WORKING PAPER 24-04

Do Credit Default Swaps Still Lead? The Effects of Regulation on Price Discovery

OFFICE OF FINANCIAL RESEARCH

July 17, 2024

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Why These Findings Are Important

Regulation implemented since the 2007-09 financial crisis has reshaped the credit default swap (CDS) market. In this paper, the author explores whether the reforms have affected the price discovery process for corporate credit by altering the primacy of CDS over corporate bonds and credit ratings as an information source.

Key Findings

1. **Single-name CDS spreads incorporate less private information prior to rating decreases and adjust more slowly after such events.**

2. **Single-name CDS spreads lead their corporate bond counterparts more weakly following margin reforms that only affect derivatives markets.**

3. **Price discovery for CDS indices, which are less affected by margin reforms, appears little changed.**

How the Author Reached These Findings

The author develops an analytical model that shows an increase in the relative cost of trading individual securities reduces agents' incentive to acquire information and drives them toward index products. He then employs a broad array of data on corporate credit markets, including supervisory data from the Depository Trust and Clearing Corporation, to establish stylized facts about CDS trading and test the predictions of the model. The author uses an event study framework to demonstrate that, after the introduction of new regulations following the 2007-09 crisis, CDS spreads incorporate less private information prior to credit rating decreases. He then estimates a series of panel vector autoregressions, which indicate that these reforms have also caused CDS spreads to lead corporate bond spreads more weakly. The author's research indicates that while post-crisis reforms have improved the resilience of the CDS market, they have also reduced its role in the price discovery process.

Do Credit Default Swaps Still Lead? The Effects of Regulation on Price Discovery*

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Abstract

This study explores whether reforms implemented since the Global Financial Crisis have affected the price discovery process for corporate credit by altering the primacy of CDS over corporate bonds and credit ratings. I develop a model that demonstrates an increase in the relative cost of trading individual securities reduces agents' incentive to acquire information and drives them toward index products. Empirically, single-name CDS incorporate less information prior to rating decreases following post-crisis reforms that makes these instruments costlier to trade. Furthermore, CDS spreads lead corporate bond spreads more weakly after the adoption of margin requirements that affect only derivatives.

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1 Introduction

Price discovery is a core function of financial markets. Historically, information on a firm's credit risk was conveyed through corporate bond trading and assessments made by credit rating agencies. The latter are slow-moving and coarse (Hilscher and Wilson, 2017), however, and a number of frictions, including high short-selling costs and dealer inventory constraints, have long compromised price efficiency in the corporate bond market (e.g., Friewald et al., 2012; Oehmke and Zawadowski, 2015; Bessembinder et al., 2018). The growth of credit derivatives in the early aughts created a new venue in which to express information on default risk. The credit default swap (CDS) market, in contrast to its bond counterpart, proved to be a relatively frictionless environment with lower transaction costs and higher levels of liquidity (Biswas et al., 2015; Oehmke and Zawadowski, 2017). CDS spreads have been shown to anticipate rating downgrades (e.g. Hull et al., 2004), thereby lessening the reliance on rating agencies to supply information about firms' creditworthiness (Chava et al., 2019; Gredil et al., 2022). Changes in CDS spreads have also been shown to lead movements in corporate bond spreads (e.g., Blanco et al., 2005). In accordance with extant research, the CDS market has come to be viewed as the primary source for granular, high-frequency measures of credit quality by academics, policymakers, and traders alike (Longstaff et al., 2005; Acharya and Johnson, 2007; Lee et al., 2018).

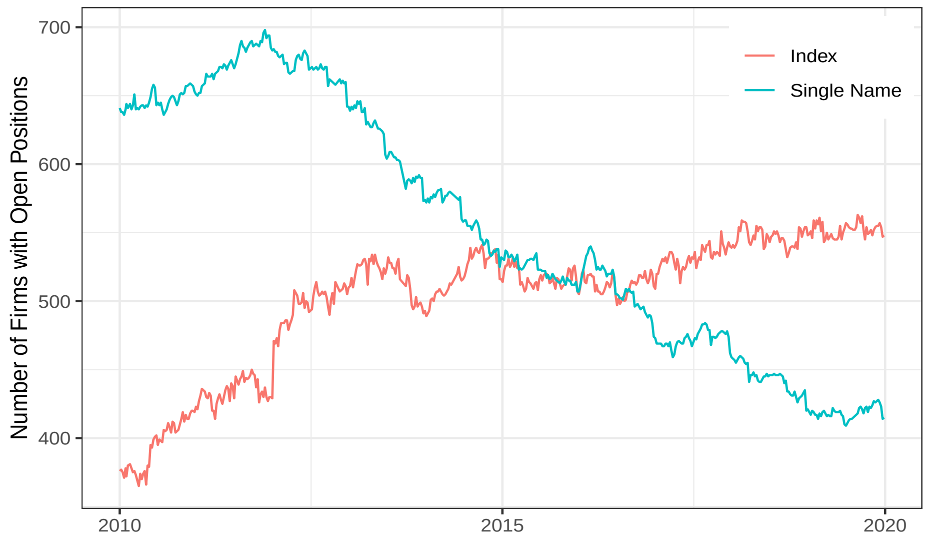
While over-the-counter (OTC) derivatives were indeed once traded with few restrictions, their role in propagating systemic turmoil during the Global Financial Crisis (GFC) led to increased scrutiny by regulators. The CDS market was deemed to be particularly culpable, as the buildup of large counterparty exposures engendered fears of cascading defaults and, ultimately, prompted the bailouts of major market participants such as AIG (Financial Crisis Inquiry Commission, 2011). Three post-crisis reforms, the Supplementary Leverage Ratio (SLR) from Basel III, the Volcker Rule from the Dodd-Frank Act, and the Uncleared Margin Rules (UMR) from the Basel Committee on Banking Supervision and the International Organization of Securities Commissions (BCBS-IOSCO) have become especially salient for derivatives trading. The SLR, a key constraint for the largest U.S. banks (Duffie, 2022), is a minimum capital requirement that adjusts leverage for swaps and other off-balance-sheet assets. The Volcker Rule prohibits dealer banks from engaging in proprietary trading and has been associated with the erosion of liquidity in various markets (Bao et al., 2018;

Bessembinder et al., 2018). Much of my analysis focuses on the UMR, which require swap parties to adhere to stringent margin practices for their uncleared bilateral positions (i.e., those that are not cleared through a central counterparty) and prevent posted collateral from being redeployed for other purposes. A growing literature studies how reforms have affected pricing and liquidity (e.g., Loon and Zhong, 2016; Collin-Dufresne et al., 2020; Riggs et al., 2020), but less work has been done to understand if they impact price discovery. In this paper, I help fill the gap.

It is not obvious ex ante how post-crisis regulation might influence the informativeness of OTC derivatives. Some measures enacted by policymakers have eased frictions that potentially limit the ability of traders to exploit private information. The SLR and UMR are more onerous for uncleared positions, so they incentivize the use of central counterparties (Onur et al., 2024). In doing so, they may promote dealer competition and alleviate concerns about counterparty risk (Loon and Zhong, 2014; Du et al., 2023; Eisfeldt et al., 2023). However, high fixed costs preclude many market participants from clearing (Bank for International Settlements, 2018) and the increased margin and intermediation costs associated with reforms (Duffie et al., 2015; Paddrik and Tompaidis, 2024) may erode liquidity. The International Swaps and Derivatives Association (ISDA), a prominent trade organization, also warned that the UMR would cause smaller participants to leave the market entirely (Kentz, 2012). I examine the veracity of this claim in Figure 1 by using confidential supervisory data to depict the trading behavior of non-dealers in recent years. In accordance with ISDA's prediction, the number of buyside firms with open single-name CDS positions has markedly decreased. If these traders are comparatively uninformed, their departure might improve price efficiency. Alternatively, without less sophisticated agents to transact against, agents that previously acquired costly information may no longer do so (Grossman and Stiglitz, 1980).

The presence of CDS indexes, which pool together the most liquid single-name reference entities, further complicates matters. Because the baskets are diversified, they tend to incur smaller capital and margin charges under post-crisis rules than single names (Bank for International Settlements, 2015; Capponi et al., 2022). Consistent with this disparity, Deutsche Bank remained a primary intermediary in the index market even after it exited the single-name segment due to regulatory costs (Burne and Henning, 2014). Figure 1 also shows that despite the decline in the use of single names, the number of buyside firms with open index positions has grown appreciably. Existing studies on this sort of substitution focus on equities and exchange-traded funds (ETFs) and yield

Figure 1: Number of Buyside Firms with Open Positions



Notes: This figure presents the number of buyside firms with open CDS positions on U.S.-domiciled single name reference entities and the two major North American CDS indices. Source: DTCC CDS, Author's calculations.

mixed predictions. In the model of Subrahmanyam (1991), noise traders exiting individual security markets after the introduction of a basket makes it more difficult to exploit private signals and, thus, leads individual security prices to reflect less security-specific information. In contrast, the framework of Bond and Garcia (2022) suggests that lowering the cost of indexing increases the informational efficiency of individual securities by pushing less informed traders to the basket. Empirically, Glosten et al. (2021) and Israeli et al. (2017) find that ETF activity reduces price efficiency for underlying securities while Huang et al. (2021) demonstrate that industry ETFs improve price efficiency for the individual constituents.

Given the competing mechanisms, I start my analysis by using a stylized, one-period model to generate hypotheses. I largely build on the sequential trading framework of Ernst (2020), which contains individual assets and a basket, then evaluate informational efficiency in the style of Biais and Hillion (1994). In the model, there are two single-name securities, A and B, with unknown payoffs and an equal-weighted index composed of both. Risk neutral market makers face either a strategic insider who knows the value of one single name or an uninformed liquidity trader. Informed agents trade either the single name whose payoff they know or the index, but they are allowed to randomize their selection. Liquidity traders are restricted to trading their associated security. Both types of agents incur a transaction cost for single name but not index trades. Market makers cannot distinguish if the agent submitting an order has insider knowledge, so they charge a bid-ask spread to avoid losses due to asymmetric information.

For a given share of informed agents, insiders exclusively trade single names if the transaction cost is sufficiently small. When this condition is not met, however, insiders trade the index with positive probability. If information acquisition is endogenized, increasing transaction costs result in fewer agents becoming informed. It also leads insiders to trade the index with more frequency. These shifts cause both single names and the index to become less informative. Because market makers do not know if potential insider index trades come from A- or B-informed agents, the reduction in informational efficiency is more pronounced for single names.

I next empirically test the predictions of the model. Given the increased trading costs (Burne and Henning, 2014) and the departure of market participants (Figure 1) associated with post-crisis regulation, I expect price discovery to have worsened. I begin by using CDS spread changes around rating decreases to measure the absolute informativeness of single names. Following Boyarchenko et al. (2018), I partition the sample window into the "Pre-Rule" period, which spans from January 2011 through December 2013 and the "Rule Implementation" period, which extends from January 2014 through December 2019. Similar to prior studies, I find that spread movements anticipate rating changes in both the Pre-Rule and Rule Implementation periods (Hull et al., 2004; Lee et al., 2018). There is no drift in spreads after rating decreases in the former period, but, consistent with the slower incorporation of information, a 1.8% post-event drift emerges in the latter. The effect is especially pronounced after the introduction of the UMR in September 2016.

To determine if less private information is impounded in CDS spreads, I test for a decline in the share of cumulative abnormal spread change (CASC) that occurs before a downgrade is announced. I compute the "pre-event ratio" (PER) by dividing the mean CASC from 90 days prior to two days prior to a rating downgrade by the mean CASC from 90 days prior to one day after a downgrade. This ratio will equal one if the CDS market fully anticipates rating changes and decrease if, instead, spreads rise in the narrow window around a downgrade date. I find that the PER falls from 90% in the Pre-Rule period to 78% after the adoption of the UMR. Though this analysis is not causal, it indicates that CDS spreads have become less informative over time.

To demonstrate that post-crisis reforms and not structural changes to rating policies drive the previous results, I next study if the UMR also alter the lead-lag relationship between CDS and corporate bond spreads. While Basel III and the Volcker Rule affect trading costs in both markets, margin reforms apply only to derivatives. I therefore classify September 2016 onward as the Post-UMR period and test for changes around this implementation date. Similar to Hilscher et al. (2015) and Lee et al. (2018), I use panel vector autoregressions (VARs) of percentage spread changes to measure the strength of the lead-lag relationship. I find that less information flows from CDS to bonds after margin rules are introduced. In the Pre-UMR period, a 1% increase in CDS spread is associated with a 0.2% increase in bond spread the following day. In the Post-UMR period, the same increase in CDS spread corresponds to only a 0.11% increase in bond spread.

