# Central Clearing, Counterparty Risk, and Repo Specialness *


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**Abstract**

European repo transactions clear bilaterally (OTC) or through central counterparties (CCPs). Using transaction-level data from the euro-area repo market, we document that borrowing costs for identical securities are systematically higher in OTC trades than in CCP-cleared trades, and that this differential compresses sharply during the March 2020 COVID-19 shock. We develop a model in which repo rates are convex in borrower risk. Because OTC markets price borrower-specific risk while CCPs pool counterparties, this convexity generates the level gap and its compression under stress. The model further predicts that compression is weaker for riskier borrowers and stronger for higher-quality collateral, which we confirm empirically.



**Keywords:** Repo markets, Central clearing, Counterparty risk, Collateral scarcity, Asymmetric information

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# 1 Introduction

Repurchase agreements (repos) are the primary mechanism through which market participants obtain cash and borrow securities, and represent a core component of modern financial markets (BIS 2017). In security-driven reverse repos, agents obtain specific collateral to support short selling, meet delivery obligations, or manage margin requirements. The interest rates on reverse repos reflect the scarcity value ("specialness") of the underlying asset. A central puzzle is that identical securities command different borrowing costs depending on the clearing arrangement. In the European repo market, reverse repos are cleared either bilaterally over-the-counter (OTC) or through central counterparties (CCPs). Despite involving the same collateral and transaction terms, borrowing costs are typically larger in bilateral trades than in CCP-cleared trades, and this CCP–OTC differential compresses during periods of market stress.

Understanding this difference is increasingly important as policymakers expand central clearing in repo markets, particularly in the United States (U.S. Securities and Exchange Commission 2023), and given the vulnerability of repo markets during episodes of stress such as the Global Financial Crisis, the September 2019 turmoil, and the COVID-19 shock (Brunnermeier 2009, Mancini et al. 2016, Infante & Saravay 2020, Tilford et al. 2019, Duffie 2020*b*). This paper proposes a mechanism linking clearing structure to repo pricing. In OTC markets, lenders observe borrower identity and price counterparty risk at the individual level, while CCPs pool counterparty risk across participants. Because repo rates are non-linear in borrower risk, averaging borrower-specific prices (OTC) differs from pricing the pooled borrower (CCP), generating systematic differences in borrowing costs across clearing arrangements.

Using transaction-level data from the euro-area interbank repo market, we document two novel empirical facts. First, for the same securities, average repo rates in bilateral OTC transactions are more negative than those in CCP-cleared trades, implying higher security borrowing cost. Second, this CCP–OTC rate differential compresses sharply during the onset of the COVID-19 pandemic in March 2020[1]. Importantly, we document that there is no change in borrower risk composition between CCP and OTC markets during this period, which could explain this phenomenon.

The empirical facts are difficult to reconcile with existing explanations of repo pricing. Standard models of specialness emphasize collateral scarcity and search frictions but abstract from

[1]The outbreak of the COVID-19 pandemic provides an exogenous shock for a period in which detailed transaction level data is available.

counterparty risk and therefore do not explain differences in prices across markets. 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 mechanism linking 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. Each borrower therefore 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, exposures are novated to the clearinghouse and defaults are mutualized through a default fund. Counterparty risk is therefore pooled across market participants, and pricing reflects the risk of the average borrower in the clearing pool rather than the risk of individual borrowers. The key mechanism is that repo pricing is convex in borrower risk, so averaging borrower-specific prices (OTC) differs from pricing the average borrower (CCP).

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. In the model, the repo rate is determined by the lender's break-even condition, which implies that the equilibrium repo rate is a non-linear function of borrower and collateral risk. As a result, averaging borrower-specific prices differs from pricing the pooled borrower whenever borrower risk is heterogeneous. This distinction generates a CCP–OTC differential in specialness: bilateral markets produce more negative average repo rates than CCP markets even when the underlying securities are identical.

The model delivers novel cross-sectional predictions that allow us to test the proposed mechanism. The compression of the CCP–OTC differential varies systematically with both borrower risk and collateral quality. First, the compression is weaker for riskier borrowers, who benefit more from counterparty-risk pooling in CCP markets. Second, the compression is stronger for high-quality collateral, whose scarcity value becomes more important for repo pricing when borrower-specific risk is pooled.

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 substantial share of the secured euro money market. Our empirical strategy exploits within-security comparisons across clearing venues around the World Health Organization's pandemic announcement on 11 March 2020, a period characterized by sharp increases in bank CDS spreads and financial market uncertainty but preceding major policy interventions.

Our empirical results support the mechanism proposed by the model. In normal times, special securities trade at significantly more negative rates in bilateral OTC markets than in CCP-cleared markets, generating a negative CCP–OTC differential. Following the COVID-19 uncertainty shock, this differential compresses markedly. Consistent with the model's cross-sectional implications, the compression is weaker for riskier borrowers and stronger for high-quality collateral.

Our granular dataset allows us to control for a wide variety of factors which could influence repo rates, including trade volume, haircut, tenor or the quality of collateral. Our findings remain unchanged when our empirical specifications are saturated with varying set of fixed effects and remain stable even when controlling for the changes in actual and perceived borrowers risk using borrower-transaction day fixed effects. Several additional analyses and sensitivity tests further support the validity and robustness of our results. Importantly, dynamic estimations refute the possibility that repo rates adjusted prior to the WHO announcement and the use of alternative measures of collateral quality yield results consistent with baseline specifications.

Overall, our findings show that clearing arrangements shape the pricing of both counterparty risk and scarce collateral in repo markets. In normal times, special securities trade at more negative rates in bilateral markets than in CCP-cleared markets, reflecting the pricing of borrower-specific risk in OTC transactions. When counterparty uncertainty increases, the CCP–OTC differential compresses because CCP clearing pools counterparty risk while bilateral markets price borrowers individually. Consistent with this mechanism, the compression varies systematically across borrowers and collateral: it is weaker for riskier borrowers and stronger for high-quality collateral. 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. These results have direct implications for ongoing policy initiatives to expand central clearing in repo markets, particularly in the United States, by highlighting that greater central clearing not only affects market resilience but also alters the pricing of collateral and the transmission of counterparty risk across market participants.

**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. 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 counterparty pooling in centrally cleared markets affects 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 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.

The remainder of the paper is organized as follows. Section 2 describes the institutional setting and presents the key stylized facts. Section 3 develops the model. Section 4 describes the dataset and the identification of security-driven repos. Section 5 outlines the empirical strategy. Section 6 presents the results, and Section 7 concludes.

## 2 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.

### 2.1 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.[2] 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]

## 2.2 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 are negotiated and settled bilaterally, and counterparties are identified. Counterparty risk is therefore priced at the borrower level through the repo rate and haircut.[3] In CCP markets, transactions are 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.

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

[3] 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).

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.

### 2.3 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.

[Insert Figure 2 here]

We phrase the rationale for borrowing the security in terms of short selling, but alternative motives are borrowing the security to answer to variation margins or margin calls in swap contracts or to lend out the security to a client.

