The Effect of COVID-19 Business Subsidies on Corporate Insolvencies

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Outline

Disclaimer: The views and opinions expressed herein are those of the author.

Introduction

Introduction (1)

Governmental support during COVID-19 pandemic

- Lockdowns to contain the spread of infections
- To counteract negative economic consequences: Huge public aid measures
- Measured in GDP: Austria among the strongest governmental supporters in EU
- Until June 2022: 600 different aid measures[1]
- Governmental support in Austria: $\sim$ 48 billion €[2]

Sources: Rechnungshof (2023), Köppl-Turyna et al. (2021), IMF (2021)

[1] Across all economic sectors

[2] Disbursed volumes until December 2022. Further details see figure 6 in Appendix. Source: BMF (2022).

Introduction (2)

Possible economic effects of the COVID-19 support measures

Stabilizing positive effects

+ Prevent the insolvency of companies
+ Maintain employment and consumption

Possible unintended negative effects

– Inefficient allocation
– Support of unprofitable or economically bad performing but still operating firms

Sources: Konings et al. (2023), Elsinger et al. (2022)

Research Questions

1. Is there a significant impact of COVID-19-related business support in Austria on the insolvency probability of subsidized firms?
2. Is there any evidence regarding the specificity and operationalization of the legal definitions for eligibility criteria?

Literature

Literature

- Theoretical and empirical work on the causal effect of subsidies on firms' probability to survive:
  - Find positive effect (Pellegrini and Muccigrosso, 2017; Zhang and Xu, 2019; Mao and Xu, 2018; Smith et al., 2018)
- Studies that explicitly examine the effects of COVID-19 subsidies:
  - Find positive effect as well (Lalinsky and Pál, 2022; Konings et al., 2023; Davies et al., 2023)
  - However, discussion on efficacy and targeting of COVID-19 measures (Konings et al., 2023 vs. Elsinger et al., 2022).

My contribution

- Construction of a unique database
  - Utilizes most recent available data, permitting a more extended consideration of insolvency time lags
  - Uses firm-level data on Austrian short-time work for scientific purposes for the first time (to the best of my knowledge)
  - Distinguishes precisely between insolvencies and other exit cases
- Pointing out selection issues and potential mitigation strategy
- Highlighting the necessity for precise and operationalizable legal definitions

Data & Descriptives

Data – Overview

Data source	Data description	Period for which data is available
Austrian Central Bank (OeNB) and Austrian Company Register	Master data, identifiers, statistical classifications	1842-2024
Austrian Insolvency Register	Insolvency data	2004-2024
Austrian Public Employment Service (AMS)	COVID-19 short-time work aid data	2020-2023
COVID-19 Transparency Portal (COFAG)	COVID-19 subsidy data	2020-2024
SABINA	Balance sheet data	2017-2021
Statistics Austria	Register and survey data	2016-2021

Table 1: Data Sources – Overview

Data – Development of Insolvencies

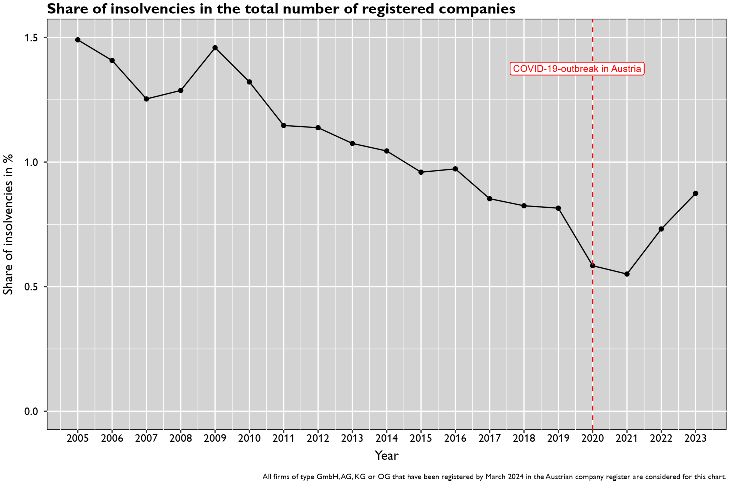

Figure 1: Share of insolvencies over time

Appendix: Top 5 insolvency industries

Data – Subsidies

AMS- and COFAG-subsidies

- COFAG-subsidies: 14.09 billion euros
  - Able to match[3]: 10.49 billion euros
- AMS-subsidies: 8.34 billion euros
  - Able to match[4]: 7.71 billion euros
- $\sim$ 75,000 subsidized firms remaining after merging data sources: ($\frac{1}{3}$ COFAG, $\frac{1}{3}$ AMS, $\frac{1}{3}$ both)

Appendix: Overview Subsidies by Legal Form

[3] Sole proprietorships, "other" entities, and branch offices of foreign firms had to be excluded.