I next exploit the cross-section of CDS reference entities to further the case that margin reforms cause the decline in informativeness. Sequential trading models suggest that in markets liquid enough to sustain informed trading, each incremental transaction contributes to price discovery. It follows that reference entities with appreciable amounts of uncleared trading should be particularly affected by the UMR. I therefore classify entities as High- or Low-Volume based on their average daily notional traded in the quarter immediately preceding the adoption of the margin rules, then estimate separate panel VARs for each group in both periods and conduct a difference-in-differences test. The drop in informativeness indeed stems from High-Volume entities. Decomposing the time periods into finer bins reveals no evidence of differential trends in the Pre-UMR period.

As noted previously, the UMR apply only to bilateral positions and not those cleared through a central counterparty (CCP). The erosion of the lead-lag relationship between CDS and bond spreads should, therefore, be starkest for underlyings that are least likely to be centrally cleared. To test this prediction, I compute the clearing propensity of each reference entity by dividing its cleared gross open interest before the adoption of the UMR by the sum of its cleared and uncleared gross open interest. I then partition the High Volume group into three finer categories—Non-Clearable, Low Clearing Propensity, and High Clearing Propensity—and estimate separate panel VARs for each group in both the Pre- and Post-UMR periods. The first lag CDS change coefficient in bond spread regressions declines in all three categories across periods, but the magnitude of the change is monotonically decreasing in clearing propensity. Consistent with the UMR causing the deterioration of price discovery, the difference for the Non-Clearable group is significant at the 1% level but its counterpart for the High Propensity group fails to achieve significance at even the 10% level.

Margins imposed by the UMR are determined using Value at Risk models. Reference entities whose spread changes are highly correlated with those of the primary CDS indices are thus likely to incur the largest margin charges because they will tend to offer the least portfolio diversification benefit. If the UMR are behind the decline in price discovery, these highly correlated entities should exhibit the sharpest decreases in informativeness. I therefore compute correlations between single-name and index spread changes prior to the introduction of the UMR, then estimate a panel regression on bond spread changes that includes triple interactions of lagged spread changes, a post-UMR indicator variable, and the correlation coefficient. The point estimate for the triple interaction term that includes the first lag of CDS spread changes is negative and statistically significant, which again accords with the UMR causing the erosion of the lead-lag relationship.

I lastly study whether price discovery for CDS indices has been affected by regulation. The indices are highly liquid and diversified, so they generate smaller margin and capital charges under post-crisis rules than single names. Figure 1 also indicates that market participants have substituted into the index segment. The model therefore suggests that the erosion in informational efficiency will be less pronounced for indices. Directly measuring the informativeness of baskets is difficult, so I again test for differential changes in the CDS and corporate bond markets. Panel VARs using index spread changes show that CDS indices lead corporate bond indices across the entire sample period and that the strength of this relationship is stable over time. The results are consistent with the model's prediction that reforms hinder price discovery more for single names than for indices.

Together, my results demonstrate that post-crisis regulation has eroded the informativeness of single name CDS. While work based on earlier sample periods establishes the primacy of CDS over corporate bonds (Blanco et al., 2005; Zhu, 2006; Lee et al., 2018) and credit ratings (Hull et al., 2004; Norden and Weber, 2004; Lee et al., 2018), my findings indicate that the latter are becoming increasingly important sources of information on default risk.[1] The results also apply to other derivative classes, such as foreign exchange swaps, that remain largely uncleared and add to the ongoing debate about the effects of indexing on price discovery. It should be noted that from the perspective of policymakers, the losses in informational efficiency associated with reforms may be

[1] Evidence regarding the lead-lag relationship between credit derivatives and equities is more mixed. Acharya and Johnson (2007) show that information flows from the CDS to the stock market, while Norden and Weber (2009) and Hilscher et al. (2015) conclude that information runs from equities to CDS. In related work, Marra et al. (2019) find that the ability of CDS-unique information to predict future stock returns decreases after a reference entity is made eligible for voluntary central clearing.

worth the corresponding reductions in systemic risk. While welfare analysis is beyond the scope of this paper, I highlight a lesser-studied channel that warrants consideration in such an exercise.

2 Background

In this section, I provide an overview of the CDS market and the relevant regulatory measures that have been implemented since the GFC. Further institutional details and a review of the literature on CDS can be found in Boyarchenko et al. (2019) and Augustin et al. (2016), respectively, while additional information on post-crisis regulation pertaining to derivatives trading is available in Boyarchenko et al. (2018).

2.1 Credit Default Swaps

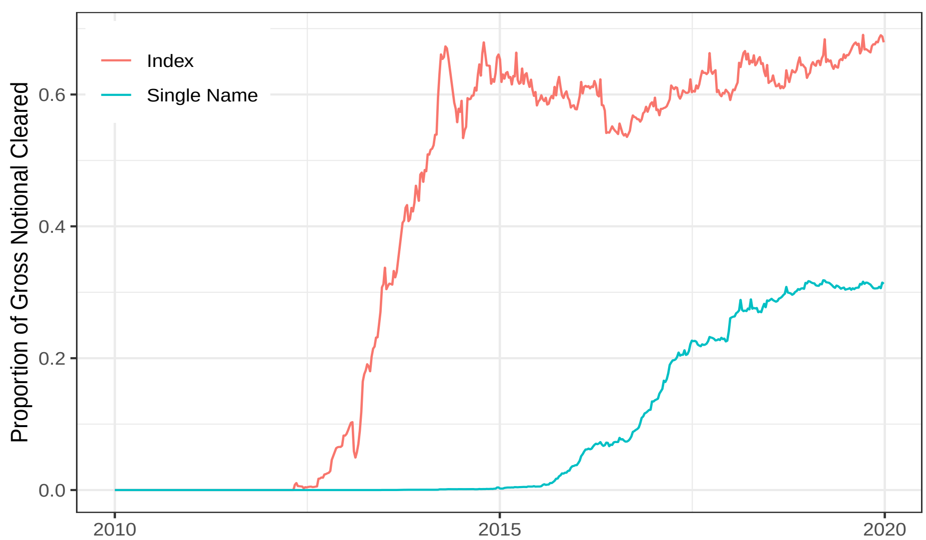
A CDS is a derivative contract that provides synthetic insurance against a credit event affecting the underlying. Single-name CDS reference individual firms and require the seller to pay the buyer the notional amount of the contract times one minus the recovery rate of the underlying bond if a credit event occurs before the expiry of the swap. As in equity markets, there exist index contracts that pool together CDS on a specified set of constituents. The two major North American corporate indices, the CDXNAIG and the CDXNAHY, are composed of the most heavily traded investment grade and high yield single names, respectively. Both indices are equal-weighted and rolled with an updated set of reference entities biannually.

2.2 Central Clearing

Prior to the crisis, CDS were traded in a traditional, dealer-intermediated OTC market. Because swaps are bilateral contracts, market participants bear *counterparty risk* (i.e., the risk that their trading partner fails to meet its obligations). The turmoil caused by the declines of Lehman Brothers, Bear Stearns, and AIG in 2008 made apparent the threat that large counterparty exposures pose to financial stability. Central clearing was introduced after the crisis, and many regulatory measures passed in the post-crisis period were intended to incentivize market participants to clear their trades. Under the clearing model, parties enter contracts facing a tightly-governed CCP instead of one another. Thus, the only source of counterparty risk is the CCP itself. Clearinghouses are capitalized by their members, which are typically large dealer banks, and require that trading parties adhere to margin terms that can be appreciably more stringent than those implied by standard Value-at-Risk rules (Capponi et al., 2022).

Dealers began voluntarily clearing transactions in 2009 and client-clearing services have been offered since 2013. Between March and September of the latter year, the Commodity Futures Trading Commission (CFTC) phased in a series of rules that require many market participants to centrally clear standard contracts referencing the major indices. In Figure 2, I use confidential supervisory data to plot the proportions of buyside firms' gross notional exposures on U.S. single names and North American indices that are centrally cleared. The share for indices rose quickly and stood at roughly 70% in December 2019. In contrast, uptake for single names was virtually non-existent until 2016 and reached only 30% at the end of 2019. According to market participants, adoption was limited because the margin required by CCPs on single-name portfolios far exceeded the amounts demanded by dealers on uncleared positions (Rennison, 2015).

Figure 2: Centrally Cleared Proportion of Buyside Firms' Gross Notional Outstanding



Notes: This figure presents the proportions of buyside firms' gross notional exposures that are centrally cleared. Single name shares are computed using open positions on U.S.-domiciled reference entities, while index shares are computed using open positions on the CDXNAIG and CDXNAHY. Source: DTCC CDS, Author's calculations.

2.3 Basel III

The Basel III regulatory framework was also developed in response to the financial crisis. A key component of Basel III is the Supplementary Leverage Ratio (SLR), which has become the most binding constraint for many swap dealers (Duffie, 2022). The US version of the ratio was proposed in July 2013, finalized in 2014, and officially took effect in 2018.[2] The SLR numerator is equal to Tier 1 capital, while the denominator is the sum of on-balance sheet and certain off-balance sheet assets. The ratio is computed without applying risk adjustments to protect against model and measurement error that may arise from risk-based weights.

Both the replacement values and potential future exposures (PFEs) of a bank's CDS positions are included in its SLR denominator. The former are based on the mark-to-market values of outstanding contracts, while the latter are calculated using both net and gross notional positions. Per SLR guidelines, netting across counterparties is not allowed when computing PFEs. Because dealers have large gross exposures relative to their net positions, this restriction makes it costly to intermediate derivative markets that, like the single-name CDS market, have a sizable uncleared segment. The SLR is less onerous for index intermediation, as all cleared trades face the CCP and are therefore able to be netted.

2.4 Volcker Rule

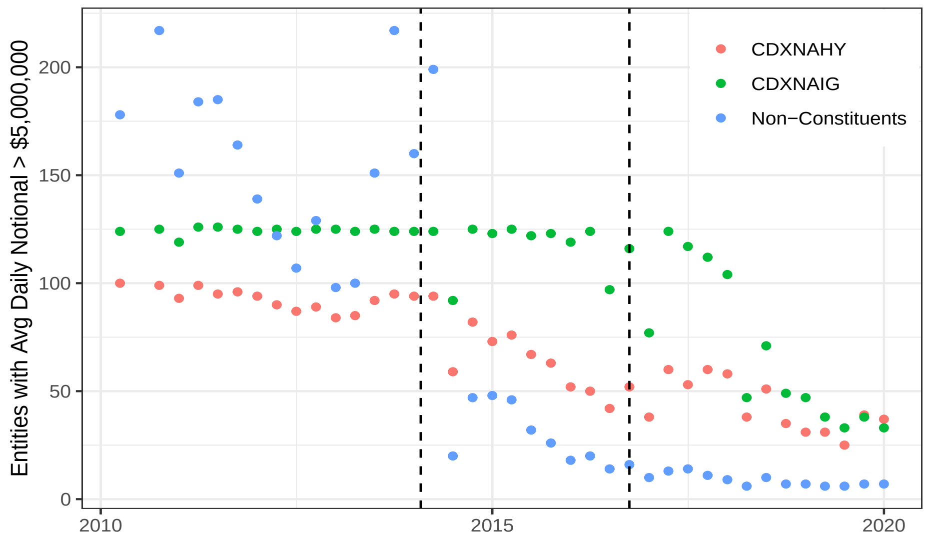
Section 619 of the Dodd Frank Act, also known as the Volcker Rule, was initially proposed in 2011, but was not implemented until April 2014. It prohibits large dealer banks from engaging in proprietary trading and limits their ability to sponsor or invest in hedge funds and private equity funds. The Volcker Rule is intended to prevent incidents such as the London Whale scandal of 2012, in which large CDS positions taken by a derivatives trader at JPMorgan resulted in losses exceeding $6 billion. The rule permits depository institutions to trade for market making purposes, but compliance costs have proven to be burdensome and the rule has negatively impacted intermediation in the corporate bond market (Bao et al., 2018; Bessembinder et al., 2018).

Figure 3 suggests that post-crisis regulation hurt single-name CDS liquidity as well. Using

[2] Choi et al. (2020) show that while compliance was not required until 2018, institutions affected by the SLR began adjusting their securities holdings and deleveraging immediately after the finalization date in 2014. They find no evidence of additional changes around the actual compliance date.

public data published by the Depository Trust & Clearing Corporation (DTCC), I group North American corporate single names by index membership and plot the number of reference entities with an average daily notional greater than \$5MM in a given quarter. Trading volume began to decline in January 2014, which corresponds to beginning of what Boyarchenko et al. (2018) term the "Rule Implementation Period".

