Illiquidity Meets Intelligence: AI-Driven Price Discovery in Corporate Bonds[†]

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Abstract

We study the contribution of AI-generated reference prices to intraday price discovery in markets with infrequent trading. Using corporate bond transactions and MarketAxess CP+ quotes, we find that CP+ is more informative about future trade prices than the last trade. Regression analysis shows that CP+ quote updates are systematically related to market-wide movements in bond, equity, and options markets, as well as bond-specific non-public information from the RFQ process. CP+ provides broad coverage across bonds and trading days. Its contribution to price discovery exhibits a bell-shaped relationship with liquidity and increases under market uncertainty. Following a trade report, CP+ updates quickly in the direction of the trade. We show that this can limit its contribution during periods driven by large transitory price shocks.

Keywords: Artificial Intelligence, Corporate Bonds, Reference Prices, Price Discovery

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A central function of financial markets is to facilitate price discovery, enabling buyers and sellers to assess the fair value of assets. This allows them to trade when both sides perceive a benefit, leading to more efficient markets. Academic research has identified transparency, defined as observable prices and quantities of completed trades ("post-trade") as well as the best available bid and ask quotes ("pre-trade"), as a key market design feature that supports this process. A recent development in this context is the emergence of Artificial Intelligence (AI) based reference prices, generated by algorithmic tools that apply data science and machine learning (ML) techniques. This article examines the broader implications of AI-driven models for price discovery and market resiliency in over-the-counter (OTC) fixed income markets.

We focus on the U.S. corporate bond market for several reasons. Unlike equities, which primarily trade on electronic venues with firm, executable quotes, corporate bond liquidity is typically provided by dealer firms offering indicative rather than binding quotes. These quotes are shared selectively with market participants. The market lacks a centralized quotation system to aggregate dispersed quotes and identify the best available prices. To improve transparency, regulators have instead focused on improving post-trade disclosure, requiring dealers to report completed secondary market trades through FINRA's TRACE system. Empirical studies have shown that these trade disclosures have reduced customer trading costs and increased market activity in fixed income markets.[1]

However, when a long time has elapsed since the last transaction, the information content of that trade becomes stale. Thus, the effectiveness of post-trade transparency diminishes when trading activity is sparse.[2] In our sample from 2017 to 2023, the average corporate

[1] See Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007), Schultz (2012), Gao, Schultz, and Song (2017), O'Hara, Wang, and Zhou (2018), Schultz and Song (2019) and Chalmers, Liu, and Wang (2021).

[2] Among bonds that do trade, the market is segmented between institutional round lots ($1 million or more) and retail odd-lots ($150,000 or less). Institutional trades primarily drive price formation, while retail trades, despite accounting for about 70% of reported trades, are rarely used in pricing benchmarks. Bessembinder, Kahle, Maxwell, and Xu (2008) recommend eliminating non-institutional trades from the TRACE data in the calculation of bond abnormal returns in order to increase the power of the tests.

bond does not report a non-retail trade on 60% of bond-days (see Figure 1, Panel A) and 27% of bond-weeks, with infrequent trading especially pronounced among smaller bond issues (Panel B). These patterns suggest that alternative mechanisms capable of signaling bond value in the absence of transaction data could unlock substantial gains from trade.

One such mechanism is the use of AI-based pricing algorithms, which generate reference prices by processing large volumes of data, including market movements and other relevant signals, with speed and consistency. MarketAxess, a major electronic bond trading platform, provides reference bid and ask prices through its proprietary algorithm known as CP+.[3] CP+ quotes combine public data, such as TRACE-reported transactions and interest rate benchmarks, with proprietary inputs, including request-for-quote (RFQ) responses and executed trades on the MarketAxess platform. In our sample, the average corporate bond receives 30 or more CP+ quotes on 95% of bond-days, with slightly lower coverage (75%) for smaller issues (see Figure 1). This broad availability suggests that algorithmic tools like CP+ could support price discovery in markets with infrequent trading.[4]

In this study, we examine whether AI-generated reference prices help improve price discovery in the corporate bond market. Our analysis uses a dataset of 24.9 million non-retail trades and 11.8 billion CP+ quotes across 20,335 corporate bond issues from the 2017 to 2023 period. First, we test whether the most recent CP+ quote provides more accurate estimates of the current trade price than the most recent observed trade. Second, we explore the source of CP+'s informational advantage: whether it comes from timely incorporation of public data or also reflects access to proprietary RFQ data. Third, we analyze CP+'s contribution to price discovery across bonds with varying liquidity, during periods of heightened market

[3]MarketAxess plays an important role in U.S. corporate bond trading. In March 2025, the platform facilitated approximately 20% of all TRACE reported trading volume for investment grade bonds and 13% for high yield bonds. See details from MarketAxess Trading Volume Statistics.

[4]A recent industry report highlights the ongoing difficulties market participants face in aggregating disparate data: "As desks push to digitize liquidity inputs, the challenge isn't just data volume, it's structure. Many of the most important signals, like dealer runs and axes, still arrive via chat, email, or unstructured files. For buy-side firms trying to automate decisions off that flow, the tools remain a work in progress." TabbFORUM, Fixed Income Trading Technology, State of the Market Report, May 26, 2025.

uncertainty, and around bond-specific events that result in large price movements.

There are additional reasons to focus on corporate bonds when evaluating pricing algorithms. AI models rely on high-quality, timely and reliable data to train and adapt effectively. However, compared to equities, currencies, and commodities, the corporate bond market offers limited quotation data and less frequent trading, restricting data availability. In addition, price discovery in this market often depends on informal, relationship-based information exchanged during bilateral negotiations.[5] These interactions often convey 'market color', that is, valuable but unstructured signals that human traders are better equipped to interpret. Academic research suggests that current AI systems remain limited in processing these social and contextual signals (e.g., Garcia et al., 2024), and no systematic data exists for these interactions.[6] Further, bond prices are highly sensitive to macroeconomic developments, credit events, and policy interventions, particularly during periods of stress. Because algorithmic models are trained on historical data, they may struggle to respond to rare or unexpected events. Finally, the signal-to-noise ratio for forecasting returns in bond models is generally low, increasing the risk of overfitting ML models. Collectively, these limitations present significant challenges for model development and can reduce the accuracy and reliability of AI-generated reference prices in the corporate bond market.

We begin by comparing price staleness between trades and CP+ quotes. To do so, we estimate daily return autocorrelations for equally weighted bond portfolios constructed using time-weighted average trade prices and CP+ quote midpoints. We find that trade-based portfolios exhibit higher positive return autocorrelation than quote-based portfolios. This greater autocorrelation indicates that trade-based returns adjust more slowly to new information, reflecting stickiness due to stale prices. Cross-sectional analysis further reveals

[5]Several studies have examined the impact of dealer networks and trading relationships in the fixed income market, including Di Maggio, Kermani, and Song (2017), Hollifield, Neklyudov, and Spatt (2017), Li and Schürhoff (2019), Issa and Jarnecic (2019), and Hendershott, Li, Livdan, and Schürhoff (2020).

[6]See, for example, *Wall Street Journal*, AI Can't Compete With Humans When It Comes to Reading the Room, May 23, 2025.

that the relative advantage of quote-based returns diminishes significantly for high-yield bonds.

To assess CP+'s contributions to price discovery, we compare each non-retail trade price to two benchmarks: (i) the price of the most recent non-retail trade, and (ii) the CP+ quote midpoint, defined as the average of the quoted bid and offer. We use two versions of the CP+ midpoint: the prior day's closing quote, and the last standing quote immediately prior to the trade. The former is relevant for asset pricing studies that use CP+ to construct daily bond returns, while the latter serves as a common pre-trade benchmark in microstructure research. This comparison between CP+ and the recent trade data is particularly relevant because regulators place significant emphasis on the value of timely trade data. We also examine a sub-sample where both the current and prior trades are in the same direction (e.g., both buyer-initiated), and the CP+ benchmark is the corresponding side of the quote (e.g., bid for sells and ask for buys).

We conduct a paired difference test to compare the absolute deviation between the current trade price and each benchmark.[7] When more than five days have passed since the previous trade, both the prior day's closing quote and last standing quote show smaller deviation from the current trade price than the most recent observed trade. The same pattern holds, though the differences are smaller, when the time between trades is from one to five days. When the previous trade occurs on the same trading day, the last trade price becomes more informative than the prior day's closing quote; however, the last standing quote still outperforms, and the difference grows materially after eight hours. Only when the last trade occurs within one hour does the trade price outperform CP+.

These findings indicate that the most recent CP+ quote is more informative than the

[7] Bid-ask bounce does not bias our comparison of trade and CP+ quote deviations. In expectation, trade deviations include the full spread in half of the cases and none in the other half, while CP+ deviations using quote midpoint always include a half spread, implying that differences in average deviation are not mechanically inflated. To verify this further, we report results for a subsample where trade direction is consistent and the CP+ quote is the corresponding bid or ask price. In this case, bid-ask bounce does not affect either deviation measure. The results for this subsample are similar to those for the full sample.

most recent trade price, even when that trade is relatively recent. The results are robust across several sub-samples, such as restricting trade size to exceed $1 million, excluding riskless principal trades, and allowing the prior trade to be a retail trade. CP+ outperforms more notably for investment-grade than high-yield bonds, and for private versus public firms, with no clear pattern by issue size.

To better understand the informational value of CP+, we examine its updates between successive trades that exhibit large returns. These cases reflect periods when price discovery is driven by public or proprietary signals rather than trade-based information. We find that CP+ incorporates a substantial share (30% to 60%) of new information associated with these large valuation shifts.

We next examine the sources of CP+'s informational advantage. One key benefit is the algorithm's ability to quickly respond to public data reflecting broader market conditions. To assess this, we compare CP+ quotes to the previous non-retail trade price, adjusted for market movements between the two trades. Specifically, the treasury-adjusted trade price incorporates the return on a maturity-matched Treasury bond from the time of the previous trade to the prior day's close or one minute before the current trade. The credit index-adjusted trade price reflects the return on the relevant bond index (for example, investment-grade or high-yield) from the time of the previous trade to the prior day's close.

We find that CP+ quotes incorporate information beyond what is captured by standard adjustments for interest rates and credit risk premia. Although differences are smaller when using adjusted trade prices, the contributions of CP+ to price discovery between trades remain economically significant. Regression analysis shows that CP+ quote updates are systematically related to market-wide information not only from bond markets but also from the equity and options market. We regress CP+-based returns, measured using the daily closing quote prior to each trade, on contemporaneous returns from the Treasury, credit, equity, and options markets and find strong associations. For example, the coefficient on the maturity-matched Treasury bond return is positive and highly significant, with an R^2 of 28.5%; the full model incorporating all macro factors yields an R^2 of 36%.

In addition to public market signals, the CP+ pricing engine also leverages data from the MarketAxess request-for-quote (RFQ) platform. We find large performance gains for CP+ when a non-traded RFQ inquiry or delayed spot RFQ is observed between trades: the outperformance of CP+ quotes relative to the previous trade increases by 1.4x to 5.0x, depending on the time between trades. Our results indicate that RFQ data provide powerful forward-looking information that significantly improves CP+ performance, particularly for bonds that are not actively traded.

