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Central clearing and the pricing of specialness in repo markets

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Abstract

Repo markets clear either bilaterally over the counter (OTC) or through central counterparties (CCPs), which differ in how counterparty risk is priced. In bilateral markets, repo rates reflect borrower-specific risk, while CCP clearing pools counterparties and applies a common pricing rule. We develop a model of security-driven repo in which repo rates are non-linear in borrower risk. As a result, averaging borrower-specific OTC prices yields more negative rates than pricing the pooled borrower in CCP markets. The model predicts that the CCP–OTC specialness gap compresses during periods of counterparty uncertainty and varies with borrower and collateral characteristics. Using transaction-level data from the euro-area interbank repo market around the March 2020 COVID-19 shock, we find evidence consistent with these predictions. Our results show that central clearing dampens specialness in normal times but stabilizes repo pricing during stress.

Keywords: Asymmetric information, Counterparty risk, Uncertainty, Collateral risk, Interbank markets

JEL Codes: D47, D82, G14, G15, G21

Non-technical summary

The paper studies how the structure of the euro area interbank repo market affects the cost of borrowing collateral via over the counter (OTC) or centrally cleared (CCP) transaction. In repo transactions, one party provides cash and receives a security as collateral, agreeing to reverse the transaction at maturity. When the primary motive is to obtain a specific security rather than cash, the transaction is referred to as security–driven (or reverse repo). In Europe, repos can be traded either bilaterally in OTC markets, where counterparties know each other's identity and directly bear counterparty risk, or via CCPs, where trades are anonymous and the CCP becomes the buyer to every seller and the seller to every buyer. In CCP markets, counterparty risk is pooled and mutualised through a default fund. This institutional difference has important pricing implications: in OTC markets, repo rates reflect borrower-specific risk, while in CCP markets rates reflect the average risk of the participant pool.

The paper develops a theoretical model of security-driven repo tailored to the institutional features of the European market. A central insight of the model is that repo rates are a non-linear function of borrower default risk. In bilateral OTC markets, lenders can condition prices on borrower identity, setting a specific rate for each borrower type. The observed market rate is therefore an average of borrower-specific prices. In CCP markets, by contrast, pricing applies to the pooled "average borrower", since individual identities are not reflected in transaction-level prices. Because the pricing function is non-linear, averaging borrower-specific prices is not the same as pricing the average borrower. As a result, the average OTC rate is more negative than the CCP rate. Intuitively, in OTC markets lenders fully internalize borrower-specific risk while in CCP markets, risk is diluted across the pool. This aggregation effect generates a systematic wedge between OTC and CCP rates.

The model delivers three main predictions that align closely with the empirical findings. First, in normal times, special securities should trade at more negative rates in OTC markets than in CCP markets, reflecting the non-linear pricing of borrower-specific risk. Second, when counterparty uncertainty increases – as during the COVID-19 shock – the CCP–OTC differential should compress. The reason is that as lenders become more concerned about the distribution of borrower types, pooling risk in CCP markets becomes relatively more costly, raising CCP rates towards OTC levels. Third, the magnitude of this compression should depend on borrower and collateral characteristics. When borrower quality deteriorates, the non-linearity in pricing becomes stronger, so identity-based OTC pricing remains more distinct from pooled CCP pricing, dampening the compression. By contrast, when collateral is of particularly high quality and therefore highly valued, the interaction between counterparty risk and collateral risk becomes more pronounced in CCP markets, amplifying the compression for safe assets.

Using a differences-in-differences setting applied to confidential transaction-level data from the Eurosystem's Money Market Statistical Reporting (MMSR) dataset, we test the model predictions about the differential cost of borrowing on CCP and OTC repos around the Covid-19 pandemic. Following the COVID-19 uncertainty shock, the CCP–OTC differential compresses sharply. Borrowing costs in CCP markets increase relative to OTC markets by roughly 6 basis points. This compression is heterogeneous: it is weaker for riskier borrowers – measured using non-performing loan (NPL) ratios and credit default swap (CDS) spreads – and stronger for high-quality collateral, proxied by core euro-area government bonds. These findings are robust to a wide range of alternative specifications and fixed effects.

These results have several policy-relevant implications. For the euro area and the ECB, they highlight that central clearing does not only affect the resilience of funding markets but also the equilibrium price of scarce collateral. By pooling counterparties and introducing anonymity, CCPs dampen the level of specialness in normal times. At the same time, they help stabilise pricing during stress by reducing the dispersion in borrower–specific rates and by providing continued access to trading when bilateral relationships may become strained. In periods of heightened uncertainty, lower-quality borrowers benefit relatively more from CCP participation, as their individual risk is partially diluted within the pool. Conversely, high-quality collateral becomes relatively more expensive to source through CCPs during stress, reflecting the higher value attached to safe assets when counterparty risk rises.

From a broader perspective, the findings underline a trade-off inherent in market design. Identity-based bilateral markets allow for more granular risk-sensitive pricing, but they may be more fragile in periods of stress. Pooled and anonymous CCP markets reduce price dispersion and can act as shock absorbers, but they also redistribute risk across participants and alter the pricing of collateral. For central banks, which rely heavily on repo markets for the transmission of monetary policy and for the smooth functioning of collateral frameworks, understanding these mechanisms is crucial. The paper therefore contributes to the assessment of central clearing policies and to the broader discussion on how financial market infrastructure shapes the allocation and pricing of risk in the euro area.

1 Introduction

Repurchase agreements (repos) are an integral component of the financial plumbing of modern economies (BIS 2017) and represent the primary source of short-term funding and security borrowing for banks. In the European interbank repo market, transactions can be cleared either bilaterally over-the-counter (OTC) or through central counterparties (CCPs). Despite involving identical securities, repo rates often differ systematically across these clearing venues: bilateral OTC trades frequently occur at more negative rates than centrally cleared trades, and the resulting CCP–OTC differential varies markedly during periods of market stress. Understanding why identical securities command different borrowing costs across clearing arrangements is important for both market participants and policy makers, especially given the growing role of central clearing in repo markets. Repo markets have also proven vulnerable to episodes of instability, as evidenced during the Great Financial Crisis (Brunnermeier 2009, Mancini et al. 2016, Infante & Saravay 2020), the repo market turmoil in September 2019 (Tilford et al. 2019), and the COVID-19 pandemic in March 2020 (Duffie 2020*b*). This paper studies how clearing arrangements affect the pricing of reverse repos.

Using transaction-level data from the euro-area interbank repo market, we document a set of new empirical facts. First, for the same securities, the average OTC rate is more negative than the corresponding centrally cleared rate. Second, this CCP–OTC differential compresses sharply during the onset of the COVID-19 pandemic in March 2020. These patterns are difficult to reconcile with existing explanations of repo pricing. Standard models of specialness focus on collateral scarcity and search frictions but abstract from counterparty risk. Conversely, models of funding markets emphasize asymmetric information about borrower risk but do not consider security-driven repos or the institutional differences between bilateral and centrally cleared markets.

We propose a simple mechanism that links clearing structure to the pricing of special collateral. In bilateral OTC trades, lenders observe the identity of the borrower and can price counterparty risk individually, so each borrower faces a different repo rate and the observed market rate reflects the average of borrower-specific prices. In CCP-cleared trades, by contrast, counterparties are anonymous and exposures are pooled, so pricing reflects the average risk of the participant pool. The key distinction is therefore between averaging borrower-specific prices in OTC markets and pricing the average borrower in CCP markets. We formalize this mechanism in a model of security-driven repo in which borrowers differ in default risk and use repos to obtain scarce securities that can be short sold. Because the lender's break-even repo rate is convex in borrower risk, averaging borrower-specific prices differs from pricing the pooled borrower when borrower risk is heterogeneous. As a result, bilateral markets produce more negative average repo rates than CCP markets, generating systematic CCP–OTC differences in specialness.

The model reconciles the novel empirical facts; in normal times, special securities trade at more negative rates in OTC markets than in CCP markets, and increases in counterparty uncertainty compress the CCP–OTC differential. Furthermore, the model delivers two testable predictions. First, the compression in the the CCP–OTC differential is weaker for riskier borrowers and second, the compression is stronger for high-quality collateral.

We test these predictions using the European Central Bank's Money Market Statistical Reporting (MMSR) dataset, which covers the largest euro-area banks and a large share of the secured Euro money market. Our identification relies on within-security comparisons across clearing venues around the World Health Organization's pandemic announcement, a period characterized by sharp increases in bank CDS spreads and safe-asset yields but prior to major policy interventions.

Our empirical results are consistent with the mechanism proposed by the model. In normal times, special securities trade at more negative rates in bilateral OTC markets than in centrally cleared markets, generating a negative CCP–OTC differential. Following the COVID-19 uncertainty shock, this differential compresses significantly. Consistent with the model's cross-sectional implications, the compression is weaker for riskier borrowers, who benefit relatively more from counterparty pooling in CCP markets, and stronger for high-quality collateral, whose scarcity value increases when counterparty risk is pooled.

Overall, our findings show that clearing arrangements shape not only the stability of funding markets but also the equilibrium pricing of scarce collateral. By pooling counterparty risk, CCP clearing dampens specialness in normal times but makes repo pricing more resilient during periods of stress. More broadly, the paper shows how financial market infrastructure that aggregates counterparty risk can systematically affect the pricing of scarce assets and the functioning of collateral markets.

The remainder of the paper is organized as follows. Section 2 reviews the literature and highlights the contribution. Section 3 describes the institutional setting and the data. Section 4 presents the model. Section 5 describes the dataset and the identification of security–driven repos, Section 6 outlines the empirical strategy. Section 7 reports the results, and Section 8 concludes.

2 Related Literature

This paper contributes to the literature on security-driven repo (reverse repo) and the pricing of specialness. In the euro area, a large share of repo transactions are motivated by the need to source particular securities rather than by cash funding needs. In such transactions, repo rates often fall below policy rates and may be accompanied by negative haircuts, reflecting the scarcity value of the collateral. Our paper studies how the pricing of special collateral depends on the clearing arrangement and, in particular, how anonymity and counterparty pooling in centrally cleared markets affect the transmission of counterparty risk into specialness.

A first strand of the literature studies the determinants of repo specialness and collateral scarcity. Early theoretical work shows how search frictions and limited security supply generate specialness premia in repo markets (Duffie 1996, Vayanos & Weill 2008). Empirical studies document how central bank asset purchases and fluctuations in collateral supply affect repo rates and market segmentation (Corradin & Maddaloni 2020, Boissel et al. 2017). Recent work using regulatory transaction-level data emphasizes that repo activity is increasingly collateral-driven and documents the prevalence of zero or negative haircuts, consistent with security-borrowing motives and scarcity rents (Hermes et al. 2025, Bejarano et al. 2025).

A second strand examines how clearing arrangements shape repo pricing and stability. Bilateral markets expose participants to counterparty risk that is priced at the borrower level, while centrally cleared markets transform bilateral exposures into pooled exposures through anonymity, novation and default funds. Empirical work shows that centrally cleared repo markets can act as shock absorbers during periods of stress (Mancini et al. 2016, Affinito & Piazza 2021), while disruptions in bilateral markets have been linked to balance sheet constraints and limited netting efficiency (Duffie 2020*a*, He et al. 2022). Our paper contributes to this literature by focusing on security-driven reverse repos and by isolating the information channel generated by anonymity, novation and default fund in CCP markets.

A third strand studies asymmetric information and segmentation in wholesale funding markets. Theoretical work shows that private information about counterparty risk can lead to liquidity hoarding and market breakdowns (Freixas & Holthausen 2005, Heider et al. 2015, Martin et al. 2014, Acharya & Skeie 2011). Empirical evidence indicates that funding markets become more relationship-based during stress and that low-quality borrowers may lose access to bilateral funding (Copeland et al. 2014, Krishnamurthy et al. 2014, Hüser et al. 2021). Centrally cleared or anonymous trading venues may instead provide continued access to funding by pooling counterparty risk (Mancini et al. 2016, Affinito & Piazza 2021).

Recent work also studies how counterparty risk and collateral constraints shape the structure and pricing of wholesale funding markets. Coen (2026) develop a structural model of interbank network formation in which banks endogenously select counterparties under counterparty risk, and analyze the implications for contagion and systemic risk. Coen & Huser (2026) study how heterogeneous collateral demand affects funding spreads and the allocation of collateral across counterparties in repo markets. Our paper differs from this work by focusing on how the clearing arrangement—bilateral versus centrally cleared—affects the pricing of special collateral through differences in information aggregation and counterparty-risk pooling.

We contribute to these strands by developing a model of security-driven repo in which OTC contracts condition on borrower identity, while CCP-cleared contracts price the average borrower. Because repo rates are non-linear in borrower risk, pricing the average borrower differs from averaging borrower-specific prices. This distinction generates systematic CCP–OTC wedges in specialness. Using transaction-level data from the euro-area interbank repo market around the March 2020 COVID-19 shock, we show that the CCP–OTC specialness differential compresses in periods of uncertainty and varies systematically with borrower risk and collateral quality. We provide new theory and evidence on how market structure and counterparty information jointly shape the pricing of scarce collateral.

3 Institutional Background and Stylized Facts

This section describes the institutional structure of the European repo market and highlights the key features relevant for our analysis, with particular attention to developments around the World Health Organization (WHO) pandemic announcement in March 2020.

3.1 Repo Contracts and Trading Motives

A repurchase agreement (repo) is a secured transaction in which one party obtains cash by posting a security as collateral, with an agreement to reverse the exchange at maturity. A transaction used to obtain a security in exchange for cash is referred to as a reverse repo (Figure 1a). Operationally, repos and reverse repos are symmetric; the distinction lies in the trading motive. Repos are cash-driven transactions initiated by borrowers seeking funding, while reverse repos are security-driven transactions initiated by borrowers seeking a specific security. During our sample period, most transactions are security-driven, and we therefore focus on reverse repos.

A reverse repo is characterized by three contract terms: the cash amount, the security exchanged, and the repo rate. When the transaction is security-driven, a more negative repo rate reflects a higher cost of borrowing the security and therefore greater specialness. The ratio of the value of the security to the cash exchanged is summarized by the haircut,

$$h = 1 - \frac{\text{Cash}}{\text{Security}}.$$

Under this convention, a lower haircut implies that more cash is posted per unit of security and therefore provides greater protection to the security lender.[1] In environments with high demand for specific securities, haircuts may become negative, implying that the cash collateral exceeds the market value of the security.

Repo rates and haircuts jointly allocate risk between the contracting parties. Two sources of risk are central. Counterparty risk reflects the possibility that the borrower fails to return the security at maturity. Security risk reflects fluctuations in the value, liquidity, and availability of the underlying collateral. Securities that are scarce or in high demand typically trade at lower repo rates and lower haircuts.

