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RESEARCH ARTICLE

The man in the middle—liquidity provision under central clearing in the credit default swap market: A regression discontinuity approach

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Abstract

In this study, I analyze the effect of central clearing on credit default swap (CDS) market breadth, depth, and resiliency using a regression discontinuity design. I find evidence for a decrease in absolute bid–ask spreads and bid–ask spread resiliency and an increase in gross trading volume with the beginning of central clearing. However, we observe positive effects of central clearing on CDS market liquidity only for CDS contracts of high fundamental and liquidity risk. Further results indicate that lower trading frictions, that is, counterparty risk and regulatory capital charges, may explain the positive effects of central clearing on CDS market liquidity.

KEYWORDS

central clearing, credit default swaps, market liquidity, regression discontinuity

JEL CLASSIFICATION

G12, G15, G18, G23, G28

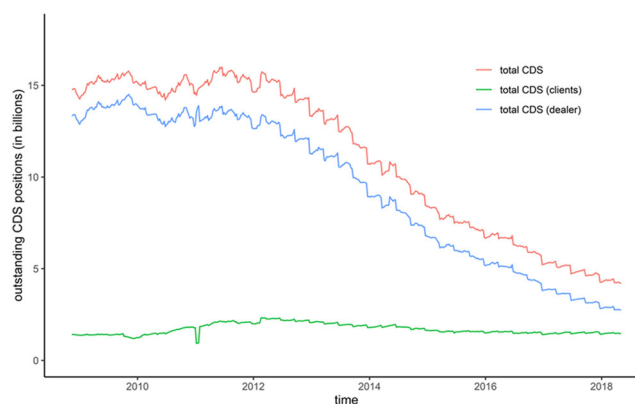
1 | INTRODUCTION

The purpose of this paper is to explore the effect of voluntary central clearing in the market liquidity of Credit Default Swaps (CDSs). Centrally cleared trades differ from bilaterally cleared trades with respect to clearing fees, margin requirements, regulatory capital charges, netting opportunities, and post-trade transparency. These differences may in turn affect order-processing costs, inventory costs, and adverse selection in the market. As a consequence, CDS dealers may adjust transaction costs (market tightness), the capacity to trade large orders (market depth), and the continuous provision of liquidity (market resiliency) for centrally cleared trades. This study examines the effect of the possibility of CDS central clearing on these three liquidity dimensions and attributes this effect to groups of contracts with different risk characteristics and to different economic channels. As a first contribution of this paper, it provides evidence that central clearing eligibility does not affect all dimensions of market liquidity in a similar way. While market tightness and market depth seem to increase with the beginning of central clearing, market resiliency seems to decrease in terms of bid–ask spreads. To the best of my knowledge, previous studies only focus on market tightness and market depth (Akari et al., 2019; Loon & Zhong, 2014; Silva et al., 2018; Slive et al., 2012). The dimension of market resiliency, however, may be of particular relevance for assessing the potential of a central counterparty (CCP) to make the CDS market more robust in

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FIGURE 1 Time series of aggregate CDS gross positions from 2009 to 2018. This figure shows the time series of total CDS gross positions (red), dealers' CDS gross positions (blue), and clients' CDS gross positions (green). Time series are displayed in billion USD notional value. CDS, credit default swap



times of stress when market liquidity needs to be replenished within a short period of time. The second contribution of this paper is that I find central clearing to exhibit the most pronounced positive effects on market liquidity for CDS contracts of high fundamental and liquidity risk. As a third contribution, my results suggest counterparty risk and inventory risk to be economic channels through which central clearing affects CDS market liquidity. The fourth contribution of this study is of methodological nature: I use a regression discontinuity design (RDD) as the main empirical model, as it is particularly suitable to tackle endogeneity problems associated with the nonrandom selection of CDS contracts and transactions for central clearing by CCPs and market participants. To the best of my knowledge, an RDD has not been used so far for this study question, so that it expands the range of econometric techniques within this strand of literature.

The effect of central clearing on CDS market liquidity is relevant due to the effect of market liquidity on financial stability and price efficiency. Figure 1 shows clearly that CDS dealers have withdrawn from the CDS market since the onset of the financial crisis.¹ This may have different negative implications: first, reduced liquidity provision in the CDS market may lead to a divergence between CDS premium and fundamental value of CDS contracts and affect investment or risk management decisions that are based on CDS premia as proxy for credit risk (Arakelyan & Serrano, 2016; Bongaerts et al., 2011; Tang & Yan, 2007). Second, it remains unclear in this scenario, whether the CDS market can continue to keep its leading role in price discovery and price efficiency compared with the corporate bond market (Blanco et al., 2005; Norden & Weber, 2004; Zhu, 2006). Third, market liquidity is important for the risk management of CCPs, since the replacement of open positions of defaulting clearing members may incur high trading costs if market liquidity is low.

Figure 1 indicates that the financial crisis has triggered an increase in risk aversion of CDS market participants towards the underlying risk sources of CDS contracts: fundamental risk, liquidity risk, and counterparty risk. This increasing risk aversion may explain the shift from corporate CDS contracts to sovereign CDS contracts and the shift from bilateral clearing to central clearing on the CDS market (Aldasoro & Ehlers, 2018). A very well-capitalized CCP that guarantees contractual payments at all times may restore the trust of market participants in the CDS market and encourage trading activity also for riskier contracts. Indeed, I find central clearing to exhibit the most pronounced positive effects on market liquidity for CDS contracts of high fundamental and liquidity risk. This is plausible, since contracts of low market liquidity and high fundamental risk require more complex valuation techniques in comparison to the liquid end of the spectrum of derivatives contracts.

My results suggest counterparty risk and inventory risk to be economic channels through which central clearing affects measures of CDS market liquidity to a statistically and economically significant extent. As a potential driver of inventory costs, I examine regulatory capital charges. I find lower regulatory capital charges for centrally cleared positions to exhibit a considerable negative (positive) effect on inventory costs (CDS market liquidity).

As a response to the financial crisis, the leaders of the G20 nations agreed in 2009 to foster central clearing of previously bilaterally cleared over-the-counter derivatives. In the United States and EU, only a few CDS index products are mandated for central clearing, but an increasing number of single-name CDSs have been made eligible for central clearing in recent years. Akari et al. (2019) show that the results on the impact of central clearing in the market liquidity of single-name CDS are highly sensitive to the chosen methodological approach. One reason may be that the

¹Increased use of trade compression may partly explain the decrease in gross positions. We see, however, a very similar development for net positions.

endogeneity problem in this study question is twofold: first, the selection of CDS contracts for clearing eligibility by CCPs is not random. The probability of a CDS contract to be selected for central clearing is positively affected by market liquidity and trading activity and negatively affected by the default probability of the reference entity (Loon & Zhong, 2014; Silva et al., 2018; Slive et al., 2012). High trading volume offer economies of scales for the CCP and low liquidity risk and fundamental risk minimize the probability of risk management failures. Once voluntary central clearing is introduced, a second endogeneity issue emerges: market participants tend to clear CDS contracts of low liquidity risk rather bilaterally and CDS contracts of higher liquidity risk rather centrally (Bellia et al., 2018). To tackle these endogeneity issues, I use an RDD. An RDD allows me to capture the endogenous relationship between treatment effect and outcome variable by including an event time trend that can take different functional forms before and after the treatment occurs. These dynamic features make an RDD more flexible and suitable to tackle the endogeneity problem than static matching approaches (as in Loon & Zhong, 2014; Silva et al., 2018; or Slive et al., 2012) or pure fixed effects models (Akari et al., 2019). Furthermore, an RDD allows me to use the staggered admission to central clearing of many single-name CDS contracts over time as clean empirical identification strategy. To the best of my knowledge, an RDD has not so far been used for examining the impact of central clearing on CDS market liquidity.

I use a panel data set with time series of weekly bid–ask spreads, CDS premia, and weekly trading volume for clearing eligible CDS contracts on 100 different reference entities. The observation period reaches from 2009 to 2017. To provide a more comparable measure of market liquidity across contracts, I calculate relative bid–ask spreads by taking the ratio between the absolute bid–ask spread and the corresponding CDS premium. As proxies for market depth, I use gross and net trading volume from Trade Information Warehouse (TIW) reports of the Depository Trust & Clearing Corporation (DTCC). I proxy the resiliency of CDS spreads and bid–ask spreads by regressing their first differences on their levels in a rolling regression on a daily basis. The coefficient of the lagged level variable indicates to what extent past liquidity shocks affect liquidity provision in the next period.

From the findings provided in this study, we can infer different economic implications. In line with the literature, dealers seem to compete more aggressively for order flow with the beginning of central clearing eligibility by posting narrower bid–ask spreads (Loon & Zhong, 2014; Mayordomo & Posch, 2016; Slive et al., 2012). Since I find counterparty risk to play a smaller role for determining market liquidity with the introduction of central clearing, the increase in CDS market liquidity may be attributable to a higher activity of high-risk dealers (Mayordomo & Posch, 2016). This increasing competition for order flow in centrally cleared markets and subsequent lower profits per trade for dealers may incentivize dealers to generate higher trading volumes to keep total revenues from liquidity provision stable. Furthermore, dealers seem to increase liquidity provision for high-risk contracts. This is plausible, as high-risk and illiquid contracts are more complex in terms of valuation and risk management. The results imply that the option to trade with an arguably very creditworthy CCP that focuses only on risk management without any other trading motives, may be of particular value to market participants for contracts with an elevated risk profile. The negative effect on bid–ask spread resiliency and partly price resiliency, however, questions, how robust the increase in liquidity provision is. Higher collateral demand may cause collateral shortage in the course of demand surges for CDS protection and prevent subsequent liquidity provision so that it takes market liquidity and prices longer to revert to former levels.

2 | LITERATURE REVIEW

The economic hypotheses about the effect of central clearing on market liquidity are not straightforward. Changes in order-processing costs, inventory costs, and adverse selection due to the introduction of central clearing may positively or negatively affect market liquidity.²

First, additional explicit costs like clearing fees of CCPs may generally increase bid–ask spreads and decrease trading volumes (M. Aitken et al., 2017; Demsetz, 1968; Domowitz et al., 2001) but can also foster dealer competition and decrease bid–ask spreads (Degryse et al., 2017, 2016). In contrast to bilateral trading agreements, CCPs require clearing fees for every trade as compensation for the provision of clearing and settlement services. Higher clearing fees decrease the profits of dealers for providing liquidity. As a result, dealers may widen bid–ask spreads to remain constant in profits per trade. Existing studies estimate that order-processing costs (e.g., clearing fees) make up between

²Figure A.1 from the Supporting Information illustrates the potential effects of central clearing on CDS market liquidity and their economic channels.