Figure 3: Number of Frequently Traded Single-Names



Notes: This figure presents the number of North American single name reference entities on DTCC's Top 1000 list with an average daily notional volume greater than \$5MM. The CDXNAIG and CDXNAHY groups are composed of members of the respective indices, while Non-Constituents are underlyings not listed on either index. The first dashed vertical line represents the boundary between the Rule Writing and Rule Implementation periods of Boyarchenko et al. (2018), while the second represents the beginning of UMR phase-ins. Source: DTCC OTC Repository Data, Author's calculations.

2.5 Uncleared Margin Requirements

To mitigate the counterparty risk associated with bilateral swap trading, market participants may exchange collateral. Such collateralization takes two forms: *initial margin*, which is posted at trade inception and retained until a contract is terminated or matures, and *variation margin*, which is exchanged during the life of the contract to cover changes in its market value over time. Traditionally, margin terms were negotiated bilaterally and, thus, quite varied. Dealers, for example, did not exchange initial margin with one another, while clients would often exchange variation margin with dealers but post initial margin only unilaterally.

To standardize and strengthen collateralization practices, BCBS-IOSCO introduced the UMR in September 2016. The new requirements were made intentionally stringent, as regulators aimed to promote central clearing (Bank for International Settlements, 2015). The UMR mandate that all market participants exchange both initial and variation margin. To prevent rehypothecation, they also stipulate that collateral be held by third-party custodians. Required initial margin may be computed using either a standard schedule or a regulator-approved model that assesses the risk of the entire portfolio. Dealers and other sophisticated traders tend to use the latter approach, as it accounts for diversification within portfolios. Regulatory guidelines dictate that models set initial margin according to the 99% loss quantile of the netting set over a horizon of 10 days.

The first phase of the UMR, which levied initial margin requirements on the largest market participants, was implemented in September 2016. Variation and initial margin rules impacting an increasing number of traders have since been instituted. These provisions have made it substantially costlier for both dealers and buyside firms to hold uncleared positions and Figure 2 indicates they prompted some market participants to begin clearing trades. The declines in trading volume after the second dashed line in Figure 3, which corresponds to the first UMR phase-in date, also suggest that margin reform harmed liquidity and did not simply shift trading to clearinghouses.

3 Theoretical Framework

I begin the analysis by using a stylized framework to generate predictions about the effects of regulatory changes on price discovery in the CDS market. I build upon the sequential trading model of Ernst (2020), which features two single-name securities and an index, by adding transaction costs and endogenous information acquisition. All proofs are presented in Appendix A.

3.1 Setting

There are two periods: $t = 0, 1$. The market consists of single-name securities, A and B, and an index, I, composed of the two. At future date 1, the single names pay independent liquidating dividends, $\hat{V}_A$ and $\hat{V}_B$, that are equally likely to be 0 or 1. The index is equal-weighted, so $\hat{V}_I = (1/2)\hat{V}_A + (1/2)\hat{V}_B$.

At time 0, risk neutral, competitive market makers face either a strategic insider who knows the value of one of the single names or an uninformed liquidity trader. Market makers begin with prior beliefs $P(\hat{V}_A = 1) = P(\hat{V}_B = 1) = 1/2$, and, similar to other models in the style of Glosten and Milgrom (1985), update their expectations based on the observed order. Market makers do not know if an agent is informed, so their only signal is the order itself.

Initially, a fraction α of traders are informed. Half of these agents observe the final value of security A, while the other half observe the final value of security B. Informed agents are risk neutral and strategic. They submit orders that maximize their expected profits. These agents trade either the single-name security whose value they know or the index, but they are allowed to randomize the choice.

The remaining $1 - \alpha$ fraction of agents are uninformed and trade in response to unmodeled inventory shocks. To keep the share of informed traders constant across asset classes, a quarter of the uninformed agents are security A liquidity traders, a quarter are security B liquidity traders, and the remaining half are index liquidity traders. Uninformed agents are restricted to trading a single unit of their associated security. They buy and sell with equal probabilities. Informed agents must mimic the order sizes of their uninformed counterparts, because market makers would price discriminate if they could determine the identities of traders based on the quantities demanded.

Both informed and uninformed agents incur a linear transaction cost, c, when trading security A or B. As in Oehmke and Zawadowski (2017), c reflects dealers' cost of efficient liquidity provision and inventory management in addition to expenses, such as initial margin, that are directly borne by customers. There is no analogous c for trading indices, consistent with the empirical evidence that such costs are larger for single names (e.g., Biswas et al., 2015; Collin-Dufresne et al., 2020).

3.2 Equilibrium

In equilibrium, all agents act optimally. Informed traders submit orders that maximize their profits and market makers quote prices that earn them zero expected profit. Rational expectations also hold. Informed traders correctly determine how their orders will affect prices and market makers correctly infer the strategies of these insiders.

After establishing how transaction costs affect the equilibrium for a given level of α, I endogenize information acquisition and study the effects of increases in c. In these exercises, the expected profits of informed agents must equal the cost of acquiring information, which I denote g. To streamline exposition, I focus solely on symmetric equilibria. That is to say, I limit discussion to cases where security A and security B informed traders employ the same strategies.

3.3 Bid-Ask Spreads and Informational Efficiency

Before presenting the central propositions about informed trader strategies, I prove two lemmas about market maker beliefs and informational efficiency. Absent asymmetric information, market makers would set the price of each security equal to its unconditional expected value. The presence of informed traders forces market makers to charge a bid-ask spread to avoid expected losses. Since the latter are competitive,

$$
\begin{aligned}
ask_j =& P(\hat{V}_j = 1 | \text{buy } j) \quad j \in \{A, B\} \\
ask_I =& 1 \cdot P(\hat{V}_A = 1 \ \& \ \hat{V}_B = 1 | \text{buy } I) + \\
& \quad 0.5 \cdot P(\hat{V}_A = 1 \ \& \ \hat{V}_B = 0 | \text{buy } I) + 0.5 \cdot P(\hat{V}_A = 0 \ \& \ \hat{V}_B = 1 | \text{buy } I)
\end{aligned}
$$

and similar for the bids. As shown in the following lemma, because all agents trade the same quantities, market makers' inferences are based solely on the signs of orders.

Lemma 1. *Let ϕ_j be the probability that a j-informed agent trades the single-name security $j \in \{A, B\}$ instead of the index. The bid and ask prices for security j are*

$$
\begin{aligned}
ask_j &= \frac{4\phi_j \alpha + 1 - \alpha}{4\phi_j \alpha + 2 - 2\alpha} \\
bid_j &= \frac{1 - \alpha}{4\phi_j \alpha + 2 - 2\alpha}.
\end{aligned}
$$

For symmetric equilibria, $\phi_A = \phi_B = \phi$, so for the index

$$
\begin{aligned}
ask_I &= \frac{2\alpha - 3\alpha\phi + 1}{2(\alpha - 2\alpha\phi + 1)} \\
bid_I &= \frac{1 - \alpha\phi}{2(\alpha - 2\alpha\phi + 1)}.
\end{aligned}
$$

In both cases, bids decrease and asks increase as information asymmetry becomes more pronounced. Informed traders directing more of their orders towards the index therefore narrows the bid-ask spread for single names but widens it for the index.

My ultimate goal is to understand how increases in transaction costs affect the informativeness of markets. Let $E[\hat{V}_j|Q]$ be the expected value of security j conditional on the observed order Q. As in Biais and Hillion (1994), the difference between the conditional expectation of the security value and its true value, $E[\hat{V}_j|Q] - V_j$, can be interpreted as an estimation error. As the variance of this error increases, the informational efficiency of the market decreases. Expressions for the estimation errors of the single-name securities and the index are derived in the following lemma.

Lemma 2. *The estimation error for single-name security j conditional on order Q is*

$$Var(E[V_j|Q] - V_j) = \frac{1}{4} - \frac{\phi^2\alpha^2}{4(2\phi\alpha - \alpha + 1)} - \frac{(1-\phi)^2\alpha^2}{8(\alpha - 2\phi\alpha + 1)}$$

with $j \in \{A, B\}$. For the index it is

$$Var(E[V_I|Q] - V_I) = \frac{1}{8} - \frac{\phi^2\alpha^2}{8(2\phi\alpha - \alpha + 1)} - \frac{(1-\phi)^2\alpha^2}{8(\alpha - 2\phi\alpha + 1)}.$$

3.4 Informed Trader Strategies

I now explore how the transaction cost, c, affects informed traders' strategies and, by extension, the informativeness of the single-name securities and index. Informed agents choose whether to mimic single name or index liquidity traders based on which order will yield a higher payoff. With a fixed share of informed traders, α, the lower the transaction cost, the more profitable it is to trade single names. As shown in the following proposition, it is therefore the case that when c is small, informed agents opt to only trade single-name securities.

Proposition 1. *For a given level of informed trading, α, the pure-strategy equilibrium in which informed agents always trade single names prevails when the transaction cost, c, is sufficiently small. Increasing c leads the fraction of informed traders to decrease and, as a result, reduces the informational efficiencies of both the single-name securities and the index.*

Market makers learn about the true index value from informed single-name trades, so the informational efficiency of the index drops as α declines, even in the pure-strategy equilibrium where all informed agents trade the single names. As shown in the following proposition, increasing c does not affect informativeness in the pure-strategy equilibrium where insiders only trade the index, because doing so does not decrease expected profits.

Proposition 2. *For a given level of informed trading, α, the pure-strategy equilibrium in which informed agents always trade the index obtains when the transaction cost, c, is sufficiently large. The informational efficiencies of both the single-name securities and the index are unaffected by increases in c.*

The estimation error for single names in the equilibrium in which informed agents only trade the individual securities is

$$\frac{1}{4}\left[1 - \frac{\alpha^2}{1+\alpha}\right].$$

In the equilibrium in which informed agents only trade the index it is

$$\frac{1}{4}\left[1 - \frac{\alpha^2}{2(1+\alpha)}\right].$$

The first quantity is clearly smaller for $\alpha \in (0, 1)$, which implies that for a fixed share of informed traders, informational efficiency is higher in the former equilibrium. The estimation error for the index in both equilibria is, however,

$$\frac{1}{8}\left[1 - \frac{\alpha^2}{1+\alpha}\right].$$

The decrease in informational efficiency for the single-name securities makes intuitive sense because all trading in the markets for A and B becomes uninformed. Furthermore, index trades provide only a noisier signal of single name values because, from the perspective of market makers, informed orders could stem from either A- or B-informed agents. This uncertainty does not affect the accuracy of market makers' expectations for the final index value.

Thus far, I have considered only pure-strategy equilibria that obtain when transaction costs are sufficiently small or large. As discussed in the following proposition, for intermediate values of c, informed traders randomize between the single-name securities and the index.

Proposition 3. *For intermediate transaction costs, informed agents mix between single names and the index. When the transaction cost, c, is increased, the share of informed traders, α, decreases and* *the probability of trading the index, ϕ, rises. These shifts lead to reduced informational efficiency of both the index and the single-name securities, but the decline is less pronounced for the index.*

Mixed strategies prevail under certain conditions, as they allow informed agents to exploit their insider knowledge while simultaneously tempering information revelation. Changes in the transaction cost alter the share of informed agents as well as their mixing probabilities, so they ultimately affect informational efficiency.

3.5 Empirical Implications

The model predicts that the increased transaction costs associated with post-crisis regulation will lead to less informed trading in all segments of the CDS market. As single names become relatively more costly to trade, insiders will direct more of their orders toward indices. This change will ultimately lead the decline in informational efficiency to be more pronounced for single names than for indices. While the hypotheses may seem intuitive, the existing literature, which primarily centers on equities and the adoption of ETFs, yields mixed predictions about the effects such shifts in trading behavior will have on informativeness. In the baseline model of Bond and Garcia (2022), for example, a relative decrease in indexing costs leads less-informed agents to exit single-name markets and enter index markets. The change in participation causes price efficiency to increase for single names and decline for indices.

Two aspects of the institutional setting may initially seem at odds with the theoretical framework. First, CDS are traded OTC, but dealers in the model are unable to ascertain if a customer is informed. This feature is based on the finding from Jiang et al. (2021) that market participants simultaneously hold CDS positions for multiple purposes including hedging, basis trading, and speculating. The ambiguity about customers' motives implies that dealers cannot perfectly screen informed trades despite knowing their counterparties' identities. Second, the framework includes only two single-name securities, so it may be unclear if the hypotheses hold when the number of index members is large. While liquidating dividends in the model are purely idiosyncratic, price movements of single names are correlated in practice. Indices with many constituents therefore remain a viable alternative for exploiting private information that pertains to multiple reference entities.