Next, we examine the factors that influence whether a bond receives CP+'s coverage, a decision made by MarketAxess, not the issuer. Approximately 10% of bonds in our sample are never covered, while only a small additional group displays intermittent coverage, dropping out for a period (e.g., a month) before resuming. Coverage is available on nearly all trading days for most bonds, including smaller and less liquid ones. Regression results indicate that larger, younger and investment-grade bonds are both more likely to be covered and receive a greater number of quote updates. However, the strongest determinant of CP+ coverage is a bond's recent trading activity.

We further show that our measure of CP+'s value added to price discovery follows a nonlinear, bell-shaped pattern with bond liquidity (see Figure 6). For infrequently traded bonds (the left tail of the distribution), the incremental value of AI-driven reference pricing is limited, either due to limited CP+ coverage or reduced quote generation when trading activity is sparse. For highly active bonds (the right tail of the distribution), the benefit is also modest, as trades occur in close succession, and recent trades already provide timely benchmarks. The greatest value added is observed for bonds with moderate trading frequency, where CP+ fills the informational gap between less frequent trades. We confirm this non-monotonic relationship by estimating piecewise-linear regressions of average CP+ value added on bond characteristics. In addition, we find that CP+ adds more value between successive trades during periods of heightened market-wide uncertainty (e.g., the onset of COVID-19), with the benefits pronounced for less actively traded bonds.

Next, we study how CP+ quote updates evolve shortly *after* a trade. Our results indicate that much of the price discovery occurs within five minutes of the trade report. The gap between the trade price and the CP+ benchmark declines significantly, and remains near that level for the next two hours. Quote adjustments are larger when the prior trade occurred more than five days earlier, though a similar but smaller pattern is observed even when the last trade was within the past hour.

We also examine the evolution of CP+ quotes around block trades with large ex-post permanent and temporary price effects. AI-algorithms can help stabilize markets by detecting information events and generating reference prices that speed convergence to fundamental value. However, CP+ is designed to estimate the likely price of the next trade, not the bond's fundamental value. Around bond-specific events, trading activity often declines or reflects fire sales and unusual conditions. If such trades influence reference prices, those estimates could affect subsequent negotiations and unintentionally amplify pricing distortions. We find that CP+'s reliance on recent trades limits its contribution following block trades with large transitory price effects, suggesting that it can be affected by temporary shocks such as noise trading or fire sales.

Literature. This article contributes to the growing literature on pre-trade pricing sources in the corporate bond market, including proprietary dealer quotes, electronic RFQ platforms, and alternative trading systems (ATSs). Dealers disseminate indicative quotes for institutional trade sizes via Bloomberg messages known as "runs", which are selectively broadcast to potential institutional clients. Hendershott et al. (2025) show that runs are informative, helping investors identify better prices and leverage quotes in bilateral negotiations. Harris (2021) finds that dealer indicative quotes are often more informative than trade prices.

Dealers also respond to RFQ inquiries (e.g., those submitted via MarketAxess) but unlike runs, these quotes are visible only to the inquiring client (Hendershott and Madhavan, 2015). Kargar, Lester, Plante, and Weill (2023) show that clients who reject initial RFQ quotes and continue to search, often receive improved quotes from new dealers. Quotes on ATS platforms are publicly visible, but limited to retail trade sizes and account for only a small fraction of total bond trading volume (Harris, 2015; Kozora et al., 2020).

Our contribution is to document the informativeness of a novel pre-trade pricing source that applies data science techniques: reference prices generated by AI algorithms. We show that CP+ provides broad and stable coverage, including for smaller and less liquid bonds that trade infrequently. Its contribution to price discovery is strongest for bonds with moderate liquidity, where transactions data alone are insufficient for timely pricing, yet the algorithm can generate informative price updates.

The non-executable nature of AI-generated quotes distinguishes them from firm, executable quotes in markets such as equities. Executable quotes are disciplined by the risk of adverse selection and potential losses from trading with better-informed counterparties. In contrast, reference quotes are indicative and not exposed to the same incentives or market discipline. As these reference prices become more widely used, our findings point to the importance of considering market design features and feedback mechanisms that encourage their convergence to fundamental values, especially during periods with elevated uncertainty.

There is growing interest in applying ML techniques to financial markets to uncover new signals, improve price forecasts, and build investment strategies that can outperform traditional methods. ML algorithms offer advantages by capturing nonlinearities, modeling complex interactions, and using high-dimensional or unstructured data (see Goldstein, Spatt, and Ye, 2021). In equity markets, studies such as Gu, Kelly, and Xiu (2020) and Freyberger, Neuhierl, and Weber (2020) demonstrate that ML methods outperform linear models in forecasting stock returns.

Similar evidence has emerged in fixed income markets: ML techniques have been shown to improve predictions of government and corporate bond returns (Bianchi, Büchner, and Tamoni, 2021; Bali et al., 2020) and to capture nonlinearities in credit risk premia (Cherief, Ben Slimane, Dumas, and Fredj, 2022). Other applications include the use of tree-based models to classify trade direction (Fedenia, Nam, and Ronen, 2021) and to forecast corporate bond illiquidity (Cabrol, Drobetz, Otto, and Puhan, 2024), outperforming benchmarks by better disentangling liquid from illiquid bonds. Our study adds to this literature by examining whether AI-generated reference prices from a major electronic trading platform improve intraday price discovery in the corporate bond market, which is characterized by infrequent trading, lower transparency, and fragmented market structure.

1. Description of Data

1.1. Sample Selection

We utilize three data sources to examine how reference prices generated from ML techniques contribute to price discovery in the corporate bond market. Specifically, we merge the Mergent Fixed Income Securities Database (FISD), which includes corporate bond-specific information, with Trade Reporting and Compliance Engine (TRACE) data, which includes corporate bond transactions, and with MarketAxess CP+ data, which provides bid and ask reference prices for a broad set of bonds at a high frequency (often each minute).

MarketAxess is the largest electronic trading marketplace for U.S. corporate bonds. CP+ quotes are generated in real time using machine learning (ML) models trained on a combination of public data (such as TRACE trade reports) and proprietary MarketAxess data. The proprietary inputs include trading activity completed on the MarketAxess platform, TraX market trading data across asset classes, and the entire stack of RFQ inquiry dealer responses, regardless of whether the RFQ process led to a trade. Although CP+ benefits from public signals from the broader market, the model does not include explicit features from other asset classes. The models are trained nightly to "produce the price the market is most likely to trade at, without a rich or cheap bias," optimizing a Minimized Absolute Deviation (MAD) objective (Alexandre and Amalunweze, 2024).

The algorithm incorporates signals related to time (most recent), trade size and type (e.g., institutional-size customer trades in principal capacity, portfolio trades, trades in same bond and related bonds, etc.), trade side (spreads), and pricing sources (trade prints and RFQ responses). CP+ leverages RFQ stacks from both completed and unexecuted inquiries after implementing screens to exclude low-quality dealer quotes. Importantly, MarketAxess does not allow the algorithm to incorporate RFQ data unless the outcome (trade or no-trade) is known. If an RFQ results in a trade, CP+ reflects that information only after the trade is publicly reported (typically within the 15-minute TRACE reporting window, though exceptions exist for delayed spots or late reports). This approach prevents the algorithm from potentially front-running large block trades and ensures continued trust among market participants. For trades labeled as "missed" after the RFQ, however, CP+ can incorporate the data immediately. Delayed spot RFQ trades are incorporated into CP+ once the spread is agreed upon (e.g., at 10 a.m. rather than when it is formally reported at 4 p.m.). Less liquid bonds are priced using extrapolation relative to the pricing of more liquid bonds generated directly by the pricing engine.

Our analysis focuses on the period from May 2017 to December 2023, which corresponds to the availability of CP+ data. We first construct our initial sample of corporate bonds using FISD. We select non-puttable or convertible U.S. Corporate Debentures and U.S. Corporate Bank Notes (identified as bond type CDEB or USBN) that have complete issuance information, including offering date, issue amount, and maturity date.[8]

Next, we merge this sample of bonds with TRACE to obtain corporate bond transaction

[8]We exclude the following types of debt: retail notes, foreign government, agency, municipal, pass- through trusts, pay in kind, strips, zeros, Eurobonds/Euronotes, asset and mortgage backed, insured, and guaranteed by letters of credit, medium term notes/zeros, convertible, and foreign currency.

data. We link the FISD data to the TRACE data using the CUSIP identifier. We apply additional filters to the transactions data. We exclude bonds with fewer than five trades over the sample period. Trades are excluded if they are flagged as primary market trades, if their reported size exceeds the bond's offering amount, or if they are reported after the bond's outstanding amount falls to zero. We exclude trades coded as affiliate trades (where a FINRA registered broker dealer transfers a bond to their non-FINRA registered broker dealer affiliates) and trades by a specific dealer that reported an immediately offsetting transaction for most of its principal trades with an affiliated offshore entity, both of which result in double counting of trades.

After implementing these filters, the sample includes 22,205 distinct CUSIPs and 93 million secondary market transactions between May 2017 and December 2023. Using this sample, we merge with MarketAxess CP+ data using the 9-digit CUSIP identifier. Panel A of Table 1 details the construction and the resulting size of our trade-level sample. Of the 22,205 distinct CUSIPs in our dataset, 20,563 are successfully matched to CP+, corresponding to 91 million secondary market transactions reported in TRACE. The remaining 1,942 CUSIPs lack CP+ coverage.

We further restrict the sample to non-retail trades of at least \$150,000, reducing the trade sample to 25.6 million transactions. We focus on larger trades because institutional transactions are generally more informative about fundamental value. Prior research shows that retail-size trades are subject to higher dealer markups and exhibit greater pricing noise (Schultz, 2001; Goldstein, Hotchkiss, and Nikolova, 2021). Bessembinder, Kahle, Maxwell, and Xu (2008) show that excluding retail trades from the daily price improves the power of return-based tests for abnormal performance. Consistent with this, the CP+ algorithm considers only trades above \$150,000 in its calibrations. Finally, we keep only customer trades and require at least one last trade within the past 250 trading days and an outstanding CP+ quote. Our trade-level sample includes 20,037 distinct CUSIPs, 15.8 million non-retail secondary market transactions.

Panel B of Table 1 summarizes the total number of trades, CP+ quotes, and CP+ quote updates for bond-trading days between the bond's first and last days of CP+ coverage. In total, there are 20.6 billion CP+ reference quotes. Of these, 6.6 billion are quote updates, defined as instances where the bid, ask, or both change relative to the prior quote. We also summarize these activities by credit quality (investment grade versus high yield/unrated) and by issue size (small, medium, and large).[9] About 79% of bonds in the CP+ sample are investment grade, and bonds are roughly evenly distributed across the three issue size groups. In comparison, investment grade bonds account for about 66% of all trades, 70% of all quotes, and 96% of quote updates, reflecting greater pricing activity in this segment of the market.

Panel C of Table 1 reports the cross-sectional distribution of bond-level average daily number of trades, CP+ quotes, and CP+ quote updates over the sample period. Similar to trading activities, there are large dispersions in the frequency of quotes. While the median bond receives more than 1,000 quotes and 300 quote updates per day, bonds in the 10th percentile receive only 360 quotes and 4 quote updates per day.