### 2.4 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 empirical facts emerge:

1. Rates are negative.
2. 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.
3. The CCP–OTC differential compresses sharply following the WHO announcement. While collateral borrowing costs remain (fairly) stable in OTC markets, they increase in CCP markets, causing the difference between CCP and OTC rates to narrow.

[Insert Figure 3 here]

To highlight that the main effect of market conditions goes through prices we document, in Figure 4, that volumes remain stable over the sample period and, in Figure 5, that there is no change in composition in borrower quality, in terms of CDS spreads, between CCP and OTC.

[Insert Figure 4 here]

[Insert Figure 5 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.

# 3 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 2. 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.

## 3.1 Environment and mapping to repo institutions

There are $M < \infty$ security borrowers and $N < \infty$ security lenders. Borrowers seek to borrow a security against cash collateral. This corresponds to reverse repo as defined in Section 2: 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 $j \in [1, \dots, M]$ 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 high collateral outcomes corresponds to a decrease in short sale profitability.

**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) reflecting the empirical observation, in Figure 4, that venue differences in haircuts are stable in the time window of interest.

**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 $\delta E_0$, 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 $\alpha$ as a parameter measuring the composition of borrower types. We do not index $\alpha$ with the trading venue because we document in Figure 5 that there is no relative change in composition between OTC and CCP.

### 3.2 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.

### 3.3 Payoffs and timeline

Figure 6 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 6 here]

Figure 7 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 7 here]

### 3.4 OTC contracting with observable borrower identity

We first consider bilateral OTC contracting, where the lender can condition on borrower identity. 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,

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

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 $r^i I$, yielding $E_1 + r^i I$. 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 $\underline{E} + r^i I) + qI$.

The right-hand side of (2) captures the lender's outside option: retaining the security on balance sheet and deriving its shadow value $\delta E_0$. 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 Table 1), the OTC rate is pinned down by the lender break-even condition[4]:

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

Equation (3) implies that repo rates depend on two forces. First, the numerator contains the wedge between the shadow value of holding the security ($\delta E_0$) and the lender's state-contingent recovery values when the security is encumbered. Second, the denominator scales by expected retention of cash collateral, $(1-p_i q)I$, so the rate becomes *non-linear* in borrower risk $p_i$ when default interacts with collateral states. This non-linearity is central: it will make the average of bilateral prices differ from pooled CCP pricing.

### 3.5 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

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

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

Since a fraction $\alpha$ 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*

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

***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*

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

Using the first empirical fact, negative repo rates, allows us to calibrate the model's parameters in Lemma 1.

### 3.6 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 maintain this convention throughout. All proofs are in Appendix A.

Propositions 1 and 2 characterize, respectively, the level and the dynamic behaviour of the CCP–OTC differential. Together they account for the two stylized facts documented in Section 2: the systematic gap between OTC and CCP borrowing costs in normal times (Fact 2), and its compression around the COVID-19 uncertainty shock (Fact 3). Propositions 3 and 4 deliver novel cross-sectional predictions about how the uncertainty-induced compression varies with borrower and collateral characteristics; these are tested in Sections 6.2 and 6.3.

**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 $\Delta r$ is largest when (i) borrower heterogeneity is high (large $p_L - p_H$), (ii) the borrower pool is mixed (interior $\alpha$), and (iii) the opportunity cost of encumbering the security is large relative to the posted cash collateral ($\delta E_0 + (1-q)(\bar{E} - \underline{E}) - I$ 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 1 directly accounts for Fact 2 in Section 2: the systematic gap between OTC and CCP borrowing costs observed prior to the COVID-19 shock. Empirically, Proposition 1 corresponds to a negative coefficient on the CCP indicator in a regression of borrowing costs on the CCP dummy, conditional on security and time fixed effects. This is confirmed by the negative and significant coefficient on *CCP* reported in Column (1) of Table 2.

**Proposition 2** (Economic stress and uncertainty)**.** *Let $\alpha$ index perceived counterparty uncertainty. An increase in uncertainty compresses the CCP–OTC differential. 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 $\alpha$ 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 $\alpha$ 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 2 directly accounts for Fact 3 in Section 2: the sharp compression of the CCP–OTC differential following the WHO announcement. Empirically, we interpret the WHO pandemic announcement on 11 March 2020 as an exogenous increase in $\alpha$, consistent with the sharp rise in bank CDS spreads and safe-asset yields documented in Section 2. Proposition 2 therefore predicts a positive coefficient on the interaction *Covid* $\times$ *CCP* in Equation (8), capturing the differential increase in CCP borrowing costs relative to OTC after the shock. Table 2 confirms this prediction across all specifications.

**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 differential induced by higher uncertainty is attenuated. Given Assumption 5,*

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

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, 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 $\alpha$ 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).

Empirically, we proxy borrower risk using non-performing loan (NPL) ratios and CDS spreads. Proposition 3 predicts a negative coefficient on the triple interaction *Covid* $\times$ *CCP* $\times$ *QM* in Equation (9), where *QM* denotes the borrower-risk proxy. This prediction is tested in Section 5.2 and confirmed in Table 3.

**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 differential 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. 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).

Empirically, we proxy collateral quality using a dummy for government bonds issued by core euro-area countries (Germany, France, and the Netherlands). Proposition 4 predicts a positive coefficient on the triple interaction *Covid* × *CCP* × *SAFE* in Equation (9). This prediction is tested in Section 5.2 and confirmed in Table 4.

### 3.7 Summary and Empirical Implementation

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.

The empirical analysis is organized around the reconciliation–prediction structure of the model. Propositions 1 and 2 are consistency results: they account for the stylized facts in Section 2 and are tested in Section 5.1 using the baseline specification in Equation (8). Propositions 3 and 4 deliver novel cross-sectional predictions that are tested in Section 5.2. using the triple-interaction specifications in Equation (9).

# 4 Data

This section describes the transaction-level data, the sample construction, and the main variables used in the empirical analysis. We 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 3.7.

## 4.1 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. Reporting entities in MMSR are euro area banks which account for 79% of all transactions reported in MMSR. 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 (95%). 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.

### 4.2 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 3.7, 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 8) rose sharply around the announcement, indicating heightened counterparty and collateral risk.

To isolate the short-run pricing response, we focus on a 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.

### 4.3 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 (72% of all transactions), consistent with the institutional discussion in Section 2.

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 5.

### 4.4 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.

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.

Finally, most transactions in the sample use sovereign bonds as collateral. In CCP markets, almost all repos (99%) are backed by euro-area government bonds, while in OTC markets the share is lower (69%) 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.

## 5 Empirical Methodology

The model reconciles the empirical facts (Propositions 1 and 2) and delivers novel predictions for how the differential responds to changes in borrower and collateral quality (Propositions 3 and 4). This section implements the empirical strategy implied by the model and the mapping between theoretical objects and observables described in Section 3. We start by testing the empirical facts also in a regression analysis and then move to testing the novel empirical predictions. The main dependent variable is the absolute distance between repo rates and the deposit facility rate (DFR), introduced in Section 4.3. This distance captures the cost of borrowing the security: a larger distance from the DFR corresponds to higher borrowing costs for a given security and date. The empirical design exploits a window around the WHO announcement of Covid-19 as a global pandemic on 11 March 2020. As discussed in Section 2, this period is characterized by a sharp increase in counterparty uncertainty but precedes major policy interventions that could confound the estimates. Focusing on this window allows to isolate the information aggregation mechanism emphasized in the model. Structural features of clearing arrangements — such as default fund contributions, netting benefits, and the anonymity of CCP trading — are constant over this period. As a result, changes in the CCP–OTC differential are interpreted as responses to changes in perceived counterparty risk rather than to shifts in institutional features.