4 Empirical Analysis

4.1 Data Description

Single-name and index CDS spread data come from Markit. The vendor provides end-of-day composite spreads calculated using indicative dealer quotes. I utilize spreads for contracts written on North American corporate entities that have a five-year tenor, allow no restructuring, are denominated in U.S. dollars, and reference senior unsecured debt. Index constituent lists also come from Markit.[3]

Liquidity data for CDS come from DTCC. Every quarter, DTCC publishes trading activity metrics including the number of active dealers, trades per day, and average daily notional for each of the "Top 1000" single names. While this limit could potentially give rise to truncation issues, entities at the bottom of the list average less than 1 trade and $2.5MM notional volume per day. DTCC rounds average daily notional amounts to the nearest $2.5MM for amounts less than $25MM and up to the nearest $25MM for amounts over $25MM. Regulatory data on total and cleared gross notional open interest for U.S.-based reference entities also come from DTCC.

Bond information comes from the Mergent Fixed Income Securities Database (FISD). I consider corporate debentures and medium-term notes and, like Bessembinder et al. (2018), drop non-US and putable bonds.[4] Following Chava et al. (2019), I use obligation-level rating decreases from Mergent FISD.[5] I utilize all S&P rating event types and also require that entities have non-missing CDS spreads for 90% of trading days around event dates and that the median prior rating of the affected issues is CCC- or higher.

As in Lee et al. (2018), I use bond pricing information from TRACE. The data, which cover nearly the entire universe of public transactions during the sample period, are cleaned using the procedure outlined in Dick-Nielsen (2014). I compute bond yield spreads by subtracting maturity-matched Treasury yields from the reported transaction yields. Bonds are matched to CDS using Markit's Reference Entity Database in conjunction with header information.

[3] I use quotes instead of actual transaction spreads to facilitate comparison with prior studies (e.g., Hilscher et al., 2015; Lee et al., 2018). Furthermore, data on single-name CDS trades are only available to regulators, so market participants and the broader public have no knowledge of transaction spreads.

[4] All of the results are robust to changes in the set of bonds considered (e.g., excluding medium-term notes).

[5] Similar to prior work, I do not find significant market reactions around rating increases and therefore focus on decreases (e.g., Chava et al., 2019; Lee et al., 2018).

4.2 CDS Reaction to Rating Changes

Beginning with Hull et al. (2004), a series of papers has documented that the CDS market anticipates rating downgrades The extant literature has also shown that such decreases elicit reactions immediately around announcement dates but generate no drift after a rating event. A drop in CDS informativeness could manifest in two ways: a weaker anticipatory effect or the emergence of post-event drift. The former would suggest market participants are less inclined to exploit private information in the single-name CDS market, while the latter would indicate that prices are slower to incorporate public information. I test both channels in this section but focus primarily on the anticipatory effect. To ensure results are not driven by the GFC or the COVID-19 pandemic, both of which caused sustained disruptions in credit markets (e.g., Bessembinder et al., 2018), the sample period begins in January 2011 and ends in December 2019. Following Boyarchenko et al. (2018), I classify January 2011 through December 2013 as the "Pre-Rule" period and January 2014 onward as the "Rule Implementation" period. Given the stark effects of uncleared margin rules on trading behavior, I also separately analyze the "Post-UMR" period, which spans from September 2016 through December 2019.

For each rating change, I use data from event days -200 through -91 to estimate the model

$$SC_{it} = \beta_i MKTSC_t + \epsilon_{it}$$

where SC_{it} is the percentage change in entity i's spread on date t and, for investment grade (high yield) entities, $MKTSC_t$ is the percentage change in the CDXNAIG (CDXNAHY) spread. Similar to Loon and Zhong (2014), I then compute the abnormal percent spread change

$$ASC_{it} = SC_{it} - \hat{\beta}_i MKTSC_t$$

where $\hat{\beta}_i$ is the estimated market beta. The cumulative abnormal spread change (CASC) in the event window $[\tau_1, \tau_2]$ is thus

$$CASC_i^{(\tau_1,\tau_2)} = \left[\prod_{\tau=\tau_1}^{\tau_2}(1 + ASC_{i\tau})\right] - 1 - \hat{\beta}_i \left[\prod_{\tau=\tau_1}^{\tau_2}(1 + MKTSC_\tau) - 1\right].$$

To avoid the undue influence of outliers, I winsorize abnormal spread changes at the 0.3% and 99.7% levels. Following Hull et al. (2004), I separately consider abnormal spread changes that occur in event day windows $[-90, -2]$, $[-1, 1]$, and $[2, 10]$. Partitioning into these bins allows me to determine if spreads react prior to, during, and after rating events, respectively.

Table 1 presents the mean CASC in the three periods for each bin. The pre-event column reveals that the CDS market anticipates rating events in the Pre-Rule, Rule Implementation, and Post-UMR periods. The column corresponding to the [-1,1] bin shows that there is also significant movement in spreads during the small window around rating decreases. There is at most weak evidence of spread changes in the [2,10] window during the Pre-Rule period, but a 1.8-2.2% post-event drift emerges in the two later periods. This finding is the first indication that the CDS market may incorporate information less quickly after the adoption of post-crisis regulation.

Table 1: CDS Reactions to Rating Changes

	Period	N	[-90, -2]	[-1, 1]	[2, 10]
All	Pre-Rule	207	0.2373***	0.0147***	0.0066
			(0.0311)	(0.0046)	(0.0063)
	Rule Implementation	451	0.2124***	0.0236***	0.0184***
			(0.0235)	(0.0042)	(0.0054)
	Post-UMR	243	0.1573***	0.0286***	0.0227***
			(0.0276)	(0.0066)	(0.0081)
High Yield	Pre-Rule	112	0.2850***	0.0200***	0.0161*
			(0.0499)	(0.0069)	(0.0091)
	Rule Implementation	208	0.2854***	0.0298***	0.0277***
			(0.0415)	(0.0074)	(0.0100)
	Post-UMR	130	0.2324***	0.0385***	0.0358**
			(0.0465)	(0.0108)	(0.0138)
Investment Grade	Pre-Rule	95	0.1810***	0.0084	−0.0046
			(0.0330)	(0.0058)	(0.0084)
	Rule Implementation	243	0.1499***	0.0182***	0.0104**
			(0.0247)	(0.0045)	(0.0051)
	Post-UMR	113	0.0708***	0.0172**	0.0076
			(0.0237)	(0.0069)	(0.0069)

Notes: This table presents mean cumulative abnormal percentage CDS spread changes in various time bins around rating events. The Pre-Rule period extends from January 2011 through December 2013, the Rule Implementation runs from January 2014 through December 2019, and the Post-UMR period spans from September 2016 through December 2019. Standard errors are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: Markit, Mergent FISD, Author's calculations.

To study if less private information is impounded into CDS spreads prior to rating decreases, I compare the share of the cumulative abnormal spread response that occurs before event dates in the various time periods. The measure I construct is based on the Delayed Response Ratio used by DellaVigna and Pollet (2009) to study post-earnings-announcement drift. I first estimate the regression

$$CASC_{it}^{(\tau_1,\tau_2)} = \alpha + \beta PostPeriod_t + X_{it} + \epsilon_{it} \tag{1}$$

for $(\tau_1, \tau_2) \in \{(-90, -2), (-90, 1)\}$, where $PostPeriod_t$ is an indicator equal to one if rating event i on date t takes place in the Rule Implementation period and X_{it} is an indicator equal to one if the entity is investment grade prior to the rating change. I then compute

$$PER^{(-2,1)} = \frac{\overline{CASC}^{(-90,-2)}}{\overline{CASC}^{(-90,1)}},$$

where $\overline{CASC}^{(-90,\tau)}$ for $\tau \in \{-2, 1\}$ is calculated using regression coefficients estimated from Equation 1. For specifications with controls, ratios are calculated using the mean control values. If the CDS market fully anticipates rating events, the pre-event ratio will equal one. If, instead, an appreciable share of the spread reaction occurs only when changes are announced, the ratio will be less than one.

The first two rows in the left half of Table 2 present PERs in the Pre-Rule and Rule Implementation periods, respectively. The ratio is statistically different than one in both periods, but the third row demonstrates that the change across them is not significant. The second half of Table 2 displays results when I consider only rating events that occur in the Pre-Rule and Post-UMR periods. The statistically significant decrease in PER from 90% at the beginning of the sample to only 78% after the introduction of margin reform accords with an erosion in the informativeness of CDS spreads.

To better understand how ratios evolve over the event window, I plot $PER^{(\tau,1)}$ for $\tau \in [-90, 1]$ in the left panel of Figure 4. In the Pre-Rule period, the ratio is generally above its level in the Post-UMR period. Consistent with the prior result, however, the ratio in the latter period increases sharply around the rating date. In the right panel of Figure 4, I plot $PER^{(-2,1)}$ when rating events are grouped into six time bins of equal length. The vertical lines extending from each point represent 95% confidence intervals. The ratio is relatively stable in the early part of the sample but falls markedly in the two bins that fall entirely in the Post-UMR period.

Table 2: Changes in Pre-Event Ratios

	Rule Implementation		Post-UMR	
Pre-Rule	0.9038***	0.9066***	0.9038***	0.9040**
	(0.0297)	(0.0346)	(0.0316)	(0.0373)
Post Period	0.8488***	0.8484***	0.7765***	0.7765***
	(0.0208)	(0.0275)	(0.0373)	(0.0452)
Pre-Rule - Post Period	−0.0549	−0.0582	−0.1273***	−0.1275**
	(0.0362)	(0.0442)	(0.0489)	(0.0586)
N	657	657	449	449
Rating Control	N	Y	N	Y

Notes: The first two rows of this table present the pre-event ratio (PER) of cumulative abnormal spread changes around rating downgrades in the Pre-Rule, Rule Implementation, and Post-UMR periods. Ratios are computed by dividing the mean cumulative abnormal spread change (CASC) from event day -90 to -2 by the mean CASC from event day -90 to 1. Means are calculated using regression coefficients estimated from Equation 1. The rating control is an indicator equal to one if the entity was investment grade prior to the change. Standard errors computed using the delta method are presented in parentheses. In the first two rows, t-tests are used to determine if the ratios are statistically different than one. The third row tests if the differences across periods is statistically different from 0. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: Markit, Mergent FISD, Author's calculations.

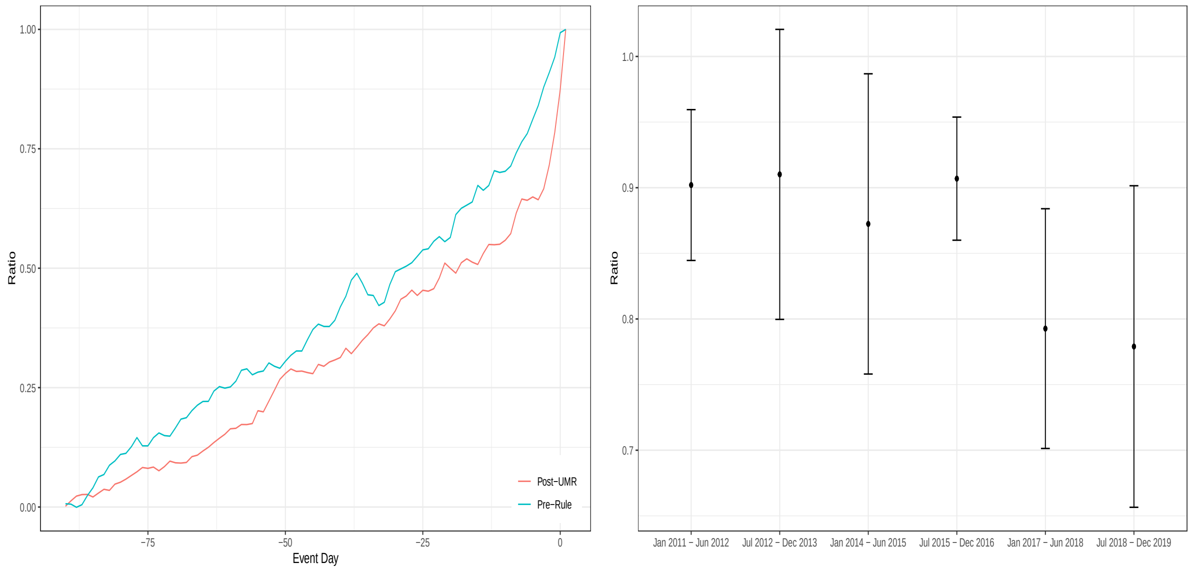
The plots further suggest that UMR have negatively affected price discovery in the CDS market. Cross-sectional analysis is ultimately required to conclude that margin reform has caused the decline, but the limited number of rating downgrades makes it difficult to conduct tests with sufficient statistical power. I address this shortcoming in the next section by studying changes in the relative informativeness of single-name CDS and corporate bond spreads.