[4] Sole proprietorships, "other" entities, branch offices of foreign firms and not clearly identifiable units had to be excluded.

Data – Subsidies per Industry over Time

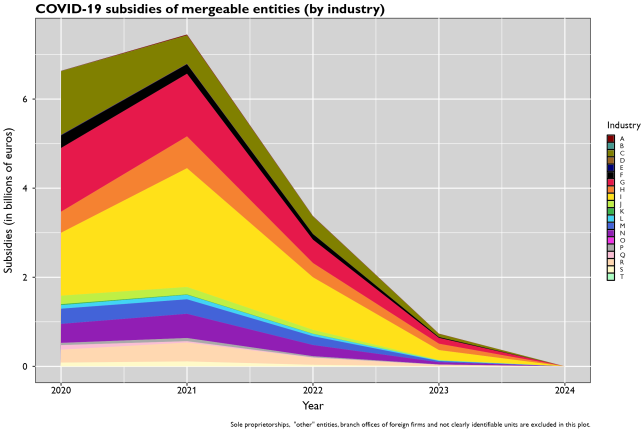

Figure 2: COVID-subsidies per Industry over time. Top 5 industries: I = Accommodation & Food Services (5.48 bn€), G = Wholesale & Retail (3.49 bn€), C = Manufacturing (2.52 bn€), H = Transportation & Storage (1.65 bn€), N = Administrative & Support Services (1.27 bn€).

Appendix: Subsidies per Industry
Appendix: Subsidies per Federal State

Data – Subsidies: Evidence for Selection on Observables

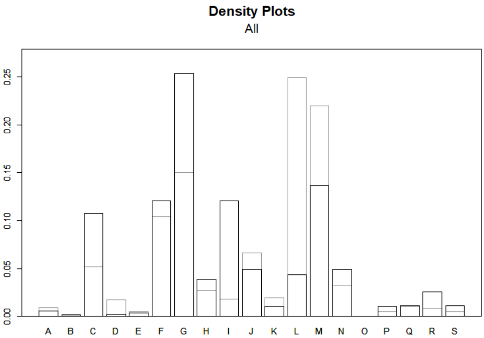

Figure 3: Initial sample balance: Distribution of treated and control group firms across different industries

- Black = treated, Grey = control
- Strongest imbalances in industries C, D, G, I, L, M
  - Either strongly subsidized industries (C, G, I), with far more treated units.
  - Or in weakly subsidized industries (D, L, M), with far more control units.

Appendix: Subsidy per Industry
Appendix: Further Evidence for Selection

Methodology

Econometric challenges

- COVID-19 economic aid targeted firms impacted by restrictive health measures
- Assignment to treatment is not random $\rightarrow$ **Selection bias**
- Idea: Selection likely determined by observable characteristics (e.g. industries heavily impacted by health measures)

Approach

- Achieve sample balance through propensity score matching
- Evaluate several matching methods[5]
- Select the one that optimizes sample balance
- Estimate treatment effect given the balanced sample

[5] Diff-in-Diff-design is not possible for the unmatched sample in the context of this study. Details see Appendix.

Estimation procedure

1. Calculate Propensity Score (PS) with Logit-regression:

$$\begin{aligned} logit(P(T=1)_i) = \beta_0 &+ \beta_1 \cdot ind_i + \beta_2 \cdot legal_i + \beta_3 \cdot age_i \\ &+ \beta_4 \cdot state_i + \beta_5 \cdot log(emp_i + 1) + \beta_6 \cdot rev\_growth_i \\ &+ \beta_7 \cdot log(rev_i + 1) + u \end{aligned}$$

2. Determine control group (either by distance ("picking") or stratum matching ("weighting"))

3. Estimate ATT as follows:

$$logit(P(insolv = 1)) = \beta_0 + \beta_1 \cdot T + \beta_2 \cdot P + \beta_3 \cdot (T \times P) + \varepsilon$$

with T = Treated and P = Post-treatment period. For NN-matching only "picked" control units are considered. For SC-matching control units are weighted.