### 5.1 CCP–OTC differential and economic uncertainty

We confirm empirical facts 2 and 3 and the corresponding Propositions 1 and 2 also in a regression analysis by interacting a CCP venue indicator, $CCP_i$, with a time dummy, $Covid_t$, using the following specification:

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

Here, $d_{i,t}$ is the absolute distance-to-DFR of transaction $i$ on day $t$. The dummy variable $\text{Covid}_t$ equals one after 11 March 2020, and $\text{CCP}_i$ equals one if the transaction is centrally cleared. $X_{i,t}$ is a vector of transaction-level controls, including transaction volume, collateral sector, issuance country, collateral rating, haircut, and tenor. Empirically, the theoretical CCP–OTC differential $\Delta r$, in Proposition 1, is identified through the coefficient $\beta_2$ on the CCP dummy within a within-security, within-day design; the dependent variable $d_{i,t} = |r_{i,t} - DFR|$ is defined so that a positive $\beta_3$ on $Covid \times CCP$ corresponds to a compression of this differential following the uncertainty shock.

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 $\alpha$. 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. The coefficient of interest is $\beta_3$, which measures the change in borrowing costs on CCP platforms relative to OTC platforms after the uncertainty shock. According to Proposition 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.

### 5.2 Borrower and collateral quality

Propositions 3 and 4 predict that the compression of the CCP–OTC differential following the uncertainty shock is weaker for riskier borrowers and stronger for safe collateral. To test these predictions, we extend the baseline specification by introducing borrower and collateral quality measures (QM). We interact them with the venue and uncertainty indicators.

We estimate the following specification:

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

Here, $QM_{j,t}$ is a measure of borrower and collateral quality for borrower $j$ at time $t$ and for collateral $j$. For borrower quality we use two proxies; first, the borrower's non-performing loan (QM=NPL) ratio from supervisory data (quarterly, measured at 2019:Q4), and second, daily changes in the borrower's CDS spread (QM=CDS).

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. Proposition 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, $\beta_7$.

Proposition 4 states that the uncertainty-induced compression of the CCP–OTC differential is stronger for higher-quality collateral. To test this prediction, we proxy for collateral quality (QM=SAFE) with a dummy variable that takes value 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. Proposition 4 states that the CCP–OTC differential responds more strongly to the uncertainty shock for higher-quality collateral. In the regression, this corresponds to a positive coefficient on the triple interaction term, $\beta_7$.

### 5.3 Identification and interpretation

Across all specifications, identification relies on within-security and within-day variation across clearing venues around the exogenous uncertainty 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. In this framework, the estimated interaction coefficients provide direct empirical counterparts to the comparative statics in Propositions 2 to 4, allowing us to test how counterparty pooling in CCP markets affects the pricing of special collateral during periods of heightened uncertainty.

# 6 Main Results

Section 3 developed four propositions about how clearing arrangements affect reverse repo pricing. Propositions 1 and 2 are *consistency* results that account for the stylized facts in Section 2: a systematic level gap between OTC and CCP borrowing costs in normal times, and its compression when counterparty uncertainty rises. Propositions 3 and 4 deliver *novel cross-sectional* predictions about how this compression varies with borrower risk and collateral quality. We test all four propositions using the regression specifications in Section 5, relying on within-security, within-day variation across clearing venues around the WHO pandemic announcement.

## 6.1 The CCP–OTC Differential and Counterparty Uncertainty

We begin by testing the two baseline predictions. Proposition 1 states that in normal times the CCP rate exceeds the OTC rate ($\Delta r < 0$), so that special securities trade at more negative rates in OTC markets. In the specification of Equation (8), this prediction maps to a *negative* coefficient $\beta_2$ on the $CCP$ dummy. Proposition 2 states that an increase in counterparty uncertainty compresses this differential, i.e. $\partial \Delta r / \partial \alpha > 0$. Because we interpret the WHO announcement as an exogenous shock to $\alpha$, this maps to a *positive* coefficient $\beta_3$ on the $Covid \times CCP$ interaction.

Table 2 presents the results for the baseline specification in Equation (8). Column (1) shows results without controlling for transaction specific variable and fixed effects. Columns (2)–(5) include transaction controls and progressively richer fixed effects specifications.

**Level gap (Proposition 1).** In Column (1), the coefficient on the $CCP$ dummy is $-5.380$ bps and statistically significant, confirming that centrally cleared transactions carry lower borrowing costs than bilateral OTC transactions in normal times. The model rationalises this gap through the convexity of the lender's break-even rate in borrower risk: because bilateral lenders price each borrower individually, the market-wide OTC rate is the average of borrower-specific prices; under CCP clearing the price is set for the average borrower. Given convexity, *averaging prices* yields a more negative rate than *pricing the average*, generating the observed level gap. The result is consistent with Proposition 1 and confirms Stylized Fact 2.

**Compression under uncertainty (Proposition 2).** The key coefficient of interest is $\beta_3$ on $Covid \times CCP$. In Column (1) this equals 6.732 bps and is highly significant. In Columns (2)–(5), which sequentially add transaction controls, borrower, lender, ISIN, day, tenor, pair, and borrower×day fixed effects, the estimate remains positive, statistically significant, and economically stable, ranging between 5.9 and 6.2 bps. The positive sign implies that CCP borrowing costs *increase relative* to OTC costs after the shock—i.e. the CCP–OTC gap closes—consistent with Proposition 2.

The economic mechanism is as follows. The WHO announcement shifts lenders' beliefs toward a higher share of risky borrowers ($\uparrow \alpha$). In CCP markets, where counterparties risk is pooled. This belief shift is immediately reflected in the price of the average borrower: the pooled default probability $1 - m$ rises and the CCP rate adjusts upward. In bilateral OTC markets, lenders continue to condition on borrower identity; the average OTC rate reweights toward the rates of the riskier type, but because the distribution shifts, the relevant dispersion of types falls, reducing the convexity premium that drives OTC rates below CCP rates. The net result is a compression of the CCP–OTC differential, confirming Stylized Fact 3.

[Insert Table 2 here]

### 6.2 Heterogeneity by Borrower Quality

Proposition 3 delivers a novel cross-sectional prediction: the uncertainty-induced compression of the CCP–OTC differential is *weaker* when borrowers are riskier ($\partial^2 \Delta r / \partial\alpha\partial p_H < 0$ and $\partial^2 \Delta r / \partial\alpha\partial p_L < 0$). Intuitively, higher borrower risk steepens the curvature of the break-even rate in $p_i$, making identity-based OTC pricing more sensitive to borrower heterogeneity and therefore sustaining the OTC premium even when the pool composition shifts. Riskier borrowers benefit relatively more from counterparty pooling in CCP markets—their individual risk is partially diluted through anonymity, novation and default fund—so the CCP–OTC wedge compresses less. In the triple-interaction specification of Equation (9), this prediction maps to a *negative* coefficient $\beta_7$ on $Covid \times CCP \times QM$, where $QM$ represents borrower risk measures.