4.3 Lead-Lag Relationship Between CDS and Bonds

A literature beginning with Blanco et al. (2005) has established that the single-name CDS market leads the corporate bond market in the price discovery process. Motivated by the decline in informativeness documented in the previous section, I investigate if the nature of this lead-lag relationship has also changed. If the results thus far are driven by structural reforms to derivatives markets, then CDS spreads should lead bond spreads less strongly toward the end of the sample period. Alternatively, if the drop in pre-event ratios and the emergence of post-event drifts are the result of other factors such as systematic modifications to S&P's rating change criteria, the lead-lag relationship between CDS and bond spreads should remain stable over time.

The corporate bond market, like its CDS counterpart, has been impacted by regulation im-

Figure 4: Disaggregated Pre-Event Ratios



Notes: The left panel plots $PER^{(\tau,1)}$ for $\tau \in [-90, 1]$. The right panel plots $PER^{(-2,1)}$ when the sample is partitioned into six bins of equal length. The vertical lines represent 95% confidence intervals for the estimates. Source: Markit, Mergent FISD, Author's calculations.

plemented since the GFC, so it bears clarifying why one might expect to find a shift in relative informativeness. Bond dealers have responded to post-crisis reforms by committing less capital to intermediation and, instead, pre-arranging trades between buyers and sellers (e.g., Choi et al., 2023; Goldstein and Hotchkiss, 2020). CDS positions may be less costly for dealers to fund, but offsetting derivatives contracts in a similar manner does not provide full regulatory relief because SLR guidelines limit the netting of gross exposures across counterparties. Furthermore, the Volcker Rule applies to the primary intermediaries in both markets, so it should have comparable effects on price discovery for CDS and bonds. In contrast to these earlier reforms, uncleared margin requirements apply only to derivative contracts. I therefore test for differences in the lead-lag relationship before and after the first phase of the UMR was introduced in September 2016.

4.4 Single Names

To measure the strength of the lead-lag relationship between single-name CDS and bonds, I estimate panel vector autoregressions (PVARs) similar to those of Hilscher et al. (2015) and Lee et al. (2018).

The model is given by the equation

$$\begin{bmatrix} \Delta S_{it}^{CDS} \\ \Delta S_{it}^{Bond} \end{bmatrix} = \begin{bmatrix} \beta_{0,i,CDS} \\ \beta_{0,i,Bond} \end{bmatrix} + \sum_{k=1}^{n} \begin{bmatrix} \beta_{k,CDS,CDS} & \beta_{k,CDS,Bond} \\ \beta_{k,Bond,CDS} & \beta_{k,Bond,Bond} \end{bmatrix} \begin{bmatrix} \Delta S_{it-k}^{CDS} \\ \Delta S_{it-k}^{Bond} \end{bmatrix} + \begin{bmatrix} \epsilon_{it}^{CDS} \\ \epsilon_{it}^{Bond} \end{bmatrix} \tag{2}$$

where ΔS_{it}^{CDS} and ΔS_{it}^{Bond} are daily percentage changes in CDS and bond spreads for firm i on date t, respectively. Entity-level bond spread changes are the volume-weighted average changes taken across individual CUSIPs. For parsimony, the lag order is fixed at two throughout the analysis. Standard errors are clustered by date and, to ensure findings are not driven by outliers, both bond and CDS spread changes are winsorized at the 0.3% and 99.7% levels. Positive $\beta_{k,Bond,CDS}$ coefficients indicate the CDS market leads the bond market in price discovery. If increased trading costs associated with the UMR cause CDS spreads to become relatively less informative, point estimates should decrease in the Post-UMR period.

Table 3 presents results when Equation 2 is estimated separately on the Pre- and Post-UMR samples. The positive, significant coefficients in the first and third rows of Columns 2 and 4 confirm that CDS lead bonds in both periods, while the smaller point estimates in Column 4 are consistent with weaker information flow in the latter. In the Pre-UMR period, a 1% increase in CDS spread is associated with a 0.20% increase in bond spread the following day. In the Post-UMR period, the same change in CDS spread corresponds to only a 0.11% increase in bond spread. Impulse response functions from the PVARs are plotted in the left panel of Figure 5. The right panel depicts the differences across periods. The solid line is the point estimate of the difference at various horizons, while the shaded area represents a 95% confidence interval recovered by bootstrapping. The difference at the one-day horizon is negative and statistically significant, affirming that CDS spreads lead bond spreads less strongly from September 2016 onward.

The findings are robust to a number of alternate specifications, including those with different lag orders and winsorization thresholds. They are also similar if I instead estimate separate panel regressions and interact the lagged spread changes with Post-UMR indicator variables. To demonstrate the decrease in relative informativeness is not driven by a secular time trend, I partition the Pre- and Post-UMR periods into bins of roughly equal length and estimate Equation 2 separately for each. The vertical lines again depict 95% confidence intervals. The first four point estimates

Table 3: Single-Name Lead-Lag Relationship

	Pre-UMR		Post-UMR	
	Δ CDS Spread	Δ Bond Spread	Δ CDS Spread	Δ Bond Spread
Δ CDS Spread L1	0.1184***	0.2014***	0.0684***	0.1089***
	(0.0116)	(0.018)	(0.0155)	(0.0291)
Δ Bond Spread L1	0.0012***	−0.1447***	0.0011***	−0.0967***
	(0.0003)	(0.0042)	(0.0003)	(0.0045)
Δ CDS Spread L2	0.0601***	0.0863***	0.0842***	0.0816***
	(0.0149)	(0.0196)	(0.0149)	(0.0267)
Δ Bond Spread L2	0.0011***	−0.0096**	0.0004	0.0036
	(0.0003)	(0.004)	(0.0003)	(0.0042)
Observations	541,095	541,095	331,721	331,721

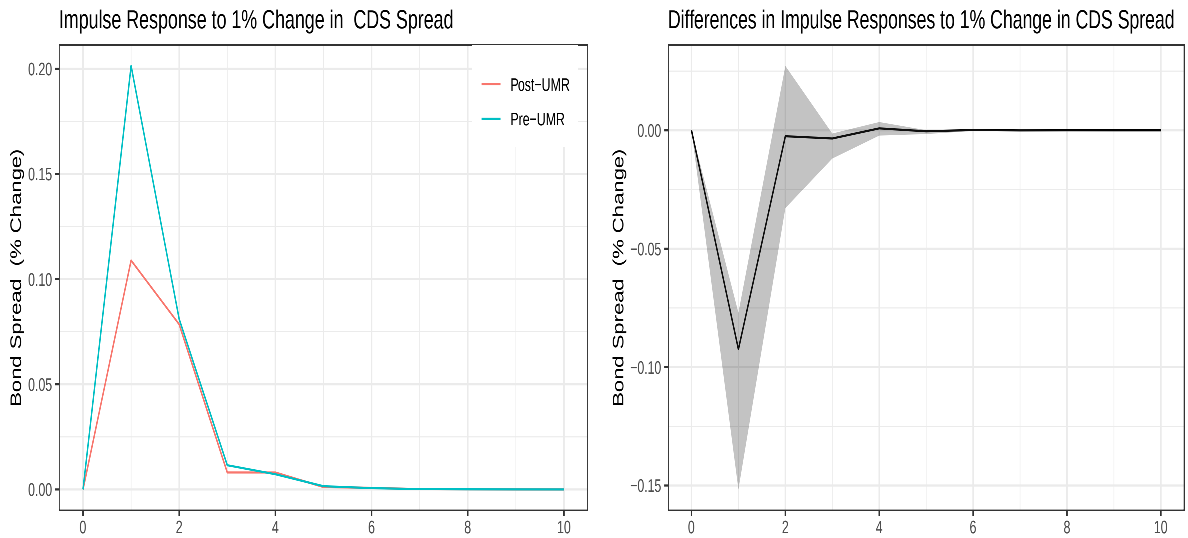
Notes: This table documents the lead-lag relationship between single-name CDS and bonds during the Pre-UMR and Post-UMR periods. The PVAR given by Equation 2 is estimated using daily percentage spread changes. All variables are winsorized at the 0.3% and 99.7% levels. Standard errors clustered by date are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: Markit, TRACE, Author's calculations.

are similar, indicating there is no trend in the Pre-UMR period and that Basel III and the Volcker Rule did not have a differential impact on CDS and bond market informativeness. The decline in the two bins comprising the Post-UMR period again suggests that margin requirements harmed price discovery for single-name CDS.

The time series evidence confirms that the lead-lag relationship between CDS and bonds does not deteriorate gradually over the sample period. It also suggests the drop in pre-event ratio and emergence of post-event drift around downgrades do not stem from revisions to S&P's rating change process. That said, it fails to demonstrate that the costs associated with the UMR, not other factors affecting CDS trading, cause the decrease in informativeness. If only certain underlyings were subject to the regulation, one could easily identify the impact of the UMR. Since the margin requirements apply to all reference entities, however, I conduct a series of cross-sectional tests to determine if the underlyings plausibly most exposed to the rules experience the sharpest declines.

I begin by testing if the lead-lag relationship between CDS and bonds deteriorates more for underlyings with large uncleared transaction volumes. Sequential trading models suggest that in markets liquid enough to sustain informed trading, each incremental transaction contributes to price discovery. It follows that reference entities with appreciable amounts of uncleared trading will be particularly adversely affected by the new margin requirements. I classify underlyings that are active in September 2016 as High Volume if they appear on DTCC's Top 1000 list in the

Figure 5: Single-Name Impulse Responses



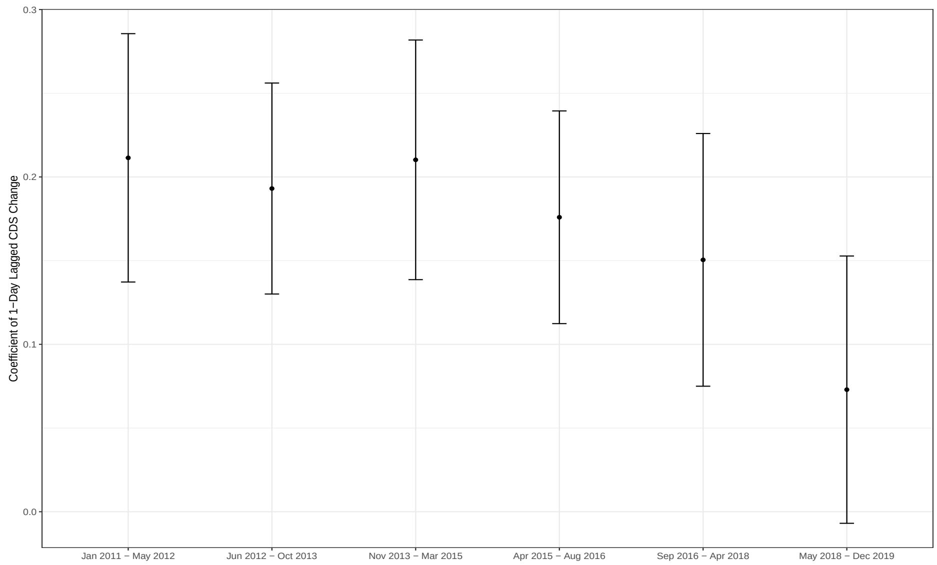
Notes: The left panel depicts the impulse responses when the PVAR given by Equation 2 is estimated using daily data. The right panel depicts the differences in the individual impulse responses at various horizons. The shaded area represents the 95% confidence interval recovered by bootstrapping. Source: Markit, TRACE, Author's calculations.

quarter immediately preceding the introduction of the UMR and Low Volume if they do not, then estimate Equation 2 separately for each group in both the Pre- and Post-UMR periods. Results are presented in Table 4. For brevity, I include estimates only when bond spreads are the dependent variable. While the first lag CDS spread change coefficient is steady across periods for Low Volume entities, there is a marked decline in the corresponding coefficient for High Volume underlyings. In the last column, I test if the relative change in the estimates is significant. Consistent with the hypothesis, the difference-in-differences estimate is economically and statistically significant for the first lag of CDS spread change.

In Figure 7, I split the Pre- and Post-UMR periods more finely and plot the first lag CDS change coefficient when Equation 2 is estimated separately for the Low and High Volume groups. The blue bars demonstrate that the point estimates for Low Volume entities are stable from mid-2012 onward. The red bars, on the other hand, reveal a large decline in the point estimates for the High Volume group after UMR adoption. As predicted, the latter group drives the weakening of the lead-lag relationship between CDS and corporate bond spreads in the Post-UMR period.

Because the UMR apply only to uncleared trades, I extend the previous test by investigating if the results are most pronounced for High Volume entities that are less likely to be centrally cleared.

Figure 6: Evolution of Lag CDS Coefficient over Time



Notes: This figure presents coefficients of first-order lagged CDS spread changes from regressions with bond spreads as the dependent variable when the PVAR given by Equation 2 is estimated separately for various time bins. The vertical lines extending from each point represent 95% confidence intervals. Source: Markit, TRACE, Author's calculations.