Appendix: Why ATT?
Appendix: Details Nearest Neighbor Matching
Appendix: Details Subclassification Matching

Results & Conclusion

Comparison of Matching Methods

Matching Method	Std. Mean Difference	Variance Ratio
Initial Balance (Pre-Matching)	1.4117	1.0869
Nearest Neighbor 1:1, No Replacements	0.9817	1.2453
Nearest Neighbor 1:1, No Replacements, Exact Industry	0.7628	1.1160
Nearest Neighbor 1:1, 10 Replacements	0.0031	1.0090
Subclassification, 50 subclasses	0.0022	0.9945
Subclassification, 100 subclasses	0.0007	0.9980
Subclassification, 640 subclasses	0.0000	1.0000

Table 2: Propensity Score Quality Metrics for the Main Matching Models

Propensity Scores – Pre- and Post-Matching (1)

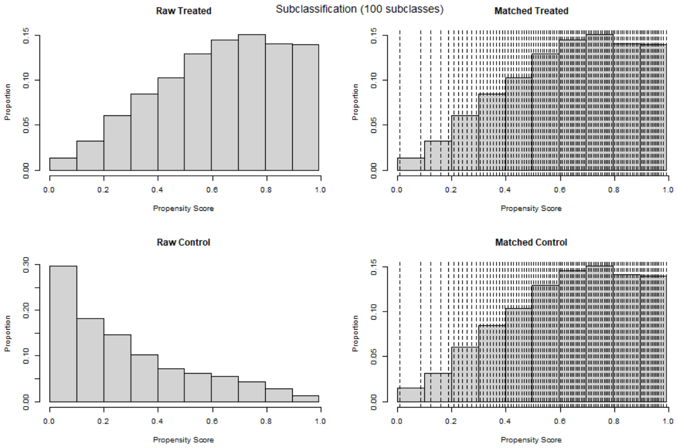

Figure 4: Propensity Score Distribution – Initial Balance vs. Balance after Subclassification-matching

Propensity Scores – Pre- and Post-Matching (2)

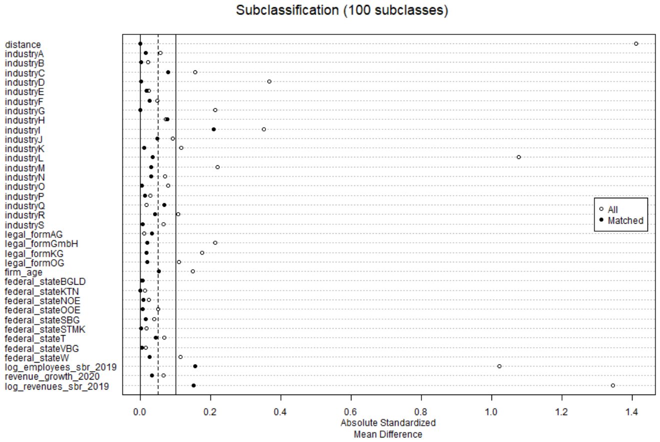

Figure 5: Propensity Score Distribution – Initial Balance vs. Balance after Subclassification-matching

Appendix: Standardized Mean Differences

The ATT – Estimation of the Treatment Effect

	Dependent variable:				
	insolvency_indicator				
	SC50	*SC100*	*SC640*	*NN10R*	*NN, ExInd*
	(1)	(2)	(3)	(4)	(5)
Constant	0.010***	0.011***	0.011***	0.012***	0.012***
	(0.0005)	(0.0005)	(0.0005)	(0.001)	(0.001)
post	0.004***	0.003***	0.003***	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
treated	-0.001	-0.001	-0.001	-0.002**	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
treated:post	0.007***	0.007***	0.007***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Matching Covariates	BL	BL	BL	BL	BL
Observations	203,082	203,082	203,082	163,360	135,852

Note: *p<0.1; **p<0.05; ***p<0.01

Baseline covariates (BL): industry, legal_form, firm_age, federal_state, log_employees_sbr_2019, revenue_growth_2020, log_revenues_sbr_2019

Table 3: Main results: The Effect of COVID-19 Business Subsidies on Corporate Insolvencies (Different Matching Techniques)

The ATT – Estimation of the Treatment Effect

	Dependent variable:					
	insolvency_indicator					
Matching Method:	*SC100*	*SC100*	*SC100*	*SC100*	*NN10R*	*SC100*
Propensity Score based on:	*treated_cofag*	*treated_cofag*	*treated_cofag*	*treated_ams*	*treated_ams*	*treated_ams*
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.010***	0.008***	0.008***	0.011***	0.008***	0.009***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
post	0.006***	0.005***	0.001	0.005***	0.005***	0.002**
	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
treated_ams				-0.002	0.002	0.001
				(0.0011)	(0.0011)	(0.0011)
treated_ams:post				0.006***	0.003**	0.002
				(0.0016)	(0.0015)	(0.0016)
treated_cofag	-0.001	0.003**	0.003**			
	(0.0011)	(0.0013)	(0.0012)			
treated_cofag:post	0.001	-0.001	0.002			
	(0.0015)	(0.0018)	(0.0018)			
Matching Covariates	BL	Spec1	Spec2	BL	Spec1	Spec2
Observations	147,564	102,746	83,976	149,098	111,192	91,760