30% and 60% of the bid–ask spread (Glosten & Harris, 1988; Shang et al., 2018; Stoll, 1989). Consequently, dealers may respond to higher-order-processing costs for centrally cleared trades by widening bid–ask spreads. This may decrease both the attractiveness of the CDS market for end-users and trading activity. Indeed, Degryse et al. (2017) show that clearing fees affect transaction costs positively.

Second, the liquidity provision of dealers can change if central clearing alters inventory costs. Inventory costs may change under central clearing due to a change in margin requirements, netting efficiency, and regulatory capital charges. CCPs may require more collateral due to their stricter risk management standards compared with bilateral clearing (Aitken & Singh, 2009; Brunnermeier & Pedersen, 2009; Duffie et al., 2015; Heller & Vause, 2012; Sidanius & Zikes, 2012; Singh, 2010). Higher collateral requirements tighten funding constraints of dealers and increase bid–ask spreads and decrease market depth and resiliency through lower liquidity provision of dealers (Brunnermeier & Pedersen, 2009; Heller & Vause, 2012; Singh, 2010). However, lower overall gross positions through increased netting opportunities of CCPs (Cont & Kokholm, 2014; Duffie & Zhu, 2011; Singh, 2010), and lower regulatory capital charges for centrally cleared trades can make inventory management more efficient and decrease inventory constraints of dealers (Hasan & Wu, 2016; Minton et al., 2009; Shan et al., 2017). This may increase the willingness of dealers to provide liquidity and allow dealers to absorb liquidity shocks faster so that markets become deeper and more resilient. However, the voluntary nature of single-name CDS central clearing makes collateral demand to depend on parameters that are unknown *ex-ante*: cleared trading volume, number of clearing members, pre-clearing dealer diversification, number of clearing eligible contracts, and number of CCPs in the market (Duffie et al., 2015; Heller & Vause, 2012). This is why the effect of central clearing on market liquidity is inherently an empirical question.

Third, central clearing may change the role of counterparty risk in the pricing of CDS contracts by CDS dealers. A high default probability of the protection seller impairs the value of the protection sold (Arora et al., 2012; Du et al., 2019; Loon & Zhong, 2014). Dealers may reflect their potentially incomplete knowledge about the default risk of their transaction partners in larger bid–ask spreads. Furthermore, low-risk dealers seem to have a competitive advantage and get compensated for their high creditworthiness (Du et al., 2019). If counterparty risk considerations become obsolete under central clearing due to the high creditworthiness of the CCP, bid–ask spreads may decrease due to a lower pricing consequence of counterparty risk and due to higher competition for order flow between low-risk and high-risk dealers (Loon & Zhong, 2014; Mayordomo & Posch, 2016; Slive et al., 2012).

Last, central clearing can affect market liquidity through its impact on post-trade transparency. Post-trade transparency has been shown to affect market liquidity on corporate bond and CDS markets (Bessembinder & Maxwell, 2008; Edwards et al., 2007; Goldstein et al., 2007; Loon & Zhong, 2016). The dominating CCP in the market for CDS, ICE Clear Credit, publishes trading volume, open interest and settlement prices on a daily level for its cleared contracts for the last 6 months. This higher level of post-trade transparency may allow market participants to infer more information on supply and demand in the CDS market and to narrow bid–ask spreads accordingly. Informed traders, however, may refrain from CDS trading if they see information advantages disappear with increasing market transparency. This may negatively affect market liquidity and price efficiency (Bloomfield & O'Hara, 1999; Lin, 2016; Pagano & Roell, 1996).

3 | DATA AND SAMPLE CREATION

I create my sample of CDS contracts by collecting all clearing eligibility dates for CDS contracts from the dominant CCP for CDS, ICE Clear Credit. ICE accounts for roughly 90% of all centrally cleared transactions in CDS with US reference entities as underlyings (CLARUS, 2019) and uses to make all relevant tenors (0–10 years) for the same reference entity eligible for central clearing on the same date.

For gathering CDS trading volume, I use the weekly TIW reports of the DTCC between November 2008 and December 2017 that capture aggregate data on the top 1000 reference entities in terms of outstanding CDS positions and trading volume and reflect 98% of all globally executed single-name CDS transactions (DTCC, 2019). This type of DTCC data only reports CDS positions or trading volume aggregated on the level of the reference entity irrespective of specific contract characteristics (e.g., maturity), which matches the clearing eligibility procedure of the ICE that affects almost all tenors as well. Therefore, clearing eligibility in my empirical setting refers to nearly all contract types that are contained in the aggregate trading volume variables provided by the DTCC. The weekly TIW reports allow me to collect two direct measures of CDS market depth: CDS gross trading volume and net trading volume.

I measure CDS market tightness by the absolute bid–ask spreads and relative bid–ask spreads (percentage spreads). As discussed above, gross and net trading volume in the TIW reports are not reported by tenor, so that the choice of the

tenor for the CDS spread variables must be grounded in economic reason. It is widely reported that the 5-year tenor is the most traded and most liquid type of CDS contract. Empirical evidence suggests that the 5-year tenor makes up more than 50% of all CDS trades for one particular reference entity so that the effect of the introduction of central clearing is highest for this type of CDS contract (Chen et al., 2011). Therefore, I use bid–ask spreads and mid quotes of CDS contracts with a maturity of 5 years. I then compute daily relative bid–ask spreads as the ratio of the absolute bid–ask spread and the CDS mid quote.

$$pct_spread_{i,t} = \frac{ba_spread_{i,t}}{cds_mid_{i,t}}. \quad (1)$$

I collapse all three variables to weekly frequency by taking their daily average for every week to match them to the weekly trading volume data from the TIW reports.³

I compute two different measures of market resiliency to examine how fast prices and market liquidity revert to former levels after deviations from these levels occur. For this purpose, I regress the change in CDS mid quotes and the change in market liquidity from $t - 1$ to t on the level of prices and market liquidity in $t - 1$ with t denoting the current day of observation (Black et al., 2016; Kempf et al., 2015). I denote the variables of interest as $Liq_{i,t}$ in the following regression:

$$\Delta Liq_{i,t} = \alpha + \beta_1 * Liq_{i,t-1} + \epsilon_{i,t}. \quad (2)$$

Principally, dealers in OTC markets aim at a desired inventory level that varies between different dealers. In efficient financial markets, prices float around an equilibrium price and revert to this price if deviations due to noninformed trades occur. This is why changes in the levels of both variables lead to an opposing effect in the change of the variables in the next period. Consequently, we expect a negative coefficient between 0 and 1 for the regression-based resiliency measures. The higher the absolute value of the coefficient, the more resilient the market is. To capture the resiliency of different dimensions of market liquidity, I use the CDS mid quote as a measure for computing price resiliency and the absolute bid–ask spread as a measure of market liquidity in this regression.⁴ I use a rolling window of 90 days for the resiliency regression and take these daily coefficients as proxies for market resiliency. Along with the other price-related variables, I collapse the resiliency measures to weekly frequency by taking the daily average for every week in our observation period. To facilitate the interpretation of the resiliency coefficients, I multiply them by -1 so that market resiliency increases in the coefficient.

I use all contracts for which data on my dependent variables are available. I use Bloomberg (CMA) as data source for absolute CDS bid–ask spreads (*ba_spread*) and CDS mid quotes (*cds_mid*). I control for other determinants of CDS market liquidity, like, hedging needs, speculation, and arbitrage opportunities (Oehmke & Zawadowski, 2017). I employ these trading motives by controlling for bond trading volume (*bond_trading*),⁵ option-implied stock volatility (*stock_vola*), and the size of the CDS-bond basis (*arbitrage*). I further control for liquidity spillovers from equity and option markets by including the stock amihud illiquidity ratio (*equity_amihud_ratio*) and option trading volume (*option_trading*) (Tang & Yan, 2007). I also control for firm-specific distance-to-default by including current market capitalization (*market_cap*) and leverage (*leverage*). Data on corporate bonds are gathered from the TRACE database and are cleaned according to Dick-Nielsen (2009, 2014). All other data are obtained from Bloomberg. Again, I collapse the price-related variables to weekly frequency by taking their daily average for each week in our sample. Weekly bond and option trading volume is computed as the sum of the daily trading volumes within the corresponding week. The leverage ratio is provided on a quarterly basis, so that each quarterly value is matched to the weeks within the respective quarter. The lack of data availability in TRACE restricts my sample to US reference entities. I neutralize outliers by excluding the first and last percentile of observations of my dependent variables. Furthermore, I restrict the data set to contracts with at least 12 weeks of observations before and after they became eligible to central clearing.

³The baseline results are robust to the use of end of week observations instead of weekly averages.

⁴For the purpose of this analysis, I assume mid quotes to mirror the variance in transaction prices. Although substantial differences between quoted and traded prices may occur at particular points in time, more than 80% of the traded prices does not differ by more than four basis points from the previously quoted prices in the long term (Mayordomo et al., 2013). Since, the effect of voluntary central clearing is likely to manifest slowly in the CDS market and rather constitutes a move to a new long-term equilibrium, the use of quote data in this empirical setting is not to be assumed to introduce a substantial bias.

⁵In line with the aggregate CDS data, I use aggregate bond trading volume with respect to all bond issues of the individual reference entities.

I do not restrict the calendar time dimension of the data set, so that the observation period can differ between the individual CDS contracts as long as sufficient pre- and post-clearing observations exist. I obtain a full set of controls for 100 reference entities that amount to 29,123 contract-week observations. Summary statistics are displayed in Table 1.

Table 1 shows that the average gross trading volume for a reference entity in our sample amounts to 20.26mn USD and the absolute bid–ask spread amounts to 6.96 basis points (bp). Since the resiliency measures are already multiplied by -1 in Table 1, their original values are negative and between 0 and 1 as expected.

Figure 2 displays the distribution of CDS contracts over all 31 clearing eligibility dates in my final sample. We observe a large variation in clearing dates and sizes of the different cohorts of contracts that become clearing eligible. Despite the difference in the cohort size, there is no single cohort that is so large that the effect of this clearing event is likely to dominate the overall statistical effect we may observe in the results. This is important as one dominant clearing date would bring the empirical setting closer to a time series setting with the problem of confounding effects that may distort the results. This is clearly not the case for this sample, which allows me to fully exploit the panel data structure. In conclusion, this sample provides a sound database for an event study using the staggered introduction of central clearing eligibility across a considerable number of eligibility events without any dominant treatment cohort.