[Insert Figure 1 here]

3.2 Trading and Clearing

In Europe, repo contracts are traded and cleared either bilaterally in over-the-counter (OTC) markets or through central counterparties (CCPs) (Figure 1b). In OTC markets, transactions

[1] Initial margins and haircuts are economically identical. Variation margins play a minor role in markets dominated by overnight transactions.

are negotiated and settled bilaterally, and counterparties are identified. Counterparty risk is therefore priced at the borrower level through the repo rate and haircut.[2] In CCP markets, transactions are anonymous and novated. The CCP becomes the counterparty to all trades and mutualizes losses through a default fund. As a result, counterparty risk is effectively pooled across CCP participants, and pricing reflects the average risk of the participant pool rather than the risk of the individual borrower.

The share of repo transactions cleared through CCPs increased substantially following the Global Financial Crisis (Affinito & Piazza 2021, Mancini et al. 2016, Boissel et al. 2017, Di Luigi et al. 2024). The main CCPs operating in the euro area are LCH RepoClear, Eurex Repo, and Cassa di Compensazione e Garanzia. Differences in pricing between CCP and OTC markets can reflect several institutional features, including balance-sheet netting benefits in CCP markets and relationship-based trading in OTC markets. These structural differences are largely stable over short horizons. In our empirical analysis, which focuses on a narrow window around the WHO pandemic announcement, such institutional features are therefore absorbed by fixed effects. As a result, short-run changes in pricing across venues are interpreted as responses to changes in perceived counterparty risk rather than to shifts in market infrastructure. In OTC markets, pricing reflects borrower-specific risk, whereas in CCP markets pricing reflects pooled counterparty risk.

3.3 Short-Selling Motives

We provide suggestive evidence for the security-borrowing motive by examining the profitability of short selling around the WHO announcement. Banks can borrow a security in the repo market, sell it in the spot market, and repurchase it at maturity. Figure 2 shows gross returns from short positions in German government bonds with maturities between one and ten years, net of financing costs measured using volume-weighted average repo rates. Short-selling returns are negative prior to the WHO announcement and turn persistently positive thereafter, increasing with maturity and ranging from approximately 12 to 150 basis points. Repo rates on German government bonds reached levels as low as −66.26 basis points on 16 March 2020. At these rates, borrowing securities through repo markets and selling them short was profitable, particularly for longer-maturity bonds.

[2] Repos may also be executed through tri-party arrangements, in which a custodian bank intermediates between the two parties. Tri-party repos are most prevalent in the U.S. market (Huber 2023).

[Insert Figure 2 here]

3.4 Stylized Facts: Repo Pricing Across Clearing Venues

We next document the main empirical patterns that motivate the analysis in the remainder of the paper. Our focus is on the difference in borrowing costs for identical securities traded in bilateral OTC markets and through central counterparties (CCPs). Figure 3 plots the average cost of borrowing securities in CCP and OTC markets in the two weeks around the World Health Organization (WHO) pandemic announcement on 11 March 2020.

Three patterns emerge. First, rates are negative. Second, prior to the pandemic announcement, borrowing costs are systematically higher in bilateral OTC transactions than in centrally cleared transactions for the same securities. This indicates that special securities trade at more negative rates in OTC markets than in CCP markets. Third, the CCP–OTC differential compresses sharply following the WHO announcement. While borrowing costs increase overall during this period of market stress, the increase is stronger in CCP markets, causing the difference between CCP and OTC rates to narrow.

[Insert Figure 3 here]

These facts highlight a systematic relationship between clearing arrangements and the pricing of special collateral. In particular, they show that reverse repos command different rates across clearing venues and that these differences vary with market conditions. The next section develops a model that explains these patterns through differences in how counterparty risk is incorporated into repo prices.

4 Model

This section develops a model of *security-driven* repo (reverse repo) that is tailored to the institutional features of European repo trading described in Section 3. The model is designed to isolate the short-horizon mechanism that differs across clearing arrangements: *how counterparty-risk information is incorporated into prices when uncertainty changes.* In particular, bilateral OTC trades condition on the identity of the counterparty, while CCP-cleared trades are anonymous, novated, and protected by a default fund so that counterparty risk is effectively priced at the level of the *pool* of CCP participants. We abstract from persistent venue-specific frictions, such as balance-sheet netting benefits in CCP markets and relationship lending and search cost in OTC markets, and focus on how changes in information about counterparty risk affect pricing across clearing arrangements.

4.1 Environment and mapping to repo institutions

There are $M < \infty$ security borrowers and $N < \infty$ security lenders. Borrowers seeks to borrow a security against cash collateral. This corresponds to reverse repo as defined in Section 3: the borrower's *motive* is to obtain the security, e.g., to support short selling or to source scarce collateral. Lenders are security holders who temporarily part with the security in exchange for cash and receive a repo rate r (which can be negative, as in the euro area during our sample). A more negative r corresponds to a higher *specialness* premium paid by the security borrower to obtain the security.

Borrowers and balance-sheet risk. Borrowers have risky balance sheets and limited liability. Each borrower $j \in [1, \ldots, M]$ is privately informed about its type $i \in \{H, L\}$. A type-H ("good") borrower succeeds with probability $1 - p_H$ and a type-L ("bad") borrower succeeds with probability $1 - p_L$, where $0 < p_H < p_L < 1$. Conditional on success, the borrower's balance-sheet project returns $R > 0$, and 0 otherwise.

Collateral value and "security risk." Security risk is captured by the collateral value realized at settlement. The security has market value E_0 at initiation and random value at settlement,

$$E_1 = (1 - q)\underline{E} + q\bar{E}, \qquad \underline{E} < E_0 < \bar{E}.$$

The parameter q governs the distribution of collateral values; shifting probability mass toward low collateral outcomes corresponds to an increase in collateral risk.

Cash collateral and haircuts. Borrowers post a fixed cash amount I as collateral. The implied haircut is

$$h = 1 - \frac{I}{E_0}.$$

This formulation accommodates both positive ($I < E_0$) and negative haircuts ($I > E_0$). In the model, I is taken as given (or slow-moving).

Lender shadow value and encumbrance. Security lenders value holding the security unencumbered, for balance-sheet, liquidity, or strategic reasons. We capture this via a shadow value δE_0, where $\delta \in (0,1)$ discounts early liquidation and encumbrance costs. This term is a reduced-form representation of institutional features such as internal liquidity value and balance-sheet management; venue-specific netting benefits can be interpreted as shifting this shadow value by a constant amount.

Beliefs. Lenders assign probability $\alpha \in (0,1)$ to a borrower being type-L and probability $1-\alpha$ to a borrower being type-H. The implied success probability is

$$m \equiv (1-\alpha)(1-p_H) + \alpha(1-p_L).$$

We treat α as a parameter indexing the composition of borrower types.

4.2 Assumptions

Assumption 1 (Balance sheet profitability) *Both borrower types have positive expected balance-sheet projects:* $(1-p_H)R > (1-p_L)R > 0$.

Assumption 2 (Short-sale profitability and collateral risk) *Short selling is profitable ex ante,* $E_1 < E_0$*, and the settlement value of the security is non-degenerate, with support on both sides of its initial value:*

$$\underline{E} < E_0 < \bar{E}.$$

Assumption 3 (Limited-liability feasibility) *The borrower's balance-sheet project generates sufficient surplus to absorb the worst collateral realization:*

$$E_0 - \bar{E} < 0 < R + E_0 - \bar{E}.$$

Assumption 4 (Balance-sheet value of retaining the security) *Security lenders derive balance-sheet value from retaining the security unencumbered, captured by* $0 < \delta < 1$.

Assumption 5 (Security Scarcity and Specialness) *The non-cash value of holding the security exceeds the cash compensation provided in the repo transaction, so that*

$$I < \delta E_0 + (1-q)(\bar{E} - \underline{E}).$$

Under this assumption, the security is scarce in the sense that its balance-sheet and short-sale value is high relative to the cash posted. Note, that this assumption allows for haircuts to be both positive and negative depending on security lenders' balance-sheet value of retaining the security and short-sale profitability.

4.3 Payoffs and timeline

Figure 4 depicts the payoff structure for a security borrower of type $i \in \{H, L\}$. The initial node corresponds to the borrower's type, which determines the probability of balance-sheet success $1 - p_i$ and failure p_i. Conditional on success, the borrower receives return R from the balance-sheet project; conditional on failure, this return is zero due to limited liability.

In each case, the value of the collateral security at settlement is stochastic. With probability $1 - q$, the collateral realizes a low value $\underline{E}$, and with probability q it realizes a high value $\bar{E}$. Payoffs shown at the terminal nodes combine the realized balance-sheet return (when applicable) with the change in the value of the security relative to its initial value E_0. This structure highlights two sources of risk relevant for pricing: borrower-specific default risk, governed by p_i, and collateral-state risk, governed by q. The interaction of these risks determines lenders' expected recoveries.

[Insert Figure 4 here]

Figure 5 summarizes the timing of events in the model. At date $t = 0$, security borrowers privately observe their balance-sheet type $i \in \{H, L\}$. Borrowers and security lenders then contract on a reverse repo agreement specifying the repo rate r, the cash collateral amount I, and the implied haircut h. After contracting, borrowers obtain the security and may short sell it in the spot market.

At date $t = 1$, uncertainty is resolved. Returns from the borrower's balance-sheet project and from the short sale are realized, and the market value of the security at settlement is determined. The contract is then closed out. If the borrower performs, it returns the borrowed security and receives back the posted cash collateral I (net of the repo interest/rebate implied by r). If the borrower defaults and fails to return the security, the lender retains the posted cash collateral and closes out the position by replacing the security at the prevailing market price. Consequently, borrower type affects expected payoffs through the probability of default, while collateral risk affects expected lender recoveries through the close-out value of the security relative to the cash collateral.

[Insert Figure 5 here]

4.4 OTC contracting with observable borrower identity

We first consider bilateral OTC contracting under symmetric information, where the lender can condition on borrower identity (or on sufficiently informative relationship-level signals), consistent with OTC relationship lending and non-anonymity. The reverse repo contract must satisfy the participation constraints of both the security borrower and the security lender.

Borrower participation. A type-i borrower accepts a contract with rate r^i if its expected payoff from entering the reverse repo weakly exceeds its outside option,

$$(1-p_i)\big(R - r^i I + E_0 - E_1 + I\big) + p_i\Big((1-q)(-r^i I + E_0 - \underline{E} + I) + qE_0\Big) \;\geq\; (1-p_i)R + I. \tag{1}$$

The left-hand side is the borrower's expected payoff from the reverse repo. With probability $1-p_i$, the borrower's balance-sheet project succeeds. In this case, the borrower earns the project return R, pays the repo interest $r^i I$, returns the borrowed security, and receives back the posted cash collateral I. Note, the rate enters negatively into the security borrower's payoff. This convention implies that equilibrium rates r^i will be absolute values of the real (negative) interest rate. In addition, the borrower realizes the net proceeds from short selling the security at $t = 0$ and repurchasing it at settlement, given by $E_0 - E_1$. Note, the security borrower is able to settle the reverse repo even if the short sale is unsuccessful by Assumption 3. The resulting payoff in the success state is $R - r^i I + E_0 - E_1 + I$. With probability p_i, the borrower's balance-sheet project fails and yields no return. In this case, the borrower returns the security and receives back the cash collateral, pays the interest and collects the short sale profit if the security value decreases to $\underline{E}$ with probability $1-q$; the short sale is profitable. If the security value increases, with probability q, the borrower defaults on the reverse repo; they do not return the security and do not receive the cash collateral back. The right-hand side of (1) represents the borrower's outside option. If the borrower does not enter the reverse repo, it cannot short sell the security and therefore earns the balance-sheet return R when successful, while retaining its cash endowment I. The participation constraint thus ensures that entering the reverse repo is privately optimal for the borrower.

Lender participation. The security lender participates if the expected payoff from lending the security weakly exceeds the value of retaining the security unencumbered,

$$(1-p_i)(E_1+r^iI)+p_i\big((1-q)(\underline{E}+r^iI)+qI\big)\ \geq\ \delta E_0. \tag{2}$$

The left-hand side of (2) is the lender's expected payoff from the reverse repo. With probability $1-p_i$, the borrower's balance sheet project is successful and, regardless of the outcome of the short sale, the borrower settles the reverse repo, returns the security, and pays the repo interest payment r^iI, yielding E_1+r^iI. Because repo rates are negative, they are a gain for the security lenders and therefore enter positively in their payoff. With probability p_i, the borrower's balance sheet project fails. The borrower is only able to settle the reverse repo if the short sale is successful, with probability $1-q$. If the short sale is unprofitable, with probability q, the lender retains the cash collateral, generating a payoff $\underline{E}+r^iI)+qI$.

The right-hand side of (2) captures the lender's outside option: retaining the security on balance sheet and deriving its shadow value δE_0. This reflects the liquidity, regulatory, or strategic value of holding the security unencumbered. The participation constraint therefore requires that the repo rate compensates the lender both for borrower default risk and for the opportunity cost of encumbering the security.

With competition among security lenders (consistent with the lower HHI for security lenders than borrowers for security-driven transactions documented in Section 5), the OTC rate is pinned down by the lender break-even condition[3]:

$$r^i=\frac{\delta E_0-(1-q)\underline{E}-q((1-p_i)\bar{E}+p_iI)}{(1-p_iq)I}. \tag{3}$$

Equation (3) implies that repo rates depend on two forces. First, the numerator contains the wedge between the shadow value of holding the security (δE_0) and the lender's state-contingent recovery values when the security is encumbered. Second, the denominator scales by expected retention of cash collateral, $(1-p_iq)I$, so the rate becomes *non-linear* in borrower risk p_i when

[3]This convention allows for the security lender to earn a constant margin without altering the main insights of the model.

default interacts with collateral states. This non-linearity is central: it will make the average of bilateral prices differ from pooled CCP pricing.

4.5 Clearing arrangements: OTC averaging versus CCP pooling

A key institutional distinction in repo markets concerns how counterparty risk is priced under different clearing arrangements. In bilateral OTC markets, contracts are negotiated and settled between identified counterparties, so pricing can condition on borrower-specific risk. By contrast, CCP clearing involves novation, anonymity and a default fund: the CCP becomes the counterparty to all trades, and individual borrower identities are not reflected in transaction-level pricing. Instead, counterparty risk is effectively pooled across CCP members.