Note:	*p<0.1; **p<0.05; ***p<0.01
Baseline covariates (BL):	industry, legal_form, firm_age, federal_state, log_employees_sbr_2019, revenue_growth_2020, log_revenues_sbr_2019
Alternative Covariate Specification 1 (Spec1):	industry, firm_age, legal_form, federal_state, log_liabilities_2019, log_employees_sbr_2019, revenue_growth_2020
Alternative Covariate Specification 2 (Spec2):	industry, firm_age, legal_form, federal_state, zombie2, revenue_growth_2020, log_revenues_sbr_2019, log_employees_sbr_2019, profit_2019

Table 4: Treatment-specific effects: Comparative Assessment of AMS and COFAG subsidies (second treatment removed for control)

Appendix: Graphical Indications
Appendix: Computation of Zombie-Variable

Conclusion

- Positive causal effect as well as effect size appears unlikely according to empirical evidence and economic theory. Selection bias seems to remain.
- But: **Selection bias cannot be entirely mitigated**, even when controlling for variables such as **revenue growth** and **industry classification**, which should theoretically influence eligibility based on legal definitions.
- This highlights the importance of precise and operationalizable legal definitions for subsidy eligibility criteria. **Current definitions may have been insufficiently specific**.
- However: Mitigation of bias proves more effective for COFAG compared to AMS subsidies.
- This suggests that the **legal definitions** for eligibility were **less specific for AMS subsidies**.
- The development of **scenario plans** for future pandemics and economic crises, incorporating **clear and specific criteria and a set of indicators** that can be relied upon in times of crisis, could support future actions of responsible authorities.

Thank you!

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Appendix – Overview COVID-19 measures

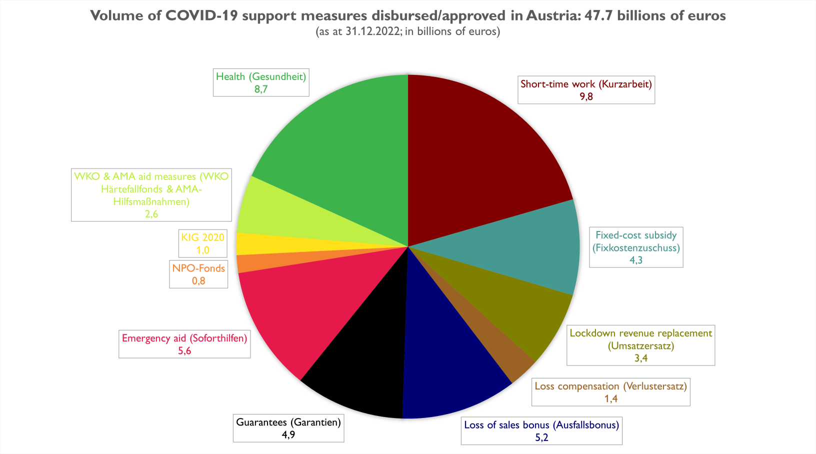

Figure 6: Source: BMF (2022)

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Appendix – Development of Insolvencies (Top 5 industries)

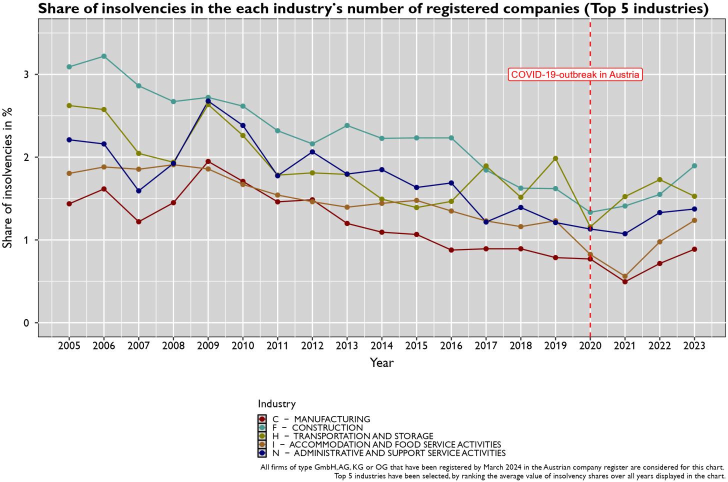

Figure 7: Share of insolvencies – Top 5 industries

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Appendix – AMS- and COFAG-subsidies