Table 3 reports the estimates, using the NPL ratio in Columns (1)–(5) and daily CDS spread changes in Columns (6)–(10).

**Baseline interaction.** Across all specifications, the coefficient on $Covid \times CCP$ remains positive and significant—at 8.979 bps in Column (1)—confirming the compression of the differential documented in Section 6.1.

**Triple interaction: NPL ratio.** The coefficient on $Covid \times CCP \times NPL\ ratio$ is negative and statistically significant across Columns (1)–(5), consistent with Proposition 3. Economically, a one-standard-deviation increase in the NPL ratio (approximately 130 bps) attenuates the uncertainty-induced increase in CCP borrowing costs by about 1 bps. This pattern reflects the model mechanism: riskier borrowers gain relatively more from the pooling of counterparty risk within the CCP default fund, so the differential between CCP and OTC pricing responds less to the uncertainty shock for these counterparties.

**Triple interaction: CDS spreads.** Columns (6)–(10) replace the NPL ratio with daily CDS spread changes, which provide a higher-frequency, market-based measure of borrower risk. The triple interaction coefficient remains negative and statistically significant across all specifications, confirming the robustness of the finding to the choice of borrower-risk proxy. The result is consistent with the interpretation that the market's real-time assessment of borrower credit quality—not only its balance-sheet fundamentals—governs the extent to which the CCP–OTC differential compresses under uncertainty.

Taken together, the results support Proposition 3: the uncertainty-induced compression of the CCP–OTC differential is heterogeneous in the cross section of borrower quality, with riskier borrowers experiencing a smaller relative increase in CCP borrowing costs after the shock.

[Insert Table 3 here]

### 6.3 Heterogeneity by Collateral Quality

Proposition 4 delivers the second novel cross-sectional prediction: the uncertainty-induced compression of the CCP–OTC differential is *stronger* for higher-quality collateral ($\partial^2 \Delta r / \partial \alpha \partial q > 0$, where a higher $q$ corresponds to collateral whose value is more likely to appreciate). The underlying mechanism is that high-quality collateral makes adverse collateral outcomes less likely and therefore raises the relative importance of counterparty pooling in determining CCP pricing: when the collateral is safe, the dominant source of lender risk is counterparty default, which is fully pooled in CCP markets. As a result, the shift in the borrower pool composition ($\uparrow \alpha$)

has a larger effect on CCP pricing for safer securities. In the triple-interaction specification of Equation (9), this maps to a *positive* coefficient $\beta_7$ on $Covid \times CCP \times SAFE$. Table 4 reports the results using a dummy for safe collateral—German, French, or Dutch government bonds—as the proxy for collateral quality $q$.

**Triple interaction: SAFE collateral.** The coefficient on $Covid \times CCP \times SAFE$ is positive and statistically significant across all specifications in Columns (1)–(5), with estimates ranging between 5.6 and 6.0 bps. This implies that, after the uncertainty shock, borrowing costs for safe securities rise more in CCP markets than for lower-quality collateral, compressing the CCP–OTC differential more strongly for high-quality bonds. The result is consistent with the model's prediction that collateral quality amplifies the effect of counterparty pooling on pricing during periods of stress.

Economically, the mechanism operates as follows. When counterparty uncertainty rises, the scarcity value of safe collateral increases and demand for safe securities intensifies. In CCP markets, this demand is priced through the pooled counterparty risk, making the CCP rate more responsive to changes in the composition of the borrower pool. In OTC markets, lenders continue to price borrower-specific risk, so the increase in demand for safe collateral is partially absorbed through type-specific rates rather than through a uniform price adjustment. The net effect is a stronger compression of the CCP–OTC differential for safe securities, consistent with Proposition 4.

[Insert Table 4 here]

### 6.4 Robustness

The empirical strategy in Section 5 relies on three identifying assumptions: (i) the absence of differential pre-trends between CCP and OTC markets prior to the shock, (ii) within-security and within-day comparisons that absorb time-invariant venue differences, and (iii) no compositional shifts in the set of trading counterparties that could confound the results. We assess each assumption in turn.

**Pre-trends (Assumption i).** We replace the *Covid* dummy in Equation (8) with a sequence of day indicators to obtain a dynamic event-study specification. Figure 9 plots the estimated

CCP differential over time. The coefficients are economically small and statistically insignificant in the days preceding the WHO announcement, supporting the parallel-trends assumption. Following the shock, the differential increases sharply, consistent with the baseline results in Table 2. The pattern holds for both security-driven and cash-driven transactions, with no significant pre-announcement dynamics in either segment.

**Alternative measure of collateral quality (Assumption ii).** We replace the $SAFE$ dummy with a continuous proxy for collateral quality and scarcity. We use the yield to maturity (YTM) of the collateral bond, where higher yields indicate lower quality. Table 5 shows a negative coefficient on $Covid \times CCP \times YTM$, confirming that the compression of the CCP–OTC differential is weaker for lower-quality collateral, consistent with Proposition 4 and with the results using the $SAFE$ indicator.

**Relationship lending (Assumption ii).** Persistent relationship-specific pricing in OTC markets could in principle confound the identification of counterparty-risk effects. To assess this, we follow Furfine (1999) and Bräuning & Fecht (2017) and construct three measures of bilateral trading intensity: the borrower preference index ($BPI$), the lender preference index ($LPI$), and a frequency-based relationship-lending measure ($RL$):

$$BPI_{i,j,T} = \frac{\sum_{t' \in T} y_{i,j,t'}}{\sum_{j'} \sum_{t' \in T} y_{i,j',t'}}, \qquad LPI_{i,j,T} = \frac{\sum_{t' \in T} y_{i,j,t'}}{\sum_{j'} \sum_{t' \in T} y_{j',i,t'}}, \qquad RL_{i,j,T} = \log\Big(1 + \sum_{t' \in T} \mathbf{1}[y_{i,j,t'} > 0]\Big)$$

Including these measures in the triple-interaction specifications does not materially affect the estimated interaction coefficients (Tables 6, 7, and 8). The results in Table 6 show that the effect of the borrower preference index weakens after the outbreak of COVID-19. This suggests that relationship-based borrowing becomes less important during the crisis. The reduction is stronger for centrally cleared transactions, indicating that the role of bilateral relationships declines more in CCP markets than in OTC markets. The main results are therefore not driven by relationship-specific pricing patterns in OTC markets, consistent with the interpretation of the CCP–OTC differential as a counterparty-risk pooling effect rather than a relationship effect.

**Collateral type (Assumption ii).** To rule out confounding factors for differences in collateral composition across venues, we restrict the sample to transactions backed exclusively by sovereign bonds. The results for the baseline specification (Table 9), the borrower-risk specifications (Tables 10 and 11), and the collateral-quality specification (Table 12) remain quantitatively and qualitatively unchanged. This confirms that the main findings are not driven by differences between sovereign and non-sovereign collateral.