1.2. CP+ vs. TRACE

Figure 1 shows the distribution of daily trade and CP+ quote frequencies, grouped into six buckets ranging from zero to more than 30 trades or quotes per bond-day. White bars represent TRACE trades, while blue bars show CP+ quotes. Panel A reports results for the full sample: nearly 60% of bond-days have no trades, and about 90% have three or fewer trades. Panel B focuses on small-issue bonds, where trading is even more limited: 80% of bond-days have no trades, and over 95% have three or fewer. These findings are consistent with the established evidence that corporate bonds trade infrequently, limiting the effectiveness of post-trade transparency. In comparison, CP+ quotes are available on

[9]We define small, medium, and large using \$500 million and \$1 billion issue size breakpoints.

nearly all trading days for most bonds, including smaller ones in Panel B. For the full sample, approximately 90% of bond-days have at least 30 CP+ quotes, and for small-issue bonds, the frequency is slightly lower, at 75% of bond-days.

Figure 2 provides the details on the extent of CP+ coverage by month. The solid white bar represents the total par value of bonds (in trillions) in the merged FISD and TRACE dataset as described in Table 1, and the solid blue bar represents the total par value of bonds also covered by CP+. The overlap is substantial—in 2023, CP+ covered approximately \$8.25 trillion in par value compared to \$9.75 trillion in the full FISD/TRACE universe. This figure also reports coverage by distinct CUSIPs (red lines) and issuers (black lines). In both cases, CP+ covers the vast majority of bonds and issuers, indicating that CP+ coverage is comprehensive and not limited to a narrow subset of corporate bonds.

2. The Informativeness of CP+ Reference Prices

When executing a trade at time *t*, traders must estimate the bond's current value using available information. In the corporate bond market, where dealer quotes are not broadly visible, the most recent transaction price, observed at time *t-1*, is a natural and often necessary benchmark for price discovery. However, as shown in Figure 1, many bonds trade infrequently, so the most recent trade may have occurred days earlier. As time passes, the informational value of the last trade declines, especially if new market- or bond-relevant information has emerged. Institutional clients of MarketAxess observe the CP+ reference quotes, which are updated more frequently, often within minutes, and can provide a more timely estimate of intraday bond value for traders making decisions in real time.

In this section, we evaluate the informativeness of CP+ reference prices relative to observed trade prices. We begin by assessing pricing staleness using autocorrelation tests that compare bond portfolio returns constructed from trades versus CP+ quotes. We then analyze CP+'s contribution to price discovery between successive transactions.

2.1. Autocorrelation Tests

We conduct daily return autocorrelation tests, following the approach of Choi, Kronlund, and Oh (2022), to assess pricing staleness by constructing daily bond portfolio returns using trade and quote prices.[10] Specifically, bonds are independently sorted into six portfolios based on credit quality (investment grade and high yield/unrated) and issue size (large, medium, and small issues). Bond daily returns are computed with daily time-weighted average prices, calculated separately for trades and quotes. If no trade or quote update is available for a bond on a given day, its daily return is set to zero. Daily portfolio returns are equal weighted averages across bonds in the portfolio. We then estimate the autocorrelation coefficients of daily portfolio returns up to 20 lags.

Table 2 reports the estimated autocorrelation coefficients using daily returns of the bond portfolios. Trade returns exhibit considerably higher autocorrelation than quote returns. For the full sample, lag-1 autocorrelation is 0.86 for trades versus 0.52 for quotes; lag-5 is 0.21 versus 0.08; and lag-10 is 0.09 versus 0.02. The differences are especially stark for small issue bonds. For investment-grade small bonds, trade autocorrelations at lags 1 and 5 are 0.91 and 0.51, compared to 0.39 and 0.11 for quotes.

Across most subsamples, trade return autocorrelations remain economically meaningful up to five lags (ranging from 0.04 to 0.51), while quote return autocorrelations are materially lower (ranging from –0.01 to 0.32). These results indicate that traders relying only on past TRACE data face greater pricing staleness than those using CP+ quotes.

2.2. Price Discovery Analysis between Successive Trades

To quantify CP+'s contributions to price discovery, we compare each non-retail trade price to two benchmarks: (i) the last non-retail trade price and (ii) the CP+ quote midpoint, defined

[10] We use bond portfolio returns to mitigate the influence of idiosyncratic noises in the measurement of daily individual bond prices.

as the average of the quoted bid and offer prices. We assess the deviation between each trade price and these reference points to evaluate which benchmark is closer to the current trade price.

As described in Section 1.1, we focus on non-retail size trades of at least $150,000 in par value, as large trades typically involve more sophisticated participants and better reflect fundamental values.

2.2.1. Price Deviation Analysis

For each trade, we identify the most recent prior trade and record its price and direction. We also record the time since the last trade, measured in trading days or, for intraday trades, in hours. If CP+ has no quote update on a particular day, like trades, we retain the last standing quote. We use two CP+ midpoint benchmarks: (i) the prior day's closing quote at 6 p.m., and (ii) the last standing quote just before the trade. Some recent studies in asset pricing research use CP+'s closing quote to calculate daily bond returns, while recent microstructure studies use the last standing CP+ quote to calculate trade execution costs (Kargar, Lester, Plante, and Weill, 2023; Shin, Zhou, and Zhu, 2025). Our analysis is designed to inform both literature.

For each trade, we calculate the trade price deviation as the absolute difference between the current trade price and the last trade price. Similarly, we compute CP+ quote deviation as the absolute difference between the current trade price and the CP+ benchmark price. In the main analysis, we require both that the last trade occurred within the last 250 trading days and that there is an outstanding quote.[11] This reduces our sample from 16.6 million trades to 15.8 million trades. To reduce the impact of outliers, we winsorize the deviations at the 1% and 99% levels.

Bid-ask bounce does not bias our comparison of CP+ quote deviations and trade-to-

[11]We eliminate 16 observations with clear errors in quotes (e.g., quotes that are negative or that exceed 200,000).

trade deviations. Both are influenced by the bid-ask spread in expectation, but in similar magnitudes that do not mechanically affect the performance gap. Suppose the true mid-price is P and the bid-ask spread is X, resulting in bid and ask prices of P - 0.5X and P + 0.5X, respectively. If trade directions alternate randomly, half of the current trades will match the direction of the previous trade (e.g., buy-buy or sell-sell), yielding a trade-to-trade deviation near zero. The other half will have opposite signs (e.g., buy-sell), incorporating the full spread X. Thus, the average trade-to-trade deviation caused by bid-ask bounce is approximately 0.5X. Similarly, CP+ deviations are measured relative to the quote midpoint, which will differ from the trade price by 0.5X, regardless of trade direction.

To verify this directly, we also present results for a subsample where the current trade has the same direction as the previous one, and we compare the current trade price to the corresponding side of the CP+ quote (i.e., the bid for sells, the ask for buys). In this setup, neither trade-to-trade deviations nor quote-based deviations reflect the bid-ask spread. If the main analysis was affected by bid-ask bounce, the deviation gap should be markedly different for this subsample.

Table 3 presents summary statistics for deviation measures across the full sample (15.7 million observations) and subsamples defined by the time gap between the current and previous trade. Trade deviations average \$0.34 and range from \$0.02 (10th percentile) to \$0.81 (90th percentile). CP+ deviations based on the prior minute are smaller, averaging \$0.25, and ranging from \$0.02 (10th percentile) to \$0.60 (90th percentile). Both measures decline steadily as the time between successive trades declines from more than five days to less than one hour.

We report paired differences comparing the absolute deviations of the last trade and the CP+ quote. Figure 4 reports the deviations in finer increments, by days when the time gap exceeds one day (Panel A and B), and by hours for same-day trades (Panel C and D). We report both mean deviations (and associated 99% confidence intervals) and median deviations (and associated 99% confidence intervals) for trades (black triangle), prior day's closing quote (blue circle), and last minute CP+ quotes (red diamond). We cluster standard errors of these differences at the current trade date level. For medians, we estimate standard errors via cluster-level bootstrapping with 1,000 replications. Table 3 report the distribution and statistical significance of these paired differences.

When more than five days have passed since the previous trade, both the prior day's closing quote and last standing quote display smaller deviation from the current trade price than the last trade price. Mean differences in deviations are economically large, averaging \$0.44, and ranging from \$-0.22 (10th percentile) to \$1.68 (90th percentile). The same pattern holds, though the differences in deviations are smaller, when the time between trades is one and five days, and when the previous trade occurs more than one hour earlier on the same trading day. Only when the last trade occurs within one hour does the trade price marginally outperform CP+, with differences averaging \$-0.01.

We find that the CP+ benchmark continues to exhibit similar performance advantages for the subsample where the current and previous trade have the same sign. Deviations decline slightly in comparison to the full sample, but the main patterns persist. Panels A–D of Figure IA.2 in the Appendix report this deviation analysis in finer time increments and confirm similar results. These results suggests that the bid-ask spread does not explain the main results. While spread dynamics marginally increase overall price dispersion, they do not bias the relative comparison used in our deviation analysis.

Overall, the most recent CP+ quote is more accurate than the most recent trade in predicting the current trade price, especially when the elapsed time between successive trades is large. When 20 or more days have passed, CP+ is closer to the new trade price in over 90% of cases. Even when trades are more recent, CP+ still adds value.

We present additional robustness tests along three dimensions. First, in Table 4, Panel A, we restrict the current and previous trade to round lot sizes, that is, those exceeding \$1 million in par value. These larger trades are more likely to involve sophisticated participants, and their prices better reflect fundamentals. Results remain similar, indicating that CP+ adds value even in the most informative trades. Second, we exclude prearranged riskless principal trades and find similar results.[12] Third, we calculate the deviations after allowing the previous trade to be a retail-size trade (that is, smaller than $150,000). Results again are similar.

Table 4, Panel B, reports additional results for subsamples based on credit rating, issue size, and issuer listing status. Across all sub-samples, the mean deviation differences remain economically large, particularly when the time between successive trades is long. CP+ consistently outperforms, with the advantage being more pronounced for investment-grade bonds relative to high-yield bonds, even after accounting for time between successive trades. This may reflect richer or more accessible information for higher-rated issuers. In contrast, the differences between public and private firms are modest, and no clear pattern emerges with respect to issue size.

2.2.2. Economic Significance of CP+ Contribution to Price Discovery

The results thus far suggest that the CP+ algorithm incorporates new information and forecasts the current trade price better than the last trade price. We next measure the economic significance of its contribution by analyzing how well CP+ quote returns anticipate trade-to-trade returns. This exercise isolates the informational value of CP+ updates between successive trades, where price discovery is not obtained from trade-based signals but from other public or proprietary signals.

Using the sample of non-retail trades, we calculate bond returns between two consecutive trades (at times t and t–1), where the previous trade occurred within the past 20 trading

[12] Prearranged blocks trades or "riskless principal" trades are those where the dealer immediately offsets the block position by executing a single opposite-direction trade within 15 minutes, effectively acting as a broker or agent. See Harris (2015) and Choi et al. (2024). We remove these trades as the successive trades may be mechanically the same price.

days. For each of these trade pairs, we compute three CP+ quote-based returns: (i) the return from the last trade price at *t-1* to the CP+ midpoint one minute before the trade at t, (ii) the return using the closing quote from one day before t, and (iii) from two days before t. We then regress trade returns on each CP+ quote return to estimate the R^2, a measure of how well CP+ captures variation in trade-to-trade price movements.

We estimate separate regressions for each trade interval, defined by the number of days between trades (from 0 to 20), and report the resulting R^2 values in Figure 5. To better understand CP+ contributions to price discovery under different information environments, the results are reported by the magnitude of between-trade returns: moderate (1–3%, Panel A) and large (>3%, Panel B).[13] Each point represents the R^2 for a given interval: red diamonds use CP+ quotes from 1 minute prior, blue circles use 1-day prior quotes, and hollow black triangles use 2-day prior quotes.