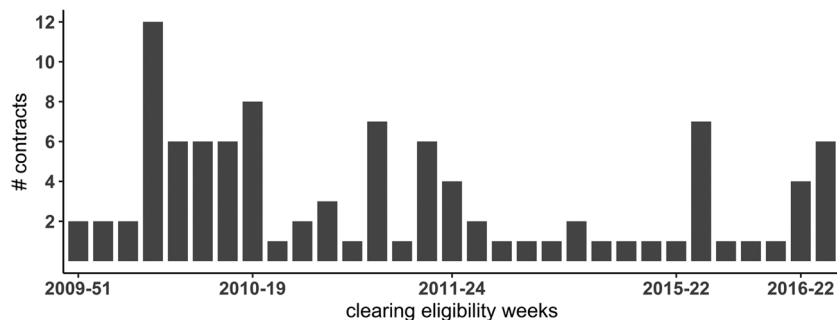
Figure 3 displays graphically the regression discontinuity (RD) of our dependent variables (without inclusion of controls) for an observation period of 150 weeks before and after the introduction of voluntary central clearing. The x-axis is measured in weeks until (after) central clearing eligibility before (after) the central line. There seems to be a positive effect on gross trading volume, whereas absolute and relative bid–ask spreads as well as resiliency measures for CDS spreads and bid–ask spreads seem to decrease. This would indicate that market tightness and market depth increase with the introduction of central clearing but market resiliency decreases.

TABLE 1 Descriptive statistics on measures of CDS market liquidity and corresponding control variables

Statistic	N	Mean	St. Dev.
<i>ba_spread</i>	29,123	6.955	5.448
<i>pct_spread</i>	29,123	0.086	0.047
<i>cds_mid</i>	29,123	105.742	108.110
<i>gross_trading</i>	29,123	−20.258	242.763
<i>net_trading</i>	29,123	−1.434	25.661
<i>price_res</i>	29,123	−0.042	0.043
<i>ba_res</i>	29,123	−0.454	0.273
<i>stock_vola</i>	29,123	25.451	12.165
<i>market_cap</i>	29,123	48.677	58.309
<i>leverage</i>	29,123	6.405	19.173
<i>arbitrage</i>	29,123	215.720	493.395
<i>bond_trading</i>	29,123	120.520	205.100
<i>option_trading</i>	29,123	88.631	238.560
<i>amihud_ratio</i>	29,123	0.0002	0.020

Note: This table shows summary statistics for our sample of CDS contracts. The sample consists of contracts for which data on the selected control variables are available. The first seven variables are the dependent variables or constituents of them: *ba_spread* (*pct_spread*) is the average absolute (relative) bid–ask spread in basis points across all CDS contracts in a given week and *cds_mid* the average CDS premium. *gross_trading* (*net_trading*) is the average gross (net) trading volume for all CDS contracts in a given week (in million USD). *price_res* and *ba_res* are the resiliency proxies for CDS mid quotes (*price_res*) and bid–ask spreads (*ba_res*) based on regression (2). *equity_amihud_ratio* is the weekly Amihud illiquidity ratio of the underlying reference entity's stock. As company-specific risk measures, I use the leverage of a reference entity (*leverage*), option-implied stock volatility (*stock_vola*), and current market capitalization in million USD (*market_cap*). *bond_trading* is the cumulative weekly trading activity in million USD on the reference entity's bonds across all issues. *option_trading* is the cumulative weekly trading activity in million USD on the reference entity's stock options. *arbitrage* is the average weekly absolute CDS-bond basis in bp. We calculate the CDS-bond basis as the difference between the CDS spread and the bond's yield to maturity over the 3-month LIBOR minus the 3-month overnight index swap.

Abbreviation: CDS, credit default swap.



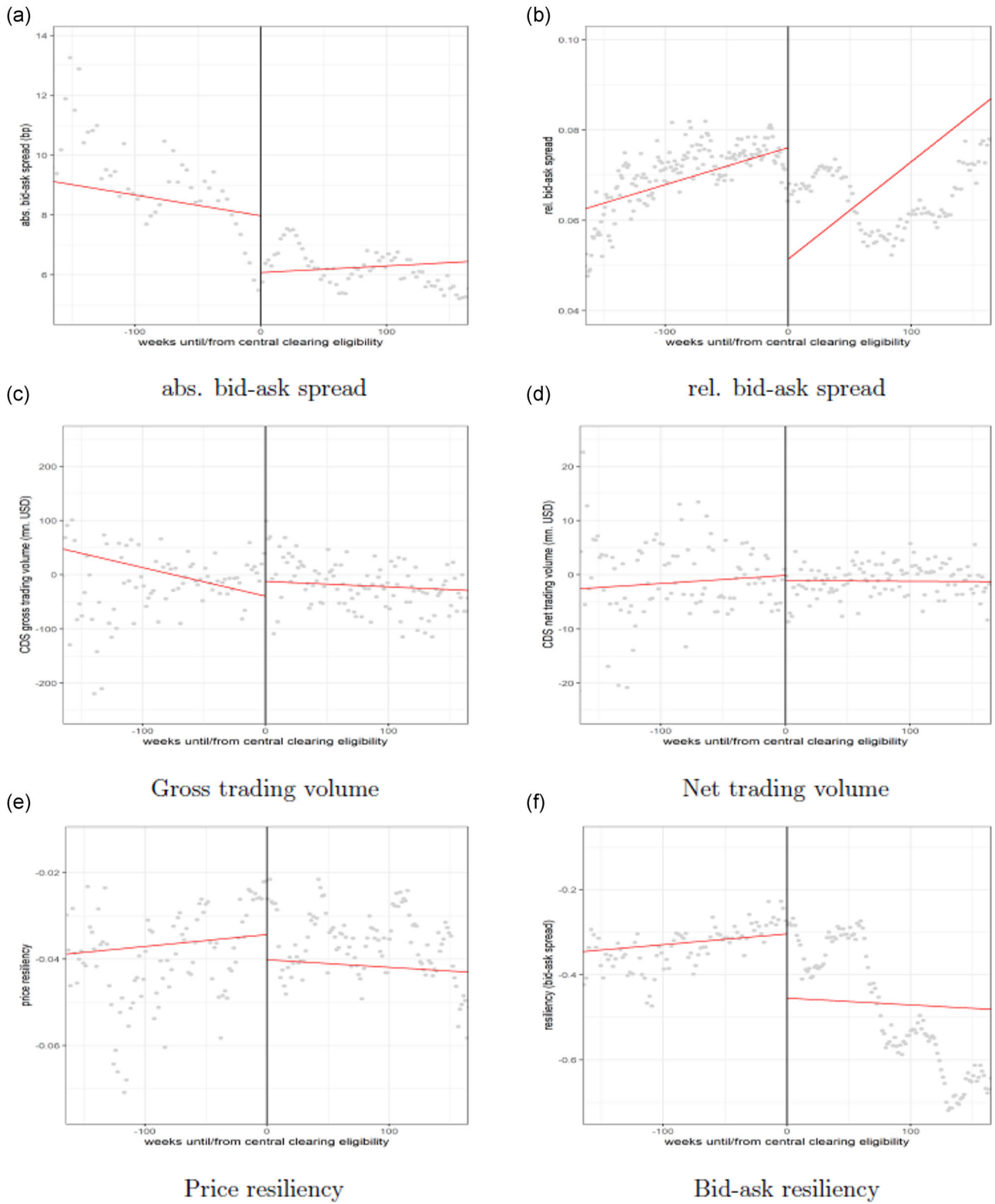


FIGURE 3 Visualization of the regression discontinuity for different measures of CDS market liquidity. These plots show average values across all contracts for all of our dependent variables (gray dots) and corresponding linear regression functions (red line) for the observation window of 150 weeks before and after the start of central clearing eligibility. CDS, credit default swap

them related to the analysis of policy or market interventions (Anderson, 2014; Bakolis et al., 2021; Bento et al., 2014). This study adds to this strand of literature.

I only use linear terms of my running variable or any other variable for multiple reasons. First, the findings of this study shall be comparable to existing studies on this subject, which exclusively use linearity assumptions. Second, the use of higher-order polynomials has been shown to potentially lead to imprecise estimates (Gelman & Imbens, 2017) or to an overfit of the RD model (Hausman & Rapson, 2018). Third, as there is no academic consensus on the functional form of market liquidity and (event) time but possibly varying functional forms across different market regimes, this linearity assumption seems to be helpful for matters of simplicity. Last, another aim of this study is to investigate differential effects of central clearing on different groups of CDS contracts and economic channels of these effects so that an in-depth econometric analysis of the behavior of market liquidity over time is not within this paper's scope.

$X_{i,t}$ contains the control variables *stock_vola*, *market_cap*, *leverage*, *arbitrage*, *bond_trading*, *option_trading*, and *equity_amihud_ratio*. γ_i and δ_i capture week and contract fixed effects. The inclusion of fixed effects allows me to control for general trends that affect all contracts, for example, macroeconomic developments (financial crisis, interest rate changes, and market volatility), and for contract-specific characteristics that do not change over time (e.g., industry).⁶ $CCP_{i,t}$ is my RD estimator.

I use the logarithm of the dependent variables *ba_spread* and *pct_spread* and of all control variables except *equity_amihud_ratio* to fit the statistical properties of the data better to the linear RD model. Since the resiliency measures are estimates from regression (2), I perform a weighted least squares regression that uses the inverse standard errors of these estimated coefficients from regression (2) as observation weights, when one of the resiliency measures is the dependent variable. *clearing_distance* models the relation between the event-related time and the dependent variable which is equivalent to an event time trend. The inclusion of the interaction term allows this relation to differ on both sides of the cutoff. The results for estimating Equation (3) are given in Table 2.

Table 2 displays results for the estimation of the effect of central clearing on CDS market liquidity in an RDD with covariates, fixed effects, and clustered standard errors. The results show a significant decrease of absolute bid-ask spreads, net trading volume, and bid-ask spread resiliency with the beginning of central clearing eligibility and a statistically significant increase in gross trading volume. Price resiliency is negatively affected by the introduction of central clearing but the effect is only marginally statistically significant and economically negligible. My baseline results indicate a positive effect of central clearing on CDS market liquidity when we consider the decrease in transaction costs and the increase in gross trading volume. The decrease in net trading volume and bid-ask spread resiliency points, however, to lower credit risk mitigation through the CDS market and lower continuous liquidity provision with the introduction of central clearing. The economic significance of the effects differs across dimensions of market liquidity. Whereas the negative effect of central clearing on bid-ask spreads is economically small (1.44% of statistical mean), the effect on resiliency measures and trading volume are economically large or even huge (6.14%–10.39% for resiliency measures and 180.19%–184.67% for trading volume measures).