OTC pricing and averaging. In OTC markets, borrower identity is observable, either directly or through relationship-specific information. As a result, the repo rate can condition on the borrower's type $i \in \{H, L\}$, yielding type-specific rates r^H and r^L derived from the lender's participation constraint in (2). Under lender competition, these rates are given by

$$r^i = \frac{\delta E_0 - (1-q)\underline{E} - q(1-p_i)\bar{E} - p_i q I}{(1-p_i q)I}, \qquad i \in \{H, L\}.$$

Since a fraction α of borrowers are type L and a fraction $1-\alpha$ are type H, the average OTC rate observed in the market is

$$r^{OTC} = \alpha r^L + (1-\alpha) r^H. \tag{4}$$

This average reflects the cross-sectional distribution of borrower types but preserves the non-linear dependence of rates on borrower-specific default risk.

CCP pooling Under CCP clearing, contracts are anonymous and novated, and losses are mutualized through the default fund. Individual counterparties are therefore not priced separately at the transaction level. Instead, the relevant object for pricing is the average risk of the CCP member pool. Formally, let $i_j \in \{H, L\}$ denote the type of borrower $j \in \{1, \ldots, M\}$. The average probability of borrower success in the CCP pool is

$$m \equiv (1-\alpha)(1-p_H) + \alpha(1-p_L).$$

Equivalently, $1-m$ is the average probability of borrower default faced by the CCP. This pooled success probability summarizes counterparty risk under CCP clearing and replaces borrower-specific probabilities $1-p_i$ in the pricing problem.

The CCP rate is determined by the same economic forces as the OTC rate—default risk, collateral risk, and the opportunity cost of encumbering the security—but evaluated at the pooled level. In particular, the security lender's participation constraint under CCP clearing requires that the expected payoff from lending the security to the pooled borrower weakly exceeds the shadow value of holding the security unencumbered.

Replacing borrower-specific probabilities with the pooled success probability m in the lender participation constraint (2), and imposing lender competition, yields the CCP break-even rate

$$r^{CCP} = \frac{\delta E_0 - (1-q)\underline{E} - mq\bar{E} - (1-m)qI}{(1-(1-m)q)I}. \tag{5}$$

Relative to OTC pricing, CCP pricing replaces the type-specific default probability p_i with the pooled default probability $1-m$ both in the numerator, which captures expected losses and encumbrance costs, and in the denominator, which captures expected repayment of the cash collateral.

Equations (4) and (5) highlight the central distinction between clearing arrangements. OTC rates are averaged across borrower-specific prices that are non-linear in default risk, whereas CCP rates are computed as the price of the average borrower. Given non-linear pricing, this difference between *averaging prices* and *pricing averages* is the source of the level and comparative-static differences between r^{OTC} and r^{CCP} analyzed in the propositions below.

Lemma 1 (Feasibility and sign of equilibrium rates) *Fix $i \in \{H, L\}$ and let $m \equiv (1-\alpha)(1-p_H) + \alpha(1-p_L)$.*

OTC

(i) The set of OTC repo rates that satisfy both borrower and lender participation constraints, (1) and (2), is non-empty since $0 < \delta < 1$, $0 < I$, and

$$0 < \frac{(1-\delta)E_0}{(1-p_i q)I}.$$

(ii) Rates are negative if

$$I < \frac{\delta E_0 - (1-q)\underline{E} - (1-p_i)q\bar{E}}{p_i q} \quad \text{and} \quad \delta > \frac{(1-q)\underline{E} + (1-p_i)q\bar{E}}{E_0}.$$

CCP.

(i) Replacing borrower-specific probabilities with the pooled success probability m in borrower and lender participation constraints, (1) and (2), the set of pooled CCP repo rates is non-empty if

$$I > E_0 + (1-q)(\bar{E} - \underline{E}) - \frac{(1-\delta)(1-p_H q)}{\alpha(p_H - p_L)q} E_0.$$

(ii) Rates are negative if

$$I < \frac{\delta E_0 - (1-q)\underline{E} - mq\bar{E}}{(1-m)q} \quad \text{and} \quad \delta > \frac{(1-q)\underline{E} + mq\bar{E}}{E_0}.$$

4.6 Propositions

Define the CCP–OTC differential $\Delta r \equiv r^{CCP} - r^{OTC}$. The propositions focus on how news-induced changes in beliefs and risk affect rates differently across venues. Recall that equilibrium interest rates r^i are expressed in absolute values of the real (negative) rates. We continue using this convention in the following propositions. All proofs are in Appendix C.

Proposition 1 (Level difference: CCP pooling versus OTC identity pricing) *The average OTC rate exceeds the CCP rate*

$$\Delta r = -\frac{(1-\alpha)\alpha(p_L - p_H)^2 q^2 \big(\delta E_0 + (1-q)(\bar{E} - \underline{E}) - I\big)}{I(1-p_H q)(1-p_L q)(1-(1-m)q)} < 0,$$

given Assumption 5.

The CCP–OTC wedge arises because repo rates load disproportionately on tail counterparty risk. In the model, lenders incur losses only in the joint state in which the borrower defaults and the collateral outcome is adverse, reflecting limited liability and the close-out mechanics of repo contracts. As borrower default risk increases, these tail states become more relevant and the lender requires higher compensation both because expected losses increase and because the probability of receiving the repo payment falls. As a result, the lender's break-even rate is convex in borrower risk. In bilateral OTC markets, lenders observe borrower identity and set borrower-specific rates that fully reflect this tail sensitivity; the observed market rate is therefore the average of prices assigned to heterogeneous borrowers. By contrast, CCP clearing pools counterparties and prices the average borrower in the member pool. Because pricing is convex in borrower risk, averaging borrower-specific prices yields more negative rates than pricing the average borrower directly, implying stronger specialness in OTC markets. This mechanism links the pricing of special collateral to the dispersion of counterparty risk, complementing the literature on repo specialness driven by collateral scarcity and search frictions (e.g., (Duffie 1996, Vayanos & Weill 2008)) and the literature on asymmetric information and dispersion in funding markets (e.g., (Heider et al. 2015)).

The wedge, Δr, is largest when (i) borrower heterogeneity is high (large $p_L - p_H$), (ii) the borrower pool is mixed (interior α), and (iii) the opportunity cost of encumbering the security is large relative to the posted cash collateral ($\delta E_0 + (1-q)(\bar{E} - E) - I$ is large). In a negative-rate environment, this proposition implies that security specialness—measured by the magnitude of negative repo rates—is stronger in OTC markets than under CCP clearing. That is, the average OTC repo rate is more negative than the CCP repo rate, reflecting the convex pricing of counterparty risk under bilateral contracting relative to pooled pricing under CCPs.

Proposition 2 (Economic stress and uncertainty) *Let α index perceived counterparty uncertainty. An increase in uncertainty compresses the CCP–OTC gap. Given Assumption 5 and $p_H > \frac{1-2\alpha+\alpha^2 p_L q}{(1-\alpha)^2}$,*

$$\frac{\partial \Delta r}{\partial \alpha} > 0$$

An increase in α raises the perceived share of risky borrowers and therefore shifts the composition of the borrower pool toward weaker counterparties. Because CCP clearing pools counterparties, CCP pricing reflects the risk of the average borrower in the pool and adjusts directly through the pooled success probability m. In bilateral OTC markets, by contrast, lenders observe borrower identity and set borrower-specific rates, so the observed OTC rate is a weighted average of the rates charged to safe and risky borrowers. As α increases, the borrower pool shifts toward the risky type and the OTC rate reweights toward the price assigned to that type. Since the lender's break-even rate is convex in borrower risk, the CCP–OTC wedge depends on the dispersion of borrower types: OTC markets price borrower-specific risk, whereas CCP markets price the pooled average. As the distribution of borrower types shifts toward the risky type, economically relevant dispersion declines, reducing the difference between averaging borrower-specific prices (OTC) and pricing the pooled borrower (CCP) and thereby compressing the CCP–OTC differential.

Proposition 3 (Borrower quality and sensitivity to uncertainty) *When borrower quality deteriorates, that is higher p_H and/or p_L, the compression of the CCP–OTC gap induced by higher uncertainty is attenuated. Given Assumption 5,*

$$\frac{\partial^2 \Delta r}{\partial \alpha \partial p_H} < 0, \ \textit{and} \ \frac{\partial^2 \Delta r}{\partial \alpha \partial p_L} < 0.$$

Proposition 3 shows that the compression of the CCP–OTC differential induced by higher uncertainty is weaker when borrower quality deteriorates (higher p_H and/or p_L). As borrower risk increases (higher p_H or p_L), the lender's break-even repo rate becomes more sensitive to borrower default risk, increasing the curvature of the pricing function in borrower risk. This strengthens borrower-specific pricing in bilateral OTC markets, where lenders observe borrower identity and set type-specific rates. As a result, the OTC rate continues to reflect dispersion in borrower types even when the composition of the borrower pool changes. By contrast, CCP clearing prices the pooled borrower through the average success probability m. Consequently, when borrower risk is higher, changes in the composition parameter α have a smaller effect on the CCP–OTC differential.

This mechanism is consistent with the literature on counterparty risk in funding markets, which shows that higher borrower risk amplifies the role of borrower-specific information and increases the sensitivity of funding spreads to borrower heterogeneity (e.g., Freixas & Holthausen 2005, Heider et al. 2015).

Proposition 4 (Collateral quality and uncertainty interaction) *When collateral quality increases, that is q increases, implying that the short sale is more likely to be unprofitable, the compression of the CCP–OTC gap induced by higher uncertainty is amplified. Let q parameterize collateral-state risk. Define*

$$B \equiv \underline{E} - \bar{E}, \quad S \equiv \delta E_0 - (\underline{E} - \bar{E}) - I, \quad \bar{p} \equiv (1-\alpha)p_H + \alpha p_L.$$

Then given Assumption 5 and if the pool is sufficiently risky (see proof),

$$\frac{\partial^2 \Delta r}{\partial \alpha \partial q} = (p_L - p_H)\frac{S + q(2B + \bar{p}S)}{I(1-\bar{p}q)^3} - \left[\frac{B + p_L S}{I(1-p_L q)^2} - \frac{B + p_H S}{I(1-p_H q)^2}\right] > 0. \tag{6}$$

Proposition 4 examines how the effect of uncertainty depends on collateral quality. An increase in q raises the likelihood that the short position is unprofitable and therefore increases the importance of collateral outcomes in default states. As a result, lenders become more sensitive to the interaction between borrower default and collateral risk when pricing repos. Under CCP clearing, counterparty risk is pooled and pricing depends on the average borrower in the pool. When collateral quality increases, adverse collateral outcomes become more relevant for the pooled counterparty, making CCP pricing more responsive to changes in the composition of the borrower pool. In bilateral OTC markets, by contrast, lenders continue to price borrower-specific risk and collateral outcomes are partially absorbed through type-specific rates.

Consequently, improvements in collateral quality amplify the uncertainty-induced compression of the CCP–OTC differential described in Proposition 2. This mechanism complements the literature on repo specialness and collateral scarcity, which emphasizes that high-quality collateral commands larger premia when it becomes particularly valuable in adverse states (e.g., Duffie 1996, Vayanos & Weill 2008, Corradin et al. 2020).

4.7 Summary

Propositions 1 to 4 characterize how clearing arrangements affect repo pricing through differences in how counterparty risk is aggregated. In bilateral OTC markets, lenders observe borrower identity and price borrower-specific default risk, so repo rates reflect the dispersion of borrower types. Under CCP clearing, counterparties are pooled and pricing depends on the risk of the average borrower in the pool. This distinction implies that the CCP–OTC differential is fundamentally driven by the interaction between counterparty-risk dispersion and the non-linear pricing of default risk. When borrower heterogeneity is important, identity-based OTC pricing produces stronger specialness than pooled CCP pricing. Higher perceived uncertainty shifts the borrower pool toward the risky type, reducing the pricing impact of borrower heterogeneity and compressing the CCP–OTC differential. The magnitude of this effect depends on the underlying sources of risk: higher borrower risk strengthens identity-based pricing, while higher collateral quality increases the role of collateral outcomes in default states and amplifies the response of pooled CCP pricing.

Taken together, the model highlights how central clearing changes the transmission of counterparty risk into repo rates by pooling exposures and reducing the role of borrower-specific pricing. As a result, CCP clearing dampens specialness in normal times but becomes relatively more important for price formation when counterparty uncertainty increases.

4.8 Empirical predictions and implementation

This section links the model's primitives to observables in the data and derives the empirical predictions tested in Section 6. The key object in the model is the CCP–OTC differential for a given security and date,

$$\Delta r_{s,t} \equiv r_{s,t}^{CCP} - r_{s,t}^{OTC}.$$

Empirically, we capture this differential using a CCP indicator and exploit variation across clearing venues around an exogenous increase in counterparty uncertainty.

Prediction 1 (Level difference). Proposition 1 implies that, in normal times, the CCP–OTC differential is negative,

$$\mathbb{E}[\Delta r_{s,t}] < 0.$$

Empirically, this corresponds to a negative coefficient on the CCP indicator in a regression of borrowing costs on the CCP dummy, conditional on security and time controls. This coefficient captures the difference between pooled CCP pricing and borrower-specific OTC pricing.

Prediction 2 (Uncertainty). The parameter α captures the perceived share of risky borrowers. We interpret the WHO pandemic announcement as an exogenous increase in α. Proposition 2 predicts that higher uncertainty compresses the CCP–OTC differential,

$$\frac{\partial \Delta r}{\partial \alpha} > 0.$$

Empirically, this prediction maps to a positive coefficient on the interaction between the CCP indicator and a post-announcement dummy.

Prediction 3 (Borrower quality). Borrower types differ in their failure probabilities p_H and p_L. In the data, we proxy borrower risk using borrower-level measures such as CDS spreads and non-performing loan ratios. Proposition 3 predicts that the uncertainty-induced compression of the CCP–OTC differential is weaker for riskier borrowers,

$$\frac{\partial^2 \Delta r}{\partial \alpha \partial p_i} < 0.$$

Empirically, this prediction corresponds to a negative coefficient on the triple interaction between the CCP indicator, the uncertainty shock, and borrower risk.

Prediction 4 (Collateral quality). Collateral-state risk is governed by the parameter q. In the data, we proxy collateral quality using indicators for high-quality sovereign collateral. Proposition 4 predicts that the uncertainty-induced compression of the CCP–OTC differential is stronger for higher-quality collateral,

$$\frac{\partial^2 \Delta r}{\partial \alpha \partial q} > 0.$$

Empirically, this prediction maps to a positive coefficient on the triple interaction between the CCP indicator, the uncertainty shock, and the collateral-quality proxy.

Identification. The empirical design exploits within-security variation across clearing venues around the uncertainty shock. Time-invariant differences between CCP and OTC markets—such as netting benefits, relationship lending, or search frictions—are absorbed by fixed effects. Under this framework, the difference-in-differences and triple-interaction coefficients provide empirical counterparts to the comparative statics in Propositions 2–4.

