HETEROGENEOUS TREATMENT EFFECTS AND COUNTERFACTUAL POLICY TARGETING USING DEEP NEURAL NETWORKS

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Available at https://rmmomin.github.io/wp/Chapter_2_

RESEARCH QUESTION

- The Federal Reserve introduced the corporate credit facilities (CCFs) in March 2020 in response to financial market disruptions.
- Did the CCFs achieve the Fed's objectives to boost real activity?
- If not, would extending eligibility to ineligible firms have improved outcomes?

PREVIEW OF RESULTS

- Paper introduces a novel two-step semi-parametric difference-in-differences (DiD) estimator to compute dynamic (heterogeneous) treatment effects and assess counterfactual treatment effects.
  - Nonparametric terms estimated using deep neural networks.
- Results suggest that the CCFs may have failed to achieve the Fed's objectives to stimulate the real economy but may have supported payouts to shareholders.
- Counterfactual treatment effects from extending eligibility to B/BB firms provide mixed to inconclusive evidence for improved investment but stronger evidence for increased leverage and payouts.

LITERATURE REVIEW

- COVID19 Papers:
  - Decline in bond spreads: Boyarchenko, Kovner, and Shachar (2022); D'Amico, Kurakula, and Lee (2020); Flanagan and Purnanandam (2020); Gilchrist et al. (2021); Haddad, Moreira, and Muir (2021); Kargar et al. (2021); Momin and Li (2025); O'Hara and Zhou (2021).
  - Record bond issuance: Becker and Benmelech (2021); Boyarchenko, Kovner, and Shachar (2022); Darmouni and Siani (2024); Dutordoir et al. (2024); Halling, Yu, and Zechner (2020); Hotchkiss, Nini, and Smith (2022).
  - Equity issuance: Dutordoir et al. (2024); Halling, Yu, and Zechner (2020); Hotchkiss, Nini, and Smith (2022).

LITERATURE REVIEW

- COVID19 Papers:
  - Demand for cash: Acharya and Steffen (2020); Darmouni and Siani (2024); Pettenuzzo, Sabbatucci, and Timmermann (2023).
  - Credit line drawdowns: Acharya and Steffen (2020); Darmouni and Siani (2024); Greenwald, Krainer, and Paul (2023).
  - Financial constraints to investment: Barry et al. (2022), Brunnermeier and Krishnamurthy (2020).
- European Experience with CCFs:
  - Increased issuance, increased payouts, no investment response: De Santis and Zaghini (2021); Grosse-Rueschkamp, Steffen, and Streitz (2019); Todorov (2020).

LITERATURE REVIEW

- Double/Debiased Machine Learning (DML) and Causal ML Papers:
  - DML: Belloni, Chernozhukov, and Hansen (2014), Chernozhukov et al. (2018).
  - Deep Net Estimation with Neyman Orthogonal Scores: Farrell, Liang, and Misra (2021a), Farrell, Liang, and Misra (2021b), Chronopoulous et al. (2023).
- Related DiD Estimators:
  - Doubly-robust DiD: Sant'Anna and Zhao (2020).
  - DML DiD (Partially Linear Model): Chang (2020).

LITERATURE REVIEW

- DML and Causal ML Applications:
  - Empirical Asset Pricing: Feng, Giglio, and Xiu (2020), Maasoumi et al. (2024), Borri et al. (2024), Hansen and Siggaard (2024), Gomez-Gonzalez, Uribe, and Valencia (2024).
  - Empirical Corporate Finance: Bilgin (2023), De Marco and Limodio (2022), Movaghari, Tsoukas, and Vagenas-Nanos (2024), Wasserbacher and Spindler (2024), Yang, Chuang, and Kuan (2020).
  - Deep Nets: Kim and Nikolaev (2024a), Kim and Nikolaev (2024b).

FED INTRODUCED CCFS TO SATISFY POLICY OBJECTIVES

March 23, 2020 press release:

> *The PMCCF will allow companies access to credit so that they are better able to maintain business operations and capacity during the period of dislocations related to the pandemic.*

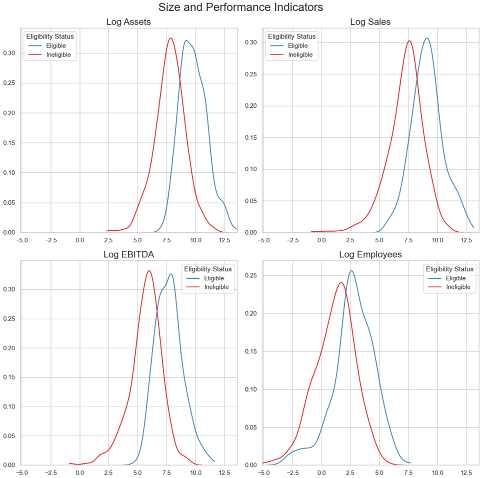
April 9, 2020 press release:

> *Increase the flow of credit to households and businesses through capital markets, by expanding the size and scope of the Primary and Secondary Market Corporate Credit Facilities (PMCCF and SMCCF).*

ELIGIBILITY CRITERIA AND ACTIVITY

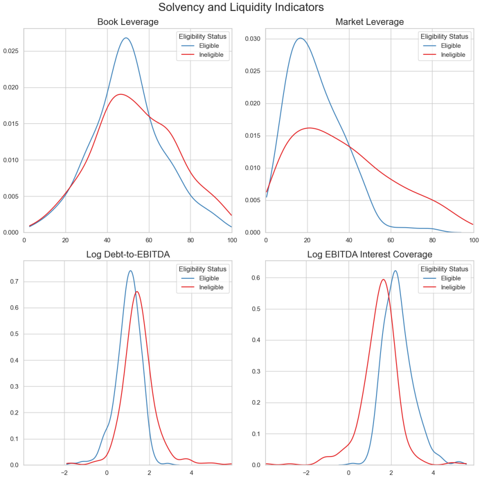
- If rated by more than one rating agency, at least two IG issuer ratings. Otherwise, sole issuer rating must be IG.
  - Initially, eligibility lost if downgraded below threshold (i.e. for Fallen Angels).
  - Later, on April 9, 2020, eligibility preserved for Fallen Angels eligible as of March 22, 2020, if rated above BB-.
- Additionally, IG ETFs initially in scope for purchases, then expanded to HY ETFs.
- Facilities designed to support up to $750 billion of financing, purchases of $14 billion.
  - Despite limited purchases, substantial contingent support priced in by markets (Haddad, Moreira, and Muir 2025).