AMS- and COFAG-subsidies

	COFAG		AMS		Total
Legal form	Subsidies (bn €)	Nr. of firms	Subsidies (bn €)	Nr. of firms[6]	Subsidies (bn €)
GmbH	8.29	37,219	6.47	50,655	14.76
Sole Propr.	3.39	64,820	0.18	728	3.57
KG	1.72	8,625	0.74	1,047	2.46
OG	0.30	3,952	0.05	114	0.35
AG	0.27	117	0.72	351	0.99
Other	0.12	2,086	0.19	426	0.31
Total	14.09	116,819	8.34	53,321	22.43

Table 5: Subsidized firms by legal type

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[6] The data of this table contain all AMS- and COFAG-subsidies, not only those of GmbHs, FlexKapGs, KGs, OGs and AGs. As described in section 2.3, AMS only provided data on firms that that need to publish a balance sheet and have received more than EUR 100,000 in STW aid. This leads to a very low number (728) of sole proprietorships in AMS-STW data. The column total of "AMS – Subsidies (bn €)" (8.34) is correct. The sum of the individual values does not add up exactly to the column total due to rounding inaccuracies.

Appendix – AMS- and COFAG-subsidies: A regional perspective

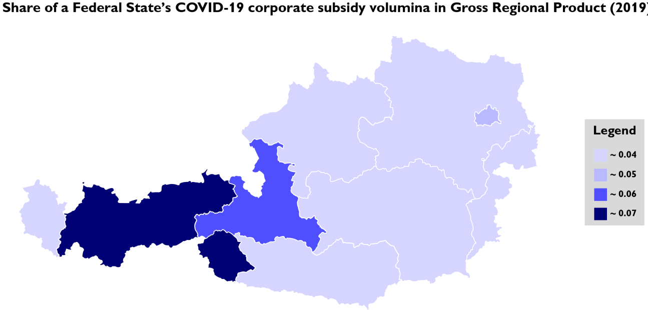

Figure 8: For further details see Table 7 in Appendix.

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Appendix – Subsidies per Industry

Industry	All (bn €)	COFAG (bn €)	AMS (bn €)
I – Accomodation, Food Service	5.48	3.98	1.50
G – Wholesale and Retail	3.49	1.91	1.58
C – Manufacturing	2.52	0.84	1.68
H – Transportation, Storage	1.65	0.96	0.68
N – Administrative and Support Services	1.27	0.73	0.54
R – Arts, Entertainment, Recreation	0.90	0.53	0.37
M – Professional, Scientific and Technical Activities	0.89	0.50	0.40
F – Construction	0.64	0.32	0.32
J – Information, Communication	0.46	0.23	0.22
L – Real Estate	0.24	0.15	0.09
S – Other Services	0.24	0.12	0.12
P – Education	0.15	0.11	0.04
Q – Human Health and Social Work	0.15	0.04	0.11
K – Finance and Insurance	0.04	0.01	0.03
A – Agriculture, Forestry, Fishing	0.04	0.03	0.01
D – Electricity, Gas, Steam supply	0.02	0.01	0.01
E – Water Supply, Sewerage, Waste Mngmt.	0.02	0.01	0.01
B – Mining, Quarrying	0.01	0.01	0.00
O – Public Administration and Defence	0.00	0.00	0.00
T – Activities of Households as Employers	0.00	0.00	0.00
Total	18.21	10.49	7.71

Table 6: Sum of COVID-19 subsidies per industry

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Appendix – Subsidies per Federal State

Federal State	Total subsidies per Federal State (bn €)	Share of subsidies in GRP 2019	Subsidies per capita (Share of subsidies in number of inhabitants 2019)
Vienna	4.90	4.91%	2573
Lower Austria	2.51	3.98%	1492
Tyrol	2.51	6.94%	3316
Upper Austria	2.48	3.65%	1670
Salzburg	1.94	6.53%	3483
Styria	1.93	3.78%	1548
Vorarlberg	0.84	4.47%	2132
Carinthia	0.75	3.49%	1334
Burgenland	0.35	3.77%	1182

Table 7: Subsidized firms by federal state

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Appendix – Further Evidence for Selection on Observables