For moderate return intervals (Panel A), the CP+ quote from one minute prior explains 50–70% of variation in future trade prices, outperforming quotes from one or two days prior, which explain 10–50%. For example, when the prior trade was 10 days earlier, the prior-minute quote return has an R^2 of 70%, compared to 53% and 45% for the lagged 1-day and 2-day CP+ closing quotes, respectively. This gap in explanatory power highlights the role of new information on the trade day as an important driver of the decision to trade.

For large return intervals (Panel B), CP+ continues to add value, with R^2s ranging from 30–60% using prior-minute quotes. Even when trade prices change sharply, CP+ captures 25% of the variation when trades are only one day apart, and up to 60% when the time gap is 10 or more days. This suggests that CP+ can incorporate a substantial share of new information around large valuation shifts between trades. Panel C illustrates the time path of CP+ price discovery. Reported are R^2s estimated using a sequence of regressions of the trade return on CP+ quote return up to each trading day before t, for the sample of trades

[13] We find qualitatively similar results from the sample with less than 1% of absolute trade returns, though with noisier estimates due to lower statistical power.

in Panel B. The R^2s increase monotonically with time between trades, with a significant increase from the day before t to the minute before the trade at t.

We also estimate similar regressions using trades where the previous trade occurred within the past 24 hours. For both moderate (Panel D) and large (Panel E) return intervals, CP+ consistently discovers 20%-70% of trade returns before the trade, and the R^2 of the prior-minute quote return is generally greater than that of the prior-hour and 2-hour quote returns.

2.3. Price Discovery Analysis Adjusting for Market Movements

The results thus far suggest that CP+ generates meaningful price discovery by filling informational gaps between trades. We further explore the sources of CP+'s informational advantage. A common challenge for traders is pricing a bond when the most recent trade occurred hours or days ago. A natural approach is to adjust the last trade price using observed returns from broader markets such as Treasury securities or credit indices. In this section, we ask whether CP+ offers pricing improvements even after adjusting the last trade price for observable market movements.

Specifically, we calculate the treasury-adjusted trade price, which incorporates the return on a maturity-matched treasury security from the time of the previous trade to the prior day's close or the minute before the trade. The maturity match is based on the benchmark ISIN assigned by CP+ on the day of the prior trade.[14] We compute daily Treasury returns using CRSP Treasury data and infer minute-level Treasury returns from CP+ quotes (details in the Internet Appendix). We also construct a credit index-adjusted trade price, based on the return of the relevant credit index, either the S&P 500 Investment Grade Corporate Bond Index or the S&P U.S. High Yield Corporate Bond Index from the time of the previous

[14]The maturity-matched Treasury benchmark helps control for duration effects, although a small mismatch might remain due to differences in coupon rates or call features.

trade to the prior day's close.[15] We match each trade to the corresponding index based on the market segments ("HI GRADE" and "HI YIELD") assigned by CP+ on the day of the previous trade.

We extend the baseline deviation analysis from Table 3 by including comparisons to adjusted last trade prices. Table 5 reports the difference in deviation between trade prices and CP+ quotes across subsamples defined by the time gap between the current and previous trade. For ease of comparison, column 1 replicates the baseline deviation difference using the CP+ quote from one minute prior to the trade from Table 3, while column 3 uses the CP+ quote from the prior day's close. Columns 2 and 4 introduce deviations after adjusting the last trade price using treasury returns up to the minute and day before the trade, respectively. Column 5 presents the deviation analysis with credit index adjustments until the day before the trade. For each comparison, we report the mean and median difference in deviations, as well as the percentage of trades for which CP+ quotes outperform the adjusted trade price.

Adjusting for treasury returns meaningfully reduces deviations when the previous trade is more than five days old. For example, mean differences fall from \$0.44 to \$0.29 when adjusting trade prices using Treasury returns until the minute prior to the current trade. However, CP+ still outperforms in 71% of cases, suggesting that it incorporates additional information beyond the maturity matched Treasury return. The improvement from adjustments declines as the time between successive trades narrows, reflecting that the last trade captures the bulk of the market movements.

Similarly, daily-level treasury adjustments reduce mean deviations when the elapsed time between successive trades is long (e.g., falling from \$0.33 to \$0.18 for gaps over five days), but the benefits of the adjustment reduce when the elapsed time is short. For trades occurring within the same day, the last trade becomes more timely than the previous day's CP+ quote. However, the prior-minute CP+ quote still exhibits smaller deviations when the last trade is

[15]Note that unlike treasury returns, which can be measured at both the daily and minute frequencies (using CP+ data), we only observe index returns at the daily frequency.

more than 5–8 hours earlier. Figure IA.3 Panels A-D illustrate these patterns graphically.

In column 5, we report differences in deviations that compare credit-index adjusted trade deviations to CP+ prior day quote deviations. Credit index adjustments offer smaller improvements. For trades with gaps over a week, mean deviations fall modestly from \$0.33 with no adjustments to \$0.29 with credit index adjustments, with limited changes in median differences. These results suggest that CP+ quotes incorporate more bond-specific or proprietary information than is reflected in credit index returns alone. Figure IA.3 (Panels A–F) illustrate these patterns graphically.

We also test robustness along two dimensions. First, we restrict the sample to trades where the current and prior trade share the same direction (e.g., both are buys). Specifically, for rows under "Trades with Same Signs" (see Table 5, Panel B and Figure IA.3 in Appendix), we adjust both for bid-ask spreads and treasury movements (columns 2 and 4) and for bid-ask spreads and credit market movements (column 5). The results are qualitatively similar to those based on all trades. Second, we restrict to round-lot trades (greater than \$1 million), which are more likely to reflect trades with higher information content. Results remain qualitatively similar: CP+ quotes still outperform, particularly when the elapsed time between trades is long.

2.4. Information Content of CP+ Reference Prices: Market Data

To better understand the information content of CP+ quotes, we estimate regressions of CP+ returns on a set of market factors. For each trade, we compute CP+ returns as the daily time-weighted average quote price from the last trade date to the trading day before the current trade. Market factors include maturity-matched Treasury returns, credit index returns, S&P 500 returns, changes in credit spreads, and changes in the VIX, all measured over the same period as the CP+ return.[16] As the independent variables can only be measured

[16]Several studies have examined the informational role of the stock market for the bond market, including Kwan (1996), Hotchkiss and Ronen (2002), and Back and Crotty (2015).

at the daily level, we only include trades with a time since the last trade of more than two days. Standard errors are clustered by issuer and date.

Table 6, Panel A reports the results. CP+ returns are strongly related to broad market signals. In columns 1–3, we regress CP+ returns on contemporaneous returns from the Treasury market, the corporate bond market, and the equity market, respectively. Each market factor loads significantly and positively when entered individually, with R^2 values around 26–28% for the Treasury and bond index models. These results are consistent with corporate bonds having positive exposure to systematic risk factors. In columns 4 and 5, changes in credit spreads and VIX exhibit negative and significant coefficients, consistent with the interpretation that rising credit risk and market volatility increase the probability of default and thus lead to lower bond returns. When multiple factors are included, the R^2 rises to 36% and 27%, respectively, in columns 6 and 7. Combined, these results indicate that CP+ quote updates respond to broad market movements from treasury, credit, equity and options markets.

Next, we examine whether CP+ quotes incorporate these broad market movements in an efficient manner by estimating predictive regressions of future CP+ returns over the five days following a trade. Table 6, Panel B reports these results. If contemporaneous changes in CP+ quotes fully incorporates market movements, then prior market conditions should not predict future quote changes. In column 1, the coefficient on Treasury return is economically small, with a zero R^2, suggesting that CP+ fully incorporates information from the treasury market. However, in the other columns, returns on corporate bond indices, stock market, and changes in credit spreads or the VIX do retain some predictive power, with R^2s of 2–4%. These results suggest that CP+ quotes incorporate non-Treasury market signals with some delay, though they still respond contemporaneously to these markets.

2.5. Information Content of CP+ Reference Prices: RFQ Data

One key advantage of the CP+ pricing engine is that, in addition to public market signals, it also leverages data from the MarketAxess electronic trading platform. This proprietary data includes the entire stack of inquiry responses sent by liquidity providers, for both inquiries that result in a trade and those that do not.

We examine the magnitude of CP+ performance gains when request-for-quotes (RFQs) are observed between realized trades. Because we focus on successive trades, we ignore completed RFQs (e.g., we only observe a completed RFQ between trades if it generates the trade at time t) and focus on non-traded inquiries and delayed spot RFQs.

A "did-not-trade RFQ" refers to an instance where a RFQ is sent by a potential buyer or seller but does not result in a completed trade; this can occur because the submitter chooses not to trade after observing the quotes or because there are no responses to the inquiry. A "delayed treasury spotting RFQ" refers to instances where the terms of a trade are agreed upon but the trade is delayed. The parties agree on a spread to a benchmark U.S. Treasury security at the time of negotiation, but the final dollar price is calculated and "spotted" at a later designated time on the same day, typically 3 p.m. or 4 p.m. For these RFQs, the CP+ engine observes spread data prior to the trade being reported to TRACE.

Table 7 reports differences in deviations between trade prices and CP+ quotes and highlights the information gained by CP+ when RFQs are observed between the current and previous trade. Panel A reports deviation differences using the CP+ quote from one minute prior to the trade, while Panel B uses the CP+ quote from the prior day's close.

In column 2 Panel A of Table 7, we focus on did-not-trade RFQs submitted after the previous trade but at least 15 minutes before the current trade. The 15-minutes buffer ensures that the algorithm observed the RFQ outcome (i.e., no resulting trade) prior to the current trade. Although we do not observe the time the inquiry was missed, in our sample for completed trades, the average time between submission and trade agreement is eleven minutes. This suggests that, for the vast majority of RFQs, the outcome is known within 15 minutes. In column 2 of Panel B, we restrict the analysis to trades with a did-not-trade RFQ after the previous trade and at least a trading day prior to the current trade.

In column 5 of Panel A in Table 7, we focus on delayed spot RFQs that were negotiated after the last trade, and for consistency with column 2, at least 15 minutes prior to the current trade. In column 5 of Panel B, we identify trades with a delayed spot RFQ after the last trade and at least one trading day prior to the current trade.[17] Columns 1 and 4 report deviation differences for trades for which a did-not-trade (column 2) or delayed spot (column 4) RFQ was not observed between trades. Columns 3 and 6 present the incremental improvement in CP+ performance when an RFQ is observed between successive trades versus when it is not.

Comparing column 1 and 2 of Table 7, we observe clear performance gains for CP+ when did-not-trade RFQs are observed prior to the current trade. When the time between trade exceeds five days, the average deviation difference increases from \$0.35 (no did-not-trade RFQ) to \$0.51 (with RFQ), a sizable improvement of \$0.16. Although the effect is more pronounced when the time between successive trades is long, performance gains are also observed when the time between trades is one to five days and less than one day. Results are similar when we restrict the sample to successive trades of the same sign (using the corresponding bid or ask quote instead of the midpoint) and to trades of at least \$1 million. Panel B, columns 1-3 further show CP+ continues to benefit even when the did-not-trade RFQ is observed, at the earliest, the day before the current trade.