ELIGIBLE ISSUERS ARE LARGER, WITH MORE SUBSTANTIAL CASH FLOWS



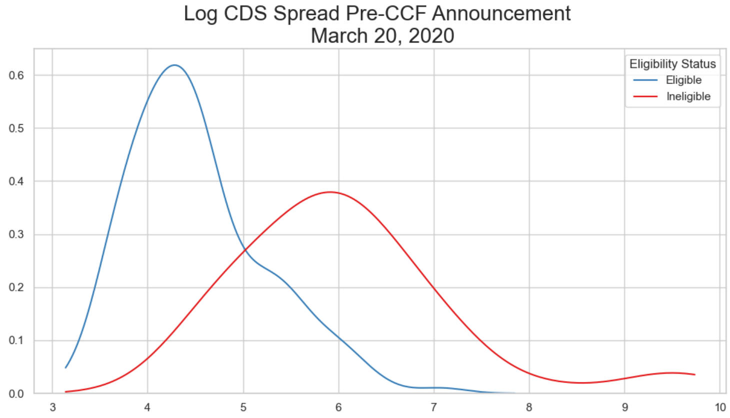
- Identification Assumptions
- Eligible
- Ineligible

ELIGIBLE ISSUERS ARE ALSO MORE LIQUID WITH LOWER LEVERAGE



- Identification Assumptions
- Eligible
- Ineligible

CDS SPREADS CONSISTENT WITH HIGHER DEFAULT RISK OF INELIGIBLE FIRMS



‣ Identification Assumptions ‣ Eligible ‣ Ineligible

HETEROGENEOUS TREATMENT EFFECTS

- Let $\mathcal{F}$ denote the realized information for firms by the end of 2019.
- Let $h = t - 2020$, where t is the year. Define $\Delta y_i^h = y_i^h - y_i^{-1}$, which is the difference in the outcome variable for some year 2020 or later and its value in 2019.
- I restrict attention to all covariates realized by the end of 2019, with less than 1% of observations missing: $x_i \subset \mathcal{F}$.
- Binary treatment, z_i, is defined to equal 1 if a firm's cash bonds were eligible for direct purchase by the Fed CCFs at the announcement date.
- All together this gives the following potential outcomes model:

$$\Delta y_i^h = \alpha(x_i) + \beta(x_i) z_i + e_i \tag{1}$$

HETEROGENEOUS TREATMENT EFFECTS

- Let $Y^h(z)$ be the potential outcome at time h where Z denotes the treatment status. Then,

$$\begin{aligned}\mathbb{E}[\Delta Y_t^h | X = x, Z = z] &= \mathbb{E}[\Delta Y_t^h(z) | X = x, Z = z] \\ &= \mathbb{E}[\Delta Y_t^h(z) | X = x] \\ &= \alpha(x) + \beta(x) z\end{aligned}$$

  where the first equality follows from the consistency assumption (the potential outcome is consistent with the treatment assignment) and the second equality follows from the unconfoundedness and overlap assumptions.

‣ Features ‣ Deep Net Architecture

‣ Size and Performance ‣ Liquidity and Solvency ‣ CDS Spreads

HETEROGENEOUS TREATMENT EFFECTS

- Taking the difference in the differences in the outcome variables yields:

$$\mathbb{E}[\Delta Y^h(1) - \Delta Y^h(0) | X = x] = \beta(x)$$

- Hence, the CATE is given by $\beta(x)$ and ATE, incorporating in heterogeneity, is given by:

$$\mu = \mathbb{E}[\beta(x)]$$

- Relax unconfoundedness to conditional parallel trends and no anticipation to obtain the average treatment effect on the treated.
- Another quantity of interest: $\mathbb{E}[\alpha(x)]$.
  - Average potential outcome absent treatment.
  - Referred to as the base effect.

INFLUENCE FUNCTION ESTIMATOR

- Let the parameter vector be given by $\theta = (\alpha, \beta)$, then the expression for the influence function estimator is:

$$\psi(y_i^h, z_i, x_i, \theta(x_i)) = H(x_i, \theta(x_i)) - (\nabla_\theta H)(\mathbb{E}[l_{\theta\theta}|X = x]^{-1} l_\theta)$$

where l the loss function, $l_\theta = \frac{\partial}{\partial\theta} l$ is the score function, and $l_{\theta\theta} = \frac{\partial^2}{\partial\theta\partial\theta'} l$ is the Hessian.

- Given a mean squared error loss function, we can express l as:

$$l(\Delta y^h, z, \theta(x)) = l(\Delta y^h, z, \alpha(x), \beta(x)) = \frac{1}{2}(\Delta y^h - \alpha(x) - \beta(x)z)^2$$

▸ Base Effect ▸ ATE ▸ Counterfactual Effect

INFLUENCE FUNCTION ESTIMATOR

- Consequently, the expression for the score is:

$$l_\theta = -\begin{pmatrix} 1 \\ z \end{pmatrix} (\Delta y^h - \alpha(x) - \beta(x) z)$$

- And likewise, for the Hessian:

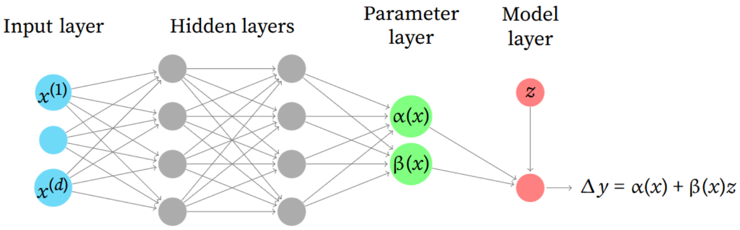
$$l_{\theta\theta} = \begin{pmatrix} 1 & z \\ z & z^2 \end{pmatrix}$$

- Let $\Lambda(x) = \mathbb{E}[l_{\theta\theta} | X = x]$. Hence,

$$\Lambda(x) = \begin{pmatrix} 1 & p(x) \\ p(x) & p(x) \end{pmatrix}$$

  where, $p(x) \equiv \Pr(z | X = x)$ is the propensity score.