4.2 | The effect of central clearing on CDS market liquidity for CDS contracts of different fundamental risk and liquidity risk

In this section, I examine whether the effect of central clearing on CDS contracts differs with their fundamental risk or liquidity risk. For this purpose, I calculate the average CDS mid quote and gross trading volume over the whole pre-clearing period for all CDS contracts in the sample and sort all contracts into quintiles. A low quintile number for a contract indicates a low average pre-clearing risk measure, that is, low CDS mid quote or high gross trading volume. If the CCP is considered a highly creditworthy counterparty, CDS market participants may trust more in the delivery of the contractual payments for centrally cleared transactions in case of the default of a reference entity. Consequently, the introduction of central clearing may change the risk aversion of CDS market participants to trade contracts with high fundamental or liquidity risk, that is, contracts for which the occurrence of a credit event and corresponding payment streams are more likely and ease of trading lower.

⁶We check the residuals of the estimated models for panel unit roots according to Maddala & Wu (1999). We can reject the null hypotheses that all time series contain a unit root. Results can be found in Table A.1 in the Supporting Information.

TABLE 2 Effect of central clearing on market liquidity in a regression discontinuity design

	Dependent variable					
	<i>ba_spread</i> (1)	<i>pct_spread</i> (2)	<i>gross_trading</i> (3)	<i>net_trading</i> (4)	<i>price_res</i> (5)	<i>ba_res</i> (6)
<i>CCP</i>	−0.100** (0.044)	−0.020 (0.037)	37.410*** (11.559)	−2.584*** (0.760)	−0.003* (0.002)	−0.047*** (0.017)
<i>clearing_distance</i>	−0.094*** (0.034)	−0.031 (0.026)	−35.898* (18.307)	−2.303* (1.381)	0.001 (0.002)	−0.010 (0.022)
<i>log(leverage)</i>	0.089 (0.054)	0.038 (0.052)	9.858 (5.972)	0.397 (0.570)	0.003 (0.003)	0.031* (0.017)
<i>log(stock_vola)</i>	0.105*** (0.035)	−0.060*** (0.022)	16.719*** (5.860)	−0.659 (0.606)	−0.003** (0.001)	0.022 (0.018)
<i>log(option_trading)</i>	0.008 (0.008)	−0.013** (0.006)	5.374*** (1.848)	0.073 (0.183)	0.0004 (0.0004)	0.003 (0.005)
<i>log(market_cap)</i>	−0.325*** (0.046)	0.338*** (0.041)	−7.613 (7.738)	−0.193 (0.423)	−0.002 (0.002)	−0.052** (0.024)
<i>log(bond_trading)</i>	0.022*** (0.008)	−0.014* (0.007)	5.394*** (1.558)	−0.197 (0.187)	0.0003 (0.0004)	−0.004 (0.004)
<i>log(arbitrage)</i>	−0.073*** (0.017)	0.030* (0.017)	−0.924 (2.893)	−0.211 (0.360)	0.001 (0.001)	−0.016 (0.013)
<i>equity_amihud_ratio</i>	−0.030 (0.027)	−0.034 (0.029)	26.905*** (10.058)	−4.404 (3.879)	0.008 (0.005)	−0.070** (0.027)
<i>CCP:clearing_distance</i>	0.001*** (0.0003)	0.001*** (0.0003)	0.480*** (0.152)	−0.019*** (0.006)	−0.00001 (0.00001)	−0.0003*** (0.0001)
Contract FE	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES
<i>F</i> statistics	223.6779	218.4453	47.2822	6.3008	18.1111	40.0492
Observations	29,123	29,123	29,123	29,123	29,123	29,123
Adjusted <i>R</i> ²	0.811	0.808	0.472	0.093	0.248	0.430

Note: This table shows results for regression (3), the semiparametric regression discontinuity estimate around the beginning of central clearing for all dependent variables. We use a polynomial function of order 1. I apply flexible polynomial functions, that is, I allow the regression functions to be different on both sides of the cutoff. The main independent variable, *CCP*, is a dummy variable which takes the value of 1 if a contract is eligible for central clearing. I include week and contract fixed effects and cluster standard errors by contract and week. In parentheses, I display standard errors which are computed according to Arellano (1987).

Abbreviations: CCP, central counterparty; CDS, credit default swap; FE, fixed effects.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Hedging credit risk on bilaterally cleared CDS markets requires market participants to take on counterparty risk and liquidity risk. Furthermore, a high default probability of the reference entity means a higher default probability of the protection-selling counterparty that has to make the contractual payments in case of a credit event (wrong-way risk). If a CCP is available in the market, market participants may be more willing to buy such high-risk CDS contracts since they know that the CCP steps in if one of their original counterparties defaults. This reduced counterparty risk of the CCP may decrease liquidity risk because the counterparty is safe and decreases the need to sell CDS positions quickly in times of market stress, and may lower the fundamental risk if the CCP is creditworthy enough to guarantee all contractual payments. This is why high-risk contracts may benefit more strongly from the introduction of central clearing on the CDS market in terms of CDS market liquidity.

To analyze whether the market liquidities of CDS contracts with low fundamental and liquidity risk are differently affected by the introduction of central clearing than contracts with high fundamental or liquidity risk, I estimate the following fixed effects regression:⁷

$$\begin{aligned}
 CDS_{i,t} = & \alpha + \beta_1 * risk_quint1_i + \beta_2 * risk_quint2_i + \beta_3 * risk_quint3_i \\
 & + \beta_4 * risk_quint4_i + \beta_5 * CCP_{i,t} * risk_quint1_i \\
 & + \beta_6 * CCP_{i,t} * risk_quint2_i + \beta_7 * CCP_{i,t} * risk_quint3_i \\
 & + \beta_8 * CCP_{i,t} * risk_quint4_i + \beta_9 * CCP_{i,t} * risk_quint5_i \\
 & + \zeta * X_{i,t} + \gamma_t + \delta_i + \epsilon_{i,t}.
 \end{aligned} \tag{4}$$

$CDS_{i,t}$ denotes the dependent variables for contract i at time t from regression (3). $risk_quint1_i$ ($risk_quint2_i$, etc.) is a dummy variable that indicates whether a contract belongs to the lowest (second-lowest, etc.) quintile of contracts in terms of one of the above specified average pre-clearing fundamental or liquidity risk measures: CDS mid quote and gross trading volume. I include week and contract fixed effects and the full set of control variables.

Table 3 shows results of the effect of central clearing on different quintiles of CDS contracts according to their fundamental risk in terms of their average pre-clearing CDS mid quote (mid_quint1_i , mid_quint2_i , etc.). We see that the negative effect of central clearing on absolute bid–ask spreads can only be observed for CDS contracts with the highest fundamental risk, whereas the negative effect on bid–ask spread resiliency seems to only affect contracts with low fundamental risk. Furthermore, we observe a positive effect of central clearing also in terms of the relative bid–ask spreads for CDS contracts with high fundamental risk and a negative effect on price resiliency for contracts with low fundamental risk. We see the positive effect of central clearing on gross trading volume for contracts of high and low fundamental risk. The results clearly show that the effect of central clearing introduction can differ across contracts with different risk characteristics and I find CDS market liquidity mainly to increase (decrease) for contracts of high (low) fundamental risk with the beginning of central clearing.

Table 4 shows results on the effect of central clearing on different quintiles of CDS contracts according to their liquidity risk in terms of their average pre-clearing gross trading volume ($gross_quint1_i$, $gross_quint2_i$, etc.). These results show a negative effect of central clearing on absolute bid–ask spreads for contracts that are strongly traded and for contracts that are thinly traded before the introduction of central clearing. Interestingly, we see a strong positive effect of central clearing eligibility on gross trading volume for contracts that are thinly traded before the introduction of central clearing but a strong negative effect on contracts that are strongly traded before the introduction of central clearing. Consequently, resiliency measures largely decrease for contracts of low pre-clearing gross trading volume. These results may point to a shift in trading volume from low-risk contracts to high-risk contracts with the beginning of central clearing, that may lead to a higher risk in the CDS portfolios of CDS market participants.

4.3 | The effect of counterparty risk and inventory risk on CDS market liquidity before and after the introduction of central clearing

My results show effects of CDS central clearing on all three dimensions of market liquidity. In this section, I would like to examine two potential economic channels for the effects of central clearing on market liquidity that we observe. One reason could be that the counterparty risk of dealers becomes less relevant for price discovery and trading activity under central clearing due to the uniform counterparty risk of the CCP to all CDS market participants. Furthermore, regulatory capital charges differ for centrally cleared positions and may change the inventory risk-taking capacity of CDS market participants.

⁷Due to the inclusion of fixed effects, the individual coefficients of variables included in the interaction terms are not displayed in the regression output.

TABLE 3 RD effect of central clearing on CDS market liquidity across contracts for different levels of pre-clearing fundamental risk

	Dependent variable					
	<i>ba_spread</i> (1)	<i>pct_spread</i> (2)	<i>gross_trading</i> (3)	<i>net_trading</i> (4)	<i>price_res</i> (5)	<i>ba_res</i> (6)
<i>log(leverage)</i>	0.100* (0.050)	0.088* (0.046)	29.583** (13.418)	0.318 (0.680)	-0.0003 (0.003)	0.032 (0.022)
<i>log(stock_vola)</i>	0.113*** (0.040)	-0.050** (0.024)	26.414*** (8.987)	-1.135 (0.705)	-0.003** (0.001)	0.020 (0.020)
<i>log(option_trading)</i>	0.005 (0.008)	-0.018*** (0.007)	3.581* (2.009)	0.171 (0.200)	0.001** (0.0004)	0.003 (0.005)
<i>log(market_cap)</i>	-0.331*** (0.044)	0.350*** (0.046)	-4.755 (7.056)	-0.073 (0.429)	-0.004* (0.002)	-0.069*** (0.026)
<i>log(bond_trading)</i>	0.019** (0.008)	-0.006 (0.007)	5.172*** (1.677)	-0.285 (0.187)	0.0002 (0.0004)	-0.005 (0.004)
<i>log(arbitrage)</i>	-0.060*** (0.019)	0.042** (0.018)	-0.948 (2.536)	0.098 (0.362)	0.0004 (0.001)	-0.016 (0.015)
<i>equity_amihud_ratio</i>	-0.026 (0.024)	-0.006 (0.026)	29.154*** (9.513)	-4.095 (3.551)	0.005 (0.003)	-0.075** (0.029)
<i>CCP:mid Quint1</i>	-0.044 (0.046)	0.065* (0.037)	37.398** (17.858)	-3.891* (2.040)	-0.008** (0.004)	-0.152*** (0.041)
<i>CCP:mid Quint2</i>	0.041 (0.034)	-0.045 (0.081)	21.759** (10.411)	-0.252 (1.162)	-0.001 (0.001)	-0.064** (0.026)
<i>CCP:mid Quint3</i>	-0.023 (0.074)	0.019 (0.061)	26.141* (13.478)	-1.163 (1.238)	-0.003 (0.003)	-0.026 (0.028)
<i>CCP:mid Quint4</i>	-0.193*** (0.057)	-0.048 (0.054)	1.244 (15.300)	-1.086 (1.102)	-0.003 (0.002)	-0.019 (0.033)
<i>CCP:mid Quint5</i>	-0.299*** (0.068)	-0.194*** (0.065)	34.778** (15.726)	-3.424* (2.011)	-0.0001 (0.003)	-0.010 (0.030)
Contract FE	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES
F statistics	177.61	177.61	177.61	177.61	177.61	177.61
Observations	25,359	25,359	25,359	25,359	25,359	25,359
Adjusted R ²	0.791	0.809	0.451	0.092	0.258	0.422

Note: This table shows results for regression (4), the fixed effects regression estimate of the effect of central clearing on CDS contracts in different pre-clearing mid quote quintiles for all dependent variables. I include week and contract fixed effects and cluster standard errors by contract and week. In parentheses, I display standard errors which are computed according to Arellano (1987).