5 Data

This section describes the transaction-level data, the sample construction, and the main variables used in the empirical analysis. The goal is to construct a dataset that allows for within-security and within-day comparisons of CCP and OTC trades around an exogenous uncertainty shock, as motivated by the empirical implementation in Section 4.8.

5.1 Data source and sample construction

We use transaction-level data from the secured segment of the euro-area money market provided by the European Central Bank's Money Market Statistical Reporting (MMSR) dataset. MMSR is a confidential supervisory dataset collected by the Eurosystem, containing daily euro-denominated money market transactions reported by the 46 largest euro-area banks by balance sheet size since July 2016. The dataset includes detailed information on prices, volumes, maturities, collateral ISINs, and counterparties, and covers approximately 80% of the euro-area money market.

Reporting banks must disclose all secured transactions, including bilateral trades with banks and non-bank financial institutions as well as trades conducted via central counterparties (CCPs). This feature allows us to compare repo pricing across clearing venues for the same securities and time periods. To ensure comparability across trading venues and isolate counterparty-risk pricing, we apply three main sample restrictions.

First, we restrict the sample to transactions where the counterparty is either a euro-area bank or a CCP. This removes confounding factors related to differences in deposit facility access and institutional features of non-bank counterparties. Second, we focus on one-day maturity transactions—overnight (O/N), tomorrow–next (T/N), and spot–next (S/N)—which constitute the majority of interbank repo trades. Concentrating on short maturities minimizes term-premium effects and aligns the data with the short-horizon mechanism emphasized in the model. Third, we limit the sample to banks that are active in both OTC and CCP markets and trade both before and after the Covid-19 announcement. This restriction mitigates composition effects and ensures that changes in pricing are not driven by shifts in the set of participating institutions.

5.2 Event window and uncertainty shock

Our empirical design exploits the World Health Organization's declaration of Covid-19 as a global pandemic on 11 March 2020 as an exogenous increase in counterparty uncertainty. Consistent with the discussion in Section **??**, we interpret this announcement as a shock to the perceived mass of risky borrowers in the market. Market-based indicators support this interpretation. Bank CDS spreads (Figure 6) and yields on German government bonds (Figure 7)—widely regarded as safe assets in the euro area—rose sharply around the announcement, indicating heightened counterparty and collateral risk.

To isolate the short-run pricing response, we focus on a narrow event window of five trading days before and five trading days after the WHO announcement. This window ends on 18 March 2020, when major policy interventions were introduced, including the ECB's Pandemic Emergency Purchase Programme (PEPP). CDS spreads peak around this date and decline thereafter, suggesting that policy announcements attenuated the uncertainty shock.

Using a symmetric five-day window around the announcement allows us to capture the immediate response to the shock while avoiding confounding effects from subsequent policy measures. For robustness, we also estimate specifications with dynamic time indicators to verify that results are not driven by the precise choice of event date.

5.3 Identifying security-driven transactions and borrowing costs

Repo transactions differ by trading motive. Cash-driven repos are initiated by borrowers seeking funding, whereas security-driven repos are initiated by borrowers seeking a specific security. During the sample period, most transactions are security-driven, consistent with the institutional discussion in Section 3.

The MMSR dataset does not directly report trading motives or order-book aggressors. Following the literature (Ballensiefen et al. 2023), we classify transactions using the relationship between the repo rate and the ECB deposit facility rate (DFR). When the repo rate is below the DFR, the transaction is interpreted as security-driven; when it is above the DFR, it is interpreted as cash-driven.

During the sample period, the DFR was -0.5%. In this environment, a more negative repo rate corresponds to a higher fee paid by the security borrower and therefore greater specialness. In line with previous literature (Ballensiefen et al. 2023), we measure the cost of borrowing a security using the absolute distance between the repo rate and the DFR. For each transaction i on day t, we define

$$d_{i,t} = \left|\text{Repo rate}_{i,t} - \text{DFR}_t\right|. \tag{7}$$

This measure captures the magnitude of the specialness premium independently of the sign of the repo rate and serves as the main dependent variable in the regressions in Section 6.

5.4 Summary statistics and key variables

[Insert Table 1 here]

Table 1 reports summary statistics for the main variables used in the empirical analysis. Average borrowing costs, measured by the distance to the DFR, are substantially larger in OTC markets than in CCP markets, indicating stronger specialness in bilateral trades. This pattern is consistent with the model's prediction that identity-based OTC pricing produces more negative rates than pooled CCP pricing.

Figure 3 shows the dynamic of the borrowing cost on CCP and OTC markets. Pre-Covid, we can observe the wedge between repo rates on OTC and CCP for security–driven trades to remain constant, with stronger specialness in bilateral trades. After the uncertainty shock on 11 March, the CCP cost of borrowing converges to the OTC rate, as predicted by the theoretical model in section 4.8.

[Insert Figure 3 here]

Repo markets are large and active over the sample period, with average daily trading volumes close to EUR 300 billion and a substantial share of activity cleared through CCPs. Average transaction sizes are considerably larger in CCP markets than in OTC markets. Importantly, total volumes and the CCP share remain stable around the WHO announcement, suggesting that the shock primarily affects pricing rather than trading activity.

Haircuts in reverse repos are often negative, implying that the value of the cash collateral exceeds the market value of the security. Under this convention, more negative haircuts provide greater protection to the security lender. Average haircuts differ slightly across venues but remain stable around the uncertainty shock. In the regressions, we control for haircuts and transaction volumes to isolate the effect on rates.

To measure borrower risk, we use two proxies. The first is the borrower's non-performing loan (NPL) ratio from supervisory FINREP data, measured at 2019:Q4. This variable provides an ex-ante balance-sheet measure of credit risk. The second is the daily change in the borrower's CDS spread, which captures time-varying market perceptions of credit risk.

Most transactions in the sample use sovereign bonds as collateral. In CCP markets, almost all repos are backed by euro-area government bonds, while in OTC markets the share is lower but still substantial. To proxy for collateral quality, we define a SAFE indicator equal to one for government bonds issued by core euro-area countries—Germany, France, and the Netherlands—and zero otherwise.

Finally, we compute Herfindahl–Hirschman indices (HHIs) for borrowers and lenders to characterize market concentration. HHIs remain below standard thresholds for concentrated markets, indicating competitive conditions. Notably, the securities-lending side of the market is more competitive than the borrowing side, consistent with the assumption of competitive lenders in the model.

6 Empirical Methodology

This section implements the empirical strategy implied by the model and the mapping between theoretical objects and observables described in Section 4.8. The key object of interest in the model is the CCP–OTC differential for a given security and date,

$$\Delta r_{s,t} \equiv r_{s,t}^{CCP} - r_{s,t}^{OTC},$$

and the model delivers predictions for how this differential responds to changes in counterparty uncertainty, borrower quality, and collateral quality (Predictions 1–4 in Section 4.8).

Empirically, we implement these predictions by interacting a CCP venue indicator with measures of economic uncertainty and borrower and collateral characteristics. The empirical design exploits a short event window around the WHO announcement of Covid-19 as a global pandemic on 11 March 2020. As discussed in Section 3, this period is characterized by a sharp increase in counterparty uncertainty but precedes major policy interventions. Focusing on this narrow window allows us to isolate the short-horizon mechanism emphasized in the model. Structural features of clearing arrangements—such as default fund contributions, netting benefits, and the anonymity of CCP trading—are effectively constant over this period. As a result, short-run changes in the CCP–OTC differential are interpreted as responses to changes in perceived counterparty risk rather than to shifts in institutional features.

Consistent with the model, we interpret the Covid-19 outbreak as an exogenous increase in the perceived mass of risky borrowers, captured by the parameter α. This shock raises lenders' sensitivity to counterparty risk. In OTC markets, rates adjust at the borrower level, while in CCP markets pricing reflects the pooled counterparty risk under anonymity. The model predicts that this difference in information aggregation leads to a compression of the CCP–OTC differential after the uncertainty shock.

6.1 Empirical strategy: Economic stress and uncertainty

The main dependent variable is the absolute distance between repo rates and the deposit facility rate (DFR), introduced in Section 5.3. This distance captures the cost of borrowing the security: a larger distance from the DFR corresponds to higher borrowing costs. We test the effect of the Covid-19 uncertainty shock on borrowing costs in CCP and OTC markets using the following specification:

$$d_{i,t} = \beta_0 + \beta_1 \text{Covid}_t + \beta_2 \text{CCP}_i + \beta_3(\text{Covid}_t \times \text{CCP}_i) + \gamma X_{i,t} + \varepsilon_{i,t}. \tag{8}$$

Here, $d_{i,t}$ is the absolute distance-to-DFR of transaction i on day t. The dummy variable Covid_t equals one after 11 March 2020, and CCP_i equals one if the transaction is centrally cleared. $X_{i,t}$ is a vector of transaction-level controls, including collateral sector, issuance country, collateral rating, haircut, and tenor. The coefficient of interest is β_3, which measures the change in borrowing costs on CCP platforms relative to OTC platforms after the uncertainty shock. According to Prediction 2, the CCP–OTC differential should compress following an increase in uncertainty. In the regression, this corresponds to a positive coefficient on the interaction term, indicating that CCP borrowing costs rise relative to OTC borrowing costs after the shock.

To absorb time-invariant differences across venues—such as netting benefits, relationship lending, or search frictions—we estimate specifications with borrower, lender, collateral ISIN, country, and day fixed effects. Under this design, the interaction coefficient captures the differential response of CCP and OTC pricing to the uncertainty shock.

6.2 Empirical strategy: Borrower quality

Prediction 3 states that the compression of the CCP–OTC differential following the uncertainty shock is weaker for riskier borrowers. To test this prediction, we extend the baseline specification by introducing borrower risk measures and interacting them with the venue and uncertainty indicators.

We estimate the following specification:

$$\begin{aligned} d_{i,j,t} =& \beta_0 + \beta_1 \text{Covid}_t + \beta_2 \text{CCP}_i + \beta_3(\text{Covid}_t \times \text{CCP}_i) + \beta_4 CR_{j,t} + \beta_5(\text{Covid}_t \times CR_{j,t}) \\ &+ \beta_6(\text{CCP}_i \times CR_{j,t}) + \beta_7(\text{Covid}_t \times \text{CCP}_i \times CR_{j,t}) + \gamma X_{i,t} + \varepsilon_{i,j,t}. \end{aligned} \tag{9}$$

Here, $CR_{j,t}$ is a measure of borrower risk for borrower j at time t. We use two proxies:

- the borrower's non-performing loan (NPL) ratio from supervisory data (quarterly, measured at 2019:Q4), and
- daily changes in the borrower's CDS spread.

In the model, borrower types differ in their failure probabilities p_H and p_L. The empirical borrower-risk proxies are interpreted as monotone transformations of these probabilities. Prediction 3 implies that the uncertainty-induced compression of the CCP–OTC differential should be weaker for riskier borrowers. In the regression, this corresponds to a negative coefficient on the triple interaction term, β_7.

6.3 Empirical strategy: Collateral quality

Prediction 4 states that the uncertainty-induced compression of the CCP–OTC differential is stronger for higher-quality collateral. To test this prediction, we replace the borrower-risk measure with a proxy for collateral quality. We estimate:

$$\begin{aligned} d_{i,j,t} =& \beta_0 + \beta_1 \text{Covid}_t + \beta_2 \text{CCP}_i + \beta_3(\text{Covid}_t \times \text{CCP}_i) + \beta_4 SF_j + \beta_5(\text{Covid}_t \times SF_j) \\ &+ \beta_6(\text{CCP}_i \times SF_j) + \beta_7(\text{Covid}_t \times \text{CCP}_i \times SF_j) + \gamma X_{i,t} + \varepsilon_{i,j,t}. \end{aligned} \tag{10}$$

Here, SF_j is a dummy variable equal to one if the collateral is a government bond issued by a core Euro-Area country (Germany, France, or the Netherlands), and zero otherwise. This variable proxies for the collateral-quality parameter q in the model. Prediction 4 states that the CCP–OTC differential should respond more strongly to the uncertainty shock for higher-quality collateral. In the regression, this corresponds to a positive coefficient on the triple interaction term, β_7.

6.4 Identification and interpretation

Across all specifications, identification relies on within-security and within-day variation across clearing venues around the exogenous uncertainty shock. Fixed effects absorb time-invariant differences across venues, counterparties, and securities, while the interaction terms capture the differential response predicted by the model.

Under this framework, the estimated interaction coefficients provide direct empirical counterparts to the comparative statics in Predictions 2–4, allowing us to test how anonymity and counterparty pooling in CCP markets affect the pricing of special collateral during periods of heightened uncertainty.

7 Main results

7.1 Economic uncertainty

Table 2 presents the results for the baseline specification in Equation (8), which tests how the CCP–OTC differential in borrowing costs responds to the Covid-19 uncertainty shock. We report several specifications in Columns (1)–(4) with progressively richer sets of fixed effects.

In Column (1), we include the Covid and CCP indicators and control for transaction characteristics such as volume and collateral haircut. The coefficient on the CCP dummy is -5.403 bps and statistically significant. This indicates that, prior to the uncertainty shock, borrowing costs in centrally cleared transactions are on average about 5.4 bps lower than in bilateral OTC transactions. This result is consistent with Prediction 1 of the model, which implies a negative average CCP–OTC wedge in normal times, arising from the pooling of borrower risk and the information structure of CCP trading. The coefficient on the Covid dummy is positive and significant, indicating that borrowing costs increase overall after the Covid-19 outbreak, consistent with a general tightening in repo market conditions.

The key parameter of interest is the interaction between the Covid and CCP indicators. This coefficient captures the differential response of CCP relative to OTC borrowing costs after the uncertainty shock. In Column (1), the interaction coefficient is 5.891 bps and highly significant. This implies that borrowing costs in CCP markets increase relative to OTC markets following the uncertainty shock. According to the model, this result reflects a compression of the CCP–OTC differential driven by an increase in perceived counterparty risk. In anonymous CCP markets, borrower risk is pooled, and lenders cannot condition prices on individual borrower quality. As uncertainty about counterparty types rises, this pooling becomes more costly, leading to a relative increase in CCP borrowing costs.

Columns (2)–(4) introduce increasingly demanding fixed effects. Column (2) includes borrower, lender, day, collateral ISIN, and tenor fixed effects. Column (3) replaces borrower and lender fixed effects with borrower–lender pair fixed effects to control for relationship-specific pricing. Column (4) includes lender fixed effects and borrower–day fixed effects to absorb time-varying borrower characteristics. Across all specifications, the interaction coefficient remains positive, statistically significant, and economically stable, ranging between 5.9 and 6.2 bps. The explanatory power of the regressions increases substantially, with R^2 values close to 90%.