**Matched trades (Assumption iii).** A potential concern is that the composition of counterparties differs across CCP and OTC markets in ways that correlate with the shock. Furthermore, results could be influenced by lender-quality characteristics in addition to borrower and collateral quality. By matching ultimate borrowing bank and lending bank pairs on OTC and CCP transaction, we can control for joint borrower and lender quality specific pricing. Because CCP transactions are anonymous in the MMSR data, we recover borrower–lender identities using transaction-level information on timing, volume, rate, haircut, and collateral ISIN to match the legs of CCP trades. We then re-estimate all main specifications on the matched sample. The estimated interaction coefficients remain stable and statistically significant (Tables 13–16), confirming that the results are not driven by compositional differences in counterparty pools or borrower-lender pair characteristics across trading venues.

**Summary.** Across all robustness exercises, the evidence consistently supports the four propositions: the CCP–OTC differential is negative in normal times, compresses following the uncertainty shock, and compresses less for riskier borrowers and compresses more for higher-quality collateral. These patterns are robust to the choice of fixed effects, borrower-risk proxies, collateral-quality measures, relationship controls, collateral type restrictions, and matched counterparty samples.

# 7 Conclusions

This paper studies how clearing arrangements affect the pricing of special collateral in repo markets. Using transaction-level data from the euro-area interbank repo market, we document two facts. First, for the same securities, borrowing costs are systematically higher in bilateral OTC trades than in CCP-cleared trades. Second, this CCP–OTC differential compresses sharply during the March 2020 COVID-19 shock.

We develop a model of security-driven repo in which repo rates are non-linear in borrower risk. In bilateral OTC markets, lenders observe borrower identity and price counterparty risk individually; in CCP markets, counterparties are pooled through anonymity, novation, and a default fund, so pricing reflects the risk of the average borrower. Because the lender's break-even rate is convex in borrower default risk, averaging borrower-specific prices in OTC markets yields more negative rates than pricing the pooled borrower in CCP markets. This aggregation mechanism reconciles both empirical facts: the systematic level gap between OTC and CCP borrowing costs in normal times, and its compression when counterparty uncertainty rises and the effective dispersion of borrower types declines.

Beyond reconciling these facts, the model delivers two novel cross-sectional predictions. First, the uncertainty-induced compression of the CCP–OTC differential is weaker for riskier borrowers, who benefit more from counterparty-risk pooling in CCP markets and whose higher default risk steepens the curvature of identity-based OTC pricing. Second, the compression is stronger for higher-quality collateral, for which adverse collateral outcomes are less likely and counterparty default therefore dominates lender risk, amplifying the response of pooled CCP pricing to shifts in borrower composition. We confirm both predictions in the data, using non-performing loan ratios, CDS spreads, and government-bond issuer quality as empirical proxies.

Our findings carry direct implications for ongoing policy initiatives to expand central clearing in repo markets, particularly the recent SEC mandate in the United States. By pooling counterparties, CCPs produce weaker specialness in normal times. During periods of heightened uncertainty, pooled CCP pricing absorbs the shift in perceived borrower composition, causing CCP borrowing costs to rise toward OTC levels and compressing the wedge between identity-based and pooled pricing. This compression highlights a channel through which expanding central clearing alters how counterparty risk is transmitted into the pricing of scarce collateral—an effect that policymakers should weigh when designing clearing mandates. More broadly, the results show that financial market infrastructure that aggregates counterparty risk does not merely affect market resilience; it systematically shapes the pricing of scarce assets and the functioning of collateral markets, with consequences for the scope of central clearing and the transmission of monetary policy.

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# A Proofs

## A.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 $\Delta r$ 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. □

## A.2 Proof of Proposition 2

From Proposition 1, write $\Delta r$ 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 $\Delta r$ with respect to $\alpha$ yields the expression:

$$\frac{\partial \Delta r}{\partial \alpha} = -(p_L - p_H)^2 q^2 (\delta E_0 + (1-q)(\bar{E} - \underline{E}) - I) \frac{(1-2\alpha)(1-p_H q) + \alpha^2 (p_L - p_H) q}{I(1-p_H q)(1-p_L q)(1-(1-m)q)^2}. \quad (10)$$

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. □

### A.3 Proof of Proposition 3

Differentiating (10) with respect to $p_H$ yields

$$\frac{\partial^2 \Delta r}{\partial\alpha\partial p_H} = -(p_L - p_H)q^2(\delta E_0 + (1-q)(\bar{E} - \underline{E}) - I) \times \frac{\alpha^3(p_L - p_H)^2 q^2 - 3\alpha^2(p_L - p_H)q(1 - p_H q) - 2(1 - p_H q)^2 + 4\alpha(1 - p_H q)^2}{I(1 - p_H q)^2(1 - (1 - m)q)^3}. \quad (11)$$

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 (10) with respect to $p_L$ yields

$$\begin{aligned}\frac{\partial^2 \Delta r}{\partial\alpha\partial p_L} =& -(p_H - p_L)q^2(\delta E_0 - I + (1-q)(\bar{E} - \underline{E})) \\ &\times \frac{1}{I(1 - p_L q)^2(1 - (1 - m)q)^3}\Big(\alpha^3(p_H - p_L)^2 q^2 + 3\alpha^2(p_H - p_L)q(1 - p_H q) \\ &+ \alpha(4 - q((6 - 3p_H q)p_H + (2 - p_L q)p_L) - (1 - p_H q)(2 - (p_H + p_L)q)\Big), \quad (12)\end{aligned}$$

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

### A.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

$$r(p) = \frac{\delta E_0 - (1-q)\underline{E} - q(1-p)\bar{E} - pqI}{(1 - pq)I}. \quad (13)$$

Define the constants

$$B := \underline{E} - \bar{E} < 0, \qquad S := \delta E_0 - \underline{E} + \bar{E} - I = \delta E_0 + (\bar{E} - \underline{E}) - I,$$

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

$$r(p) = \frac{(\delta E_0 - \underline{E}) + q\big(B + pS\big)}{(1 - pq)I}. \tag{14}$$

**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

$$\frac{\partial r}{\partial q}(p) = \frac{B + pS}{I(1 - pq)^2} =: f(p). \tag{15}$$

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

$$f'(p) = \frac{\partial}{\partial p}\left(\frac{B + pS}{I(1 - pq)^2}\right) = \frac{S + q\big(2B + pS\big)}{I(1 - pq)^3}. \tag{16}$$

**Step 2: Express $\Delta r$ 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 $\Delta r$ with respect to $q$:

$$\begin{aligned} \frac{\partial \Delta r}{\partial q} &= \frac{\partial r}{\partial q}(\bar{p}) - \alpha \frac{\partial r}{\partial q}(p_L) - (1 - \alpha)\frac{\partial r}{\partial q}(p_H) \\ &= f(\bar{p}) - \alpha f(p_L) - (1 - \alpha) f(p_H), \end{aligned} \tag{17}$$

where $f(\cdot)$ is defined in (15). Now differentiate (17) with respect to $\alpha$. Using the product rule and the chain rule,

$$\begin{aligned}\frac{\partial^2 \Delta r}{\partial\alpha\,\partial q} &= f'(\bar{p})\frac{\partial \bar{p}}{\partial \alpha} - \Big(f(p_L) - f(p_H)\Big) \\ &= (p_L - p_H)\, f'(\bar{p}) - \Big(f(p_L) - f(p_H)\Big). \end{aligned} \tag{18}$$