Abbreviations: CCP, central counterparty; CDS, credit default swap; FE, fixed effects; RD, regression discontinuity.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

4.3.1 | The effect of central clearing on CDS market liquidity through counterparty risk

I examine the effect of counterparty risk on CDS market liquidity before and after central clearing eligibility by estimating the following regression:

TABLE 4 RD effect of central clearing on CDS market liquidity across contracts for different levels of pre-clearing liquidity risk (gross trading volume)

	Dependent variable					
	<i>ba_spread</i> (1)	<i>pct_spread</i> (2)	<i>gross_trading</i> (3)	<i>net_trading</i> (4)	<i>price_res</i> (5)	<i>ba_res</i> (6)
<i>log(leverage)</i>	0.146*** (0.047)	0.106** (0.046)	28.473** (11.693)	0.689 (0.660)	-0.001 (0.003)	0.022 (0.020)
<i>log(stock_vola)</i>	0.112*** (0.041)	-0.053** (0.025)	25.634*** (8.618)	-1.082 (0.686)	-0.003** (0.001)	0.017 (0.020)
<i>log(option_trading)</i>	0.005 (0.008)	-0.019*** (0.007)	4.389** (2.085)	0.174 (0.203)	0.001* (0.0004)	0.003 (0.005)
<i>log(market_cap)</i>	-0.330*** (0.046)	0.342*** (0.046)	-2.955 (6.479)	-0.207 (0.441)	-0.003* (0.002)	-0.062** (0.027)
<i>log(bond_trading)</i>	0.020** (0.008)	-0.007 (0.007)	4.911*** (1.573)	-0.250 (0.182)	0.0002 (0.0004)	-0.004 (0.004)
<i>log(arbitrage)</i>	-0.059*** (0.019)	0.043** (0.018)	-1.032 (2.517)	0.073 (0.355)	0.0004 (0.001)	-0.019 (0.015)
<i>equity_amihud_ratio</i>	-0.033 (0.023)	-0.004 (0.026)	26.834*** (9.712)	-4.197 (3.584)	0.005 (0.003)	-0.075** (0.029)
<i>CCP:gross Quint1</i>	-0.044 (0.036)	0.014 (0.043)	-79.887*** (24.743)	3.906** (1.701)	0.001 (0.003)	-0.019 (0.031)
<i>CCP:gross Quint2</i>	-0.240*** (0.056)	-0.033 (0.038)	3.423 (12.357)	-6.727*** (1.684)	-0.002 (0.003)	-0.074** (0.031)
<i>CCP:gross Quint3</i>	-0.102 (0.082)	-0.023 (0.080)	25.650* (13.562)	-2.036** (0.872)	-0.003 (0.002)	-0.016 (0.029)
<i>CCP:gross Quint4</i>	-0.072 (0.064)	-0.128* (0.065)	42.174*** (11.201)	-0.707 (1.134)	-0.002 (0.003)	-0.024 (0.027)
<i>CCP:gross Quint5</i>	-0.149*** (0.044)	-0.017 (0.043)	88.189*** (17.958)	-0.519 (1.218)	-0.006*** (0.002)	-0.091** (0.038)
Contract FE	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES
<i>F</i> statistics	173.3918	173.3918	173.3918	173.3918	173.3918	173.3918
Observations	25,359	25,359	25,359	25,359	25,359	25,359
Adjusted <i>R</i> ²	0.787	0.807	0.454	0.093	0.258	0.419

Note: This table shows results for regression (4), the fixed effects regression estimate of the effect of central clearing on CDS contracts in different pre-clearing gross trading volume quintiles for all dependent variables. I include week and contract fixed effects and cluster standard errors by contract and week. In parentheses, I display standard errors which are computed according to Arellano (1987).

Abbreviations: CCP, central counterparty; CDS, credit default swap; FE, fixed effects; RD, regression discontinuity.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

$$\begin{aligned}
CDS_{i,t} = & \alpha + \beta_1 * CCP_{i,t} + \beta_2 * clearing_distance_{i,t} \\
& + \beta_3 * CCP_{i,t} * clearing_distance_{i,t} \\
& + \beta_4 * G14_cdsmid_mean_t \\
& + \beta_5 * G14_cdsmid_mean_t * CCP_{i,t} \\
& + \zeta * X_{i,t} + \gamma_q + \delta_i + \epsilon_{i,t}.
\end{aligned} \tag{5}$$

$CDS_{i,t}$ denotes the dependent variables for contract i at time t from regression (3). $G14_cdsmid_mean_t$ is our proxy for counterparty risk: the average CDS premium of the G14 CDS dealers in a given week. The additional interaction term estimates the effect of this variable on our measures of market liquidity after the beginning of central clearing. I used fixed effects on a quarterly level in this specification (γ_q), since $G14_cdsmid_mean_t$ is constant across all contracts on every week of observation and would cancel out with the inclusion of week fixed effects. The other variables are as described above.

Table 5 displays results for the estimation of an RD on the effect of central clearing on CDS market liquidity with the inclusion of counterparty risk as control variable. To assess the effect of counterparty risk on CDS market liquidity before and after the introduction of central clearing, I jointly consider the coefficients $G14_cdsmid_mean_t$, the interaction term $G14_cdsmid_mean_t * CCP_{i,t}$ and the difference in the treatment effect ($CCP_{i,t}$) between Tables 2 and 5. The change in $CCP_{i,t}$ from Table 2 to Table 5 is relevant since any effect from the new covariate loads on $CCP_{i,t}$ in regression (3) so that the respective change in $CCP_{i,t}$ reflects the effect of counterparty risk in regression (5).

We see a statistically significant positive baseline effect of counterparty risk on absolute bid–ask spreads and net trading volume. The interaction terms show that, given the introduction of central clearing, counterparty risk positively affects CDS market liquidity as it decreases absolute and relative bid–ask spreads and increases net trading volume. Still, counterparty risk exhibits a statistically significant negative effect on bid–ask spread resiliency under central clearing. However, the effects are economically marginal.

If we look at the change in the baseline effect $CCP_{i,t}$ from Table 2 to Table 5 for the variables that are statistically significantly affected by $CCP_{i,t}$ in Table 2, the results are very similar. In the baseline regression, central clearing affects the absolute bid–ask spread negatively. If we include counterparty risk in the regression, the effect of central clearing on absolute bid–ask spreads becomes positive. I interpret this difference to be the effect of central clearing on absolute bid–ask spreads via the economic channel of counterparty risk. Since we include counterparty risk in Equation (5), $CCP_{i,t}$ does not load negatively on absolute bid–ask spreads any more, as the mechanism between counterparty risk and absolute bid–ask spreads is affected by the introduction of central clearing itself. By reducing the role of counterparty risk as a trading friction, central clearing also seems to decrease relative bid–ask spreads and to increase net trading volume. Gross trading volume and bid–ask spread resiliency, however, are negatively affected through the counterparty risk channel.

Overall, the introduction of central clearing seems to affect CDS market tightness positively by reducing counterparty risk concerns. Market depth and market resiliency, however, seem to be negatively affected by the effect of central clearing eligibility on counterparty risk. The economic effects of central clearing through counterparty risk on CDS market liquidity are moderate. I conclude that counterparty risk is no influential determinant of CDS market liquidity. This is in line with the findings of Du et al. (2019) who put forth the hypothesis that counterparty risk is managed by CDS market participants by the selection of safe CDS dealers as transaction partners.

4.3.2 | The effect of central clearing on individual banks' inventory risk through lower regulatory capital charges

Lower regulatory capital charges may reduce inventory costs under central clearing. The lower regulatory risk-weight of centrally cleared positions can decrease financial constraints of market participants due to lower capital charges. This decrease in capital charges can increase the inventory risk-taking behavior of dealers in the CDS market. I examine quarterly FR Y-9C reports and Bank Holding Company Performance Reports (BHCP) for 25 large US banks between 2015 and 2017 with an aggregate position in credit derivatives of around 10.25bn USD. I estimate whether the total CDS positions of these banks change with the share of centrally cleared CDS transactions. I proxy the share of centrally cleared CDS transactions by the ratio of regulatory capital that must be provided for centrally cleared transactions to the regulatory capital that must be provided for all CDS transactions. I run the following regression:

TABLE 5 Counterparty risk as an economic channel for the effect of central clearing on CDS market liquidity