Overall, the results indicate that the CCP–OTC differential compresses following the uncertainty shock, consistent with Prediction 2 of the model. The evidence suggests that anonymity and counterparty pooling in CCP markets amplify the effect of uncertainty on borrowing costs relative to bilateral OTC markets, where counterparty quality can be directly priced.

[Insert Table 2 here]

7.2 Borrower quality

Table 3 reports the results of the borrower-quality specification in Equation (9). We proxy borrower risk using the NPL ratio in Columns (1)–(4) and daily changes in CDS spreads in Columns (5)–(8).

In Column (1), the coefficient on the Covid×CCP interaction remains positive and significant at 7.757 bps, confirming the increase in CCP borrowing costs relative to OTC after the uncertainty shock. The coefficient on the triple interaction term Covid×CCP×NPL ratio is negative and statistically significant. This implies that the compression of the CCP–OTC differential is weaker for riskier borrowers. In other words, borrowers with higher NPL ratios experience a smaller relative increase in CCP borrowing costs after the shock.

Economically, a one–standard-deviation increase in the NPL ratio (approximately 130 bps depending on the subsample) is associated with a reduction in the CCP-related cost increase of about 1 bps. This effect is economically meaningful and consistent with Prediction 3 of the model, which states that the uncertainty-induced compression of the CCP–OTC differential should be attenuated for riskier borrowers.

Columns (5)–(8) replace the NPL ratio with daily changes in CDS spreads, which provide a higher-frequency, market-based measure of borrower risk. The triple interaction term remains negative and statistically significant across specifications, confirming that the relative increase in CCP borrowing costs is smaller for riskier borrowers.

Taken together, these results support the mechanism emphasized in the model: when counterparty risk is pooled in anonymous CCP markets, lower-quality borrowers benefit relatively more from the increase in uncertainty, as their individual risk is partially diluted within the CCP pool.

[Insert Table 3 here]

7.3 Collateral quality

We next examine how collateral quality interacts with the uncertainty shock. Prediction 4 of the model states that the compression of the CCP–OTC differential should be stronger for higher-quality collateral. Table 4 reports the results of the collateral-quality specification in Equation (10), using a dummy for safe collateral (German, French, or Dutch government bonds).

Across specifications, the triple interaction term Covid×CCP×SAFE is positive and statistically significant. This indicates that, after the uncertainty shock, borrowing costs for safe securities increase more in CCP markets relative to OTC markets than for less-safe collateral. In economic terms, the estimates imply an additional increase of about 5–6 bps in CCP borrowing costs for safe collateral after the shock.

This finding is consistent with Prediction 4 of the model. When uncertainty about counterparties rises, the value of high-quality collateral increases, and the effects of counterparty pooling become more pronounced in CCP markets. As a result, the CCP–OTC differential compresses more strongly for high-quality securities.

[Insert Table 4 here]

7.4 Robustness

This subsection presents a series of robustness exercises to assess the stability of the main results. Across all specifications, we continue to focus on the differential response of CCP and OTC borrowing costs around the uncertainty shock.

Pre-trends. A key identifying assumption of the empirical strategy is the absence of differential pre-trends between CCP and OTC markets prior to the Covid-19 shock. To assess this, we re-estimate the baseline specification in Equation (8) by replacing the Covid dummy with a sequence of day indicators, obtaining a dynamic event-study specification. Figure 8 plots the estimated coefficients for the CCP differential over time. The estimates are economically small and statistically insignificant in the days preceding the WHO announcement, indicating the absence of pre-trends. After the shock, the differential increases sharply, consistent with the baseline results. These findings hold both for the full sample and when splitting transactions into cash-driven and security-driven segments.

Alternative measures of collateral quality. To test the robustness of the collateral-quality results, we replace the SAFE dummy with the yield to maturity (YTM) of the collateral bond, computed from daily prices. Higher yields correspond to lower-quality collateral. The results, reported in Table 5, show a negative coefficient on the triple interaction term. This implies that bonds with higher yields (lower quality) experience a smaller increase in CCP borrowing costs after the shock, consistent with the results obtained using the SAFE indicator.

We also consider an alternative measure of collateral scarcity based on the concentration of bond holdings. If a small number of banks hold a large fraction of a bond, they may exert market power in the securities lending market. We proxy collateral scarcity using the Gini index of bond holdings derived from the ECB Securities Holdings Statistics (SHSS). The Gini index for bond b is defined as

$$G_b = 100 \times \frac{1}{2n^2 \bar{x}_b} \sum_{i,j} |x_{i,b} - x_{j,b}|,$$

where $x_{i,b}$ denotes the holding of bank i of bond b, $\bar{x}_b$ is the average holding, and the summation runs over the n banks in the sample.

We re-estimate Equation (10) replacing the SAFE dummy with the Gini index. Table 6 reports the results. The triple interaction term remains positive and significant for the full sample and for security-driven transactions, indicating that the CCP–OTC differential compresses more strongly for more scarce collateral after the uncertainty shock. The cash-driven segment shows no significant response, consistent with the collateral-driven nature of the mechanism.

Relationship lending. To account for the potential role of relationship lending, we construct measures of bilateral trading intensity following Furfine (1999) and Bräuning & Fecht (2017). Specifically, we compute the borrower–preference index, the lender–preference index, and a combined relationship–lending measure based on the frequency of overnight interactions between pairs of banks.

The borrower–preference index (BPI) is expressed as the sum of all transactions in which a specific borrower i borrows from a specific borrower j in a given time period T, divided by the sum of all repos in which borrower i is borrowing. The ratio expresses the concentration of borrower i's relationships in terms of euro exposures. Conversely, the lender–preference index (LPI), as the sum of all repos in which a lender i lends to borrower j divided by the sum of all transactions in which i is lending to any counterparty, describes the concentration of lending activities of bank i. Finally, the relationship–lending measure (RL) is based on frequency interactions. We take the logarithm of one plus the number of times bank i has lend to bank j over the total frequency of bank i's lending activities.

Tables 7, 8, and 9 report the results. The inclusion of these measures does not materially affect the estimated interaction coefficients. The main results therefore do not appear to be driven by relationship-specific pricing.

Collateral type. To account for heterogeneity in the composition of collateral, we re-estimate the baseline, borrower-risk, and collateral-quality specifications using only transactions backed by sovereign bonds. Tables 10, 11, and 12 show that the results for Equations (8) and (9) remain quantitatively and qualitatively unchanged.

Similarly, Table 13 confirms that the results for safe collateral are robust when restricting the sample to government bonds. This indicates that the main findings are not driven by differences between sovereign and corporate collateral.

Matched sample. Finally, we address the concern that the results may be driven by differences in the composition of counterparties across CCP and OTC markets. We construct a matched sample of transactions where borrowers and lenders are observed in both venues and re-estimate the main specifications on this restricted sample. By default, MMSR does not match borrowers and lenders through CCP transactions, as those are typically anonymous. We make use of the granular information on transactions from MMSR on time, volume, rate, haircut and collateral to match borrower and lender banks for both legs of the CCP transactions.

Tables 14, 15, 16, and 17 report the results. The estimated interaction coefficients remain stable and statistically significant, confirming that the main findings are not driven by differences in counterparty composition across trading venues.

Overall, the robustness exercises confirm the central empirical finding: the CCP–OTC differential compresses following the uncertainty shock, with heterogeneous effects across borrower risk and collateral quality, in line with the model's predictions.

8 Conclusions

This paper studies how clearing arrangements affect the pricing of special collateral in repo markets. We develop a model in which bilateral OTC trades price counterparty risk at the borrower level, while CCP-cleared trades pool counterparties and apply a common pricing rule. Because repo rates are non-linear in borrower risk, averaging borrower-specific prices in OTC markets differs from pricing the average borrower in CCP markets. This simple aggregation mechanism generates systematic differences in specialness across clearing venues.

The model delivers three main predictions. First, special securities trade at more negative rates in bilateral OTC markets than in CCP markets. Second, increases in counterparty uncertainty compress the CCP–OTC differential. Third, this compression depends on borrower and collateral characteristics: it is weaker when borrower balance sheets deteriorate and stronger for high-quality collateral.

We test these predictions using transaction-level data from the euro-area interbank repo market around the World Health Organization's pandemic announcement in March 2020. Consistent with the model, we find that the average CCP–OTC specialness gap compresses during the uncertainty shock. Low-quality borrowers experience a smaller increase in borrowing costs in CCP markets, consistent with pooling benefits. At the same time, high-quality and scarce securities become relatively more expensive to source through CCPs, indicating that pooled counterparty risk raises the value of safe collateral during stress.

Our findings highlight a trade-off inherent in central clearing. By pooling counterparties, CCPs dampen the level of specialness in normal times, but they also stabilize repo pricing during periods of stress. More broadly, the results show how financial infrastructure that aggregates counterparty risk can shape the equilibrium prices of scarce assets. These effects are relevant for the design of repo market structure, the role of central clearing, and the transmission of monetary policy through collateral markets.

References

Acharya, V. V. & Skeie, D. R. (2011), 'A model of liquidity hoarding and term premia in inter-bank markets', *Journal of Monetary Economics* **58**, 436–447.

Affinito, M. & Piazza, M. (2021), 'Always look on the bright side? central counterparties and interbank markets during the financial crisis', *International Journal of Central Banking* **17**(1), 231–283.

Ballensiefen, B., Ranaldo, A. & Winterberg, H. (2023), 'Money market disconnect', *The Review of Financial Studies* **36**(10), 4158–4189.

Bejarano, J., Lu, L. & Wallen, J. (2025), 'Negative treasury haircuts'.

BIS (2017), Committee on the global financial system: Repo market functioning, April, 2017, Bank for International Settlements.

Boissel, C., Derrien, F., Ors, E. & Thesmar, D. (2017), 'Systemic risk in clearing houses: Evidence from the european repo market', *Journal of Financial Economics* **125**(3), 511–536.

Bräuning, F. & Fecht, F. (2017), 'Relationship lending in the interbank market and the price of liquidity', *Review of Finance* **21**(1), 33–75.

Brunnermeier, M. K. (2009), 'Deciphering the liquidity and credit crunch 2007–2008', *Journal of Economic Perspectives* **23**, 77–100.
URL: *http://pubs.aeaweb.org/doi/abs/10.1257/jep.23.1.77*

Coen, P. (2026), 'A structural model of interbank network formation and contagion', *Journal of Financial Economics* .

Coen, P. & Huser, A.-C. (2026), 'Collateral demand in wholesale funding markets', *Working Paper* .

Copeland, A., Martin, A. & Walker, M. (2014), 'Repo runs: Evidence from the tri-party repo market', *Journal of Finance* **69**, 2343–2380.

Corradin, S., Eisenschmidt, J., Hoerova, M., Linzert, T., Schepens, G. & Sigaux, J.-D. (2020), 'Money markets, central bank balance sheet and regulation'.

Corradin, S. & Maddaloni, A. (2020), 'The importance of being special: repo markets during the crisis', *Journal of Financial Economics* **137**(2), 392–429.

Di Luigi, C., Perrella, A. & Ruggieri, A. (2024), The fundamental role of the repo market and central clearing, Technical report, Bank of Italy, Directorate General for Markets and Payment System.

Duffie, D. (1996), 'Special repo rates', *Journal of Finance* **51**, 493–526.

Duffie, D. (2020*a*), Still the world's safe haven? Redesigning the US treasury market after the COVID-19 crisis, Hutchins center working paper # 62, Stanford University.

Duffie, D. (2020*b*), 'Still the world's safe haven', *Redesigning the US Treasury market after the COVID-19 crisis'. Hutchins Center on Fiscal and Monetary Policy at Brookings* .

Freixas, X. & Holthausen, C. (2005), 'Interbank market integration under asymmetric information', *The Review of Financial Studies* **18**(2), 459–490.

Furfine, C. H. (1999), 'The microstructure of the federal funds market', *Financial Markets, Institutions & Instruments* **8**(5), 24–44.

He, Z., Nagel, S. & Song, Z. (2022), 'Treasury inconvenience yields during the covid-19 crisis', *Journal of Financial Economics* **143**(1), 57–79.

Heider, F., Hoerova, M. & Holthausen, C. (2015), 'Liquidity hoarding and interbank market rates: The role of counterparty risk', *Journal of Financial Economics* **118**(2), 336–354.

Hermes, F., Schmeling, M. & Schrimpf, A. (2025), 'Bis bulletin'.

Huber, A. W. (2023), 'Market power in wholesale funding: A structural perspective from the triparty repo market', *Journal of Financial Economics* **149**(2), 235–259.

Hüser, A., Lepore, C. & Veraart, L. (2021), 'How does the repo market behave under stress? evidence from the covid-19 crisis', *Bank of England Staff Working Paper* **910**.

Infante, S. & Saravay, Z. (2020), 'What drives us treasury re-use?', *Available at SSRN 3722272* .

Krishnamurthy, A., Nagel, S. & Orlov, D. (2014), 'Sizing up repo', *Journal of Finance* **69**(6), 2381–2417.

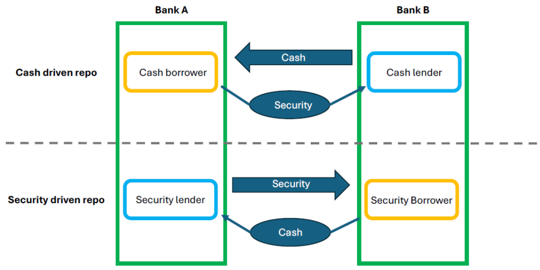
Mancini, L., Ranaldo, A. & Wrampelmeyer, J. (2016), 'The euro interbank repo market', *The Review of Financial Studies* **29**(7), 1747–1779.

Martin, A., Skeie, D. & Thadden, E.-L. v. (2014), 'Repo runs', *The Review of Financial Studies* **27**(4), 957–989.

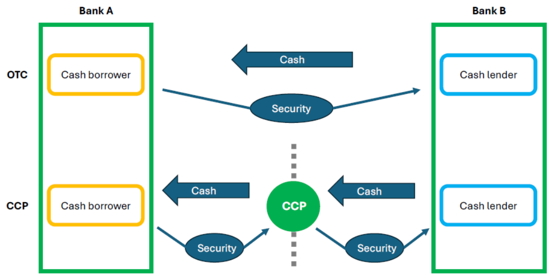
Tilford, C., Rennison, J., Noonan, L., Smith, C. & Greely, B. (2019), 'Repo: How the financial markets' plumbing got blocked', *Financial Times* .

Vayanos, D. & Weill, P.-O. (2008), 'A search-based theory of the on-the-run phenomenon', *The Journal of Finance* **63**(3), 1361–1398.