For each underlying, I compute the clearing propensity immediately prior to UMR adoption by dividing cleared open interest by total gross open interest. I then partition the High Volume group into three finer categories: Non-Clearable, Low Propensity, and High Propensity. The first group consists of underlyings that were not eligible to be cleared in September 2016, while the Low (High) Propensity group consists of eligible entities with clearing propensities below (above) the median.

Table 5 presents results when Equation 2 is estimated separately for each of the three groups in both the Pre- and Post-UMR periods. Again, I only report estimates when bond spread changes are the dependent variable. The first two columns provide coefficients for the two time periods, while the third tests if the changes across periods are statistically significant. The differences for the first lags of CDS spread changes are negative for all three groups, but the magnitudes decrease as clearing propensity increases. Moreover, while the difference for the Non-Clearable group is significant at the 1% level, its counterpart for the High Propensity group is only significant at the 10% level. The results accord with the hypothesis that uncleared margin requirements explain the decline in relative informativeness.

Initial margin required under the UMR is determined using Value at Risk style measures. All else being equal, reference entities whose spread changes are highly correlated with those of the

Table 4: Difference-in-Differences Test Around UMR Adoption

	Pre-UMR		Post-UMR		DiD
	High	Low	High	Low	
Δ CDS Spread L1	0.2427***	0.0935***	0.1118***	0.102**	0.1394**
	(0.0216)	(0.0333)	(0.0367)	(0.0419)	(0.0684)
Δ Bond Spread L1	−0.1439***	−0.1267***	−0.0889***	−0.1***	−0.0283**
	(0.0053)	(0.0084)	(0.0057)	(0.008)	(0.014)
Δ CDS Spread L2	0.1013***	0.0152	0.0916***	0.0752*	0.0698
	(0.0231)	(0.0334)	(0.0331)	(0.0402)	(0.066)
Δ Bond Spread L2	−0.0138***	-0.0002	-0.0038	0.0109	0.0011
	(0.0049)	(0.0084)	(0.005)	(0.0082)	(0.0137)
Observations	346,346	112,581	212,777	81,790	

Notes: The first four columns of this table present coefficient estimates when the panel VAR given by Equation 2 is estimated separately across periods for both High and Low Volume entities. Only coefficients when changes in bond spreads are the dependent variable are reported. Entities in the Low (High) category are those with average daily notional volume less than (at least) 2.5MM in the CDS market in the quarter immediately preceding UMR adoption. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: Markit, TRACE, Author's calculations.

CDXNAIG and CDXNAHY may incur larger margin charges than less correlated underlyings, as they offer less portfolio diversification benefit. If the UMR drive the decline in informativeness, the former set of entities are therefore likely to experience the largest effects. To test this hypothesis, I first compute correlations between single-name and index spread changes over the twelve months immediately preceding the adoption of the UMR for entities with at least 100 observations during this window. Underlyings that are investment grade (high yield) at the end of August 2016 are paired with the CDXNAIG (CDXNAHY). I then separately estimate the regressions described in Equation 2, but include interactions between the spread change variables, a post-UMR indicator, and the index correlations.[6]

Results are presented in Table 6. For brevity, I include only the regression with the change in bond spreads as the dependent variable. The focal term is the triple interaction of the first lag of CDS spread changes, the regulation indicator, and the index correlation. The corresponding coefficient estimate is negative and statistically significant, which indicates informativeness declines more sharply for reference entities that incur the largest margin charges following UMR adoption. Taken together, the time series and cross-sectional findings provide strong evidence that the UMR

[6] Nickell bias is not major concern given the length of the panel, so I use ordinary least squares instead of a dynamic panel estimator.

Table 5: Lead-Lag Relationship by Clearing Propensity

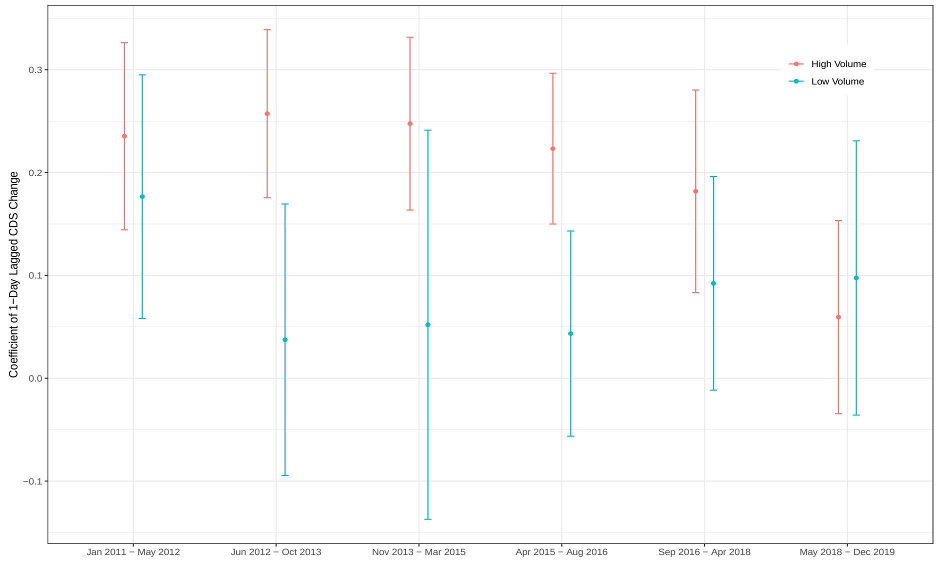
Panel A: Non-Clearable	Pre-UMR	Post-UMR	Difference
Δ CDS Spread L1	0.2136***	0.0409	0.1727***
	(0.034)	(0.0454)	(0.0567)
Δ Bond Spread L1	−0.148***	−0.088***	−0.0601***
	(0.0087)	(0.0091)	(0.0126)
Δ CDS Spread L2	0.1297***	0.022	0.1077*
	(0.0355)	(0.0462)	(0.0583)
Δ Bond Spread L2	-0.0055	-0.0042	-0.0013
	(0.0085)	(0.0089)	(0.0123)
Observations	101,250	66,004	

Panel B: Low Propensity	Pre-UMR	Post-UMR	Difference
Δ CDS Spread L1	0.2852***	0.1534***	0.1318***
	(0.0249)	(0.0414)	(0.0483)
Δ Bond Spread L1	−0.1199***	−0.0859***	−0.0339**
	(0.0103)	(0.0099)	(0.0143)
Δ CDS Spread L2	0.0689**	0.1125***	-0.0435
	(0.0285)	(0.0409)	(0.0499)
Δ Bond Spread L2	−0.0221**	-0.0085	-0.0136
	(0.0093)	(0.0099)	(0.0136)
Observations	113,376	70,928	

Panel C: High Propensity	Pre-UMR	Post-UMR	Difference
Δ CDS Spread L1	0.2189***	0.1036*	0.1154*
	(0.0276)	(0.0544)	(0.0611)
Δ Bond Spread L1	−0.1549***	−0.0916***	−0.0633***
	(0.0078)	(0.0095)	(0.0123)
Δ CDS Spread L2	0.1144***	0.1029**	0.0116
	(0.0259)	(0.0439)	(0.051)
Δ Bond Spread L2	−0.0172**	-0.0004	-0.0167
	(0.0075)	(0.0078)	(0.0108)
Observations	131,720	75,845	

Notes: The first two columns of this table present coefficient estimates when the panel VAR given by Equation 2 is estimated separately across periods for Non-Clearable, Low Clearing Propensity, and High Propensity entities. Only coefficients when changes in bond spreads are the dependent variable are reported. The Non-Clearable group consists of entities that appear on DTCC's Top 1000 list in the quarter preceding UMR adoption but are not eligible for clearing. The Low (High) Propensity group consists of clear-eligible entities that appear on the Top 1000 list with a clearing propensity below (above) the median. Clearing propensity is defined as the cleared notional outstanding divided by the total gross notional outstanding. The final column tests if the differences across periods are statistically significant. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: DTCC CDS, DTCC OTC Repository Data, Markit, TRACE, Author's calculations.

Figure 7: Evolution of Lag CDS Coefficient by Volume



Notes: This figure presents the estimates for the first-order lag CDS spread change coefficient when Equation 2 is estimated separately for High and Low volume entities in various time bins. Low (High) volume entities are those with an average daily CDS notional less than (at least) 2.5MM in the quarter immediately preceding UMR adoption. The vertical lines extending from each point represent the 95% confidence interval for the estimate. Source: DTCC OTC Repository Data, Markit, TRACE, Author's calculations.

cause the deterioration of the lead-lag relationship between single name CDS and bonds.

4.5 Indices

I next investigate if post-Crisis reforms have impacted price discovery for CDS indices. As shown in Figure 2, clearing rates for contracts referencing baskets have been appreciably higher than for those written on single names. It follows that the UMR are less burdensome for index trading. The model introduced in Section 3 predicts that an increase in the relative transaction costs of single names will drive informed agents toward index markets. As a result, price efficiency may not decrease for the CDX. It is difficult to assess the absolute informativeness of indices, so I again look for differential changes in CDS and bond markets. More specifically, I pair the CDXNAIG with the Intercontinental Exchange Bank of America (ICE BoA) US Corporate Index and then CDXNAHY with the ICE BoA High Yield Index, then estimate the panel VARs given by Equation 2 separately in the Pre- and Post-UMR periods. If the UMR cause CDS spreads to become relatively less informative, the $\beta_{k,Bond,CDS}$ estimates should decrease in the latter period. Once more, I fix the lag order at two and winsorize spread changes at the 0.3% and 99.7% levels.

Table 6: Index Correlation

	Δ Bond Spread
Δ CDS Spread L1	0.07***
	(0.02)
Δ Bond Spread L1	−0.14***
	(0.01)
Δ CDS Spread L2	0.06**
	(0.03)
Δ Bond Spread L2	−0.00
	(0.01)
Post-UMR	0.65***
	(0.13)
Δ CDS Spread L1 $\times$Post-UMR	0.00
	(0.05)
Post-UMR $\times$ Δ Bond Spread L1	0.04***
	(0.01)
Post-UMR $\times$ Δ CDS Spread L2	0.03
	(0.05)
Post-UMR $\times$ Δ Bond Spread L2	0.01
	(0.01)
Δ CDS Spread L1 $\times$ ρ^{CDX}	0.40***
	(0.06)
ρ^{CDX} $\times$ Δ Bond Spread L1	0.06***
	(0.02)
ρ^{CDX} $\times$ Δ CDS Spread L2	0.05
	(0.06)
ρ^{CDX} $\times$ Δ Bond Spread L2	−0.00
	(0.02)
Post-UMR $\times$ ρ^{CDX}	−0.29
	(0.24)
Δ CDS Spread L1 $\times$Post-UMR $\times$ ρ^{CDX}	−0.25**
	(0.11)
Post-UMR $\times$ ρ^{CDX} $\times$ Δ Bond Spread L1	−0.01
	(0.03)
Post-UMR $\times$ ρ^{CDX} $\times$ Δ CDS Spread L2	−0.05
	(0.11)
Post-UMR $\times$ ρ^{CDX} $\times$ Δ Bond Spread L2	0.01
	(0.03)
Observations	780862

Notes: This table reports results when the regressions in Equation 2 are separately estimated with additional interaction terms. Post-UMR is an indicator equal to one after the implementation of UMR in September 2016. ρ^{CDX} is the correlation coefficient between a firm's spread changes and those of the CDX over the year preceding UMR adoption. The regression includes firm fixed effects and standard errors are clustered by date. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: Markit, TRACE, Author's calculations.

Results are presented in Table 7. The positive coefficients in Columns 2 and 4 demonstrate that the CDX indices lead their corporate bond counterparts in both periods. The magnitudes of the first lag CDX change estimates are very similar across periods and their difference is not statistically significant, indicating that relative informativeness in unchanged across periods. This finding supports the notion that regulation and not some other force impacting all segments of the CDS market drives the deterioration in price discovery for single names. It also accords with the prediction of the model that informed traders migrate from single-name to index markets when the cost of trading in the former increases.

Table 7: Index Lead-Lag Relationships

	Pre-UMR		Post-UMR	
	Δ CDS Spread	Δ Bond Spread	Δ CDS Spread	Δ Bond Spread
Δ CDS Spread L1	0.059*	0.1821***	0.0187	0.1979***
	(0.0332)	(0.0169)	(0.0414)	(0.025)
Δ Bond Spread L1	0.0449	0.0213	-0.0326	-0.0217
	(0.0566)	(0.0355)	(0.044)	(0.0415)
Δ CDS Spread L2	-0.0139	0.047***	-0.0014	0.0754***
	(0.0317)	(0.0154)	(0.0422)	(0.0226)
Δ Bond Spread L2	-0.0141	0.0454	0.0296	0.105**
	(0.0506)	(0.0332)	(0.0431)	(0.0408)
Observations	2,558	2,558	1,600	1,600

Notes: This table presents coefficients when the panel VARs given by Equation 2 is estimated separately for the Pre-UMR and Post-UMR periods using daily percentage index spread changes. The CDXNAIG is paired with the ICE BoA US Corporate Index and the CDXNAHY is paired with the ICE BoA High Yield Index. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Source: Markit, FRED, Author's calculations.