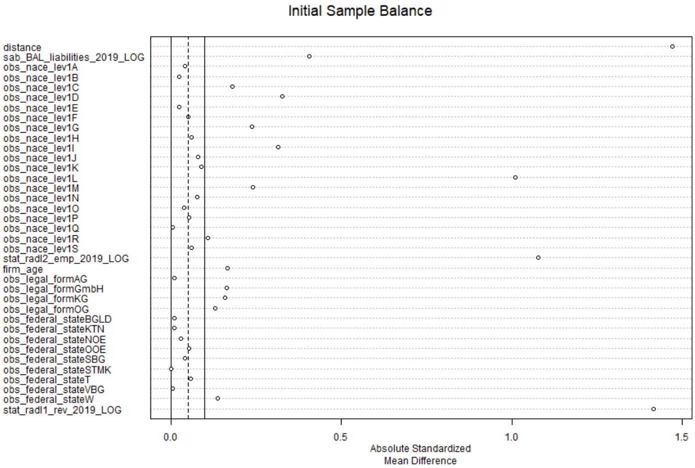

Figure 9: Initial sample balance: Absolute Standardized Mean differences

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Appendix – Standardized Mean Differences

Absolute Standardized Mean Differences have been calculated according to Ho et al. (2023) as follows:

- Pre-matching std. mean differences: $\left| \frac{\bar{X}_{T_{pre}} - \bar{X}_{C_{pre}}}{\sqrt{\frac{\sigma^2_{T_{pre}} - \sigma^2_{C_{pre}}}{2}}} \right|$
- Post-matching std. mean differences when estimating ATE: $\left| \frac{\bar{X}_{T_{post}} - \bar{X}_{C_{post}}}{\sqrt{\frac{\sigma^2_{T_{pre}} - \sigma^2_{C_{pre}}}{2}}} \right|$
- Post-matching std. mean differences when estimating ATT: $\left| \frac{\bar{X}_{T_{post}} - \bar{X}_{C_{post}}}{\sqrt{\sigma^2_{T_{pre}}}} \right|$
- Post-matching std. mean differences when estimating ATC: $\left| \frac{\bar{X}_{T_{post}} - \bar{X}_{C_{post}}}{\sqrt{\sigma^2_{C_{pre}}}} \right|$

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Appendix – Details: Nearest Neighbor matching (1)

1. Calculate Propensity Score (PS) with Logit-regression:

$$\begin{aligned} logit(P(T=1)_i) = \beta_0 &+ \beta_1 \cdot ind_i + \beta_2 \cdot legal_i + \beta_3 \cdot age_i \\ &+ \beta_4 \cdot state_i + \beta_5 \cdot log(emp_i + 1) + \beta_6 \cdot rev\_growth_i \\ &+ \beta_7 \cdot log(rev_i + 1) + u \end{aligned}$$

2. For Nearest Neighbor (NN) 1:1 matching:
   - Pick nearest neighbour(s) by minimizing the absolute difference between a treated units i's propensity score and the propensity score of an untreated unit j:

$$min(\mid P(T=1)_{T,i} - P(T=1)_{C,j} \mid)$$

   - If nearest neighbours are matched 1:1 (in R: `reuse.max = 1`) one control unit is matched to one treated unit. If 1:k-nearest neighbour matching is conducted, k control units are matched to one treated unit (in R: `reuse.max = k`).
3. Ensure common support by eliminating treatment units with a propensity score that is higher then the maximum propensity score of the donor pool.

Source: Ho et al. (2023, p. 20)

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Appendix – Details: Nearest Neighbor matching (2)

- **Nearest Neighbour Matching without replacement** is conducted in decreasing order based on propensity score size: "With propensity score matching, the default is to go in descending order from the highest propensity score; doing so allows the units that would have the hardest time finding close matches to be matched first." (Greifer, 2023)
- For **Nearest Neighbour Matching with k replacements** the matching order is not relevant, as in all cases the closest k neighbours are considered as a match.

Source: Ho et al. (2023, p. 20)

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Appendix – Details: Subclassification matching (1)

1. Calculate Propensity Score (PS) with Logit-regression:

$$\begin{aligned} logit(P(T=1)_i) = \beta_0 &+ \beta_1 \cdot ind_i + \beta_2 \cdot legal_i + \beta_3 \cdot age_i \\ &+ \beta_4 \cdot state_i + \beta_5 \cdot log(emp_i + 1) + \beta_6 \cdot rev\_growth_i \\ &+ \beta_7 \cdot log(rev_i + 1) + u \end{aligned}$$

2. For Subclassification (SC) matching
   - 2.1 Sort PS in ascending order
   - 2.2 Create k bins (also called: strata) based on PS-distribution containing approximately same number of observations
   - 2.3 Calculate stratification weights for control units (details see next slide): Control units with higher propensity scores are assigned greater weights. "[T]he control-group observations with the biggest weights are the ones most like the treated group, who were most likely to have gotten treated but didn't for some reason." (Huntington-Klein, 2021, p. 280) See slide on post-matching PS-distribution for a graphical representation of weights.
3. Ensure common support by eliminating treatment units with a propensity score that is higher then the maximum propensity score of the donor pool.