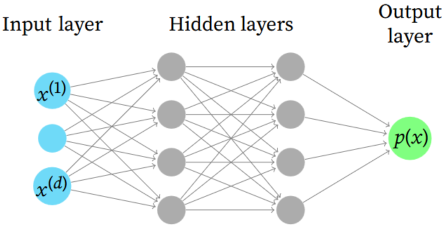
DEEP NET ARCHITECTURE FOR PARAMETERS IN POTENTIAL OUTCOMES



- Multi-layer perceptron (MLP) with rectified linear (ReLU) activation functions within hidden layers.
- Linear output layer with mean-squared loss function.

▸ Deep Net Architecture

DEEP NET ARCHITECTURE FOR PROPENSITY SCORES



- MLP with hyperbolic tangent (tanh) activation functions within hidden layers.
- Sigmoid output layer with binary cross-entropy loss function.

▸ Deep Net Architecture

COMPUTING THE BASE EFFECT WITH HETEROGENEITY

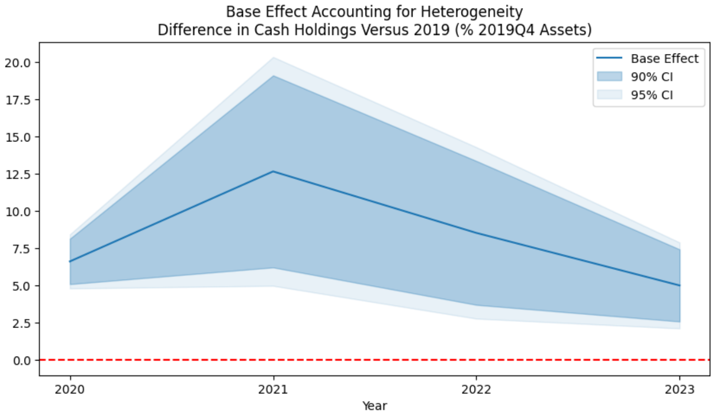
- To estimate the base effect, set $H(x, \theta(x)) = \alpha(x)$.
- This gives the following form for the IF estimator:

$$\alpha(x) + \frac{(1 - z)(\Delta y^h - \alpha(x))}{1 - p(x)}$$

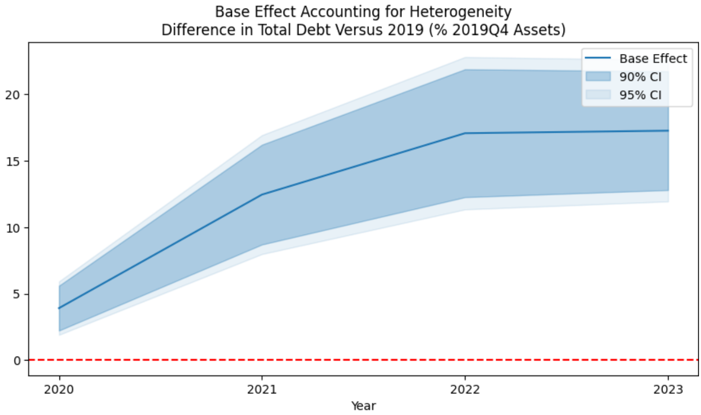
the parameters $\alpha(x), p(x)$ are estimated using deep nets.

‣ General Expression for IF Estimator

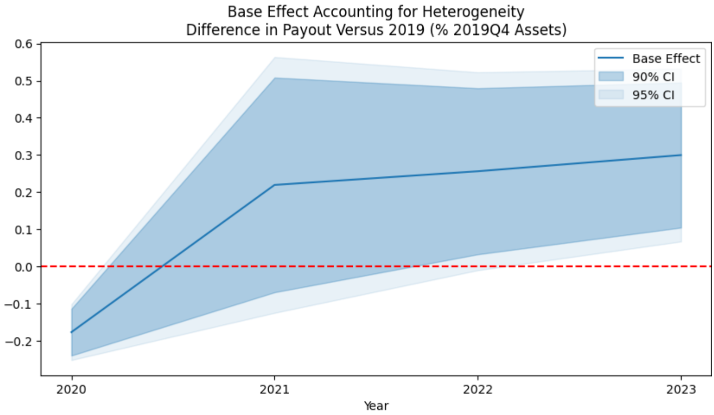
LARGE BASE EFFECT WITH INCREASE IN CASH HOLDINGS



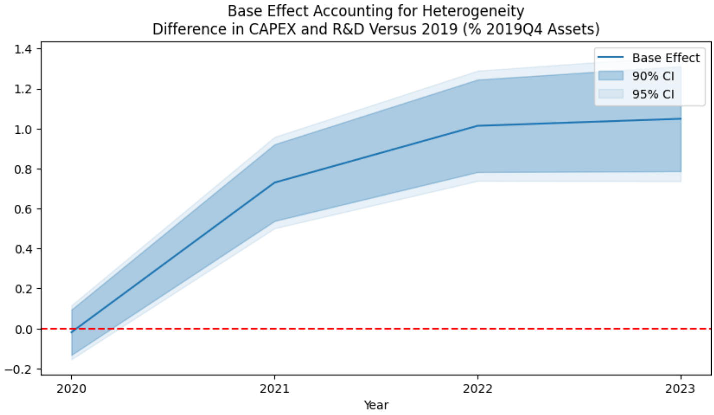
LARGE BASE EFFECT WITH INCREASE IN TOTAL DEBT