Columns 4-6 of Table 7 show that delayed spot trades provide particularly valuable information to the CP+ pricing engine. When the time between successive trades exceeds

[17] Because we require RFQs to occur at least 15 minutes before the current trade, we do not report statistics for successive trades that are less than one hour apart. In Panel B, because we require the RFQ to be at least a day prior to the current trade, we do not report statistics for successive trades that are less than one day apart.

five days, the average deviation difference increases from \$0.40 (no delayed spot RFQ) to \$0.70 (with RFQ), a substantial performance gain of \$0.30. Because the vast majority of delayed spot RFQs are executed by 2 p.m., with over 60% negotiated in the morning, CP+ is able to incorporate informative private signals well before the trade is reported to the market. Columns 4-6 of Table 7 indicate meaningful performance gains across samples restricted to same-sign successive trades, large trades, and instances when the delayed spot RFQ is observed, at earliest, in the prior day. The results in column 6 consistently shows that delayed spot RFQs are especially valuable when prior trade information is stale.

Overall, both RFQ inquiries types provide useful forward-looking information that improves CP+ performance, particularly for bonds that are not actively traded.

3. The Value Added by CP+ Reference Prices

3.1. Modeling Coverage and Quoting on CP+

The extent to which CP+ adds value to investors depends on its coverage of bonds, the availability of quotes, and the frequency of updates. As shown in Table 1, CP+ does not provide coverage for about 9% of corporate bonds in the merged FISD and TRACE dataset (1,972 of 22,505 bonds). Figures 2 and 3 further illustrate that CP+ quotes are available to most, but not all, bonds, and the volume of quotes and updates varies meaningfully across bonds and over time.

To analyze the association between CP+ coverage and bond characteristics, we estimate bond-month panel regressions for the 20,355 bonds in the CP+ sample (as shown in Table 1). Table 8 presents the results. All specifications include month fixed effects to absorb the improvement of CP+ coverage over time.

In columns (1)-(3), the dependent variable is an indicator variable that equals one if the bond has CP+ coverage in a month. The bond characteristics are issue size, age, time to maturity, investment-grade status, as well as the issuer's public status. Column (1) indicates that larger, younger, longer-maturity, and investment-grade bonds are more likely to be covered. Column (2) adds the natural log of the number of trades in the previous month, showing that a 1% increase in trade frequency is associated with more than 0.1% increase in the likelihood of coverage. Column (3) includes bond fixed effects and confirms the strong positive association between past trading and CP+ coverage.

Columns (4)-(6) examine quote frequency, with the dependent variable being the natural log of CP+ quotes in the bond-month. Results indicate that quote frequency is higher for larger and younger bonds, and again positively associated with prior trading activity. A 1% increase in trading activity in the prior month is associated with at least a 0.2% increase in the number of quotes.

Columns (7)-(9) repeat the analysis with quote updates in the bond-month as the dependent variable. Interestingly, the investment-grade dummy has a positive coefficient in the update regression, despite being negative in the quote frequency regression. Controlling for other bond characteristics, a 1% increase in the past trading activity is associated with around a 0.2% increase quote updates. Overall, we find that CP+ coverage and quoting intensity are highly sensitive to recent trading activity.

3.2. Modeling CP+ Value Added in the Cross-section

We measure the value added by CP+ for investors as the difference between the trade price deviation and the CP+ quote deviation, using the last standing quote before the current trade. This measure is constructed at the trade level, using all trades for which the previous trade occurred within the past 250 trading days. If no quote is available on the current day, we carry forward the most recent available quote. If no such quote is available, we assign a value added of zero for the trade. This approach reflects the idea that CP+ may suspend quoting when its pricing error exceeds a threshold, indicating that the algorithm cannot confidently produce reference prices that add value to price discovery.

To examine the relationship between bond liquidity and CP+ value added, we calculate the average value added across all trades for each bond-month in the CP+ sample. We then sort bonds into 100 equal-sized bins each month based on the number of trades in the previous month, a proxy for liquidity. For each bin, we compute the cross-sectional average value added within the month and then average across months.

Figure 6 presents a scatter plot of average CP+ value added by liquidity bin. The blue circles represent the average number of trades in the current month, confirming that the sorting effectively captures contemporaneous bond liquidity. The key finding is that the value added measure is consistently positive across the cross-section, indicating that, conditional on coverage, CP+ contributes meaningfully to price discovery.

In the low liquidity bins, value added begins at zero for bonds with no CP+ coverage in a given month. Importantly, this figure does not include the 9% of bonds in the merged FISD-TRACE sample for which CP+ provides no coverage. By construction, these bonds will be assigned a value added of zero.[18]

When bond liquidity is low, value added increases with liquidity, likely reflecting that additional trade data improves CP+ model training and generates a reference price that is better than the last trade price. However, this relationship is non-monotonic. Once bond liquidity exceeds the 10th bin, value added begins to decrease with liquidity and drops to almost zero for the most liquid bins. This aligns with our earlier findings: when bonds trade frequently, the last trade price already provides timely information, leaving limited room for CP+ to improve pricing.

We test this non-monotonic relationship formally by estimating piecewise-linear regressions using bond-months covered by CP+. Specifically, we regress average value added on bond

[18] In an unreported analysis, we examine the characteristics of bonds never covered by CP+. We find no significant differences in issue size or maturity between covered and uncovered bonds. However, uncovered bonds are less likely to be investment grade or issued by public firms.

characteristics and two piecewise-linear terms that split the prior month's trade count into a low and high region. Table 9 reports the results. Column (1) suggests that CP+ adds more value for smaller, older, longer-maturity, and investment-grade bonds. Column (2) adds the piecewise terms: the coefficient is positive for low liquidity bonds (less than 10 trades in the prior month) and negative for higher-liquidity bonds (more than 10 trades in the prior month). Column (3) adds bond fixed effects and obtains qualitatively similar results. Overall, these results show that CP+ value added exhibits a bell-shaped relationship with bond liquidity.

3.3. Modeling CP+ Value Added during Market Uncertainty

The results thus far show that CP+ contributes to price discovery by incorporating broader market movements between trades. We now examine whether CP+ plays an especially important role during periods of heightened uncertainty and large price movements.

We begin with visual evidence from the onset of the COVID-19 crisis, the most severe market dislocation in our 2017–2023 sample period. Using the trade-level deviation measures, we aggregate to the weekly level from February 2020 to May 2020. Figure 7, Panels A and B, report mean deviations and 95% confidence intervals based on the last trade price (blue) and the most recent CP+ quote (red). Specifically, we compute the weekly mean trade price deviation and the CP+ quote deviation, using the last standing quote before the current trade. We report results separately for less active and more active bonds, where activity is based on the number of trades in January 2020 (pre-COVID). Bonds in the bottom quartile are classified as less active, and those in the top quartile as more active.

Panel A shows that for less active bonds, CP+ quote deviations are consistently lower than trade deviations throughout the COVID period, and the differences are statistically significant at the 5% level. Panel B shows that differences in deviations are less prominent for active bonds in the pre-COVID period, however, CP+ continues to outperform with statistically lower deviations for most of the period. Overall, these results are consistent with those reported in Section 3—the benefits of CP+ are pronounced for bonds that lack active trading. In Panels C and D, we focus on the highest volatility periods of the COVID crisis from the second week of March to the end of March 2020.[19] During this period, CP+ quote deviations remain lower than trade deviations for both less and more active bonds.

We next extend our analysis to the full sample period to assess CP+ performance under varying market conditions. We start with the trade-level deviations, then aggregate to daily deviations, resulting in a mean deviation for each bond-day using both unadjusted last trade and CP+ quotes in the previous minute. We then compute the daily difference in deviations.

To capture market uncertainty, we utilize the level of the VIX in the previous week. In Figure 8, we sort daily deviation differences by the previous week's VIX decile. Deviation differences increase monotonically with the VIX decile, indicating that the value added by CP+ is particularly pronounced during periods of elevated market volatility.[20]

Overall, these results suggest that the CP+ ML engine remains effective, and perhaps becomes even more valuable, during episodes of extreme market stress and uncertainty.

4. Evolution of CP+ Following Trades

In this section, we examine the evolution of CP+ quotes following the reporting of non-retail size trades. We then study CP+ quoting behavior around block trades that exceed $15 million. We aim to understand CP+ pricing dynamics when such trades are associated with either large, permanent changes in fundamental value or large temporary dislocations.[21] Our analysis examines how effectively CP+ incorporates these shocks.

[19] On March 16, 2020, the VIX reached an all-time high of 82.69.

[20] In regressions of value added on VIX, controlling for bond fixed effects, we find a similarly positive relationship between CP+ valued added and uncertainty.

[21] Price effects surrounding large transactions and sustained customer imbalances in the corporate bond market has been examined by Cai, Han, Li, and Li (2019) and Anand, Jotikasthira, and Venkataraman (2021).

AI-based algorithms can help stabilize markets by identifying information events and producing reference prices that speed up convergence to fundamental value. However, the CP+ algorithm has a hierarchy of information, with priority on realized trade data, and is designed to estimate the price of the *next trade*, not necessarily the bond's fundamental value. Around bond-specific events, trading activity often declines or reflects fire sales and unusual conditions. If such trades influence reference prices, those estimates could affect subsequent negotiations and unintentionally amplify pricing distortions.

4.1. CP+ Adjustments Around All Trades

We begin by examining how CP+ quotes evolve shortly after a trade report. Similar to Table 3, we study the full sample of non-retail trades and compute CP+ mid-quote deviations from the current trade price at various intervals relative to the trade time: 1 day and 1 minute before, 1, 5, 10, 30, 60, 120 minutes after, as well as 1 day after the trade. The analysis focuses on both the magnitude and speed of CP+ quote updates in response to the trade report.

The results are reported in Table 10. When trades are five days apart, CP+ deviations are large at \$0.60 the day prior to the trade, declining to \$0.48 one minute before, \$0.46 one minute after, and falling sharply to \$0.28 five minutes after the trade. Thereafter, adjustments remain minimal. Similar patterns are observed when the elapsed time between trades is shorter. Relative to the deviation one minute *before* the trade, the deviation five minutes *after* the trade drops from \$0.27 to \$0.18 when trades are 1 and 5 days apart, from \$0.22 to \$0.17 for 1 hour to 1 day, and from \$0.25 to \$0.20 when less than one hour elapses between trades.

Across all subsamples, CP+ deviations change little between one minute before and after the trade, indicating that updates occur gradually rather than instantly in response to most recent trade data. By five minutes post-trade, deviations fall sharply and remain stable over the next two hours. Most price discovery occurs within five minutes of the trade report, with larger adjustments following longer elapsed time since the prior trade, though a similar but smaller pattern is observed even when the last trade was within the past hour.

4.2. CP+ Adjustments Around Trades with Large Price Effects

For the full sample of trades, we find that CP+ updates quickly in the direction of the reported trade. We next study the evolution of CP+ quotes around block trades, focusing on those associated with large information, reflected in permanent price effects, and those associated with large reversals, as measured by temporary price effects.

We begin with the sample of large block trades, defined as trades exceeding $15 million, identified in Jacobsen and Venkataraman (2025). The dataset allows us to determine trade direction (buy or sell), which is critical for correctly estimating price impact. To identify blocks with large permanent price effects, we compute time-weighted average trade prices and CP+ quotes over a 21-day window spanning ten days before and after the block. Permanent price impact is measured as the log difference between trade prices on day –10 and day +10, adjusted for the trade direction.[22] We focus on blocks in the top three deciles of permanent price impact.