	Dependent variable					
	<i>ba_spread</i> (1)	<i>pct_spread</i> (2)	<i>gross_trading</i> (3)	<i>net_trading</i> (4)	<i>price_res</i> (5)	<i>ba_res</i> (6)
<i>CCP</i>	0.129 (0.103)	0.210** (0.071)	79.433** (31.370)	-3.778*** (1.072)	-0.007 (0.005)	0.077 (0.054)
<i>clearing_distance</i>	-0.00005 (0.001)	0.0003 (0.001)	-2.261*** (0.366)	-0.033 (0.041)	-0.0001 (0.0001)	-0.001 (0.001)
<i>G14_cdsmid_mean</i>	0.002*** (0.001)	0.001 (0.0004)	0.227 (0.151)	-0.029*** (0.004)	-0.00004 (0.00004)	-0.0003 (0.0005)
$\log(\textit{leverage})$	0.100 (0.055)	0.045 (0.046)	12.207** (5.156)	0.135 (0.733)	0.003 (0.002)	0.032* (0.016)
$\log(\textit{stock_vola})$	0.111** (0.040)	-0.035 (0.035)	35.697*** (9.772)	1.520 (1.124)	-0.007* (0.003)	0.020 (0.035)
$\log(\textit{option_trading})$	0.005 (0.007)	-0.013 (0.008)	1.799 (2.429)	-0.223 (0.264)	0.0001 (0.001)	0.001 (0.005)
$\log(\textit{market_cap})$	-0.326*** (0.070)	0.344*** (0.042)	-8.930 (8.815)	-0.218 (0.504)	-0.003 (0.002)	-0.055* (0.025)
$\log(\textit{bond_trading})$	0.019** (0.007)	-0.013 (0.007)	3.147 (3.916)	-0.288 (0.254)	0.0002 (0.0004)	-0.003 (0.004)
$\log(\textit{arbitrage})$	-0.047** (0.018)	0.045** (0.016)	-4.983 (4.934)	-0.358 (0.637)	0.001 (0.001)	-0.010 (0.012)
<i>equity_amihud_ratio</i>	0.063 (0.042)	0.019 (0.019)	-3.249 (33.885)	-3.027 (7.193)	0.004 (0.004)	-0.032 (0.039)
<i>CCP:clearing_distance</i>	0.001 (0.0003)	0.0004 (0.0005)	0.417** (0.150)	-0.017* (0.009)	-0.00001 (0.00001)	-0.001** (0.0002)
<i>CCP:G14_cdsmid_mean</i>	-0.002** (0.001)	-0.002*** (0.0005)	-0.360* (0.169)	0.019** (0.008)	0.00003 (0.00004)	-0.001** (0.0004)
Contract FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
<i>F</i> statistics	910.2269	869.3844	11.648	1.9475	35.9621	151.3329
Observations	29,123	29,123	29,123	29,123	29,123	29,123
Adjusted R^2	0.788	0.780	0.042	0.004	0.125	0.381

Note: This table shows results for regression (5), the semiparametric regression discontinuity estimate of the effect of central clearing on CDS market liquidity for all dependent variables. I use a polynomial function of order 1. I apply flexible polynomial functions, that is, I allow the regression functions to be different on both sides of the cutoff. The main independent variable, *G14_cdsmid_mean*, is the weekly average CDS spread across all G14 CDS dealers. I include quarter and contract fixed effects. I cluster standard errors by contract and quarter. In parentheses, I display standard errors which are computed according to Arellano (1987).

Abbreviations: CCP, central counterparty; CDS, credit default swap; FE, fixed effects.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

$$total_cds_{i,t} = \alpha + \beta_1 * rwa_ccp_{i,t} + \zeta * X_{i,t} + \gamma_i + \epsilon_{i,t}. \quad (6)$$

$rwa_ccp_{i,t}$ is the ratio of risk-weighted assets from centrally cleared CDS positions to total risk-weighted assets from CDS positions for bank i in quarter t :

$$rwa_ccp_{i,t} = \frac{rwa_cbs_ccp_{i,t}}{rwa_cbs_total_{i,t}}. \quad (7)$$

Building on previous studies, I control for further determinants of individual banks' CDS positions ($X_{i,t}$): total assets, equity ratio, nonperforming loans, liquid assets, return on assets, return on equity, and net interest margin (Hasan & Wu, 2016; Minton et al., 2009; Shan et al., 2017). γ_i are quarter fixed effects.

I find total CDS positions to increase with an increasing fraction of centrally cleared CDS positions. Table 6 shows that the economic effect of central clearing on CDS inventory in terms of gross positions amounts to 44mn USD per 1% increase in regulatory capital from cleared CDS transactions relative to total regulatory capital from CDS transactions. Across all specifications, the effect is statistically significant at least at 10% level. The results indicate that the low risk-weight of centrally cleared positions frees up risk-taking capacity in terms of CDS gross inventory. This additional risk-taking capacity may explain the baseline positive effects of central clearing on CDS market liquidity.

5 | ROBUSTNESS CHECKS

In this section, I present different robustness checks to the baseline regression on the impact of central clearing eligibility on different dimensions of market liquidity. I follow the seminal paper by Hausman and Rapson (2018) that provides detailed guidance on testing RD estimations with time as running variable for robustness. Consequently, I check my sample for discontinuities in different exogenous covariates (Section 5.1), I test my results for their sensitivity to the selected observation period (Section 5.2), I test and account for potential autocorrelation in the dependent variables (Section 5.3), I rerun the discontinuity estimation by using a nonparametric approach (Section 5.4), and show results of a placebo test (Section 5.5).

5.1 | Testing for discontinuities in covariates

An RDD requires the assumption of smooth covariate movement around the cutoff. Otherwise, the identification of any potential effect cannot be valid since the discontinuity in the dependent variable could be caused by a discontinuity in one or more covariates. I test my covariates for a discontinuity around our cutoff in the running variable $clearing_distance_{i,t}$. I include contract and week fixed effects and cluster standard errors by contract and week.

$$Cov_{i,t} = \alpha + \beta_1 * CCP_{i,t} + \beta_2 * clearing_distance_{i,t} + \beta_3 * CCP_{i,t} * clearing_distance_{i,t} + \zeta * X_{i,t} + \gamma_i + \delta_i + \epsilon_{i,t}. \quad (8)$$

$Cov_{i,t}$ denotes different control variables for the effect of central clearing on CDS market liquidity: leverage (*leverage*), option-implied stock volatility (*stock_vola*), option trading volume (*option_trading*), market capitalization (*market_cap*), bond trading volume (*bond_trading*), the CDS-bond basis (*arbitrage*), and the equity Amihud illiquidity ratio (*equity_amihud_ratio*). γ_i and δ_i capture week and contract fixed effects.

The results for estimating Equation (8) are given in Table 7. To rule out any anticipatory effect of CDS market participants to central clearing, I exclude 2 months of observations before and after the introduction of central clearing. I do not find any statistically significant effect in the covariates around the beginning of central clearing. On the basis of this test, the assumption seems plausible that any discontinuity in the dependent variables may come from the central clearing effect and not from any confounding covariates.

TABLE 6 The impact of central clearing on individual banks' CDS positions

	Dependent variable					
	<i>total_cds</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>rwa_ccp</i>	1.916*** (0.220)	0.211* (0.112)	0.723*** (0.189)	1.640*** (0.226)	0.254** (0.121)	0.443* (0.239)
<i>total_assets</i>		0.002*** (0.0001)			0.002*** (0.0001)	0.002*** (0.001)
<i>total_loans</i>		-0.006*** (0.0005)			-0.006*** (0.001)	-0.006*** (0.001)
<i>total_deposits</i>		0.001*** (0.0004)			0.002** (0.001)	0.002 (0.002)
<i>equity_ratio</i>			-0.002 (0.003)		-0.001 (0.002)	-0.001 (0.002)
<i>non_perform_loans</i>			-0.058*** (0.012)		-0.001 (0.010)	-0.009 (0.023)
<i>liquid_assets</i>			0.004*** (0.0004)		-0.001 (0.001)	-0.001 (0.003)
<i>roa</i>				12.765 (13.661)	-3.886 (6.364)	13.485** (4.891)
<i>roe</i>				-184.599 (364.845)	1.894 (166.751)	-87.924*** (19.702)
<i>nim</i>				-18.585*** (4.708)	4.218* (2.386)	11.671*** (3.371)
Quarter FE	NO	NO	NO	NO	NO	YES
Observations	264	264	264	264	264	264
Adjusted R ²	0.221	0.847	0.561	0.259	0.846	0.871

Note: This table shows results for regression (6), the regression of individual banks' total CDS positions on the fraction of risk-weighted assets from centrally cleared CDS positions to the total risk-weighted assets from CDS positions (*rwa_ccp*). Further explanatory variables are total assets, total loans, total deposits, equity ratio, nonperforming loans, liquid assets, return on assets (*roa*), return on equity (*roe*), and net income margin (*nim*). I include quarter fixed effects in column (6). The constant is omitted in the regression output. I cluster standard errors by bank and quarter. In parentheses, I display *t* statistics which are computed according to Arellano (1987).

Abbreviations: CCP, central counterparty; CDS, credit default swap; FE, fixed effects.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.2 | Sensitivity to observation period

Since I perform an RD estimation in the context of an event study, it is important to check for robustness of the results to the chosen bandwidth around the treatment date. In this section, I provide an analysis on the sensitivity of my results to the bandwidth choice in the RDD. First, I analyze potential anticipatory trading effects in expectation of central clearing introduction. Second, I show the dependence of the treatment coefficient on bandwidth selection.

Market participants may already change their trading behavior during the weeks before a contract becomes eligible for central clearing and novate these positions when central clearing eligibility starts. Due to the

TABLE 7 Regression discontinuity estimation for covariates

	Dependent variable						
	<i>leverage</i> (1)	<i>stock_vola</i> (2)	<i>option_trading</i> (3)	<i>market_cap</i> (4)	<i>bond_trading</i> (5)	<i>arbitrage</i> (6)	<i>equity_amihud_ratio</i> (7)
<i>CCP</i>	−0.057 (0.061)	0.031 (0.032)	−0.023 (0.087)	−0.028 (0.060)	−0.079 (0.108)	−0.015 (0.048)	0.0003 (0.0002)
Contract FE	YES	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES	YES
<i>F</i> statistics	438.0605	96.3217	232.249	1075.0911	157.5871	55.4417	1.5403
Observations	28,072	28,072	28,072	28,072	28,072	28,072	28,072
Adjusted R^2	0.896	0.653	0.821	0.955	0.756	0.518	0.011

Note: This table shows results for regression (8), the semiparametric regression discontinuity estimate around the beginning of central clearing for the control variables leverage, stock volatility, option trading volume, market capitalization, bond trading volume, arbitrage and equity Amihud illiquidity ratio. I use a polynomial function of order 1. I apply flexible polynomial functions, that is, I allow the regression functions to be different on both sides of the cutoff. The main independent variable, *CCP*, is a dummy variable which takes the value of 1 if a contract is eligible for central clearing. I include contract fixed effects and cluster standard errors by contract and week. In parentheses, I display standard errors which are computed according to Arellano (1987).

Abbreviations: CCP, central counterparty; FE, fixed effects.

fundamental risk of CDS contracts, it may not be plausible to expect such anticipatory effects far in advance of the start of central clearing but only when the time until clearing eligibility is short enough to avoid any major downside risks. Principally, the event time trend $clearing_distance_{i,t}$ in my RDD captures such anticipatory effects. As an additional robustness check, I rerun regression (3) but exclude 2 months of observations before and after the start of central clearing to rule out any anticipatory trading behavior by CDS market participants before the start of central clearing.