PAYOUT BASE EFFECT INITIALLY NEGATIVE THEN INCREASES



INVESTMENT BASE EFFECT NEGATIVE BEFORE REVERTING TO NULL THEN INCREASING



COMPUTING THE ATE WITH HETEROGENEITY

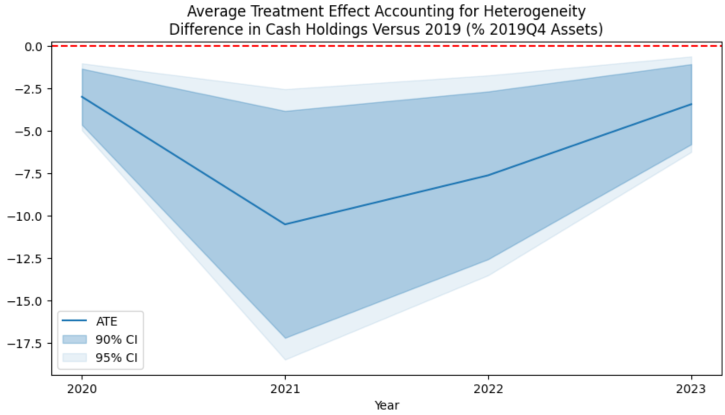
- To estimate the ATE, set $H(x, \theta(x)) = \beta(x)$.
- This gives the following form for the IF estimator:

$$\beta(x) + \frac{z(y^h - \alpha(x) - \beta(x)z)}{p(x)} - \frac{(1-z)(y^h - \alpha(x))}{1 - p(x)}$$

the parameters $\alpha(x), \beta(x), p(x)$ are estimated using deep nets.

▸ General Expression for IF Estimator

CASH ATE WITH HETEROGENEITY SHOWS LARGE NEGATIVE EFFECT



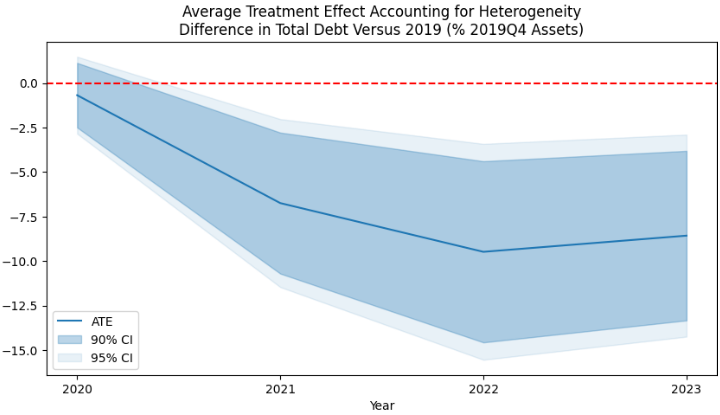
CASH TREATMENT EFFECT COMPARISON

Treatment Effect Estimates				
Cash (% 2019Q4 Assets)				
Year	Static (Homogeneous)	Dynamic (Heterogeneous) (1)	Dynamic (Homogeneous) (2)	Difference (1)-(2)
2020		-2.98 (1.00)	-3.82 (0.79)	0.84
2021		-10.50 (4.06)	-9.52 (2.42)	-0.98
2022		-7.61 (3.00)	-6.92 (2.27)	-0.68
2023		-3.42 (1.43)	-4.01 (1.09)	0.59
Eligible × Post 2020	-7.46 (2.05)			

Standard-errors in parentheses

DiD ES

DEBT ATE WITH HETEROGENEITY NEGATIVE AFTER 2020



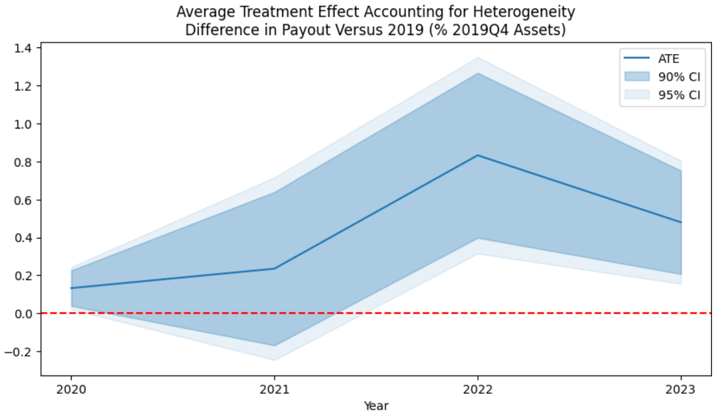
DEBT TREATMENT EFFECT COMPARISON

Treatment Effect Estimates				
Total Debt (% 2019Q4 Assets)				
Year	Static (Homogeneous)	Dynamic (Heterogeneous) (1)	Dynamic (Homogeneous) (2)	Difference (1)-(2)
2020		-0.69	-1.66	0.98
		(1.10)	(0.65)	
2021		-6.75	-5.95	-0.79
		(2.41)	(2.30)	
2022		-9.48	-9.08	-0.40
		(3.09)	(2.59)	
2023		-8.58	-8.47	-0.10
		(2.90)	(1.95)	
Eligible × Post 2020	-6.21			
	(2.73)			

Standard-errors in parentheses

DiD ES

PAYOUT ATE GENERALLY POSITIVE



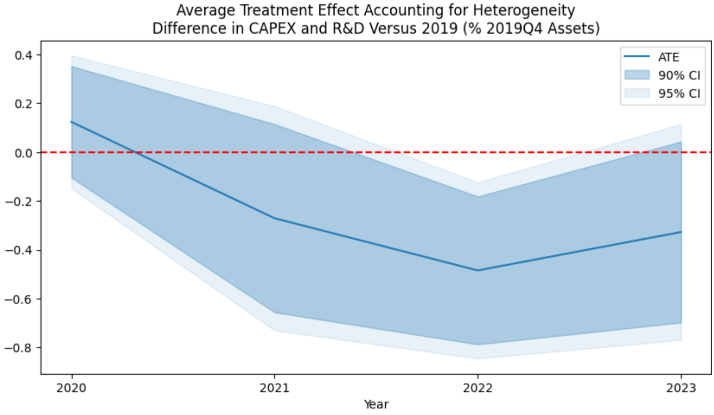
PAYOUT TREATMENT EFFECT COMPARISON

Treatment Effect Estimates				
Payout (% 2019Q4 Assets)				
Year	Static (Homogeneous)	Dynamic (Heterogeneous) (1)	Dynamic (Homogeneous) (2)	Difference (1)-(2)
2020		0.13	0.54	-0.41
		(0.06)	(0.34)	
2021		0.23	0.65	-0.42
		(0.25)	(0.36)	
2022		0.83	0.99	-0.16
		(0.26)	(0.37)	
2023		0.48	0.86	-0.38
		(0.17)	(0.39)	
Eligible ×	1.16			
Post 2020	(0.23)			