Substituting $f(p)$ and $f'(p)$ from (15)–(16) gives the closed form

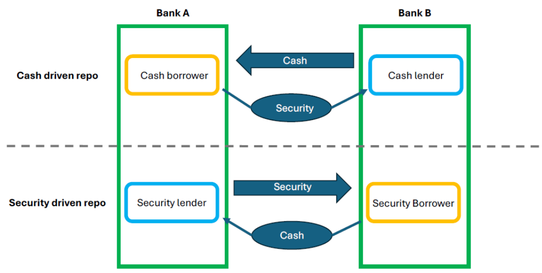
$$\frac{\partial^2 \Delta r}{\partial\alpha\,\partial q} = (p_L - p_H)\,\frac{S + q\big(2B + \bar{p}S\big)}{I(1-\bar{p}q)^3} - \left[\frac{B + p_L S}{I(1-p_L q)^2} - \frac{B + p_H S}{I(1-p_H q)^2}\right]. \tag{19}$$

**Step 4: A convenient sign characterization.** Rearranging (18) yields the equivalent condition

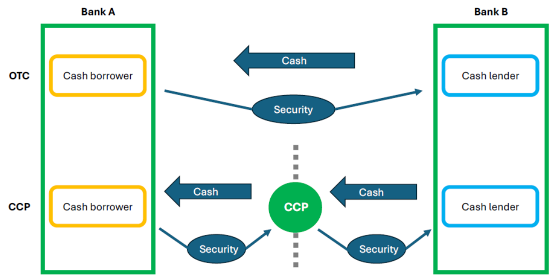
$$\frac{\partial^2 \Delta r}{\partial\alpha\,\partial q} > 0 \quad\Longleftrightarrow\quad f'(\bar{p}) > \frac{f(p_L) - f(p_H)}{p_L - p_H}. \tag{20}$$

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. □

# B 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 novate and clear a repo contract via a Central Limit Order Book (CLOB).

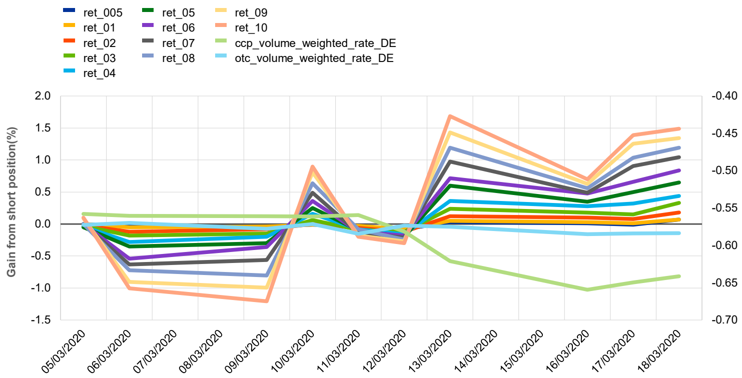



**Figure 2: Profits and losses derived from shorting bonds**. The sample ranges from March 5 2020 to March 18 2020 for German Bunds. Profits and losses are computed using daily yield curves from Deustche Bundesbank and transaction-by-transaction data from MMSR aggregated at the daily level, to compute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

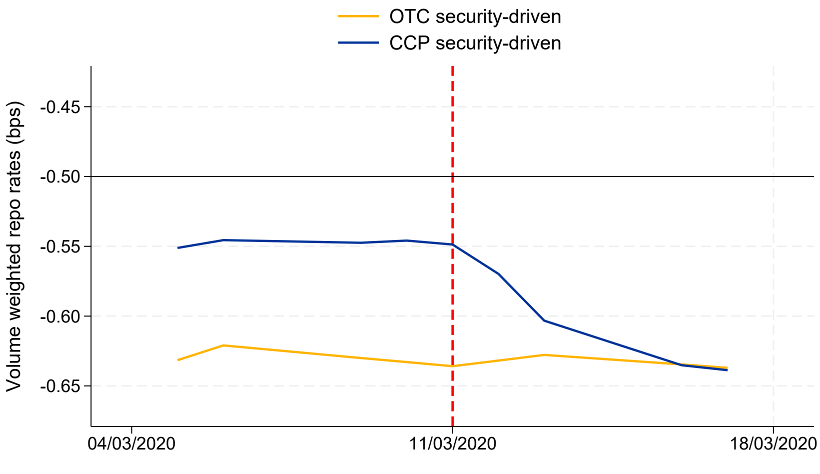



**Figure 3: Repo rates for security–driven transactions by market.** The figure represents the level of volume-weighted repo rates split by market venues (OTC and CCP) and trading motive (cash and security). Cash-driven trades occur at repo rates above the DFR. Security-driven trades occur at repo rates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

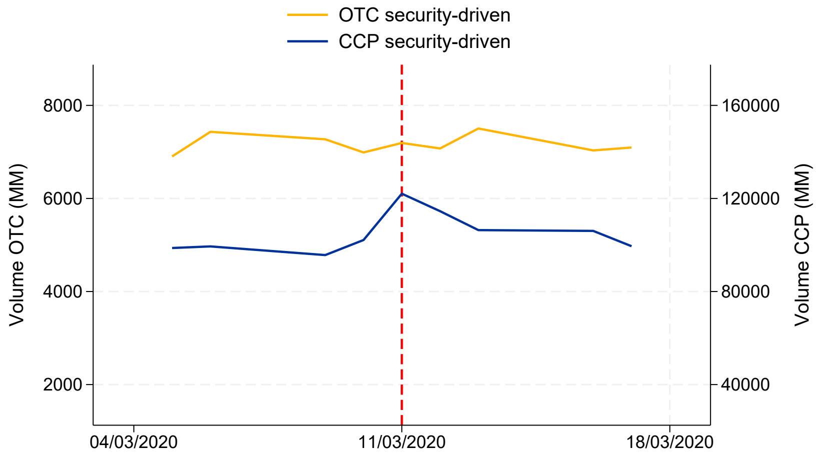



**Figure 4: Volume of repo transactions by market segment and trading motive.** Data is obtained from MMSR. The sample ranges from 5 to 18 March 2020. Trading motives arise for the cash (dashed lines) or securities (solid lines). Trades can be carried out in CCP–based markets (blue lines) or OTC (yellow lines).