A Figures



(a) Stylised repo contracts



(b) Microstructure of the repo market in the European Union.

Figure 1: Panel A: Structure of interbank repos and reverse-repo contracts. The legs of the transaction are stylised and do not take into account the type of market structure on which the contract is entered into. **Panel B: Microstructure of the repo market in the European Union.** In CCP–based markets, Central Clearing Counterparties clear and novate repo contract and ensure anonymity via a Central Limit Order Book (CLOB).

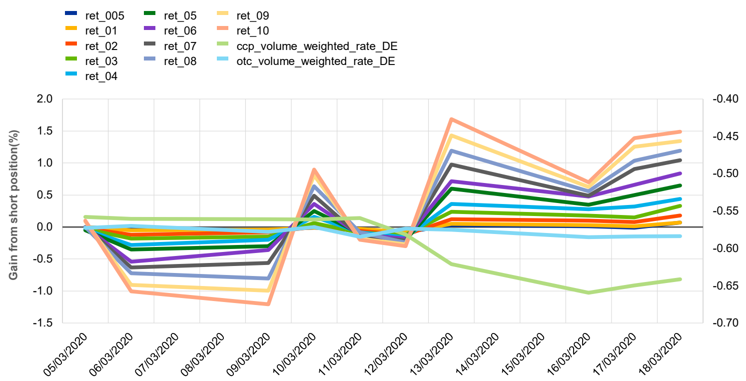


Figure 2: Profits and losses derived from shorting bonds in the sample ranging from March 5, 2020 to March 18, 2020 for German Bunds. Profits and losses are computed using daily yield curves from Deustche Bundesbank and transaction-by-transaction data from MMSR aggregated at the daily level, to compute the cost of borrowing.

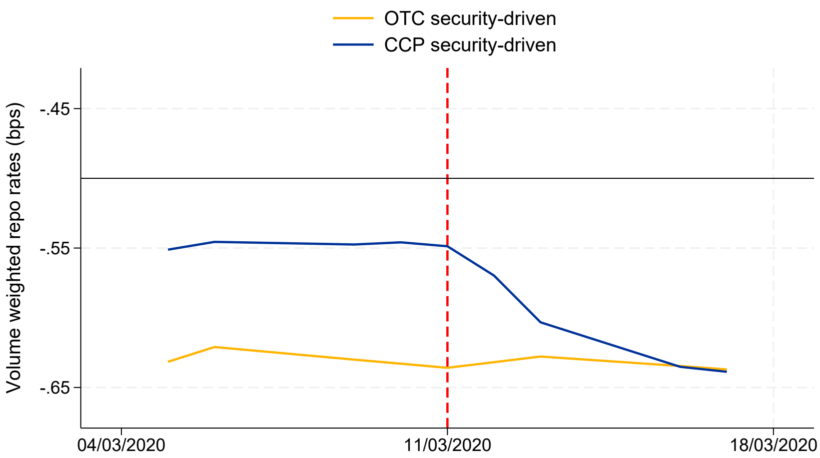


Figure 3: Repo rates for security–driven transactions by market. The figure represents the level of volume-weighted repo rates split by market venues (OTC and CCP) and trading motive (cash and security). Cash-driven trades occur at repo rates above the DFR. Security-driven trades occur at repo rates below the DFR. The DFR is −0.5 bps.

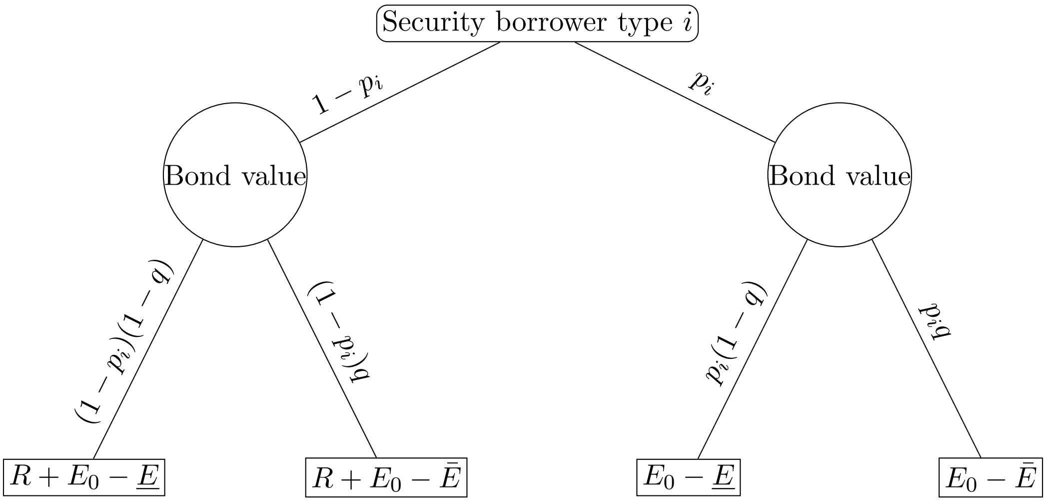


Figure 4: Payoffs

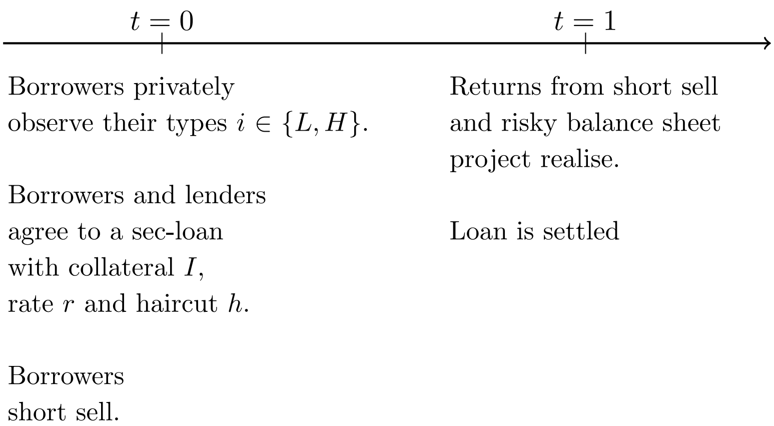


Figure 5: Timeline

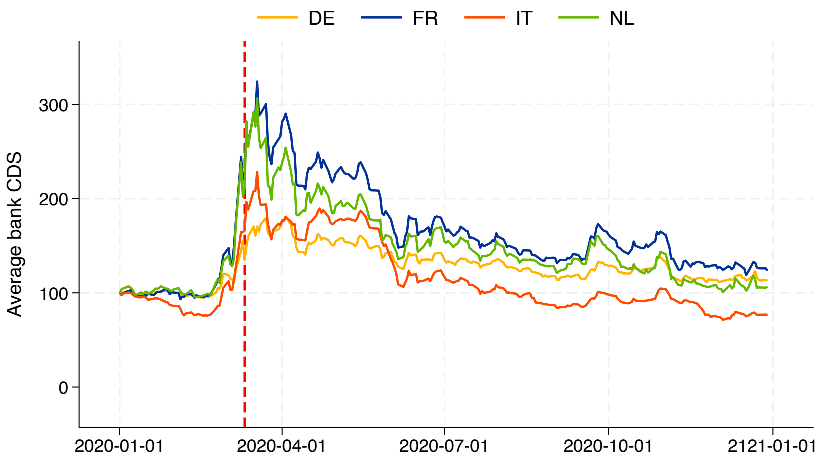


Figure 6: Average bank credit default swap. Data is obtained from Bloomberg. The sample ranges from January to December 2020.

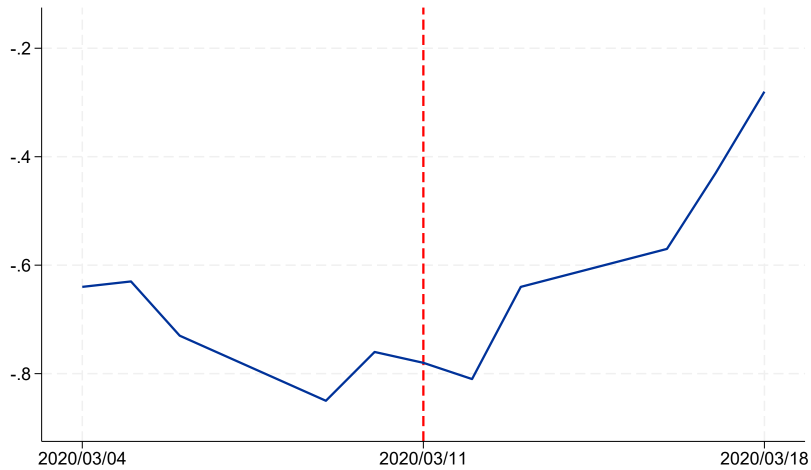


Figure 7: Interpolated Bund yields. The sample ranges from January to December 2020.

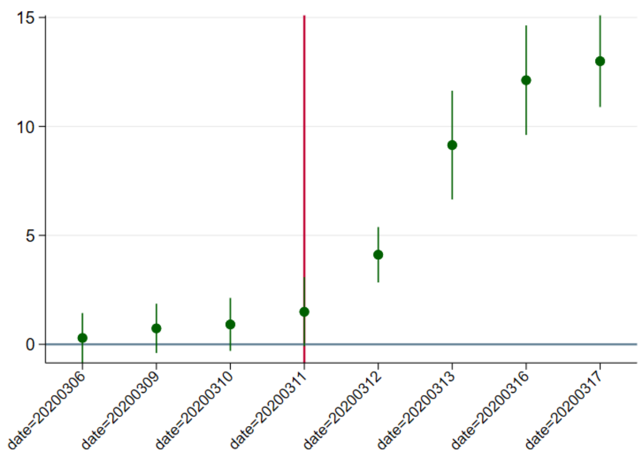


Figure 8: Coefficients of the dynamic version of Equation (8).

B Tables

		CCP market						OTC market					
		mean	sd	p25	p50	p75	count	mean	sd	p25	p50	p75	count
$d_{i,t}$	(bps)	8.65	9.41	3.00	6.00	12.00	32787	76.69	111.47	20.00	35.00	45.00	14820
Volume	(MM)	30.72	45.16	5.44	16.04	36.16	32787	4.56	16.55	0.51	1.04	2.50	14820
NPL ratio	(bps)	212.54	132.72	132.33	177.55	258.82	32787	215.57	125.17	138.65	177.55	324.77	14820
Haircuts	(bps)	-0.57	2.84	-1.49	-0.48	-0.005	32787	-1.37	3.57	-2.99	-0.89	0.23	14820
Δ CDS	(bps)	76.11	38.37	53.87	66.13	82.69	30958	102.62	58.53	62.28	79.45	129.82	12362
Share of government bonds	(%)	99.88						68.83					
HHI borrower		1500						1000					
HHI lender		850						900					

Table 1: Summary statistics. Sample ranges from March 5 to March 18, 2020. $d_{i,t} = \left|\text{Repo rate}_{i,t} - \text{DFR}_t\right|$ represents the cost of borrowing security and is given by the distance from the DFR of the repo rate in transaction i on day t measured in basis points (bps) and obtained from MMSR transaction-by-transaction data. Volume (MM) is transaction volume per trade reported in million Euros. Haircuts are defined as 1 minus the ratio of the amount of cash borrowed in the repo transaction divided by the amount of securities pledged as collateral. NPL ratio is the ratio of non-performing-loans over total loans based on banks' regulatory reportings. Δ CDS represents the day-on-day variations of banks' CDS spreads. HHI refers to the Herfindahl-Hirschman index on competition in the market. HHIs of over 2500 indicate a highly concentrated market, lower values describe increasing competition in the market.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	0.751***			
	(0.237)			
CCP	-5.403***			
	(1.816)			
Covid×CCP	5.891***	6.189***	6.174***	5.857***
	(0.382)	(0.326)	(0.317)	(0.241)
ln(Transaction amount)	-0.989***	-0.261***	-0.200***	-0.269***
	(0.233)	(0.0532)	(0.0402)	(0.0552)
Haircut	0.186***	0.177***	0.144***	0.159***
	(0.0538)	(0.0568)	(0.0471)	(0.0506)
Constant	17.67***	12.45***	12.30***	12.56***
	(1.468)	(0.177)	(0.110)	(0.165)
Observations	40,371	41,457	41,447	41,452
R-squared	0.627	0.873	0.891	0.876
Standard errors	Pair	Pair	Pair	Pair
Transaction controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		
Day FE		Yes	Yes	
Collateral ISIN FE		Yes	Yes	Yes
Tenor FE		Yes	Yes	Yes
Borrower × Day FE				Yes
Pair FE			Yes	

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Economic uncertainty. This table shows results for the estimation of Equation (8) on the CCP-OTC differential and economic uncertainty. See Table 1 for the definition of variables. *Covid* is a dummy equal to one after the WHO announcement on March 12, 2020. *CCP* is a dummy equal to one if the transaction is carried out in CCP markets. The theoretical CCP–OTC differential is identified through the coefficient CCP dummy. A positive coefficient on Covid × CCP corresponds to a compression of this differential following the uncertainty shock. Standard errors are clustered at the bank-counterparty level. Columns (1)-(4) show results for the same specification using different combinations of fixed effects for Borrower, Lender, Day, Collateral and Tenor.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)	$d_{i,t}$ (5)	$d_{i,t}$ (6)	$d_{i,t}$ (7)	$d_{i,t}$ (8)
Covid	-0.319				0.699**			
	(0.488)				(0.286)			
CCP	-5.981**				-6.098***			
	(2.491)				(2.064)			
Covid×CCP	7.757***	7.472***	7.289***	7.180***	6.593***	6.866***	6.823***	6.646***
	(0.692)	(0.478)	(0.489)	(0.448)	(0.433)	(0.340)	(0.334)	(0.276)
NPL ratio	-0.00344							
	(0.00739)							
Covid×NPL ratio	0.00479**	0.00175***	0.00109					
	(0.00205)	(0.000613)	(0.000812)					
CCP×NPL ratio	0.00185	0.00260		0.00256				
	(0.00737)	(0.00711)		(0.00709)				
Covid×CCP×NPL ratio	-0.00839***	-0.00589***	-0.00516**	-0.00556***				
	(0.00310)	(0.00225)	(0.00231)	(0.00195)				
ΔCDS					-0.00553	0.0116	0.0145*	
					(0.0192)	(0.00816)	(0.00764)	
Covid×ΔCDS					0.0188	0.0648***	0.0621***	
					(0.0129)	(0.0162)	(0.0155)	
CCP×ΔCDS					0.000163	0.00423	0.00170	0.00251
					(0.0206)	(0.00555)	(0.00463)	(0.00421)
Covid×CCP×ΔCDS					-0.122***	-0.108***	-0.102***	-0.103***
					(0.0209)	(0.0108)	(0.0103)	(0.00944)
ln(Transaction amount)	-1.010***	-0.263***	-0.202***	-0.269***	-0.900***	-0.241***	-0.197***	-0.250***
	(0.238)	(0.0527)	(0.0394)	(0.0553)	(0.225)	(0.0489)	(0.0400)	(0.0516)
Haircut	0.201***	0.177***	0.144***	0.160***	0.180***	0.163***	0.138***	0.149***
	(0.0534)	(0.0563)	(0.0468)	(0.0506)	(0.0549)	(0.0573)	(0.0472)	(0.0530)
Constant	18.59***	11.87***	12.20***	12.12***	17.58***	11.50***	11.40***	11.80***
	(2.184)	(1.110)	(0.132)	(1.090)	(1.722)	(0.181)	(0.139)	(0.151)
Observations	40,371	41,457	41,447	41,452	36,559	37,426	37,417	37,421
R-squared	0.628	0.873	0.891	0.876	0.634	0.875	0.886	0.877
Transaction controls	Yes				Yes			
Borrower FE		Yes				Yes		
Lender FE		Yes		Yes		Yes		Yes
Day FE		Yes	Yes			Yes	Yes	
Collateral ISIN FE		Yes	Yes	Yes		Yes	Yes	Yes
Tenor FE		Yes	Yes	Yes		Yes	Yes	Yes
Borrower × Day FE				Yes				Yes
Pair FE			Yes				Yes	