Standard-errors in parentheses

DiD ES

UNLIKE PAYOUTS, INVESTMENT SHOWS NO RESPONSE



INVESTMENT TREATMENT EFFECT COMPARISON

Treatment Effect Estimates				
CAPEX and R&D (% 2019Q4 Assets)				
Year	Static (Homogeneous)	Dynamic (Heterogeneous) (1)	Dynamic (Homogeneous) (2)	Difference (1)-(2)
2020		0.12	-0.49	0.62
		(0.14)	(0.58)	
2021		-0.27	-1.88	1.61
		(0.23)	(0.80)	
2022		-0.49	-0.99	0.50
		(0.18)	(0.41)	
2023		-0.33	-0.62	0.29
		(0.23)	(0.29)	
Eligible ×	-0.90			
Post 2020	(0.66)			

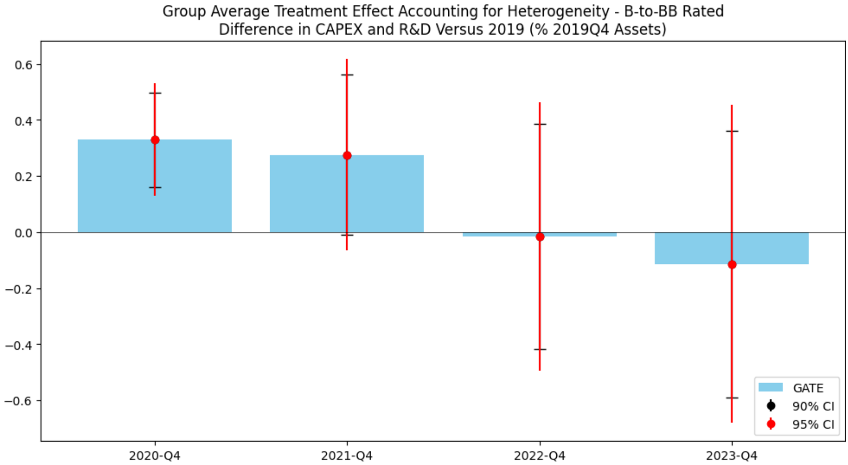
Standard-errors in parentheses

DiD ES

COUNTERFACTUAL TREATMENT EFFECTS

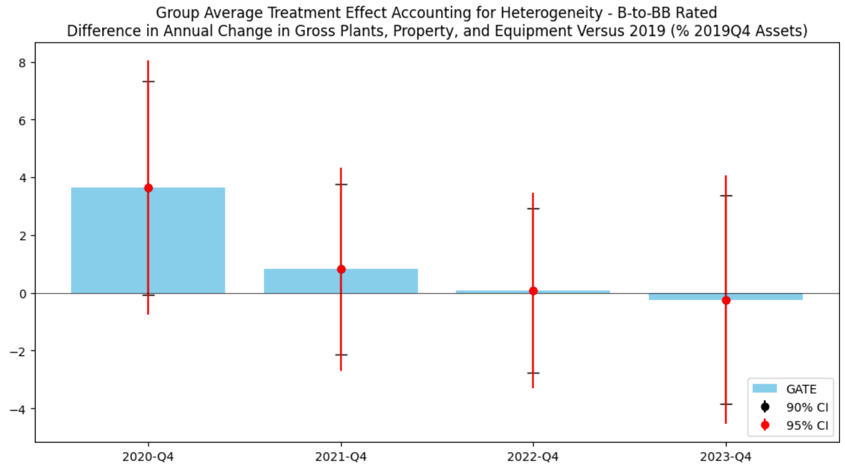
- The counterfactual treatment effect is given by the group average treatment effect (GATE) for ineligible (B/BB rated) firms: $\mathbb{E}[g\beta(x)]$.
- Set $H(x, \theta(x)) = g\beta(x)$ in the IF estimator, where g indicates if a firm is rated B or BB. ▸ General Expression for IF Estimator
- The assumption of unconfoundedness is needed for causal interpretation. If this fails, the estimator identifies a predictive effect, still useful for policy analysis.
- A simple framework, as in Brunnermeier and Krishnamurthy (2020), suggests targeting weaker credits should result in stronger real effects.
- Momin and Li (2025) find that extending direct cash bond support to ineligible issuers would have led to around 500 bps of spread tightening.

POSITIVE COUNTERFACTUAL TREATMENT EFFECT FOR INVESTMENT NOT ROBUST



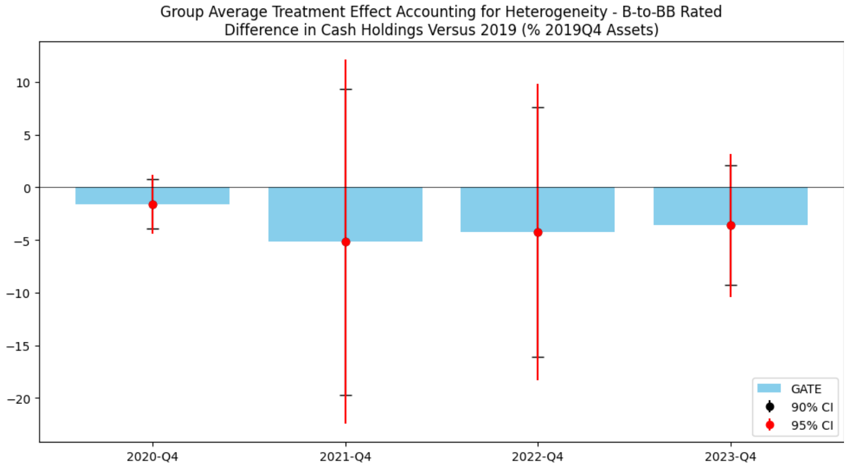
- Positive estimate for 2020 not robust to alternative investment proxy (PPE).

