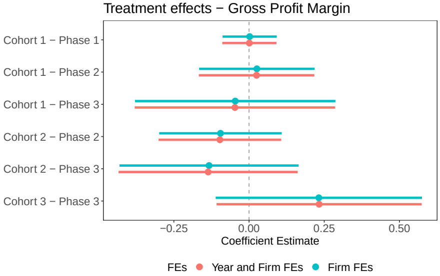
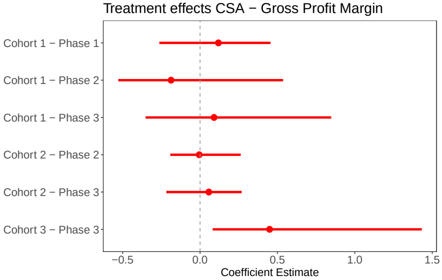
Gross profit margin





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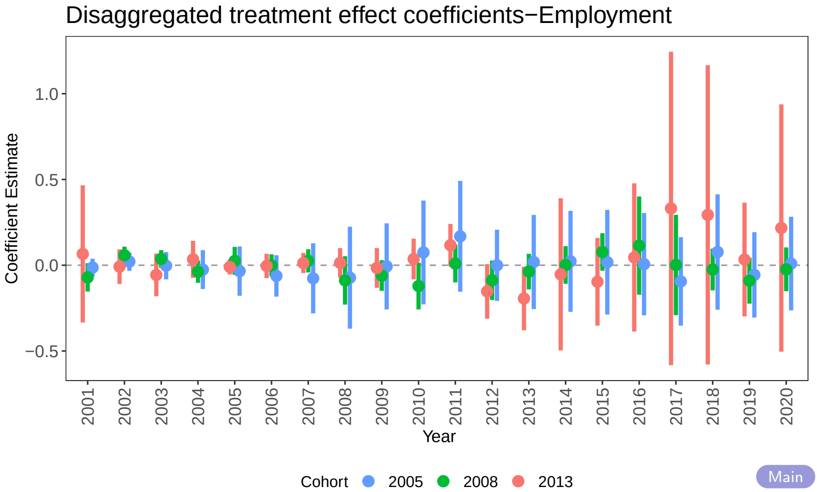
Employment - CSA dis-aggregated



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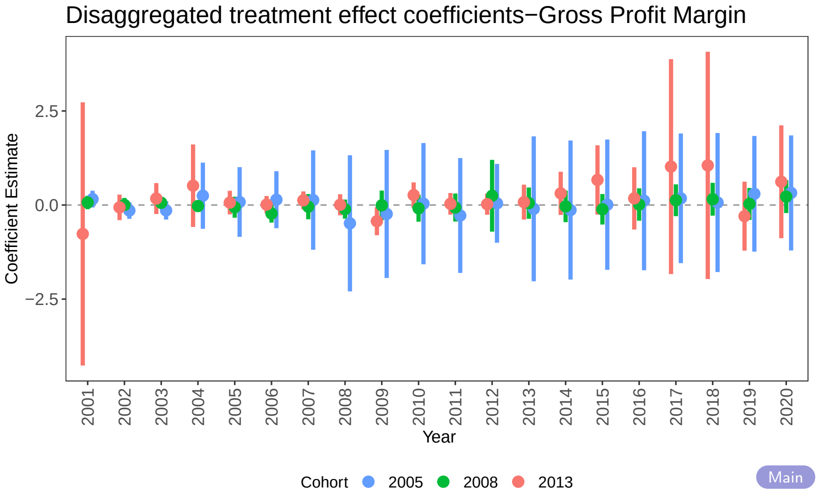
Gross profits - CSA dis-aggregated



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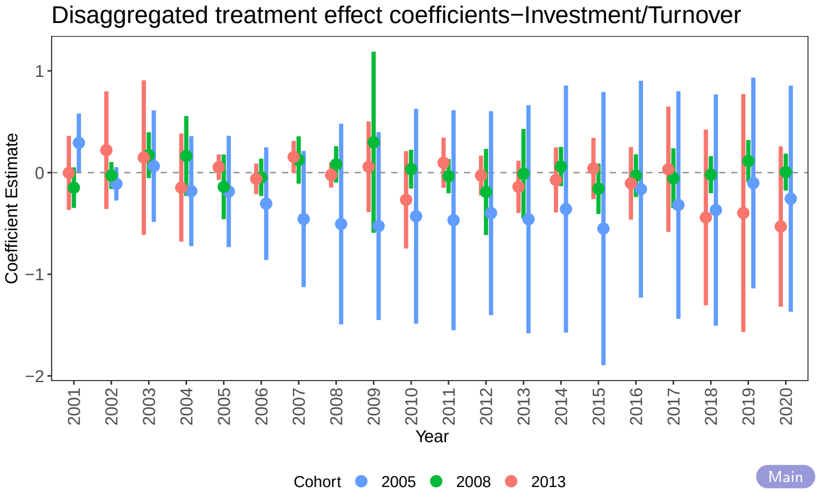
Investment ratio - CSA dis-aggregated



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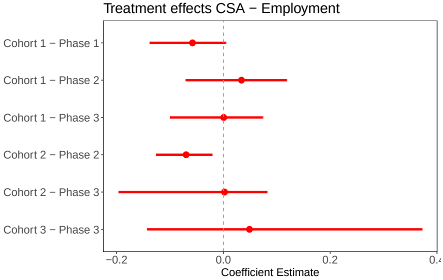
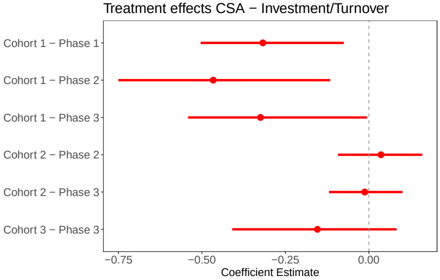
Never treated control group





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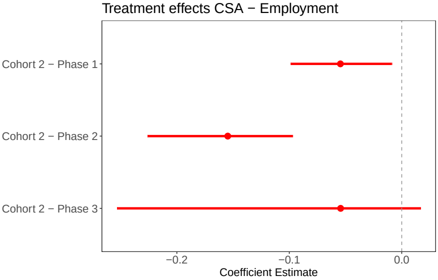
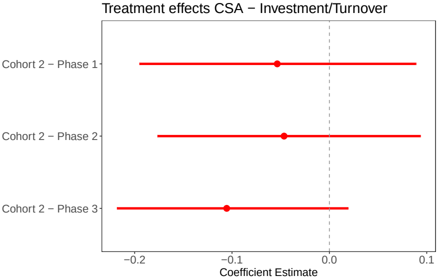
Treat cohort 2 firms as cohort 1 firms





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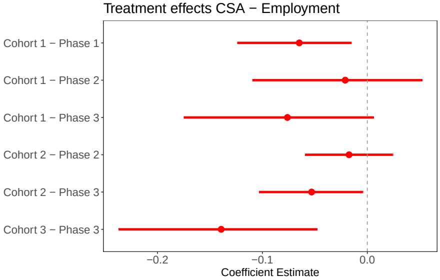
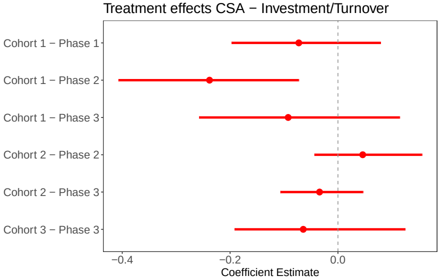
Match on trends





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