Table 8 displays results of this ‘Donut-RD.’ The results are largely robust to the exclusion of observations very close around the cutoff. However, the economic effect of central clearing on bid–ask spreads is almost three times larger. One explanation may be that clients make transactions during the weeks before clearing eligibility that is determined to be novated to the CCP as soon as the contract becomes clearing eligible. This demand may be reflected in the bid–ask spreads already before the actual clearing eligibility event. In this specification, the negative coefficient for price resiliency becomes statistically significant at the 5% level.

To get an idea on how fast the economic effects of voluntary central clearing on CDS market liquidity are incorporated into the market, I show graphically the sensitivity of the RD estimate to the chosen bandwidth in Figure 4. I estimate the baseline model with bandwidths of 13, 26, 39, 52, 78, 104, 130, 156, 182, and 208 weeks around the beginning of central clearing eligibility. Figure 4 shows the RD estimates and corresponding confidence intervals for different bandwidths. I only let the bandwidth vary for the post-clearing period and keep the pre-clearing period fixed to 52 weeks. This may provide evidence about the time frame that is needed until the effects of central clearing in a voluntary clearing scheme are incorporated into the CDS market, and new market equilibria are established.

Figure 4 visualizes that the treatment effect changes relatively strong over time for bid–ask spreads, gross trading volume, net trading volume and bid–ask spread resiliency. The results highlight the importance of considering long-term observation windows around the beginning of central clearing eligibility to get more detailed insights about the reactions of market participants to the possibility of voluntary central clearing. Considering the fact that central clearing remains voluntary after its introduction, the economic effects may be incorporated into observations further away from the cutoff. Market participants do not have to use CCPs as trading partners but can decide when and how much trading volume they shift to CCPs. This is why the economic effect of central clearing eligibility may increase over time and the direction of the effect may not be clear in the first weeks after the start of central clearing eligibility. This special context may justify choosing a large bandwidth although this is not the standard identification strategy in the context of an RDD with a large cross-section.

TABLE 8 Donut-RD estimation of the effect of central clearing on CDS market liquidity

	Dependent variable					
	<i>ba_spread</i> (1)	<i>pct_spread</i> (2)	<i>gross_trading</i> (3)	<i>net_trading</i> (4)	<i>price_res</i> (5)	<i>ba_res</i> (6)
<i>CCP</i>	−0.290*** (0.056)	−0.033 (0.043)	42.126*** (13.112)	−2.805*** (0.859)	−0.003** (0.002)	−0.059*** (0.019)
<i>clearing_distance</i>	0.001 (0.0003)	−0.029 (0.026)	−37.204* (19.062)	−2.061 (1.392)	0.0004 (0.002)	−0.003 (0.021)
<i>log(leverage)</i>	0.090 (0.061)	0.034 (0.052)	9.312 (6.077)	0.450 (0.598)	0.003 (0.003)	0.033** (0.017)
<i>log(stock_vola)</i>	0.200*** (0.032)	−0.060*** (0.022)	16.751*** (5.789)	−0.624 (0.619)	−0.003** (0.001)	0.021 (0.019)
<i>log(option_trading)</i>	0.0003 (0.008)	−0.013* (0.007)	5.575*** (1.784)	0.052 (0.177)	0.0004 (0.0004)	0.003 (0.005)
<i>log(market_cap)</i>	−0.341*** (0.046)	0.336*** (0.042)	−6.144 (7.792)	−0.400 (0.435)	−0.002 (0.002)	−0.053** (0.026)
<i>log(bond_trading)</i>	0.021*** (0.007)	−0.015** (0.007)	5.435*** (1.489)	−0.147 (0.191)	0.0003 (0.0004)	−0.004 (0.004)
<i>log(arbitrage)</i>	0.007 (0.018)	0.029* (0.017)	−0.212 (2.803)	−0.166 (0.370)	0.001 (0.001)	−0.014 (0.013)
<i>equity_amihud_ratio</i>	0.089* (0.050)	−0.035 (0.029)	29.463*** (10.171)	−5.699 (3.742)	0.009* (0.005)	−0.063** (0.027)
<i>CCP:clearing_distance</i>	0.001*** (0.0003)	0.001*** (0.0003)	0.515*** (0.160)	−0.021*** (0.006)	−0.00001 (0.00001)	−0.0004*** (0.0001)
Contract FE	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES
<i>F</i> statistics	712.6967	212.8965	47.8434	6.0813	17.6461	38.5032
Observations	28,072	28,072	28,072	28,072	28,072	28,072
Adjusted <i>R</i> ²	0.734	0.809	0.484	0.092	0.250	0.429

Note: This table shows results for regression (3), the semiparametric regression discontinuity estimate around the beginning of central clearing for all dependent variables. I exclude eight weeks prior to before and after the beginning of central clearing eligibility. I use a polynomial function of order 1. I apply flexible polynomial functions, that is, I allow the regression functions to be different on both sides of the cutoff. The main independent variable, *CCP*, is a dummy variable which takes the value of 1 if a contract is eligible for central clearing. I include week and contract fixed effects. I cluster standard errors by contract and week. In parentheses, I display standard errors which are computed according to Arellano (1987).

Abbreviations: CCP, central counterparty; CDS, credit default swap; FE, fixed effects; RD, regression discontinuity.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.3 | Accounting for autocorrelation

Serial correlation in the dependent variable or error terms can bias the estimate of the treatment effect in an RD setting with time as the running variable, since serial dependence during the shift from the pretreatment period to the posttreatment period distorts the observed treatment effect (Hausman & Rapson, 2018). In the baseline regression (3), I account for serial correlation in the error terms by clustering standard errors across time and contracts. In this section, I examine potential effects of serial dependence in the dependent variables on the RD estimates from Table 2

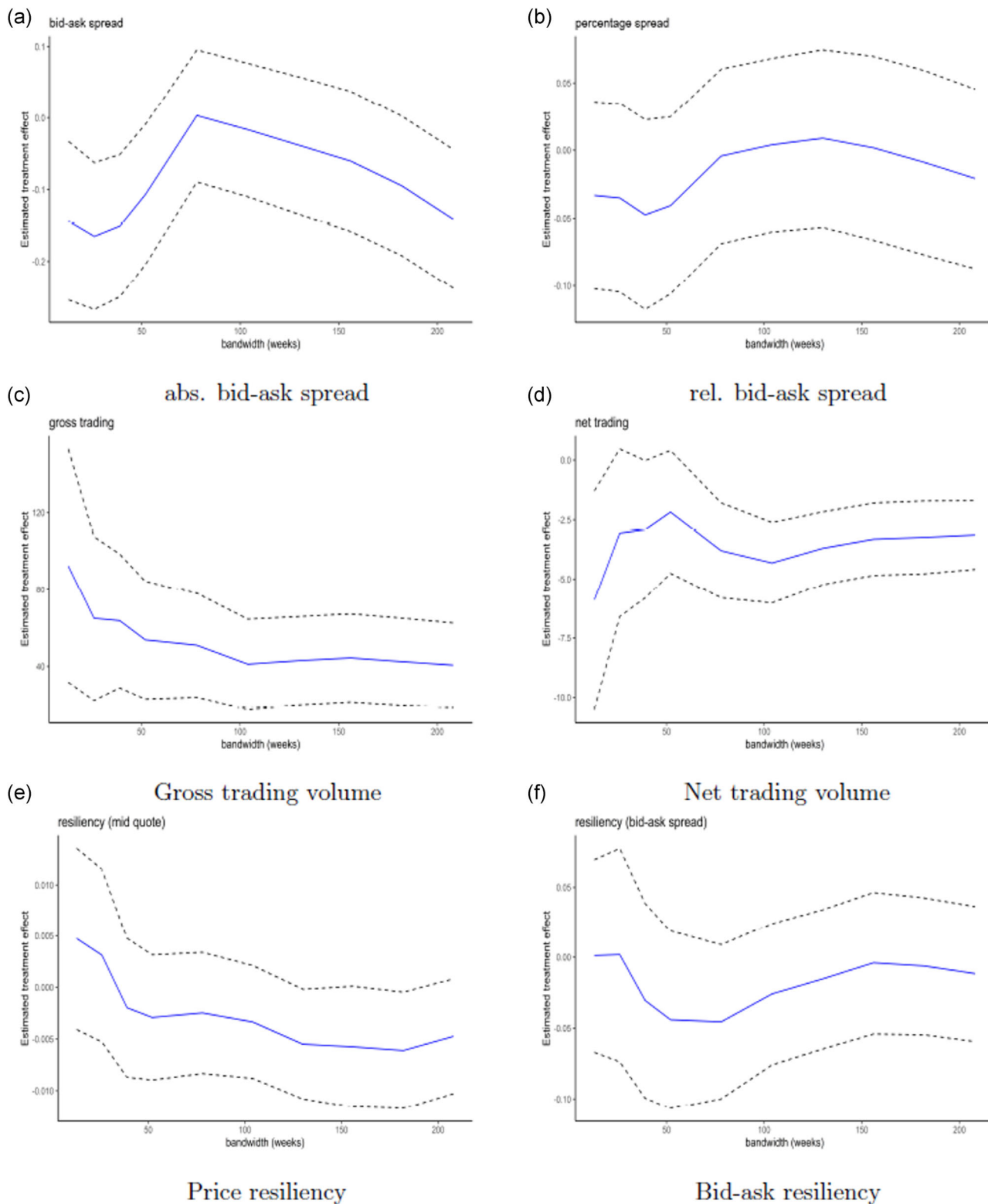


FIGURE 4 RD treatment effect and confidence intervals for different post-clearing bandwidths. These figures show RDD estimates and corresponding confidence intervals for all dependent variables of regression (3) depending on different post-clearing bandwidths. Apart from the bandwidth selection, I estimate the RDDs according to regression (3). RD, regression discontinuity; RDD, regression discontinuity design

by estimating the following dynamic RD model that includes the first lag of the dependent variable in the regression:⁸

$$\begin{aligned} CDS_{i,t} = & \alpha + \beta_1 * CCP_{i,t} + \beta_2 * clearing_distance_{i,t} \\ & + \beta_3 * CCP_{i,t} * clearing_distance_{i,t} + \beta_4 * CDS_{i,t-1} \\ & + \zeta * X_{i,t} + \gamma_i + \delta_i + \epsilon_{i,t}. \end{aligned} \quad (9)$$

$CDS_{i,t}$ denotes the dependent variables for contract i at time t from regression (3). $CDS_{i,t-1}$ is the lagged dependent variable that captures potential serial correlation. The other variables are as described above. Since the simultaneous inclusion of fixed effects and lagged terms in panel models is a potential source of bias, I do not include any fixed effects (Nickell, 1981). The results for estimating Equation (9) are given in Table 9.