NO IMPROVEMENT FOR INVESTMENT WITH ALTERNATIVE PROXY



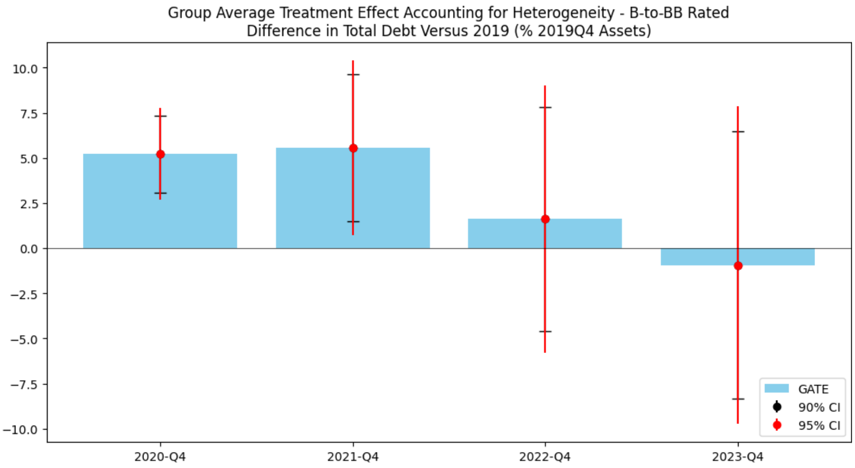
- Investment proxy: annual change in gross property, plant, and equipment.

NULL COUNTERFACTUAL TREATMENT EFFECTS FOR CASH



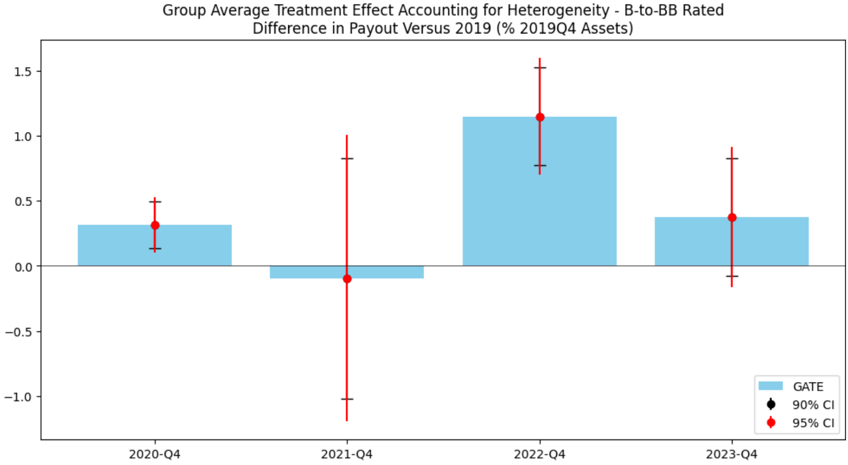
- Null effects estimated across different model specifications and horizons.

POSITIVE COUNTERFACTUAL TREATMENT EFFECT FOR DEBT



- Positive and statistically significant effects for 2020 for models with at least 5 years of feature history.

POSITIVE COUNTERFACTUAL TREATMENT EFFECT FOR PAYOUTS



- Positive and statistically significant effects for 2020 and 2022.

NOVEL TWO-STEP SEMI-PARAMETRIC DID ESTIMATOR

- Estimates dynamic (heterogeneous) treatment effects, comparable to an event study with two-way fixed effects.
- Structural equation:
  - **Potential outcomes** = Non-parametric intercept + (Treatment indicator × Non-parametric slope).
  - Slope term captures **individual-level heterogeneity** (Conditional Average Treatment Effects).
- Intercept, slope, and propensity scores estimated via deep neural networks using high-dimensional characteristics.
- Identification relies on **unconfoundedness & overlap** conditions; can relax to **parallel trends** assumption.

APPLICATION: FEDERAL RESERVE'S CORPORATE CREDIT FACILITIES

- **Findings:**
  - All firms increased **leverage & cash holdings**, but **CCF-eligible firms increased less** than ineligible ones.
  - **No significant investment response** from eligible firms ⇒ **limited real effects** of CCFs.
  - Eligible firms **increased shareholder payouts** instead.
  - **Counterfactual treatment effects** for ineligible (B/BB) firms:
    - ☐ **Mixed to inconclusive** evidence for improved investment.
    - ☐ **Stronger evidence** for increased leverage (2020) and payouts (2020, 2022).

DESCRIPTIVE STATISTICS - ELIGIBLE

	Median	Mean	Standard Deviation	Observations
Common Equity at Market Value (Millions)	22,421.93	58,526.71	122,246.57	321
Total Debt (Millions)	5,718.30	13,352.45	22,580.30	358
Total Assets (Millions)	17,642.35	39,488.83	73,815.12	358
Employees (Thousands)	16.30	56.42	146.44	345
Book Leverage (Percent)	49.03	49.86	17.21	345
Market Leverage (Percent)	21.84	24.00	13.64	321
Sales (Millions)	8,980.15	25,430.24	51,988.78	358
EBITDA (Millions)	2,211.30	5,106.62	10,418.35	340
EBITDA Interest Coverage	9.44	13.77	17.03	338
Debt-to-EBITDA	2.87	3.17	1.82	340

▸ Size and Performance ▸ Liquidity and Solvency ▸ CDS Spreads

DESCRIPTIVE STATISTICS - INELIGIBLE

	Median	Mean	Standard Deviation	Observations
Common Equity at Market Value (Millions)	2,075.07	5,054.11	10,387.18	460
Total Debt (Millions)	1,043.55	2,532.42	4,979.49	464
Total Assets (Millions)	2,502.09	5,584.92	10,617.85	465
Employees (Thousands)	3.63	10.82	22.73	458
Book Leverage (Percent)	52.47	53.71	20.14	412
Market Leverage (Percent)	33.16	37.43	23.93	459
Sales (Millions)	1,667.11	3,556.65	6,182.18	462
EBITDA (Millions)	228.18	488.68	1,182.23	461
EBITDA Interest Coverage	3.86	3.89	16.70	452
Debt-to-EBITDA	3.65	3.92	25.65	460