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Borrower quality. The table shows results for the estimation of Equation (9). See Table 1 and Table 2 for the definition of variables. *NPL Ratio* is a continuous variable representing the ratio of non-performing-loans over total loans expressed in basis points. ΔCDS represents the day-on-day variations of banks' CDS spreads expressed in basis points. A negative coefficient on the triple interaction corresponds to a compression of the CCP-OTC differential that is weaker for riskier borrowers. Standard errors are clustered at the bank-counterparty level. Columns (1)-(4) show results for the same specification using different combinations of fixed effects for Borrower, Lender, Day, Collateral and Tenor.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	0.794			
	(0.663)			
CCP	-9.724***			
	(3.225)			
Covid×CCP	2.318***	3.180***	3.024***	2.706***
	(0.793)	(0.404)	(0.390)	(0.365)
SAFE		-8.248	-2.951	-8.259
		(5.788)	(2.196)	(5.726)
Covid×SAFE	-0.339	0.212	-0.00855	-0.0753
	(0.943)	(0.181)	(0.189)	(0.209)
CCP×SAFE	7.928***	-1.395	-1.752	-1.439
	(2.472)	(3.397)	(2.611)	(3.400)
Covid×CCP×SAFE	5.993***	5.670***	5.897***	5.871***
	(1.088)	(0.536)	(0.540)	(0.587)
ln(Transaction amount)	-1.199***	-0.319**	-0.270**	-0.324**
	(0.319)	(0.139)	(0.129)	(0.142)
Constant	18.49***	33.69***	30.68***	33.91***
	(1.861)	(3.243)	(0.714)	(3.198)
Observations	43,918	47,500	47,494	47,495
R-squared	0.476	0.954	0.955	0.954
Transaction controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Collateral ISIN FE		Yes	Yes	Yes
Tenor FE		Yes	Yes	Yes
Borrower × Day FE				Yes
Pair FE			Yes	

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Collateral quality. The table shows results for the estimation of Equation (10). See Table 1 and Table 2 for the definition of variables. *SAFE* is a dummy variable equal to one for transactions with safe collateral, i.e., German, French or Dutch bonds. A positive coefficient on the triple interaction corresponds to a compression of the CCP-OTC differential that is stronger for better quality collateral. Standard errors are clustered at the bank-counterparty level. Columns (1)-(4) show results for the same specification using different combinations of fixed effects for Borrower, Lender, Day, Collateral and Tenor.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	0.272			
	(0.263)			
CCP	-4.383**			
	(1.754)			
Covid×CCP	6.390***	6.585***	6.439***	6.340***
	(0.376)	(0.362)	(0.343)	(0.338)
ytm	0.378	0.321	-0.00801	0.270
	(0.395)	(0.221)	(0.149)	(0.221)
Covid×ytm	0.249*	0.0599	0.0445	0.150*
	(0.136)	(0.0717)	(0.0536)	(0.0841)
CCP×ytm	-0.191	-0.387	-0.0308	-0.350
	(0.456)	(0.255)	(0.183)	(0.249)
Covid×CCP×ytm	-0.697***	-0.356**	-0.329**	-0.397***
	(0.194)	(0.150)	(0.142)	(0.141)
Constant	15.65***	12.41***	11.98***	12.49***
	(1.432)	(0.477)	(0.256)	(0.483)
Observations	39,108	40,121	40,112	40,116
R-squared	0.619	0.645	0.722	0.649
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Alternative collateral quality: yield-to-maturity. The table shows results for the estimation of Equation (10), using yield-to-maturity as a measure of collateral quality. See Table 1 and Table 2 for the definition of variables. *ytm* is the yield-to-maturity for the respective bond being borrowed and serves as a measure of quality of the bond. A high yield indicates lower quality. A negative coefficient on the triple interaction corresponds to a compression of the CCP-OTC differential that is weaker for lower quality collateral. Standard errors are clustered at the bank-counterparty level. Columns (1)-(4) show results for the same specification using different combinations of fixed effects for Borrower, Lender, Day, Collateral and Tenor.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	-7.414			
	(6.073)			
CCP	79.69***			
	(17.22)			
Covid×CCP	-20.30**	-25.92***	-28.72***	-23.43***
	(8.965)	(4.975)	(4.970)	(5.236)
Gini index	0.955***			
	(0.179)			
Covid×Gini index	0.0851	0.0249	-0.00290	0.0499*
	(0.0663)	(0.0229)	(0.0228)	(0.0287)
CCP×Gini index	-0.930***	-0.107	-0.0716	-0.106
	(0.187)	(0.155)	(0.125)	(0.154)
Covid×CCP×Gini index	0.299***	0.364***	0.393***	0.331***
	(0.100)	(0.0572)	(0.0571)	(0.0588)
ln(Transaction amount)	-0.968***	-0.145	-0.0928	-0.151
	(0.276)	(0.161)	(0.160)	(0.163)
Constant	-69.38***	30.68***	29.42***	29.73***
	(16.29)	(9.762)	(8.034)	(9.646)
Observations	42,855	45,885	45,878	45,880
R-squared	0.503	0.952	0.954	0.953
Transaction controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Collateral ISIN FE		Yes	Yes	Yes
Tenor FE		Yes	Yes	Yes
Borrower × Day FE				Yes
Pair FE			Yes	

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Alternative collateral quality: Gini index The table shows regression results for Equation (10) to test for collateral quality using Gini index by bond. See Table 1 and Table 2 for the definition of variables. Gini index is a concentration measure of bond holdings computed using the Security Holdings Statistics (SHSS) database for the MMSR reporting banks. A positive coefficient on the triple interaction corresponds to a compression of the CCP-OTC differential that is stronger for higher quality collateral. Standard errors are clustered at the bank-counterparty level. Columns (1)-(4) show results for the same specification using different combinations of fixed effects for Borrower, Lender, Day, Collateral and Tenor

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	0.0844			
	(0.548)			
CCP	-7.701***			
	(2.496)			
Covid×CCP	7.347***	7.542***	7.172***	7.207***
	(0.678)	(0.499)	(0.534)	(0.534)
weighted BPI	-6.725	0.111	3.002**	
	(5.519)	(3.924)	(1.418)	
Covid×weighted BPI	1.947	1.569***	0.621	
	(1.659)	(0.584)	(0.720)	
CCP×weighted BPI	5.549	2.425	-1.961	2.591
	(5.443)	(4.950)	(4.035)	(5.019)
Covid×CCP×weighted BPI	-5.214**	-4.918***	-3.855**	-4.397***
	(2.241)	(1.570)	(1.681)	(1.536)
Constant	20.14***	11.75***	11.76***	11.99***
	(2.327)	(0.719)	(0.743)	(0.917)
Observations	40,371	41,457	41,447	41,452
R-squared	0.629	0.873	0.891	0.876
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Borrower relationship activity. The table shows results for the estimation of Equation (9) to test for relationship lending using the Borrower preference index (Bräuning & Fecht 2017). See Table 1 and Table 2 for the definition of variables. BPI is a concentration measure for borrower–lender dependencies, calculates as the sum of all borrowing of i from j during T divided by the total borrowing of i during T: $BPI_{i,j,t} = \frac{\sum_{t' \epsilon T} y_{i,j,t'}}{\sum_j \sum_{t' \epsilon T} y_{i,j,t'}}$. Standard errors are clustered at the bank-counterparty level. Columns (1)-(4) show results for the same specification using different combinations of fixed effects for Borrower, Lender, Day, Collateral and Tenor.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	-0.507			
	(0.763)			
CCP	-7.042**			
	(2.905)			
Covid×CCP	7.283***	6.266***	6.085***	6.915***
	(0.961)	(0.562)	(0.582)	(0.514)
weighted LPI	-5.297	-10.46***	-4.040**	
	(6.025)	(3.091)	(1.573)	
Covid×weighted LPI	4.663*	1.024	0.466	
	(2.752)	(0.731)	(0.751)	
CCP×weighted LPI	4.498	7.121**	-1.766	9.701***
	(6.039)	(3.586)	(3.027)	(3.670)
Covid×CCP×weighted LPI	-5.068	-0.810	-0.0543	-4.258**
	(3.483)	(1.756)	(1.769)	(1.884)
Constant	19.45***	13.85***	13.81***	10.55***
	(2.634)	(0.737)	(0.653)	(0.791)
Observations	40,371	41,457	41,447	41,452
R-squared	0.627	0.874	0.891	0.876
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Lender relationship activity. The table shows results for the estimation of Equation (9) to test for relationship lending using the Lender preference index (Bräuning & Fecht 2017). See Table 1 and Table 2 for the definition of variables. LPI is a concentration measure for lender–borrower relationships, as the sum of all lending of i to j during T divided by the total lending of i during T: $LPI_{i,j,t} = \frac{\sum_{t' \epsilon T} y_{i,j,t'}}{\sum_j \sum_{t' \epsilon T} y_{i,j,t'}}$. Standard errors are clustered at the bank-counterparty level. Columns (1)-(4) show results for the same specification using different combinations of fixed effects for Borrower, Lender, Day, Collateral and Tenor.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	3.706			
	(3.541)			
CCP	-10.99			
	(7.099)			
Covid×CCP	3.818	9.169***	8.668***	7.873***
	(3.714)	(2.385)	(2.109)	(1.962)
weighted RL	-0.966	-0.344	0.142	
	(1.149)	(0.419)	(0.158)	
Covid×weighted RL	-0.565	0.169	0.171*	
	(0.635)	(0.178)	(0.0922)	
CCP×weighted RL	0.947	0.860	0.214	0.895
	(1.153)	(0.611)	(0.369)	(0.634)
Covid×CCP×weighted RL	0.395	-0.525	-0.452	-0.347
	(0.668)	(0.414)	(0.370)	(0.350)
Constant	23.26***	10.49***	10.25***	8.992***
	(6.987)	(1.432)	(1.329)	(2.541)
Observations	40,371	41,457	41,447	41,452
R-squared	0.628	0.873	0.891	0.876
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Relationship frequency. The table shows results for the estimation of Equation (9) to test for relationship lending using the frequency of interactions (RL) (Bräuning & Fecht 2017). See Table 1 and Table 2 for the definition of variables. RL is a frequency–based concentration measure for lender–borrower pairs: $RL_{i,j,t} = log(1 + \sum_{t' \epsilon T} I(y_{i,j,t'} > 0))$. Standard errors are clustered at the bank-counterparty level. Columns (1)-(4) show results for the same specification using different combinations of fixed effects for Borrower, Lender, Day, Collateral and Tenor.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	0.626			
	(0.429)			
CCP	-4.395***			
	(1.591)			
Covid×CCP	5.774***	5.806***	6.011***	5.308***
	(0.506)	(0.383)	(0.326)	(0.312)
ln (Transaction amount)	-0.512***	-0.177***	-0.155***	-0.185***
	(0.124)	(0.0394)	(0.0371)	(0.0395)
Constant	11.91***	7.174***	7.023***	7.392***
	(1.499)	(0.136)	(0.108)	(0.141)
Observations	31,803	32,628	32,619	32,620
R-squared	0.532	0.753	0.767	0.759
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: Robustness - Economic uncertainty. The table shows regression results for a sample of repo transactions using only government issued securities. See Table 1 and Table 2 for the definition of variables and interpretation of the coefficients.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	-1.192*			
	(0.627)			
CCP	-5.894**			
	(2.974)			
Covid×CCP	8.429***	7.564***	7.636***	6.870***
	(0.772)	(0.495)	(0.481)	(0.509)
NPL	-0.00429			
	(0.00660)			
Covid×NPL	0.00696***	0.00338***	0.00301***	
	(0.00236)	(0.000841)	(0.000856)	
CCP×NPL	0.00527	-0.00690		-0.00732
	(0.00668)	(0.0104)		(0.0104)
Covid×CCP×NPL	-0.0109***	-0.00754***	-0.00708***	-0.00590***
	(0.00317)	(0.00226)	(0.00224)	(0.00208)
Constant	13.21***	8.146***	6.697***	8.700***
	(2.846)	(2.033)	(0.123)	(2.034)
Observations	31,803	32,628	32,619	32,620
R-squared	0.533	0.754	0.768	0.759
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Robustness - Counterparty quality. The table shows regression results for Equation (9) to test for borrower quality via NPL ratio on a sample of repo transactions using only government issued securities. See Table 1 and Table 2 for the definition of variables and interpretation of the coefficients.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	0.542			
	(0.529)			
CCP	-5.305***			
	(1.795)			
Covid×CCP	6.500***	6.410***	6.638***	6.034***
	(0.604)	(0.396)	(0.365)	(0.368)
ΔCDS	-0.0340	0.0275**	0.0162*	
	(0.0209)	(0.0116)	(0.00911)	
Covid×ΔCDS	0.0356**	0.0802***	0.0754***	
	(0.0172)	(0.0158)	(0.0142)	
CCP×ΔCDS	0.0332	-0.00966	0.00205	-0.0158**
	(0.0220)	(0.00922)	(0.00606)	(0.00719)
Covid×CCP×ΔCDS	-0.136***	-0.113***	-0.107***	-0.101***
	(0.0229)	(0.0125)	(0.0104)	(0.0133)
Constant	12.46***	6.717***	6.572***	7.239***
	(1.717)	(0.170)	(0.149)	(0.158)
Observations	29,589	30,286	30,275	30,278
R-squared	0.523	0.746	0.755	0.752
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Robustness - Counterparty quality. The table shows regression results for Equation (9) to test for borrower quality via differences in CDS prices on a sample of repo transactions using only government issued securities. See Table 1 and Table 2 for the definition of variables and interpretation of the coefficients.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	1.224***			
	(0.461)			
CCP	-0.411			
	(1.313)			
Covid×CCP	1.925***	1.794***	2.179***	1.496***
	(0.640)	(0.563)	(0.434)	(0.483)
Covid×SAFE	-1.491***	-1.229***	-0.914***	-1.450***
	(0.515)	(0.459)	(0.306)	(0.460)
CCP×SAFE	-6.765***	-5.361**	-2.042	-5.465**
	(2.549)	(2.675)	(2.557)	
Covid×CCP×SAFE	6.184***	6.160***	5.843***	6.332***
	(0.771)	(0.630)	(0.531)	(0.627)
Constant	12.42***	10.66***	8.436***	10.87***
	(1.379)	(1.578)	(1.641)	(1.569)
Observations	31,803	32,628	32,619	32,620
R-squared	0.544	0.765	0.779	0.769
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Robustness - Collateral quality. The table shows regression results for Equation (10) to test for collateral quality via the SAFE dummy on a sample of repo transactions using only government issued securities. See Table 1 and Table 2 for the definition of variables and interpretation of the coefficients.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	0.583*			
	(0.353)			
CCP	-3.163	-0.418	-3.573*	-0.142
	(2.120)	(2.092)	(1.934)	(2.137)
Covid×CCP	6.723***	7.104***	7.142***	6.520***
	(0.669)	(0.506)	(0.507)	(0.524)
ln (Transaction amount)	-2.157***	-0.434	-0.310	-0.437
	(0.442)	(0.322)	(0.313)	(0.325)
Constant	24.34***	45.90***	47.10***	45.86***
	(1.488)	(2.390)	(2.323)	(2.411)
Observations	23,719	26,889	26,851	26,889
R-squared	0.427	0.955	0.956	0.955
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Robustness - Economic uncertainty (2). The table shows regression results for Equation (8) using a sample of matched pairs of banks. See Table 1 and Table 2 for the definition of variables and interpretation of the coefficients.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	-0.634			
	(0.773)			
CCP	-5.748*	-4.853*	-10.63***	-4.666
	(3.249)	(2.927)	(2.797)	(2.947)
Covid×CCP	8.928***	8.524***	8.620***	7.974***
	(1.010)	(0.678)	(0.691)	(0.710)
NPL	-0.0110			
	(0.00895)			
Covid×NPL	0.00541*	0.00171	0.00173	
	(0.00326)	(0.00123)	(0.00118)	
CCP×NPL	0.00720	0.0224**	0.0343***	0.0227**
	(0.00856)	(0.00924)	(0.00837)	(0.00944)
Covid×CCP×NPL	-0.0101***	-0.00734***	-0.00771***	-0.00694***
	(0.00343)	(0.00205)	(0.00211)	(0.00195)
Constant	27.29***	45.79***	47.05***	45.88***
	(2.589)	(2.468)	(2.405)	(2.429)
Observations	23,719	26,889	26,851	26,889
R-squared	0.429	0.955	0.956	0.955
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Robustness - Counterparty quality (2). The table shows regression results for Equation (9) using a sample of matched pairs of banks. See Table 1 and Table 2 for the definition of variables and interpretation of the coefficients.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	0.294			
	(0.417)			
CCP	-3.211	-1.023	0.323	-0.687
	(2.338)	(1.741)	(2.214)	(1.761)
Covid×CCP	7.837***	7.988***	8.067***	7.612***
	(0.766)	(0.562)	(0.561)	(0.605)
ΔCDS	-0.0222	0.0235***	0.0223***	
	(0.0240)	(0.00693)	(0.00698)	
Covid×ΔCDS	0.0471**	0.0297**	0.0339***	
	(0.0194)	(0.0122)	(0.0129)	
CCP×ΔCDS	-0.00198	-0.00134	-0.00181	-0.00283
	(0.0254)	(0.0116)	(0.0108)	(0.0130)
Covid×CCP×ΔCDS	-0.155***	-0.0998***	-0.104***	-0.108***
	(0.0270)	(0.0180)	(0.0175)	(0.0193)
Constant	23.56***	49.08***	48.25***	49.23***
	(1.668)	(2.443)	(2.510)	(2.464)
Observations	20,541	23,549	23,509	23,549
R-squared	0.440	0.956	0.956	0.956
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Robustness - Counterparty quality (2). The table shows regression results for Equation (9) using a sample of matched pairs of banks. See Table 1 and Table 2 for the definition of variables and interpretation of the coefficients.