Table 9 shows that my results also hold in a dynamic panel data setting. Overall, the coefficients are considerably smaller but the significance levels remain largely similar. Only the treatment coefficient on net trading volume becomes insignificant in this specification, whereas the treatment coefficient on relative bid-ask spreads and price resiliency are negative and statistically significant at the 1% level.⁹ I conclude that serial dependence in my dependent variables does not seem to significantly bias the estimated treatment effects in regression (3).

5.4 | Nonparametric RDD

Another approach to estimate an RD is to use a nonparametric approach. In this approach, weights are assigned to observations according to a kernel function. Observations close to the cutoff get higher weights than observations further away from the cutoff. As a kernel function, I use a triangular kernel. Bandwidth selection is employed according to Imbens and Kalyanaraman (2012) and I use bandwidth bias-correction according to Calonico et al. (2014). I estimate the RD with covariates and fixed effects. Results are displayed in Table 10.

Despite much smaller bandwidth estimates, the results are largely consistent with the results from Table 2. Absolute bid-ask spreads and bid-ask spread resiliency are negatively affected at the 5% statistical significance level and gross trading volume and resiliency of CDS mid quotes are positively affected at the significance level of 1% and 10% respectively.

5.5 | Placebo tests

In this section, I provide results on a placebo event study using an RDD. I run placebo tests to rule out that the observed effect around the beginning of central clearing eligibility is a random event. I construct a new treatment dummy that simulates a treatment at a random date before the actual beginning of central clearing. I replace the original treatment dummy in regression (3) with this placebo dummy. I restrict the observation period to the estimated bandwidths according to Imbens and Kalyanaraman (2012) and Calonico et al. (2014) from the nonparametric RD estimations in Section 5.4, since this shorter observation window is the most restrictive specification, for which I find statistically significant effects of central clearing eligibility on CDS market liquidity. Apart from this, the specification of the RDD is identical to Equation (3). I repeat the placebo test 1000 times.

If the observed effect in Table 2 is not random, I expect to observe 100 (50; 10) treatment coefficients that are significant at 10% (5%; 1%) level at random treatment dates. I perform the placebo test on all dependent variables since any large deviations from the theoretical expectations may indicate a misspecification of my baseline RDD. I do not construct placebo dummies that simulate treatment after the beginning of central clearing. Since treated contracts are eligible but not mandated for central clearing, market participants can still decide during the treatment period whether they want to clear their transactions bilaterally or centrally. Any date after central clearing eligibility could therefore

⁸Table A.2 in the Supporting Information shows results for the Woolridge test on serial correlation in linear panel data models. We can reject the null hypothesis of no autocorrelation in the panel data time series for all dependent variables except CDS net trading volume.

⁹Since the time series dimension is large (which reduces Nickell's bias), I estimate the dynamic RD model again with fixed effects. The results are largely identical, but the treatment coefficients for price resiliency and relative bid-ask spreads (as in the baseline regression) become insignificant again. The results are also robust if standard errors are clustered.

TABLE 9 RD effect of central clearing on CDS market liquidity in a dynamic model

	Dependent variable					
	<i>ba_spread</i> (1)	<i>pct_spread</i> (2)	<i>gross_trading</i> (3)	<i>net_trading</i> (4)	<i>price_res</i> (5)	<i>ba_res</i> (6)
<i>CCP</i>	-0.020*** (0.003)	-0.015*** (0.003)	18.538*** (6.283)	-0.497 (0.665)	-0.002*** (0.0005)	-0.010*** (0.002)
<i>clearing_distance</i>	0.0001*** (0.00002)	0.0001*** (0.00002)	-0.511*** (0.042)	0.014*** (0.004)	0.00000 (0.00000)	0.00001 (0.00001)
<i>lag[log(ba_spread)]</i>	0.906*** (0.003)					
<i>lag[log(pct_spread)]</i>		0.915*** (0.003)				
<i>lag(gross_trading)</i>			-0.065*** (0.006)			
<i>lag(net_trading)</i>				0.003 (0.006)		
<i>lag(price_res)</i>					0.900*** (0.003)	
<i>lag(ba_res)</i>						0.963*** (0.002)
<i>log(leverage)</i>	0.006* (0.003)	0.005 (0.003)	8.671 (6.785)	0.044 (0.719)	0.0002 (0.0005)	0.0001 (0.002)
<i>log(stock_vola)</i>	0.019*** (0.002)	-0.003 (0.002)	25.563*** (4.885)	0.563 (0.517)	0.001*** (0.0003)	0.004*** (0.001)
<i>log(option_trading)</i>	0.002** (0.001)	-0.002* (0.001)	4.666** (1.925)	-0.051 (0.204)	-0.001*** (0.0001)	-0.001* (0.001)
<i>log(market_cap)</i>	-0.036*** (0.003)	0.032*** (0.003)	-13.770** (5.914)	-0.059 (0.626)	-0.001 (0.0004)	-0.002 (0.002)
<i>log(bond_trading)</i>	0.002* (0.001)	-0.001 (0.001)	5.639*** (1.783)	-0.079 (0.189)	-0.00002 (0.0001)	0.0004 (0.0005)
<i>log(arbitrage)</i>	0.0002 (0.002)	0.011*** (0.002)	-0.029 (3.125)	-0.530 (0.331)	-0.0005** (0.0002)	0.001 (0.001)
<i>equity_amihud_ratio</i>	0.019 (0.037)	0.055 (0.037)	-3.437 (76.791)	0.858 (8.134)	-0.004 (0.005)	-0.001 (0.021)
<i>CCP:clearing_distance</i>	0.0001*** (0.00002)	0.0001*** (0.00002)	0.424*** (0.043)	-0.014*** (0.005)	-0.00000 (0.00000)	0.00000 (0.00001)

(Continues)

TABLE 9 (Continued)

	Dependent variable					
	<i>ba_spread</i> (1)	<i>pct_spread</i> (2)	<i>gross_trading</i> (3)	<i>net_trading</i> (4)	<i>price_res</i> (5)	<i>ba_res</i> (6)
<i>F</i> statistics	15258.4677	26556.8537	37.0277	1.4467	10884.8744	31770.1531
Observations	25,304	25,304	25,304	25,304	25,304	25,304
Adjusted R^2	0.869	0.920	0.012	-0.004	0.825	0.932

Note: This table shows results for regression (9), the semiparametric regression discontinuity estimate around the beginning of central clearing for all dependent variables. We use a polynomial function of order 1. I apply flexible polynomial functions, that is, I allow the regression functions to be different on both sides of the cutoff. The main independent variable, *CCP*, is a dummy variable which takes the value of 1 if a contract becomes eligible for central clearing. Next to the baseline covariates, I include the lagged value of the dependent variable as external regressor. In parentheses, I display standard errors which are computed according to Arellano (1987).

Abbreviations: CCP, central counterparty; CDS, credit default swap; FE, fixed effects; RD, regression discontinuity.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

TABLE 10 Nonparametric regression discontinuity estimation

	<i>ba_spread</i>	<i>pct_spread</i>	<i>gross_trading</i>	<i>net_trading</i>	<i>price_res</i>	<i>ba_res</i>
<i>CCP</i>	-0.0375**	0.0055	32.4456***	-1.3881	0.0027*	-0.0272**
Std. Err.	0.0153	0.0164	12.0268	1.2966	0.0015	0.0123
<i>p</i> value	0.0143	0.7379	0.007	0.2843	0.0779	0.027
Bandwidth	60.8062	59	81.7971	113	63.914	53.4979
Observations (untreated)	2456	2398	2962	3500	2540	2253
Observations (treated)	4190	4052	5666	7852	4404	3699
Order of polynomial	1	1	1	1	1	1

Note: This table shows the estimates of the effect of central clearing eligibility on all dependent variables using a nonparametric regression discontinuity design based on regression (3). We use a linear functional form and allow the regression functions to be different on both sides of the cutoff. The bandwidth is estimated according to Imbens and Kalyanaraman (2012). I include the same covariates as in Table 2 and include contract and week fixed effects. Weights are assigned to the observations using a triangular kernel function. Robust bias-corrected confidence intervals are computed according to Calonico et al. (2014).

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

still capture effects of increased use of central clearing, and significant coefficients of placebo dummies could not be interpreted as confounding effects. That is clearly not the case before the beginning of central clearing. Furthermore, I do not allow the placebo treatment date to be later than 12 weeks before the actual clearing date to rule out any economic effects in anticipation of the clearing eligibility event.

Detailed results of the placebo tests can be found in Table A.3 in the Supporting Information. Generally, the placebo tests provide evidence for the nonrandomness of the clearing effect on the liquidity measures as shown in Table 2. For most of the dependent variables, I find a number of statistically significant coefficients on all significance levels that do not deviate to a large extent from the theoretical expectations. These moderate deviations from the theoretical ideal do not provide sufficient and consistent evidence that the results in this paper do not point into the correct direction in terms of the relation between central clearing and CDS market liquidity.

6 | CONCLUSION

I empirically examine the effect of central clearing on different dimensions of market liquidity: tightness, depth, and resiliency. The empirical results show that dealers narrow bid-ask spreads, increase gross trading volume but seem to provide market liquidity less continuously in terms of bid-ask spreads with the beginning of central clearing eligibility of CDS single-name contracts. Similarly, price resiliency seems to decrease.

The effects of central clearing on CDS market liquidity differ across groups of contracts with similar fundamental and liquidity risk. In almost all cases, I find positive (negative) effects of central clearing on CDS market liquidity for contracts with high (low) fundamental and liquidity risk. My results also point to a lower relevance of counterparty risk, leading to a reduction in bid–ask spreads. Furthermore, I find CDS inventories to increase in the fraction of risk-weighted assets from centrally cleared positions. Higher inventory risk-taking capacity through lower regulatory capital charges for centrally cleared positions may explain the higher gross trading volumes with the introduction of central clearing.

My analysis leads to interesting implications as avenues for future research. My findings point to a shift in CDS trading activity from low-risk contracts to high-risk contracts as a result of central clearing introduction. This potential increase in CDS portfolio risk must be covered by CCP risk management standards and may affect financial stability. If proper CCP risk management standards are in place, the results of this study encourage regulators to expand mandatory clearing to contracts of high fundamental and liquidity risk, as they benefit most from central clearing introduction in terms of CDS market liquidity.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the Depository Trust & Clearing Corporation (DTCC), the Trade Reporting and Compliance Engine (TRACE), and Bloomberg/Credit Market Analysis, and from FR Y-9C reports and Bank Holding Company Performance Reports (BHCPR). Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the author with the permission of the named third parties.

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