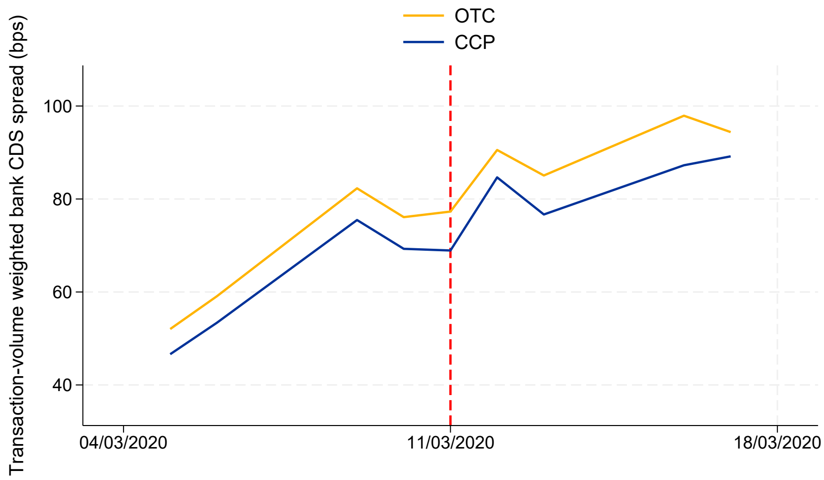



**Figure 5: Transaction-volume weighted credit default swaps of banks.** The sample ranges from 5 to 18 March 2020. Trades can be carried out in CCP–based markets (blue lines) or OTC (yellow lines). Repo transactions considered are security–driven transactions for the purpose of borrowing securities against cash–collateral.

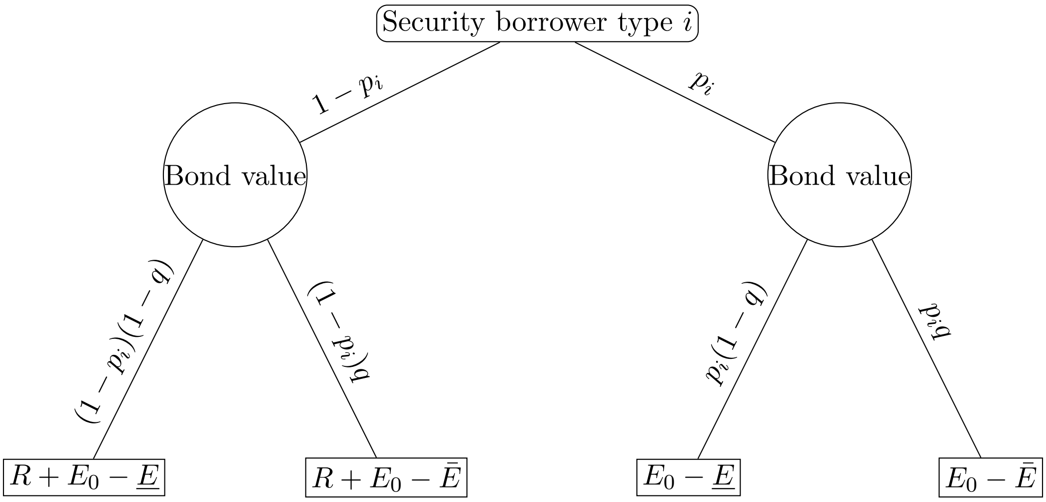



**Figure 6: Payoffs**

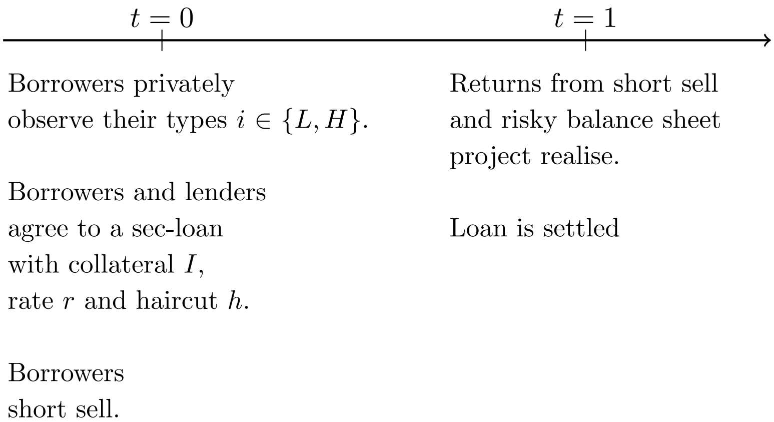



**Figure 7: Timeline**

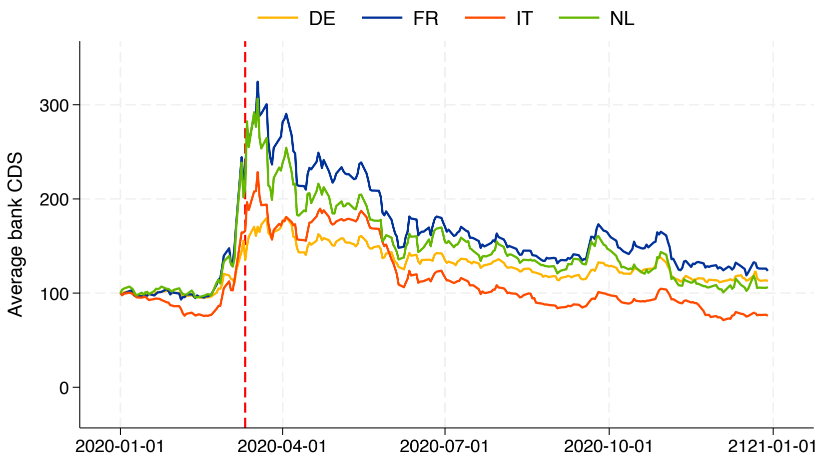



**Figure 8: Average bank credit default swap.** Data is obtained from Bloomberg. The sample ranges from January to December 2020.