Variable	$d_{i,t}$ (1)	$d_{i,t}$ (2)	$d_{i,t}$ (3)	$d_{i,t}$ (4)
Covid	0.777			
	(0.631)			
CCP	-7.602**	2.335	0.267	2.775
	(3.264)	(1.721)	(2.013)	(1.831)
Covid×CCP	1.930***	3.063***	3.061***	2.508***
	(0.741)	(0.531)	(0.525)	(0.502)
Covid×SAFE	-0.273	0.257	0.0874	0.00646
	(0.906)	(0.193)	(0.194)	(0.223)
CCP×SAFE	6.979***	-3.814	-5.493***	-4.193
	(2.433)	(2.691)	(1.941)	(2.769)
Covid×CCP×SAFE	6.655***	5.883***	5.983***	6.147***
	(1.198)	(0.660)	(0.667)	(0.682)
SAFE		-6.731	0.867	-7.180
		(5.919)	(2.901)	(6.099)
Constant	24.13***	49.39***	46.59***	49.62***
	(1.681)	(3.870)	(2.833)	(3.919)
Observations	23,719	26,889	26,851	26,889
R-squared	0.435	0.955	0.956	0.956
Transaction Controls	Yes			
Borrower FE		Yes		
Lender FE		Yes		Yes
Day FE		Yes	Yes	
Tenor FE		Yes	Yes	Yes
Borrower x Day FE				Yes
Pair FE			Yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Robustness - Collateral quality (2). The table shows regression results for Equation (10) using a sample of matched pairs of banks. See Table 1 and Table 2 for the definition of variables and interpretation of the coefficients.

C Proofs

C.1 Proof of Proposition 1

Under lender competition, the type-specific OTC rate is given by (3). The average OTC rate is

$$r^{OTC} = \alpha r^L + (1-\alpha) r^H,$$

while CCP pooling implies (5). Substituting $m = (1-\alpha)(1-p_H) + \alpha(1-p_L)$ into (5) and taking the difference yields

$$\Delta r = r^{CCP} - r^{OTC}.$$

Algebraic simplification delivers

$$\Delta r = -\frac{(1-\alpha)\alpha(p_L - p_H)^2 q^2 \big(\delta E_0 + (1-q)(\bar{E} - \underline{E}) - I\big)}{I(1-p_H q)(1-p_L q)(1-(1-m)q)}.$$

Since $I > 0$, $(1-p_H q) > 0$, $(1-p_L q) > 0$, and $(1-(1-m)q) > 0$ under feasibility, the sign of Δr is determined by $\delta E_0 + (1-q)(\bar{E} - \underline{E}) - I$. If $I < \delta E_0 + (1-q)(\bar{E} - \underline{E})$, then $\Delta r < 0$, completing the proof.

C.2 Proof of Proposition 2

From Proposition 1, write Δr as

$$\Delta r = -K(\alpha) \cdot \big(\delta E_0 + (1-q)(\bar{E} - \underline{E}) - I\big),$$

where the prefactor $K(\alpha) > 0$ collects the remaining terms. Differentiating Δr with respect to α yields the expression:

$$\frac{\partial \Delta r}{\partial \alpha} = -(p_L - p_H)^2 q^2 (\delta E_0 + (1-q)(\bar{E} - \underline{E}) - I) \frac{(1-2\alpha)(1-p_H q) + \alpha^2 (p_L - p_H) q}{I(1-p_H q)(1-p_L q)(1-(1-m)q)^2}. \quad (11)$$

Under $I < \delta E_0 + (1-q)(\bar{E} - \underline{E})$, the leading factor is negative. Therefore $\frac{\partial \Delta r}{\partial \alpha} > 0$ holds whenever

$$(1-2\alpha)(1-p_H q) + \alpha^2 (p_L - p_H) q < 0,$$

which is equivalent to

$$p_H > \frac{1 - 2\alpha + \alpha^2 p_L q}{(1-\alpha)^2 q}.$$

This is the stated sufficient condition.

C.3 Proof of Proposition 3

Differentiating (11) with respect to p_H yields

$$\frac{\partial^2 \Delta r}{\partial \alpha \partial p_H} = -(p_L - p_H)q^2(\delta E_0 + (1-q)(\bar{E} - \underline{E}) - I) \times \frac{\alpha^3 (p_L - p_H)^2 q^2 - 3\alpha^2 (p_L - p_H) q (1 - p_H q) - 2(1 - p_H q)^2 + 4\alpha(1 - p_H q)^2}{I(1 - p_H q)^2 (1 - (1-m)q)^3}. \quad (12)$$

Under $I < \delta E_0 + (1-q)(\bar{E} - \underline{E})$, the leading factor is negative given that $(p_L - p_H) > 0$. The remaining fraction is positive for $\alpha > \frac{1}{2}$. Under additional, mild regularity restrictions the fraction is positive also for $\alpha < \frac{1}{2}$, implying $\frac{\partial^2 \Delta r}{\partial \alpha \partial p_H} < 0$.

Similarly, differentiating (11) with respect to p_L yields

$$\frac{\partial^2 \Delta r}{\partial \alpha \partial p_L} = -(p_H - p_L)q^2(\delta E_0 - I + (1-q)(\bar{E} - \underline{E})) \times \frac{1}{I(1 - p_L q)^2 (1 - (1-m)q)^3} \Big(\alpha^3 (p_H - p_L)^2 q^2 + 3\alpha^2 (p_H - p_L) q (1 - p_H q) + \alpha(4 - q((6 - 3p_H q)p_H + (2 - p_L q)p_L) - (1 - p_H q)(2 - (p_H + p_L)q) \Big), \quad (13)$$

Under $I < \delta E_0 + (1-q)(\bar{E} - \underline{E})$, the leading factor is negative given that $(p_L - p_H) > 0$. The remaining fraction is positive for $\alpha < \frac{1}{2}$. Under additional, mild regularity restrictions the fraction is positive also for $\alpha > \frac{1}{2}$, delivering $\frac{\partial^2 \Delta r}{\partial \alpha \partial p_L} < 0$.

C.4 Proof of Proposition 4

Recall that for a borrower with failure probability $p \in (0,1)$ the (reverse repo) rate can be written as

$$r(p) = \frac{\delta E_0 - (1-q)E_u - q(1-p)E_b - pqI}{(1-pq)I}. \quad (14)$$

Define the constants

$$B := E_u - E_b < 0, \qquad S := \delta E_0 - E_u + E_b - I = \delta E_0 + (E_b - E_u) - I,$$

and note that $I > 0$. A direct simplification gives

$$r(p) = \frac{(\delta E_0 - E_u) + q\big(B + pS\big)}{(1 - pq)I}. \tag{15}$$

Step 1: Derivatives of $r(p)$ w.r.t. q. Differentiate $r(p)$ with respect to q holding p fixed. Since $(1 - pq)I$ depends on q only through $(1 - pq)$, quotient rule yields

$$\frac{\partial r}{\partial q}(p) = \frac{B + pS}{I(1 - pq)^2} =: f(p). \tag{16}$$

Differentiate again with respect to p (keeping q fixed) to obtain

$$f'(p) = \frac{\partial}{\partial p}\left(\frac{B + pS}{I(1 - pq)^2}\right) = \frac{S + q\big(2B + pS\big)}{I(1 - pq)^3}. \tag{17}$$

Step 2: Express Δr using the pooled default probability. Under the maintained structure,

$$r^{OTC} = \alpha r(p_L) + (1 - \alpha) r(p_H), \qquad r^{CCP} = r(\bar{p}),$$

where the pooled failure probability equals

$$\bar{p} = (1 - \alpha) p_H + \alpha p_L, \qquad \frac{\partial \bar{p}}{\partial \alpha} = p_L - p_H.$$

Hence

$$\Delta r = r^{CCP} - r^{OTC} = r(\bar{p}) - \alpha r(p_L) - (1 - \alpha) r(p_H).$$

Step 3: First take $\partial/\partial q$, then $\partial/\partial \alpha$. Differentiate Δr with respect to q:

$$\begin{aligned} \frac{\partial \Delta r}{\partial q} &= \frac{\partial r}{\partial q}(\bar{p}) - \alpha \frac{\partial r}{\partial q}(p_L) - (1 - \alpha)\frac{\partial r}{\partial q}(p_H) \\ &= f(\bar{p}) - \alpha f(p_L) - (1 - \alpha) f(p_H), \end{aligned} \tag{18}$$

where $f(\cdot)$ is defined in (16). Now differentiate (18) with respect to α. Using the product rule and the chain rule,

$$\frac{\partial^2 \Delta r}{\partial \alpha\, \partial q} = f'(\bar{p}) \frac{\partial \bar{p}}{\partial \alpha} - \Big(f(p_L) - f(p_H) \Big)$$
$$= (p_L - p_H)\, f'(\bar{p}) - \Big(f(p_L) - f(p_H) \Big). \tag{19}$$

Substituting $f(p)$ and $f'(p)$ from (16)–(17) gives the closed form

$$\frac{\partial^2 \Delta r}{\partial \alpha\, \partial q} = (p_L - p_H)\, \frac{S + q\big(2B + \bar{p}S\big)}{I(1 - \bar{p}q)^3} - \left[\frac{B + p_L S}{I(1 - p_L q)^2} - \frac{B + p_H S}{I(1 - p_H q)^2} \right]. \tag{20}$$

Step 4: A convenient sign characterization. Rearranging (19) yields the equivalent condition

$$\frac{\partial^2 \Delta r}{\partial \alpha\, \partial q} > 0 \quad \Longleftrightarrow \quad f'(\bar{p}) > \frac{f(p_L) - f(p_H)}{p_L - p_H}. \tag{21}$$

Thus the cross-partial is positive if and only if the marginal sensitivity $f'(\bar{p})$ evaluated at the pooled default probability $\bar{p}$ exceeds the secant slope of $f(\cdot)$ between p_H and p_L. This completes the proof.

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