‣ Size and Performance ‣ Liquidity and Solvency ‣ CDS Spreads

DIFFERENCE-IN-DIFFERENCES REGRESSIONS

- Static (homogeneous) treatment effects are estimated using a difference-in-differences (DiD) regression.
- The specification is:

$$y_{i,t} = \beta_0 + \beta_1 \text{Eligible}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Eligible}_i \times \text{Post}_t) + \gamma_i + \epsilon_{i,t} \quad (2)$$

where $y_{i,t}$ is the outcome variable of interest, Eligible_i is an indicator variable with value 1 if firm i was eligible for cash bond purchases under the CCFs, Post_t is an indicator variable equal to 1 if date t is 2020 or later, and γ are two-digit NAICS industry fixed effects. The static treatment effect is given by β_3. The DiD regressions are computed over 2017 to 2023. Standard errors are clustered by issuer and date.

DEBT LEVELS AND CASH HOLDINGS BROADLY INCREASED, WITH NEGATIVE TREATMENT EFFECT FOR ELIGIBLE FIRMS

Dependent Variables:	Cash (% 2019Q4 Assets)		Total Debt (% 2019Q4 Assets)	
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	10.01***		36.37***	
	(0.9476)		(2.943)	
Eligible (Fed CCFs)	-4.477***	-3.120***	-10.54***	-12.49***
	(0.9565)	(1.009)	(1.969)	(2.010)
Post 2020	9.866***	9.903***	23.16***	23.17***
	(2.015)	(2.005)	(4.075)	(4.082)
Eligible (Fed CCFs) × Post 2020	-7.295***	-7.464***	-6.141**	-6.212**
	(2.042)	(2.046)	(2.733)	(2.729)
Fixed-effects				
NAICS (2-Digit)		Yes		Yes
Fit statistics				
Observations	9,912	9,912	9,502	9,502
R^2	0.03349	0.07229	0.07234	0.10256
Within R^2		0.02740		0.07712

Clustered (Issuer & Date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

‣ Cash ‣ Debt

ELIGIBLE FIRMS' PAYOUT SHOWS POSITIVE EFFECT; NO EFFECT SEEN FOR INVESTMENT

Dependent Variables:	Dividends and Buybacks (% 2019Q4 Assets)		Capital Expenditures and R&D (% 2019Q4 Assets)	
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	1.062***		2.456***	
	(0.2192)		(0.2956)	
Eligible (Fed CCFs)	0.9875***	0.8328***	-1.217***	-1.150***
	(0.2433)	(0.2519)	(0.3103)	(0.3168)
Post 2020	-0.1769	-0.1554	1.240*	1.305*
	(0.2470)	(0.2473)	(0.6771)	(0.6843)
Eligible (Fed CCFs) × Post 2020	1.180***	1.158***	-0.8407	-0.9016
	(0.2377)	(0.2345)	(0.6597)	(0.6642)
Fixed-effects				
NAICS (2-Digit)		Yes		Yes
Fit statistics				
Observations	9,641	9,641	9,798	9,798
R^2	0.00907	0.01695	0.00988	0.03614
Within R^2		0.00657		0.00882

Clustered (Issuer & Date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

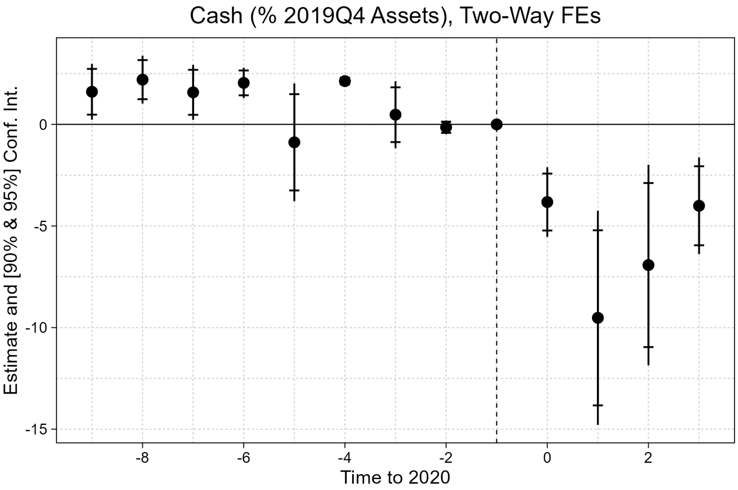
EVENT STUDY REGRESSIONS

- To study the dynamic impact of the CCF intervention, I employ event study regressions with two-way fixed effects.
- These have the functional form:

$$y_{i,t} = \sum_{\tau=-3}^{-2} \beta_\tau D_t^\tau \text{Eligible}_i + \sum_{\tau=0}^{3} \beta_\tau D_t^\tau \text{Eligible}_i + \gamma_i + \zeta_t + \epsilon_{i,t} \tag{3}$$

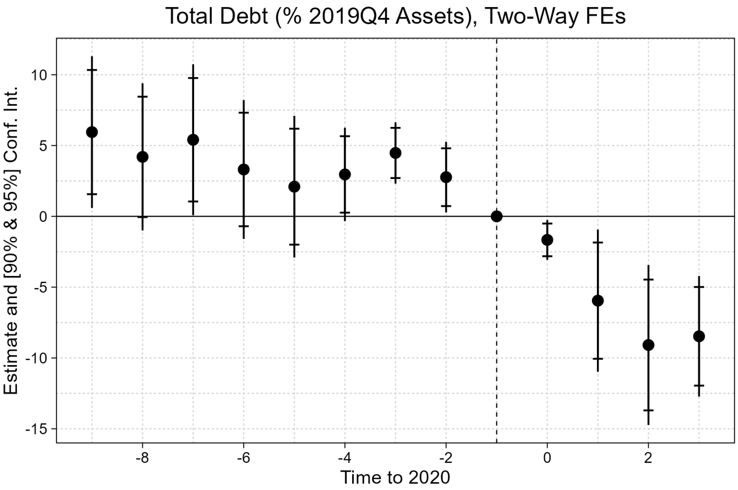
  where $y_{i,t}$ is the outcome variable of interest, $D^\tau = \mathbf{1}\{t - 2020 = \tau\}$ is an indicator variable equal to 1 if the difference between the year t and 2020 is equal to τ, Eligible is an indicator variable with value 1 if the firm was eligible for direct cash bond purchases under the CCFs, 0 otherwise, and finally, β_τ are the coefficients being estimated.
- Two-way unit and time fixed effects are given by γ_i for issuer and ζ_t for year, respectively. The event study regressions are computed over the window 2017 to 2023. Standard errors are clustered by issuer and year.