5 Conclusion

In this paper, I investigate how post-crisis regulation has impacted price discovery in the CDS market. Using windows around rating downgrades, I find evidence that single-name CDS spreads impound less private information and are slower to incorporate public information following the introduction of stringent margin rules for uncleared swaps. Estimates from panel VARs reveal that single-name CDS spreads also lead corporate bond spreads less strongly in the Post-UMR period. The deterioration of informativeness is driven by reference entities that are most exposed to the new rules, including those with the most uncleared trading volume. Price discovery for CDS indices, which are primarily centrally cleared and thus less exposed to the UMR, appears to be unharmed.

The results accord with a model in which increases in single-name transaction costs lead informed agents to trade indices instead.

My findings highlight a lesser-studied channel through which post-crisis regulation has affected financial markets. A decline in CDS informativeness is especially noteworthy, as it gives the corporate bond market and credit rating agencies a renewed role in the price discovery process. Given that other derivative classes, such as foreign exchange swaps, also have large uncleared segments, my results have implications that extend beyond corporate credit markets. It is worth noting that regulators may consider the loss of informational efficiency associated with reforms to be well worth the corresponding improvements to financial stability. That said, it remains important to fully articulate the tradeoffs of these policies in order to evaluate their efficacy.

References

Viral V Acharya and Timothy C Johnson. Insider Trading in Credit Derivatives. *Journal of Financial Economics*, 84(1):110–141, 2007.

Patrick Augustin, Marti G Subrahmanyam, Dragon Y Tang, and Sarah Q Wang. Credit default swaps: Past, present, and future. *Annual Review of Financial Economics*, 8:175–196, 2016.

Bank for International Settlements. Margin Requirements for Non-Centrally Cleared Derivatives. Technical report, 2015.

Bank for International Settlements. Incentives to Centrally Clear Over-the-Counter (OTC) Derivatives. Technical report, 2018.

Jack Bao, Maureen O'Hara, and Xing Alex Zhou. The Volcker Rule and Corporate Bond Market Making in Times of Stress. *Journal of Financial Economics*, 130(1):95–113, 2018.

Hendrik Bessembinder, Stacey Jacobsen, William Maxwell, and Kumar Venkataraman. Capital Commitment and Illiquidity in Corporate Bonds. *The Journal of Finance*, 73(4):1615–1661, 2018.

Bruno Biais and Pierre Hillion. Insider and Liquidity Trading in Stock and Options Markets. *The Review of Financial Studies*, 7(4):743–780, 1994.

Gopa Biswas, Stanislava Stas Nikolova, and Christof W Stahel. The Transaction Costs of Trading Corporate Credit. Working paper, 2015.

Roberto Blanco, Simon Brennan, and Ian W Marsh. An Empirical Analysis of the Dynamic Relation Between Investment-Grade Bonds and Credit Default Swaps. *The journal of Finance*, 60(5):2255–2281, 2005.

Philip Bond and Diego Garcia. The equilibrium consequences of indexing. *The Review of Financial Studies*, 35(7):3175–3230, 2022.

Nina Boyarchenko, Thomas M Eisenbach, Pooja Gupta, Or Shachar, and Peter Van Tassel. Bank-Intermediated Arbitrage. *FRB of New York Staff Report*, (858), 2018.

Nina Boyarchenko, Anna M Costello, and Or Shachar. The Long and Short of It: The Post-Crisis Corporate CDS Market. *FRB of New York Staff Report*, (879), 2019.

Katy Burne and Eyk Henning. Deutsche Bank Ends Most CDS Trades. *The Wall Street Journal*, 2014.

Agostino Capponi, Wan-Schwin Allen Cheng, Stefano Giglio, and Richard Haynes. The collateral rule: Evidence from the credit default swap market. *Journal of Monetary Economics*, 126:58–86, 2022.

Sudheer Chava, Rohan Ganduri, and Chayawat Ornthanalai. Do credit default swaps mitigate the impact of credit rating downgrades? *Review of Finance*, 23(3):471–511, 2019.

Dong Beom Choi, Michael R Holcomb, and Donald P Morgan. Bank Leverage Limits and Regulatory Arbitrage: Old Question-New Evidence. *Journal of Money, Credit and Banking*, 52(S1): 241–266, 2020.

Jaewon Choi, Yesol Huh, and Sean Seunghun Shin. Customer liquidity provision: Implications for corporate bond transaction costs. *Management Science*, 2023.

Pierre Collin-Dufresne, Benjamin Junge, and Anders B Trolle. Market Structure and Transaction Costs of Index CDSs. *The Journal of Finance*, 75(5):2719–2763, 2020.

Stefano DellaVigna and Joshua M Pollet. Investor Inattention and Friday Earnings Announcements. *The Journal of Finance*, 64(2):709–749, 2009.

Jens Dick-Nielsen. How to Clean Enhanced TRACE Data. Working Paper, 2014.

Wenxin Du, Salil Gadgil, Michael B Gordy, and Clara Vega. Counterparty risk and counterparty choice in the credit default swap market. *Management Science*, 2023.

Darrell Duffie. *Fragmenting Markets: Post-crisis Bank Regulations and Financial Market Liquidity*. Walter de Gruyter GmbH & Co KG, 2022.

Darrell Duffie, Martin Scheicher, and Guillaume Vuillemey. Central Clearing and Collateral Demand. *Journal of Financial Economics*, 116(2):237–256, 2015.

Andrea L Eisfeldt, Bernard Herskovic, Sriram Rajan, and Emil Siriwardane. Otc intermediaries. *The Review of Financial Studies*, 36(2):615–677, 2023.

Thomas Ernst. Stock-Specific Price Discovery from ETFs. Working paper, 2020.

Financial Crisis Inquiry Commission. The Financial Crisis Inquiry Report: Final report of the National Commission on the Causes of the Financial and Economic Crisis in the United States. Commission report, United States Government, January 2011.

Nils Friewald, Rainer Jankowitsch, and Marti G Subrahmanyam. Illiquidity or credit deterioration: A study of liquidity in the us corporate bond market during financial crises. *Journal of financial economics*, 105(1):18–36, 2012.

Lawrence Glosten, Suresh Nallareddy, and Yuan Zou. Etf activity and informational efficiency of underlying securities. *Management Science*, 67(1):22–47, 2021.

Lawrence R Glosten and Paul R Milgrom. Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders. *Journal of financial economics*, 14(1):71–100, 1985.

Michael A Goldstein and Edith S Hotchkiss. Providing liquidity in an illiquid market: Dealer behavior in us corporate bonds. *Journal of Financial Economics*, 135(1):16–40, 2020.

Oleg R Gredil, Nishad Kapadia, and Jung Hoon Lee. On the information content of credit ratings and market-based measures of default risk. *Journal of Financial Economics*, 146(1):172–204, 2022.

Sanford J Grossman and Joseph E Stiglitz. On the impossibility of informationally efficient markets. *The American economic review*, 70(3):393–408, 1980.

Jens Hilscher and Mungo Wilson. Credit ratings and credit risk: Is one measure enough? *Management science*, 63(10):3414–3437, 2017.

Jens Hilscher, Joshua M Pollet, and Mungo Wilson. Are Credit Default Swaps a Sideshow? Evidence that Information Flows from Equity to CDS Markets. *Journal of Financial and Quantitative Analysis*, pages 543–567, 2015.

Shiyang Huang, Maureen O'Hara, and Zhuo Zhong. Innovation and informed trading: Evidence from industry etfs. *The Review of Financial Studies*, 34(3):1280–1316, 2021.

John Hull, Mirela Predescu, and Alan White. The Relationship between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements. *Journal of Banking & Finance*, 28 (11):2789–2811, 2004.

Doron Israeli, Charles MC Lee, and Suhas A Sridharan. Is there a dark side to exchange traded funds? an information perspective. *Review of Accounting Studies*, 22:1048–1083, 2017.

Wei Jiang, Jitao Ou, and Zhongyan Zhu. Mutual fund holdings of credit default swaps: Liquidity, yield, and risk. *The Journal of Finance*, 76(2):537–586, 2021.

Mike Kentz. ISDA Pushes Back on Swaps Margin Rules. *Reuters*, 2012.

Jongsub Lee, Andy Naranjo, and Guner Velioglu. When do CDS Spreads Lead? Rating Events, Private Entities, and Firm-Specific Information Flows. *Journal of Financial Economics*, 130(3): 556–578, 2018.

Francis A Longstaff, Sanjay Mithal, and Eric Neis. Corporate yield spreads: Default risk or liquidity? new evidence from the credit default swap market. *The Journal of Finance*, 60(5): 2213–2253, 2005.

Yee Cheng Loon and Zhaodong Ken Zhong. The Impact of Central Clearing on Counterparty Risk, Liquidity, and Trading: Evidence from the Credit Default Swap Market. *Journal of Financial Economics*, 112(1):91–115, 2014.

Yee Cheng Loon and Zhaodong Ken Zhong. Does Dodd-Frank Affect OTC Transaction Costs and Liquidity? Evidence from Real-Time CDS Trade Reports. *Journal of Financial Economics*, 119 (3):645–672, 2016.

Miriam Marra, Fan Yu, and Lu Zhu. The Impact of Trade Reporting and Central Clearing on CDS Price Informativeness. *Journal of Financial Stability*, 43:130–145, 2019.

Lars Norden and Martin Weber. Informational Efficiency of Credit Default Swap and Stock Markets: The Impact of Credit Rating Announcements. *Journal of Banking & Finance*, 28(11):2813–2843, 2004.

Lars Norden and Martin Weber. The Co-movement of Credit Default Swap, Bond and Stock Markets: An Empirical Analysis. *European financial management*, 15(3):529–562, 2009.

Martin Oehmke and Adam Zawadowski. Synthetic or real? the equilibrium effects of credit default swaps on bond markets. *The Review of Financial Studies*, 28(12):3303–3337, 2015.

Martin Oehmke and Adam Zawadowski. The Anatomy of the CDS Market. *The Review of Financial Studies*, 30(1):80–119, 2017.

Esen Onur, David Reiffen, and Rajiv Sharma. The impact of margin requirements on voluntary clearing decisions. *Journal of Financial Markets*, 68:100892, 2024.

Mark E Paddrik and Stathis Tompaidis. Intermediation Networks and Derivative Market Liquidity: Evidence from CDS Markets. Working paper, 2024.

Joe Rennison. Hurdles Remain in Reviving Single-Name CDS. *Financial Times*, 2015.

Lynn Riggs, Esen Onur, David Reiffen, and Haoxiang Zhu. Swap Trading after Dodd-Frank: Evidence from Index CDS. *Journal of Financial Economics*, 137(3):857–886, 2020.

Avanidhar Subrahmanyam. A Theory of Trading in Stock Index Futures. *The Review of Financial Studies*, 4(1):17–51, 1991.

Haibin Zhu. An empirical comparison of credit spreads between the bond market and the credit default swap market. *Journal of financial services research*, 29:211–235, 2006.