We compute trade deviations as the difference between the time-weighted daily price on day t and the time-weighted daily price on day +10. For CP+, we analogously compute deviations from the day +10 trade price using the CP+ quote on day t. Unlike our earlier successive trade methodology, which assumes that the current trade accurately reflects fundamental value, this methodology allows prices to move toward a long-run fundamental value (day +10), and the deviation dynamics capture gradual adjustment or temporary mispricing. Bonds are classified by trade activity over the pre-block window (days –10 to –1), with the bottom quartile defined as less active and the top quartile as more active.

[22] If a bond does not trade on these days, we retain the last trade. We obtain similar results using CP+ prices at the same horizons.

Results for blocks with permanent price impact are presented in Figure 9 Panels A and B. Because we are interested in the short period around the block trade, we report deviation statistics for the five trading days before and after the block, separately for less and more active bonds. Panels A and B show that for both groups, deviations from the day +10 price are large prior to the block, decline sharply once the block is reported, and continue to decline over the subsequent trading days. For less active bonds, CP+ deviations are slightly lower than trade deviations during the pre-block period, though differences are not statistically significant, but not lower during the post-block period. For more active bonds, CP+ deviations closely track trade deviations throughout, indicating that the CP+ algorithm reacts to realized trade data.[23]

Some trades cause temporary dislocations in price—consider a large block sell by a customer that pushes prices down as the market absorbs the supply. We next examine whether CP+ quotes track these short-lived price dislocations. To identify blocks associated with large temporary price impact, we compute (i) the immediate price impact on day 0, measured as the log difference between the time-weighted trade price on day 0 and day –1 (signed based on whether the block is a buy or sell), and (ii) the subsequent reversal, measured as the log difference between the trade price on day 0 and day +10 (signed based on trade direction). We classify a block as having a meaningful temporary impact if three conditions hold: (1) the day 0 impact is large and falls in the top three deciles of the distribution, (2) the post-block price move is large in the opposite direction (i.e., reverses), and (3) the magnitude of the reversal is at least 10% of the initial day 0 impact.

For this sample, we calculate trade deviations as the difference between the time-weighted daily price on day t and the day +10 trade price. CP+ quote deviations are computed analogously, relative to the day +10 trade price. Figure 9, Panels C and D report the results. Before the report of the block trade, CP+ deviations are relatively small. Following the block

[23] The results are robust to using CP+ quotes on days –10 and +10 to compute permanent price impact.

trade, CP+ deviations increase and closely track trade price deviations, peaking on days 1 and 2, and gradually declining as the temporary price impact reverses. For less active bonds, CP+ quote deviations (red) are consistently lower than trade deviations (blue) during the temporary price impact period, though the differences are not statistically significant. For more active bonds, CP+ deviations track trade price deviations closely, even during sharp reversals, reflecting the algorithm's strong reliance on recent trades in active markets.

Overall, we find that CP+'s reliance on recent trades limits its contribution following block trades with large transitory price effects, suggesting that it can be affected by temporary shocks such as noise trading or fire sales.

5. Conclusion

We study the U.S. corporate bond market, where dealer quotes are often indicative and shared selectively with established institutional clients. Prices and quantities of completed secondary market trades are disseminated real time by FINRA's TRACE system. However, trading activity in corporate bonds is typically sparse, which limits the effectiveness of post-trade transparency. In this setting with limited pricing information, we explore whether AI-generated reference prices made available by MarketAxess, a major electronic bond trading platform, help improve intraday price discovery.

Our research uses a comprehensive dataset of 24.9 million non-retail bond trades and 11.8 billion CP+ quotes across 20,335 corporate bonds from 2017 to 2023. We benchmark trade prices against CP+ midpoints, both from the prior day and just before each trade and assess informational content using deviation tests and return autocorrelations. We also study the nature of CP+'s informational advantage by adjusting the trade price for market movements between successive trades and using regressions on broad market factors.

We find that the most recent CP+ quote is more informative about current trade price than the most recent trade price, particularly when trade intervals are long. The results are robust in subsamples that account for same-direction trades and transaction size. CP+ incorporates broad movements in bond, equity, and options markets, and information from non public RFQ platform. Even after adjusting the previous trade price for market movements, CP+ quotes are closer to current trade prices, suggesting that CP+ also incorporates granular bond-level information. Daily return autocorrelation tests show that trade-based portfolios exhibit greater pricing staleness than quote-based portfolios. We study how CP+ quote updates evolve shortly *after* a trade. Our results indicate that much of the price discovery occurs within five minutes of the trade.

The benefits of observing a well-calibrated reference price that is informative about the next trade price are clear—it reduces the time investors need to search for information and helps ensure that trading decisions are based on timely, high-quality data. Our findings suggest that AI-driven pricing tools can generate timely reference values. CP+'s contributions to price discovery exhibit a bell-shaped pattern with bond liquidity: value added is greatest for bonds with moderate liquidity, where trades are infrequent but data quality is high enough for the algorithm to support updates. In contrast, for illiquid bonds, limited quote generation reduces the value of AI-driven algorithms; for highly active bonds, trades themselves provide sufficient pricing signals. We also find that CP+ adds more value between successive trades during periods of heightened market-wide uncertainty.

The CP+ algorithm is designed to estimate where the next trade is likely to occur, not necessarily where the bond's fundamental value lies. This creates a potential trade-off between predicting short-term transaction prices and providing reference prices that reflect fundamental value. During stress markets, trading activity often declines, and those transactions that do occur may involve distressed sellers or be otherwise unrepresentative. This can disproportionately influence reference price estimates. We examine the evolution of CP+ quotes around block trades with large ex-post permanent and temporary price effects. We find that CP+'s reliance on recent trades limits its contribution following block trades with large transitory price effects. Our results suggest that AI-generated reference prices can be affected by temporary shocks such as noise trading or fire sales.

Since CP+ quotes are indicative and not subject to execution risk, they lack the market discipline that shapes firm, executable quotes in markets such as equities. Yet because they are widely observed and can influence trading behavior, there is a risk that they may contribute to feedback loops or "echo chamber" effects during periods of market stress that reinforce temporary price distortions. As AI-generated reference prices gain wider use, careful design and oversight may be needed to build in mechanisms that anchor reference prices to fundamental value, especially during volatile market conditions.

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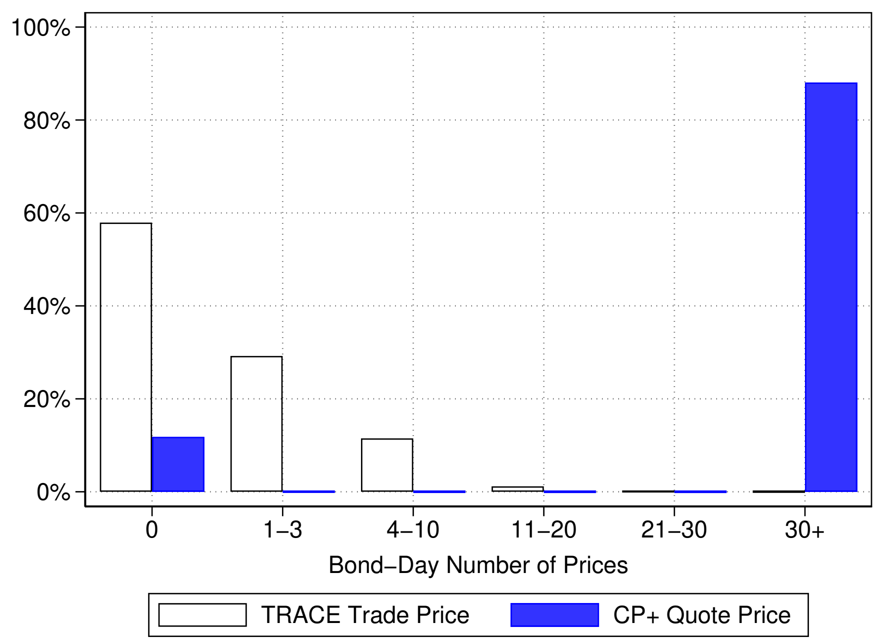
(a) All Bonds



(b) Small Issue Bonds

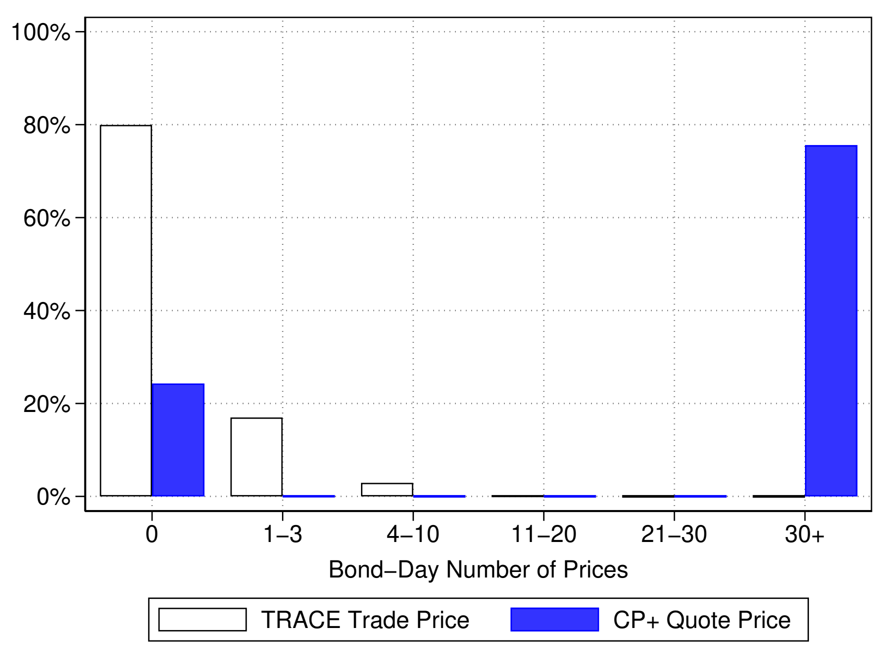


Figure 1: **Distribution of the Number of Prices Per Bond-Day.**
This figure presents the distribution of the numbers of trade prices and CP+ quote prices at the bond-day level. In Panel A, the sample includes all bonds in FISD and TRACE and their trading days between the bond's first and last days in CP+. In Panel B, the sample includes only bonds with an issue size less smaller than $500 million.