Sources: Ho et al. (2023, p. 20), Hong (2010, p. 507)

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Appendix – Details: Subclassification matching (2)

- For each stratum a **"stratum propensity score" (SPS)** is calculated as follows: $SPS = \frac{n_{T,S}}{n_S}$, with n_S being the number of units in a stratum and $n_{T,S}$ being the number of treated units in a stratum.
- **Stratification weights** (also call "marginal mean weight") are computed according to the standard inverse probability weighting formula. Each unit of the same subclass receives the same weight depending whether it has been treated or not:
  - When estimating **ATE**, i.e. the average treatment effect in the population, both – treated and control units – are weighted:
    - Weights of treated units: $\frac{1}{SPS}$
    - Weights of control units: $\frac{1}{1-SPS}$
  - When estimating **ATT**, i.e. the average effect of treatment for those who received treatment, only control units are weighted:
    - Weights of treated units: 1
    - Weights of control units: $\frac{SPS}{1-SPS}$
  - When estimating **ATC**, i.e. the average treatment in the control group, only treated units are weighted:
    - Weights of treated units: $\frac{1-SPS}{SPS}$
    - Weights of control units: 1

Sources: Ho et al. (2023, p. 20), Hong (2010, p. 507)

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Appendix – Treatment effects

ATE vs. ATT

- **ATE**:
  - Average Treatment Effect in the whole population
  - In the context of this paper: The ATE relates the effect of COVID-19 subsidies on insolvencies of firms, who received a subsidy, to the whole population. This includes the whole donor pool and therefore also units, that might even have not even been eligible for treatment (= subsidies).
- **ATT**
  - Average Treatment Effect on the Treated
  - In the context of this paper: The ATT relates the effect of COVID-19 subsidies on insolvencies of firms, who received a subsidy, to the control group – i.e. a part of the donor pool. This control group only contains control units that are comparable to the treated units and would therefore have been eligible for treatment.
  - Therefore, ATT is considered as being more relevant in the context of my work and research question.

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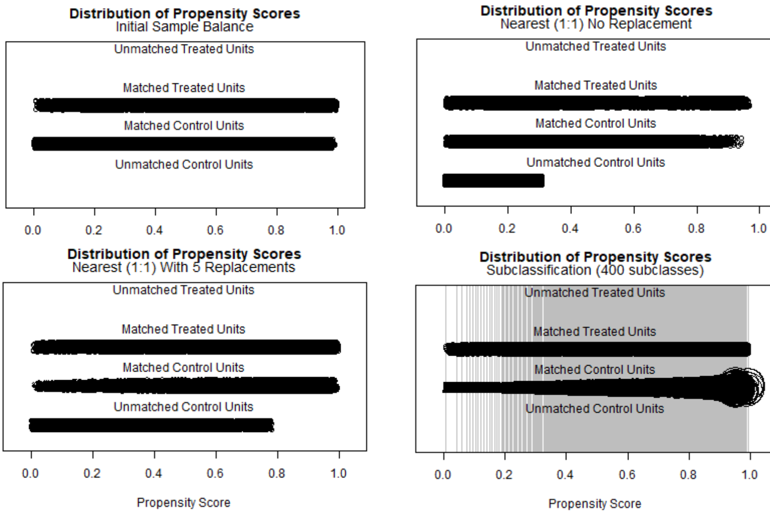
Appendix – Propensity Score Distributions



Appendix – Subsidies and Revenue Growth

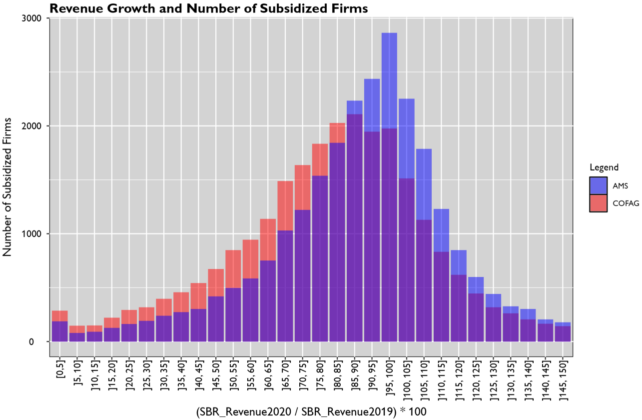


Figure 10: Subsidized Firms and Revenue Growth from 2019 to 2020 (SBR Revenues)