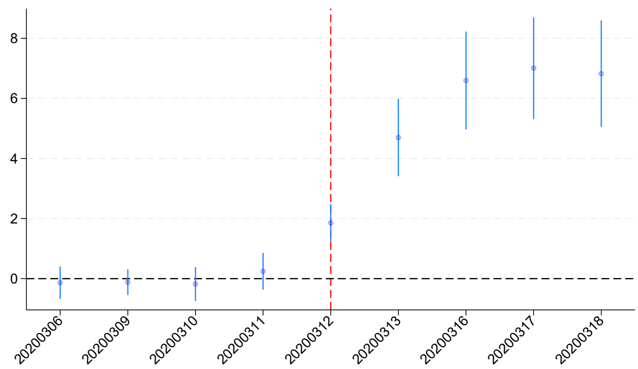



**Figure 9: Robustness checks.** Coefficients of the dynamic version of Equation (8).

# C Tables

| Summary statistics | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 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 |
| Haircuts | (bps) | -0.57 | 2.84 | -1.49 | -0.48 | -0.005 | 32787 | -1.37 | 3.57 | -2.99 | -0.89 | 0.23 | 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 |
| $\Delta$ 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. $\Delta$ 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) | $d_{i,t}$ (5) |
|---|---|---|---|---|---|
| Covid | 0.489 | 0.751*** | | | |
| | (0.359( | (0.237) | | | |
| CCP | -5.380*** | -5.403*** | | | |
| | (1.849) | (1.816) | | | |
| Covid×CCP | 6.732*** | 5.891*** | 6.189*** | 6.174*** | 5.857*** |
| | (0.541) | (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 | 16.80*** | 17.67*** | 12.45*** | 12.30*** | 12.56*** |
| | (1.454) | (1.468) | (0.177) | (0.110) | (0.165) |
| Observations | 43,918 | 40,371 | 41,457 | 41,447 | 41,452 |
| R-squared | 0.458 | 0.627 | 0.873 | 0.891 | 0.876 |
| Standard errors | Pair | Pair | Pair | Pair | Pair |
| Transaction controls | | Yes | Yes | Yes | 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)-(5) show results for the same specification using different combinations of transaction controls and 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) | $d_{i,t}$ (9) | $d_{i,t}$ (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Covid | -0.781 | -0.319 | | | | 0.224 | 0.699** | | | |
| | (0.792) | (0.488) | | | | (0.421) | (0.286) | | | |
| CCP | -7.484** | -5.981** | | | | -5.920*** | -6.098*** | | | |
| | (3.062) | (2.491) | | | | (2.018) | (2.064) | | | |
| Covid×CCP | 8.979*** | 7.757*** | 7.472*** | 7.289*** | 7.180*** | 7.735*** | 6.593*** | 6.866*** | 6.823*** | 6.646*** |
| | (1.004) | (0.692) | (0.478) | (0.489) | (0.448) | (0.609) | (0.433) | (0.340) | (0.334) | (0.276) |
| NPL ratio | -0.00805 | -0.00344 | | | | | | | | |
| | (0.00893) | (0.00739) | | | | | | | | |
| Covid×NPL ratio | 0.00557* | 0.00479** | 0.00175*** | 0.00109 | | | | | | |
| | (0.00327) | (0.00205) | (0.000613) | (0.000812) | | | | | | |
| CCP×NPL ratio | 0.00716 | 0.00185 | 0.00260 | | 0.00256 | | | | | |
| | (0.00878) | (0.00737) | (0.00711) | | (0.00709) | | | | | |
| Covid×CCP×NPL ratio | -0.0101** | -0.00839*** | -0.00589*** | -0.00516** | -0.00556*** | | | | | |
| | (0.00390) | (0.00310) | (0.00225) | (0.00231) | (0.00195) | | | | | |
| ΔCDS | | | | | | -0.0144 | -0.00553 | 0.0116 | 0.0145* | |
| | | | | | | (0.0243) | (0.0192) | (0.00816) | (0.00764) | |
| Covid×ΔCDS | | | | | | 0.0458** | 0.0188 | 0.0648*** | 0.0621*** | |
| | | | | | | (0.0189) | (0.0129) | (0.0162) | (0.0155) | |
| CCP×ΔCDS | | | | | | 0.00573 | 0.000163 | 0.00423 | 0.00170 | 0.00251 |
| | | | | | | (0.0258) | (0.0206) | (0.00555) | (0.00463) | (0.00421) |
| Covid×CCP×ΔCDS | | | | | | -0.160*** | -0.122*** | -0.108*** | -0.102*** | -0.103*** |
| | | | | | | (0.0267) | (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 | 18.97*** | 18.59*** | 11.87*** | 12.20*** | 12.12*** | 16.74*** | 17.58*** | 11.50*** | 11.40*** | 11.80*** |
| | (2.758) | (2.184) | (1.110) | (0.132) | (1.090) | (1.639) | (1.722) | (0.181) | (0.139) | (0.151) |
| Observations | 43,918 | 40,371 | 41,457 | 41,447 | 41,452 | 39,832 | 36,559 | 37,426 | 37,417 | 37,421 |
| R-squared | 0.459 | 0.628 | 0.873 | 0.891 | 0.876 | 0.467 | 0.634 | 0.875 | 0.886 | 0.877 |
| Transaction controls | | Yes | Yes | Yes | Yes | | Yes | Yes | 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. $\Delta CDS$ 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)-(5) and columns (6)-(10) show results for the same specification using different combinations of fixed effects for Borrower, Lender, Day, Collateral and Tenor, respectively.

| Variable | $d_{i,t}$ (1) | $d_{i,t}$ (2) | $d_{i,t}$ (3) | $d_{i,t}$ (4) | $d_{i,t}$ (5) |
|---|---|---|---|---|---|
| Covid | 0.775 | 0.794 | | | |
| | (0.669) | (0.663) | | | |
| CCP | -10.73*** | -9.724*** | | | |
| | (3.298) | (3.225) | | | |
| Covid×CCP | 2.402*** | 2.318*** | 3.180*** | 3.024*** | 2.706*** |
| | (0.789) | (0.793) | (0.404) | (0.390) | (0.365) |
| SAFE | | | -8.248 | -2.951 | -8.259 |
| | | | (5.788) | (2.196) | (5.726) |
| Covid×SAFE | -0.370 | -0.339 | 0.212 | -0.00855 | -0.0753 |
| | (0.952) | (0.943) | (0.181) | (0.189) | (0.209) |
| CCP×SAFE | 8.231*** | 7.928*** | -1.395 | -1.752 | -1.439 |
| | (2.507) | (2.472) | (3.397) | (2.611) | (3.400) |
| Covid×CCP×SAFE | 5.942*** | 5.993*** | 5.670*** | 5.897*** | 5.871*** |
| | (1.112) | (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 | 16.62*** | 18.49*** | 33.69*** | 30.68*** | 33.91*** |
| | (1.910) | (1.861) | (3.243) | (0.714) | (3.198) |
| Observations | 43,918 | 43,918 | 47,500 | 47,494 | 47,495 |
| R-squared | 0.469 | 0.476 | 0.954 | 0.955 | 0.954 |
| Transaction controls | | Yes | Yes | Yes | 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 (9). 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)-(5) show results for the same specification using different combinations of transaction controls and 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 | Yes | Yes | 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: Alternatives collateral quality: yield-to-maturity.** The table shows results for the estimation of Equation (9), 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 | 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 | Yes | Yes | 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 6: 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 | Yes | Yes | 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: 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 | Yes | Yes | 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: 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 | Yes | Yes | 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: 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 | Yes | Yes | 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 - 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. 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 | Yes | Yes | 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 differences in CDS prices on a sample of repo transactions using only government issued securities. 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 | Yes | Yes | 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 - Collateral quality.** The table shows regression results for Equation (9) to test for collateral quality via the SAFE dummy on a sample of repo transactions using only government issued securities. Table 2 for the definition of variables and interpretation of the coefficients.

# Internet Appendix

| 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 | Yes | Yes | 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 - Economic uncertainty (2).** The table shows regression results for Equation (8) using a sample of matched pairs of banks. 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 | Yes | Yes | 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 - Counterparty quality (2).** The table shows regression results for Equation (8) using a sample of matched pairs of banks. 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 | Yes | Yes | 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) to test for borrower quality via differences in CDS prices on a sample of matched pairs of banks. 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 | Yes | Yes | 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 - Collateral quality (2).** The table shows regression results for Equation (9) to test for collateral quality via the SAFE dummy on a sample of matched pairs of banks. Table 2 for the definition of variables and interpretation of the coefficients.