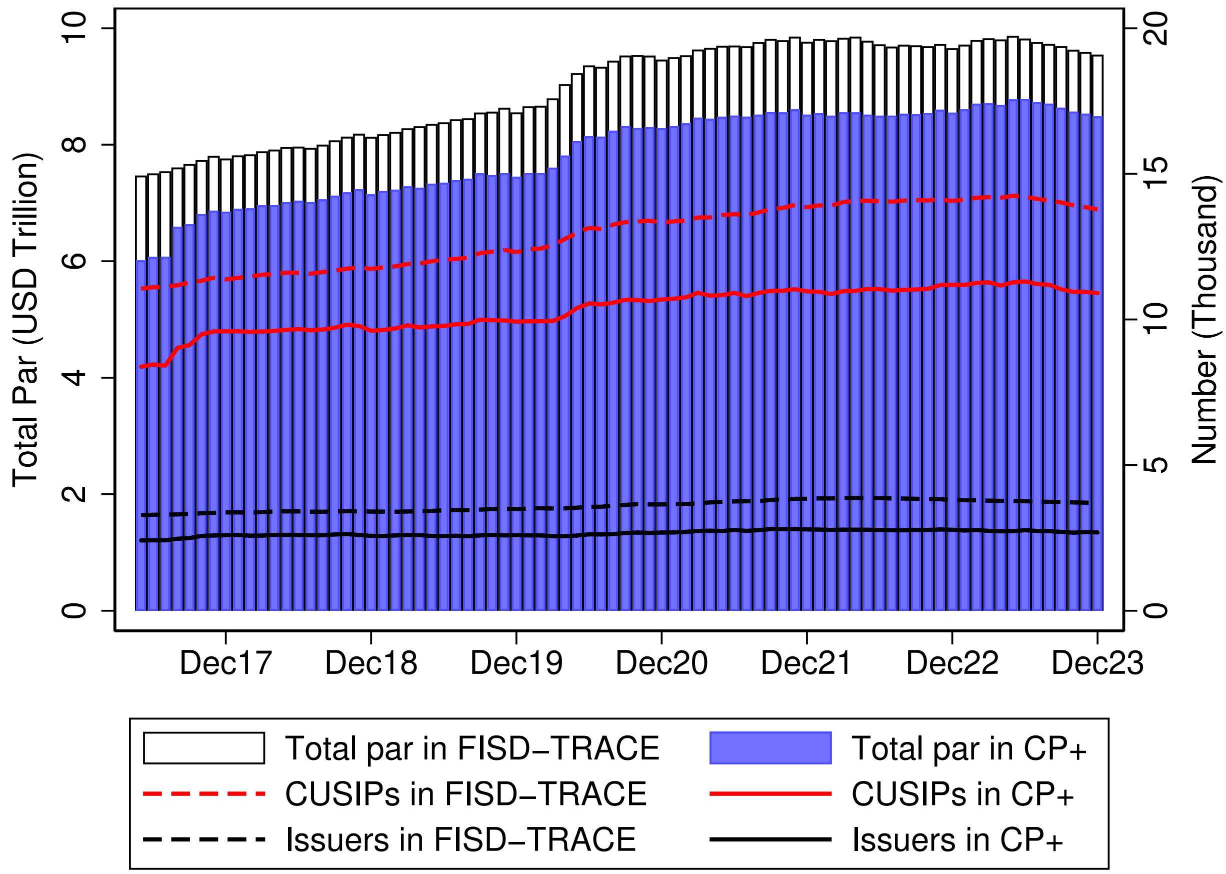
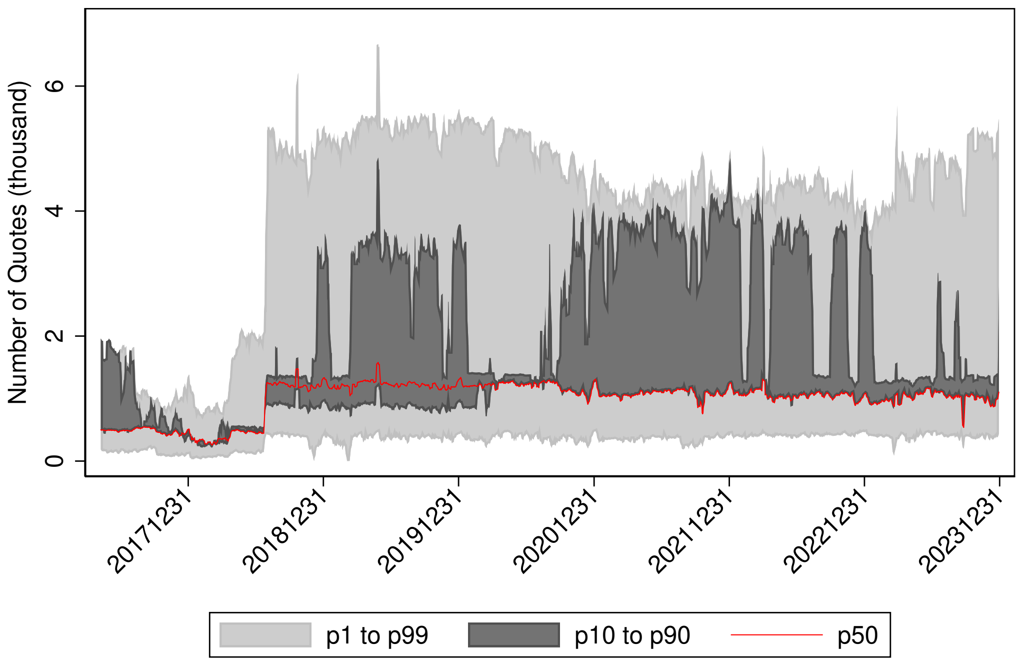


Figure 2: **CP+ Coverage of Corporate Bonds by Month.**
This figure presents the monthly coverage of CP+ among corporate bonds in FISD and TRACE. Blue and white bars indicate the total bond par values (USD trillion) in CP+ and in FISD-TRACE, respectively. Solid and dashed red lines indicate the number of unique CUSIPs in CP+ and in FISD-TRACE, respectively. Solid and dashed black lines indicate the number of unique issuers in CP+ and in FISD-TRACE, respectively.

(a) CP+ Quote Prices



(b) CP+ Quote Updates

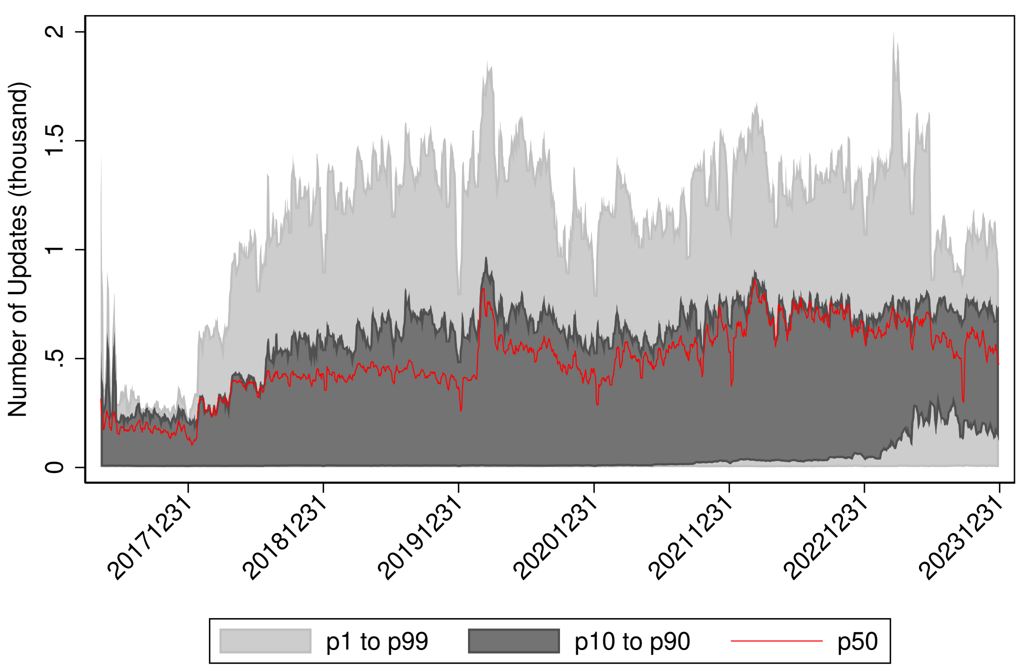


Figure 3: **Daily Cross-Sectional Distribution of the Number of CP+ Prices.** This figure presents daily cross-sectional distribution of the number of CP+ reference prices. Panel A presents the distribution of the number of quotes. Panel B presents the distribution of the number of updates. Red line indicates the daily median number of quote prices across bonds. Dark and light gray shaded areas indicate the ranges of the 10th to 90th percentiles and the 1st to 99th percentiles, respectively.

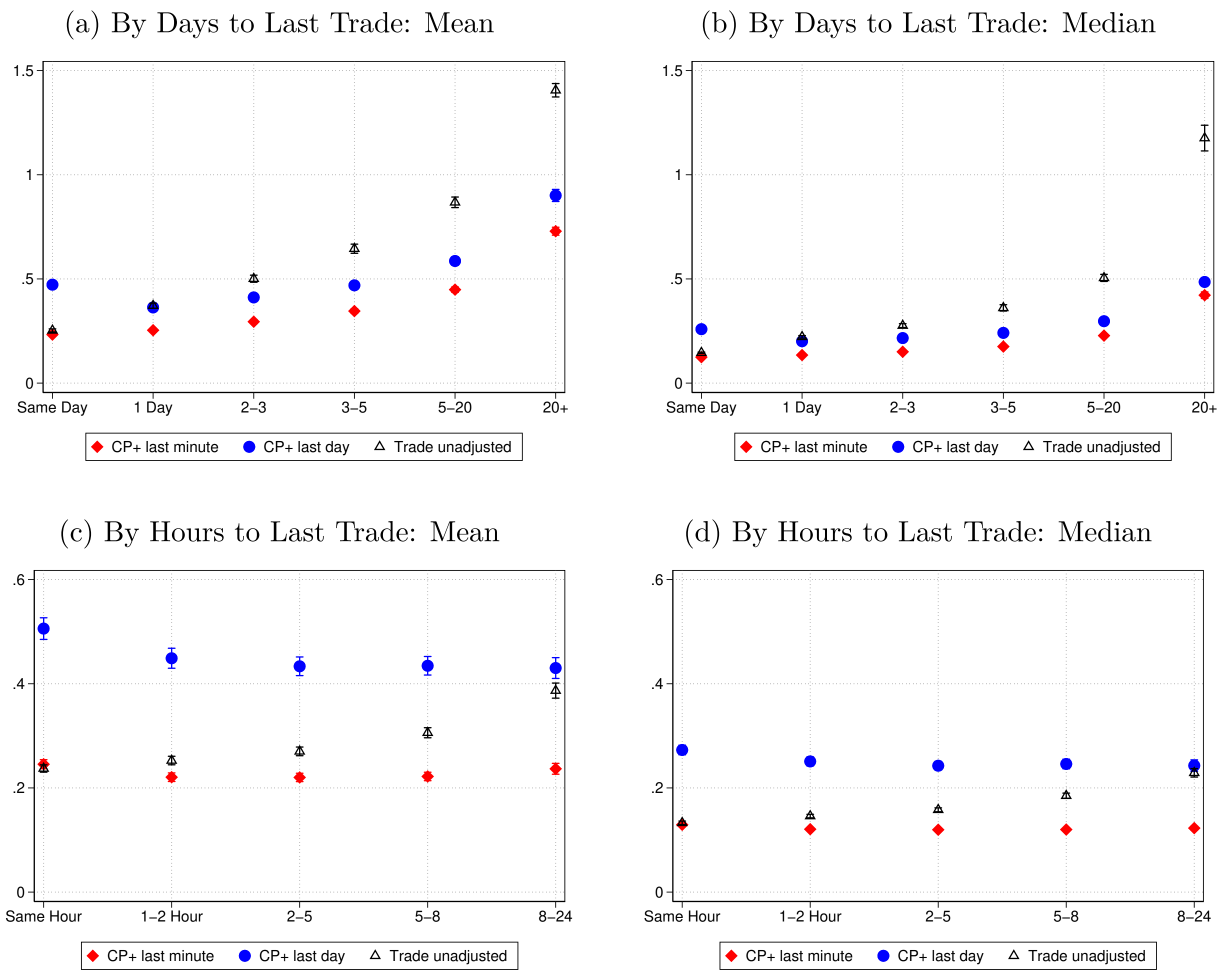
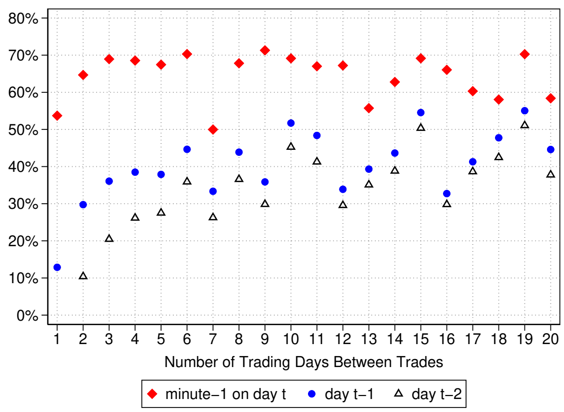
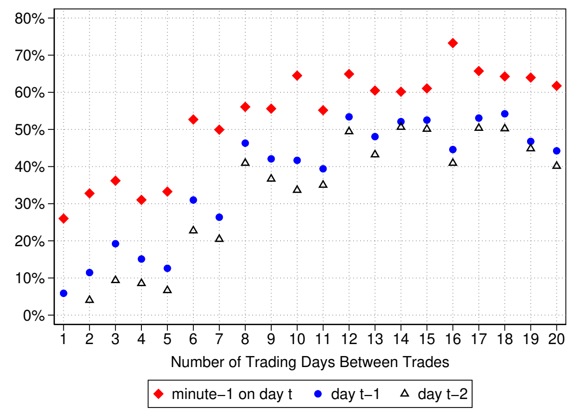