ELIGIBLE FIRM CASH HOLDINGS SHOW RELATIVE DECLINE, BEFORE REVERTING

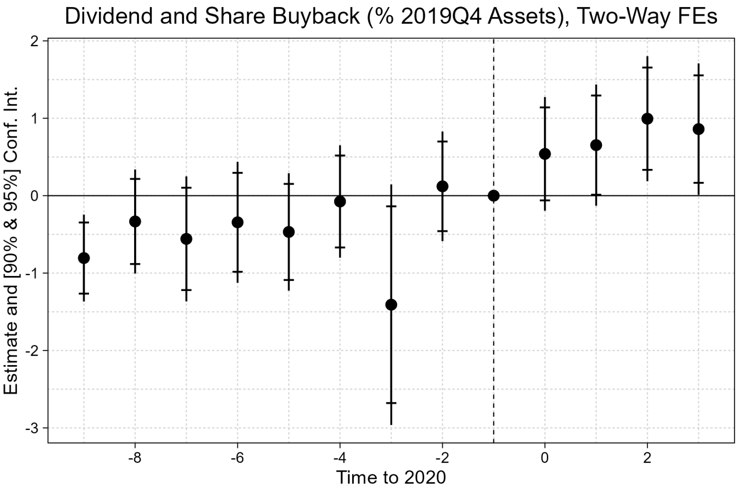


▸ IF Estimator

RELATIVE LEVERAGE OF INELIGIBLE FIRMS RISE

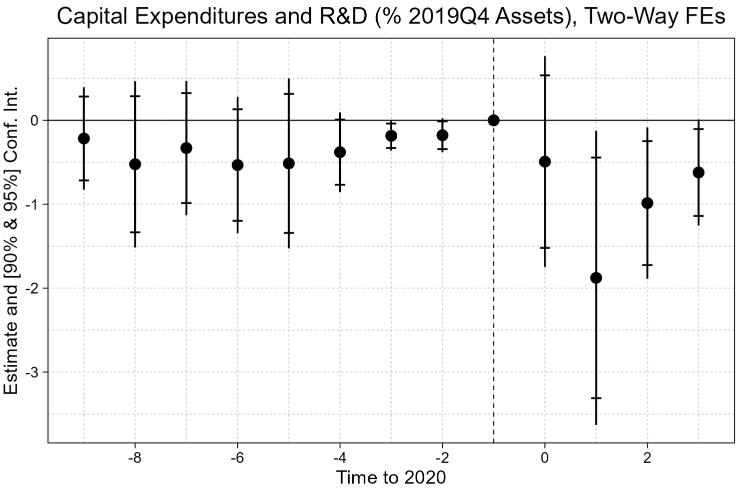


RELATIVE PAYOUTS BY ELIGIBLE FIRMS RISE



‣ IF Estimator

ELIGIBLE FIRMS DISPLAY RELATIVE DECLINE IN INVESTMENT



‣ IF Estimator

FEATURES WITH LESS THAN ONE PERCENT MISSING OBSERVATIONS

Variable	Description
accrual	Accruals/Average Assets
adv_sale	Advertising Expenses/Sales
aftret_eq	After-tax Return on Average Common Equity
aftret_equity	After-tax Return on Total Stockholders Equity
aftret_invcapx	After-tax Return on Invested Capital
at_turn	Asset Turnover
capital_ratio	Capitalization Ratio
cash_debt	Cash Flow/Total Debt
cash_lt	Cash Balance/Total Liabilities
cfm	Cash Flow Margin
de_ratio	Total Debt/Equity
debt_assets	Total Debt (ltq)/Total Assets
debt_at	Total Debt (dlcq+dlttq)/Total Assets
debt_capital	Total Debt/Capital
debt_ebitda	Total Debt/EBITDA
debt_invcap	Long-term Debt/Invested Capital
equity_invcap	Common Equity/Invested Capital
evm	Enterprise Value Multiple
gpm	Gross Profit Margin
gprof	Gross Profit/Total Assets
lt_debt	Long-term Debt/Total Liabilities
lt_ppent	Total Liabilities/Total Tangible Assets
npm	Net Profit Margin
opmad	Operating Profit Margin After Depreciation
opmbd	Operating Profit Margin Before Depreciation
pcf	Price/Cash flow
pe_exi	P/E (Diluted, Excl. EI)
pe_inc	P/E (Diluted, Incl. EI)
pe_op_basic	Price/Operating Earnings (Basic, Excl. EI)
pe_op_dil	Price/Operating Earnings (Diluted, Excl. EI)
ps	Price/Sales
ptpm	Pre-tax Profit Margin
rd_sale	Research and Development/Sales
roa	Return on Assets
roce	Return on Capital Employed
staff_sale	Labor Expenses/Sales
totdebt_invcap	Total Debt/Invested Capital

Identification Assumptions

DEEP NET ARCHITECTURE

	Feature History (Years)		
	1	5	10
Number of Features	333	1342	3204
Hidden Layer Architecture	[300, 150, 75, 35, 15]	[1500, 750, 375, 150, 75, 35, 15]	[2700, 1350, 675, 300, 150, 75, 35, 15]
Dropout Rate	20%		

- Identification Assumptions
- Potential Outcomes
- Propensity Scores