A Proofs

Proof of Lemma 1. As in Glosten and Milgrom (1985), market makers use Bayes' rule to update their beliefs about the final values of securities A and B given the sign of the observed order. Because market makers are risk neutral and competitive, they set bids and asks equal to their revised conditional expectations. Thus,

$$
\begin{aligned}
ask_A &= P(\hat{V}_A = 1|\text{buy } A)\\
&= \frac{P(\text{buy } A|\hat{V}_A = 1)P(\hat{V}_A = 1)}{P(\text{buy } A|\hat{V}_A = 1)P(\hat{V}_A = 1) + P(\text{buy } A|\hat{V}_A = 0)P(\hat{V}_A = 0)}\\
&= \frac{4\phi_A\alpha + 1 - \alpha}{4\phi_A\alpha + 2 - 2\alpha}\\
bid_A &= P(\hat{V}_A = 1|\text{sell } A)\\
&= \frac{P(\text{sell } A|\hat{V}_A = 1)P(\hat{V}_A = 1)}{P(\text{sell } A|\hat{V}_A = 1)P(\hat{V}_A = 1) + P(\text{sell } A|\hat{V}_A = 0)P(\hat{V}_A = 0)}\\
&= \frac{1 - \alpha}{4\phi_A\alpha + 2 - 2\alpha}.
\end{aligned}
$$

Since I focus on symmetric equilibria, $\phi = \phi_A = \phi_B$. For the index

$$
\begin{aligned}
ask_I =& 1 \cdot P(\hat{V}_A = 1 \;\&\; \hat{V}_B = 1|\text{buy } I)+\\
&0.5 \cdot P(\hat{V}_A = 1 \;\&\; \hat{V}_B = 0|\text{buy } I) + 0.5 \cdot P(\hat{V}_A = 0 \;\&\; \hat{V}_B = 1|\text{buy } I).
\end{aligned}
$$

Note that

$$
\begin{aligned}
P(\hat{V}_A = 1 \;\&\; \hat{V}_B = 1|\text{buy } I) &= \frac{P(\text{buy } I \mid \hat{V}_A = 1 \;\&\; \hat{V}_B = 1)P(\hat{V}_A = 1 \;\&\; \hat{V}_B = 1)}{P(\text{buy } I)}\\
&= \frac{(1-\phi)\frac{\alpha}{2} + (1-\phi)\frac{\alpha}{2} + \frac{1-\alpha}{4}}{4\left[(1-\phi)\frac{\alpha}{2} + \frac{1-\alpha}{4}\right]}.
\end{aligned}
$$

Applying the same logic again gives

$$
\begin{aligned}
ask_I &= \frac{(1-\phi)\frac{\alpha}{2} + (1-\phi)\frac{\alpha}{2} + \frac{1-\alpha}{4}}{4\left[(1-\phi)\frac{\alpha}{2} + \frac{1-\alpha}{4}\right]} + \frac{(1-\phi)\frac{\alpha}{2} + \frac{1-\alpha}{4}}{4\left[(1-\phi)\frac{\alpha}{2} + \frac{1-\alpha}{4}\right]} \\
&= \frac{2\alpha - 3\alpha\phi + 1}{2(\alpha - 2\alpha\phi + 1)} \\
bid_I &= \frac{\frac{1-\alpha}{4}}{4\left[(1-\phi)\frac{\alpha}{2} + \frac{1-\alpha}{4}\right]} + \frac{(1-\phi)\frac{\alpha}{2} + \frac{1-\alpha}{4}}{4\left[(1-\phi)\frac{\alpha}{2} + \frac{1-\alpha}{4}\right]} \\
&= \frac{1 - \alpha\phi}{2(\alpha - 2\alpha\phi + 1)}.
\end{aligned}
$$

□

Proof of Lemma 2. Without loss of generality, I start by considering the case of security A. Since security B trades convey no information about the true value of A,

$$
\begin{aligned}
Var(E[V_A|Q]) =& P(\text{B Trade}) \cdot 0 + \\
& P(\text{A Trade})[0.5(ask_A - 0.5)^2 + 0.5(0.5 - bid_A)^2] + \\
& P(\text{Index Trade})[0.5(ask_I - 0.5)^2 + 0.5(0.5 - bid_I)^2] + \\
=& \left(\frac{\alpha\phi}{2\alpha\phi - \alpha + 1}\right)^2 \left(\frac{\phi\alpha}{2} + \frac{1-\alpha}{4}\right) + \left(\frac{\alpha(1-\phi)}{2(\alpha - 2\phi\alpha + 1)}\right)^2 \left((1-\phi)\alpha + \frac{1-\alpha}{2}\right) \\
=& \frac{\phi^2\alpha^2}{4(2\phi\alpha - \alpha + 1)} + \frac{(1-\phi)^2\alpha^2}{8(\alpha - 2\phi\alpha + 1)}.
\end{aligned}
$$

Applying similar logic gives

$$
\begin{aligned}
Cov(E[V_A|Q], V_A) =& \frac{\phi^2\alpha^2}{4(2\phi\alpha - \alpha + 1)} + \frac{(1-\phi)^2\alpha^2}{8(\alpha - 2\phi\alpha + 1)}, \\
Var(E[V_A|Q] - V_A) =& \frac{1}{4} - \frac{\phi^2\alpha^2}{4(2\phi\alpha - \alpha + 1)} - \frac{(1-\phi)^2\alpha^2}{8(\alpha - 2\phi\alpha + 1)}.
\end{aligned}
$$

For the index

$$
\begin{aligned}
Var(E[V_I|Q]) =& P(\text{Index Trade})\left[0.5\,(ask_I - 0.5)^2 + 0.5\,(0.5 - bid_I)^2\right] + \\
& P(\text{A Trade})\left[P(V_A = 1)\left(\frac{ask_A}{2} + \frac{1}{4} - 0.5\right)^2 + P(V_A = 0)\left(0.5 - \frac{bid_A}{2} - \frac{1}{4}\right)^2\right] + \\
& P(\text{B Trade})\left[P(V_B = 1)\left(\frac{ask_B}{2} + \frac{1}{4} - 0.5\right)^2 + P(V_B = 0)\left(0.5 - \frac{bid_B}{2} - \frac{1}{4}\right)^2\right] + \\
=& \left(\frac{\alpha\phi}{4\alpha\phi - 2\alpha + 2}\right)^2\left(\phi\alpha + \frac{1-\alpha}{2}\right) + \left(\frac{\alpha(1-\phi)}{2(\alpha - 2\phi\alpha + 1)}\right)^2\left((1-\phi)\alpha + \frac{1-\alpha}{2}\right) \\
=& \frac{\phi^2\alpha^2}{8(2\phi\alpha - \alpha + 1)} + \frac{(1-\phi)^2\alpha^2}{8(\alpha - 2\phi\alpha + 1)} \\
Cov(E[V_I|Q], V_I) =& \frac{\phi^2\alpha^2}{8(2\phi\alpha - \alpha + 1)} + \frac{(1-\phi)^2\alpha^2}{8(\alpha - 2\phi\alpha + 1)}
\end{aligned}
$$

and so

$$
Var(E[V_I|Q] - V_I) = \frac{1}{8} - \frac{\phi^2\alpha^2}{8(2\phi\alpha - \alpha + 1)} - \frac{(1-\phi)^2\alpha^2}{8(\alpha - 2\phi\alpha + 1)}.
$$

□

Proof of Proposition 1. In order for informed agents to always trade single names, the expected payoff of doing so must be higher when they mimic security A or B liquidity traders than when they mimic index liquidity traders. Bids and asks are determined by setting $\phi = 1$ in the expressions derived in Lemma 1. For the representative case of security A informed trader when $\hat{V}_A = 1$,

$$
\begin{aligned}
E[\text{Payoff from trading A}] &> E[\text{Payoff from trading Index}] \\
E[\hat{V}_A] - ask_A - c &> (0.5E[\hat{V}_A] + 0.5E[\hat{V}_B]) - ask_I \\
1 - \frac{3\alpha + 1}{2\alpha + 2} - c &> \frac{1}{4}.
\end{aligned}
$$

The left-hand side is decreasing in c, which implies that c must be sufficiently small in order for the inequality to hold.

Now, let g denote the cost of acquiring information about security A or B. In this equilibrium, the proportion of informed traders α is then such that

$$
\begin{aligned}
g &= E[\text{Payoff from trading A}] \\
&= 1 - \frac{3\alpha+1}{2\alpha+2} - c
\end{aligned}
$$

As previously established, the right-hand side is decreasing in c. Further,

$$\frac{\partial}{\partial\alpha} E[\text{Payoff from trading A}] = \frac{-1}{2(1+\alpha)^2}$$

which is negative for $\alpha \in [0,1]$, so expected profits are decreasing in α. It follows that in order to maintain an equilibrium, an increase in c must be offset by a decrease in α.

Setting $\phi = 0$ in the expression from Lemma 2 and differentiating gives

$$\frac{\partial}{\partial\alpha} Var(E[V_A|Q] - V_A) = \frac{-\alpha}{4(1+\alpha)^2}\left(2+\alpha\right).$$

Since the derivative is negative for $\alpha \in (0,1]$, the estimation error is decreasing in α. By the same argument, the estimation error for the index is also decreasing in α. As increases in transaction costs lead to declines in the shares of informed traders, they also result in less informational efficiency. □

Proof of Proposition 2. In order for this equilibrium to prevail, informed agents' expected payoffs must be higher when they mimic index liquidity traders than when they mimic single name liquidity traders. Bids and asks are determined by setting $\phi = 0$ in the expressions derived in Lemma 1. I get the following inequality for A-informed traders when $V_A = 1$

$$
\begin{gathered}
E[\text{Payoff from trading A}] < E[\text{Payoff from trading Index}] \\
E[\hat{V_A}] - ask_A - c < (0.5E[\hat{V_A}] + 0.5E[\hat{V_B}]) - ask_I \\
\frac{1}{2} - c < \frac{1-\alpha}{4(\alpha+1)}.
\end{gathered}
$$

The left-hand side is decreasing with c. It follows that the transaction cost must be sufficiently large for this equilibrium to obtain.

Again, let g denote the cost of acquiring information about security A or B. In this equilibrium, the proportion of informed traders α is then such that

$$
\begin{aligned}
g &= E[\text{Payoff from trading A}] \\
&= \frac{1-\alpha}{4(\alpha+1)}
\end{aligned}
$$

The expected profits of informed traders do not depend on the transaction cost. As a result, the share of informed traders α does not change as c increases. It follows that raising transaction costs will not cause a reduction in informativeness for either the single names or the index. □

Proof of Proposition 3. For this equilibrium to prevail, informed agents must be indifferent between trading single-name securities and the index. In the representative case of an A-informed trader when $V_A = 1$ I have the condition

$$E[\text{Payoff from trading A}] = E[\text{Payoff from trading Index}].$$

Substituting expressions derived in Lemma 1 yields the equation

$$\left[1 - \frac{4\phi\alpha + 1 - \alpha}{4\phi\alpha + 2 - 2\alpha} - c\right] = \left(\frac{3}{4} - \frac{2\alpha - 3\alpha\phi + 1}{2(\alpha - 2\alpha\phi + 1)}\right).$$

Now, let g once more denote the cost of acquiring information about security A or B. In this equilibrium, the proportion of informed traders α is then such that

$$g = \left[1 - \frac{4\phi\alpha + 1 - \alpha}{4\phi\alpha + 2 - 2\alpha} - c\right] = \left(\frac{3}{4} - \frac{2\alpha - 3\alpha\phi + 1}{2(\alpha - 2\alpha\phi + 1)}\right).$$

Implicitly differentiating the index profit condition and solving for the derivative of ϕ with respect to α gives

$$\frac{\partial\phi}{\partial\alpha} = \frac{1-\phi}{\alpha(1-\alpha)},$$

which is positive for $\alpha, \phi \in (0, 1)$. The sign makes intuitive sense, since increasing ϕ leads to less informed index trading, which narrows the bid-ask spread and, by extension, increases profits. This effect must be offset by an increase in the overall share of informed trading to maintain equilibrium.

Returning to the single name condition, it is clear that profits are decreasing c. Increases in transaction costs must therefore be offset by reducing α. To demonstrate that this shift leads to a decline in informational efficiency, I let

$$K_1 \equiv \frac{\phi^2\alpha^2}{2\phi\alpha - \alpha + 1}$$
$$K_2 \equiv \frac{(1-\phi)^2\alpha^2}{\alpha - 2\phi\alpha + 1}.$$

Differentiating the first equation with respect to α gives

$$\frac{\partial K_1}{\partial \alpha} = \frac{(2\alpha\phi - \alpha + 1)(2\phi^2\alpha + 2\phi\alpha^2\frac{\partial\phi}{\partial\alpha}) - (\phi^2\alpha^2)(2\phi + 2\alpha\frac{\partial\phi}{\partial\alpha} - 1)}{(2\alpha\phi - \alpha + 1)^2}.$$

The derivative will be positive whenever the numerator is greater than zero. Expanding terms and simplifying gives the inequality

$$2\alpha^2\phi^3 + \alpha\phi^2(2-\alpha) + 2\alpha^2\phi\frac{\partial\phi}{\partial\alpha}(1-\alpha) + 2\alpha^3\phi^2\frac{\partial\phi}{\partial\alpha} > 0$$

which is true for $\alpha, \phi \in (0,1)$. By a similar argument, $\frac{\partial K_2}{\partial \alpha} > 0$ for $\alpha, \phi \in (0,1)$.

The estimation errors from Lemma 2 can be rewritten as

$$Var(E[V_A|Q] - V_A) = \frac{1}{4} - \frac{1}{4}K_1 - \frac{1}{8}K_2$$
$$Var(E[V_I|Q] - V_I) = \frac{1}{8} - \frac{1}{8}K_1 - \frac{1}{8}K_2.$$

Since the derivatives of K_1 and K_2 with respect to α are both strictly positive, increases in c will lead to larger estimation errors for both single-name securities and the index. Furthermore, the corresponding loss in informational efficiency will be more pronounced for the single names.

□