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Appendix – Computation of Zombie-Dummies (1)

Literature suggests to use the Interest Coverage Ratio (ICR) ($= \frac{EBIT}{InterestExpense}$) in combination with firm age as an indicator for the "zombie status" of a firm. If the ICR is lower than 1 for X (e.g. 3) consecutive years and the firm is older then Y (e.g. 10) years, the firm is considered as a zombie firm. In addition, making losses in the last Z (e.g. 3) periods might be considered as an alternative or additional measure (Lalinsky and Pál, 2022, p. 322).

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Appendix – Computation of Zombie-Dummies (2)

As I do not have data on ICR, I construct some alternative zombie-indicators:

(1) Equity zombie-indicator = 1, if

- Equity ratio $= \frac{Equity}{BalanceSheetTotal} < 0.1$ AND Equity < 0
- for all years 2017, 2018 and 2019.

(2) Revenue zombie-indicator = 1, if

- Revenue growth < 0 OR Revenue $= 0$
- for all years 2017, 2018 and 2019.

(3) Revenue liability zombie-indicator = 1, if

- Revenue growth $<$ Liability growth
- for all years 2018, 2019 and 2020.

(4) Loss zombie-indicator = 1, if

- The firm faces a loss
- in all years 2017, 2018 and 2019.

I then create four differently restrictive indicators:

- **Zombie-indicator 1** = zombie1 = At least one of the indicators above = 1.
- **Zombie-indicator 2** = zombie2 = At least two of the indicators above = 1.
- **Zombie-indicator 3** = zombie3 = At least three of the indicators above = 1.
- **Zombie-indicator 4** = zombie4 = All four of the indicators above = 1.

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Appendix – Why especially Matching and not another microeconometric method?

- RDD: No sudden jumps in the insolvency-dummy expected, as insolvencies come with a time lag.
- Diff-in-Diff: Parallel trends are unlikely to hold. Details see next slide.

Appendix – Diff-in-Diff Parallel Trend Assumption (1)

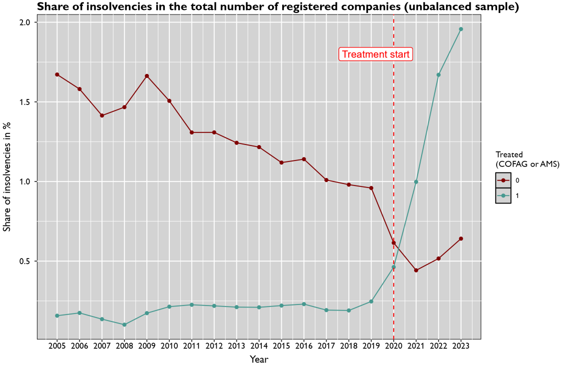

Figure 11: Share of insolvencies over time for Treatment and Control group – Unmatched Sample

Why is Diff-in-Diff Parallel Trend Assumption unlikely to hold in the unmatched sample?
Parallel Trends for treatment and control group are unlikely to hold in the context of this study, because a firm's existence at the start of the treatment is a necessary criterion to get treatment. Therefore, the insolvency share (= probability of insolvency = outcome variable) is almost equal to zero for treated units, while for all potential control observations (= donor pool) this does not have to be the case.

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Appendix – Diff-in-Diff Parallel Trend Assumption (2)

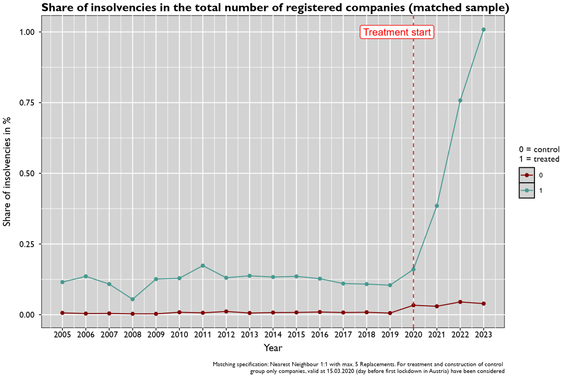

Figure 12: Share of insolvencies over time for Treatment and Control group – Matched Sample

Why is Diff-in-Diff Parallel Trend Assumption unlikely to hold in the unmatched sample?
After the application of matching, parallel trends can be established and therefore a Diff-in-Diff-estimation can be applied.

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