Figure 4: **Bond Price Deviations: CP+ vs Last Trade Price.**
This figure presents the means and medians of trade deviation and CP+ deviation. In Panels (a) and (b), the sample includes all trades. In Panels (c) and (d), the sample consists of trades for which the last trade is within the same day. Red diamonds indicate CP+ deviation using the previous minute quote (m-1), blue circles indicate using the previous day quote (d-1), and black triangles indicate trade deviation. Upper and lower bars around each marker are 99% confidence intervals. Standard errors are clustered at the trade date level. For medians, standard errors are obtained via cluster-level bootstrapping with 1000 replications.

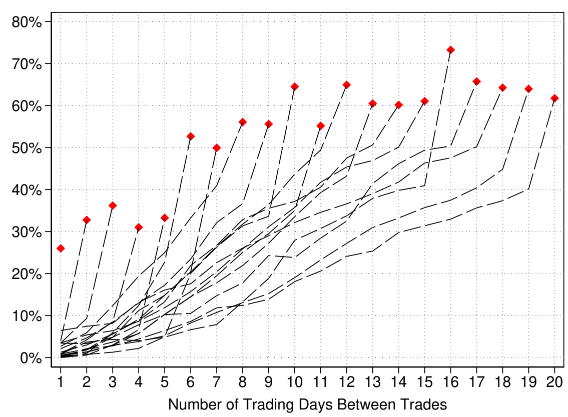
(a) $1\% \leq |ret| < 3\%$: Daily



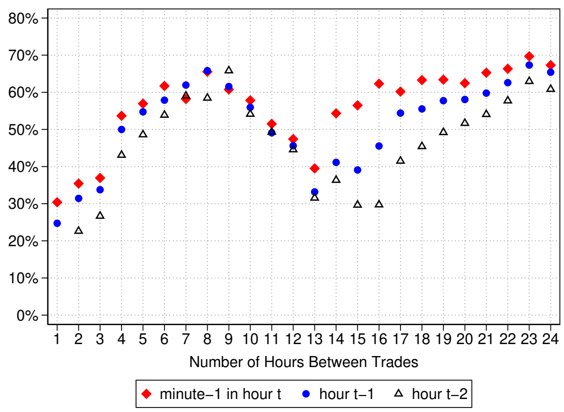
(b) $|ret| \geq 3\%$: Daily



(c) $|ret| \geq 3\%$: Daily, Path of R^2



(d) $1\% \leq |ret| < 3\%$: Hourly



(e) $|ret| \geq 3\%$: Hourly

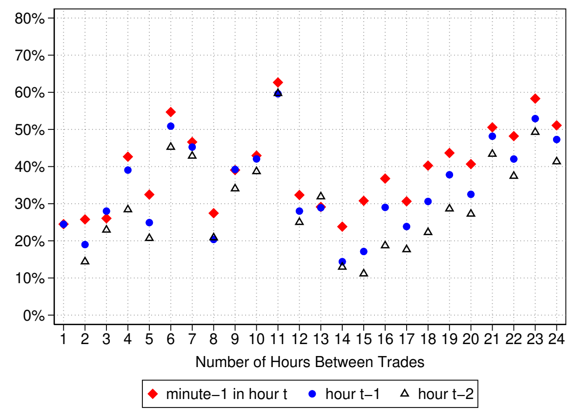


Figure 5: **CP+ Price Discovery Between Successive Trades. (Continued)**
This figure presents R^2s from regressions of bond trade return on the return from last trade price to CP+ price before trade. Panels (a), (c) include trades with an absolute trade return between 1% and 3%. Panels (b) and (d) include trades with an absolute trade return greater than 3%. Panels (a), (b) include trades for which the last trade is at least two trading days ago. Red diamonds indicate the previous minute quote midpoint, blue circles indicate the time-weighted average hourly price on the previous day, and black triangles indicate the time-weighted average price on the second last day. Panel (c) shows the time path of R^2s for Panel (b). In panels (d) and (e), the sample includes trades for which the last trade is within 24 hours. Red diamonds indicate the previous minute quote midpoint, blue circles indicate the time-weighted average hourly price during the previous hour, and black triangles indicate the time-weighted average hourly price during the second last hour.

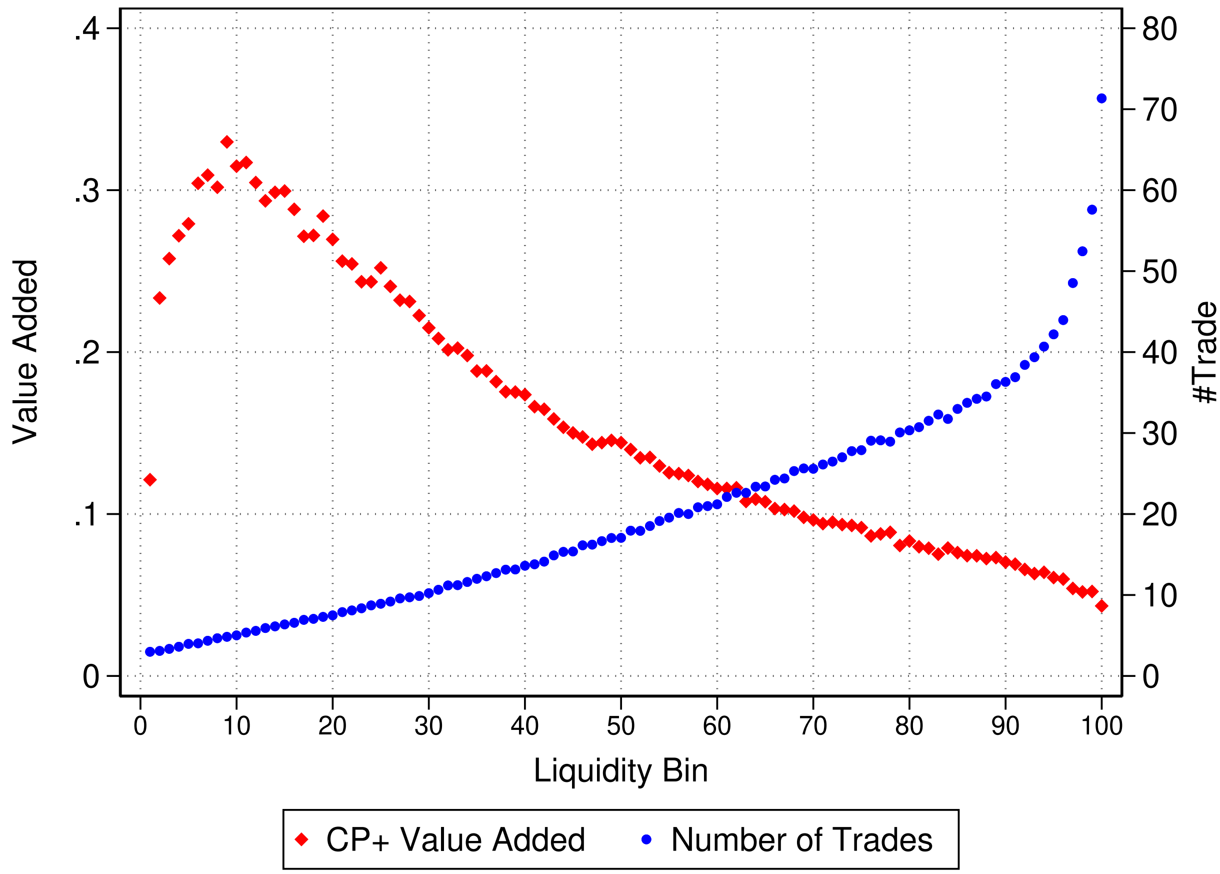
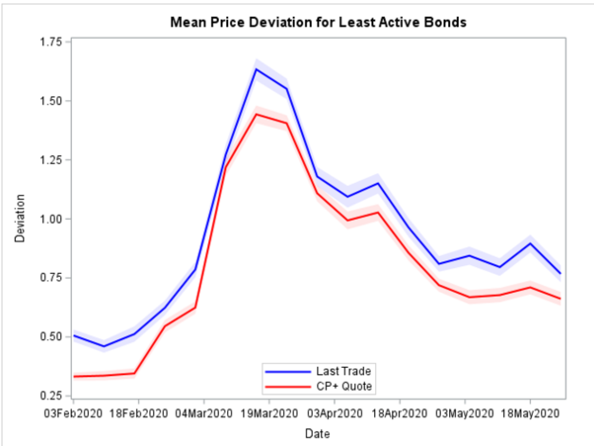
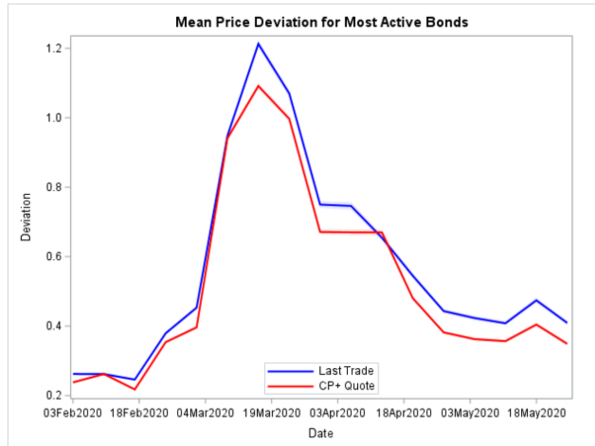


Figure 6: **Bond Liquidity and CP+ Value Added.**
This figure presents the relationship between bond liquidity and CP+ value added. For each trade, CP+ value added is defined as last trade price deviation minus CP+ (m-1) price deviation. Bond-month value added is the average of its trade-level values. Each month, bonds are grouped into 100 bins by the number of trades in the previous month. Red diamonds represent the average of CP+ value added within each bin across months. Blue circles represent the average of number of trades in the current month within each bin across months.

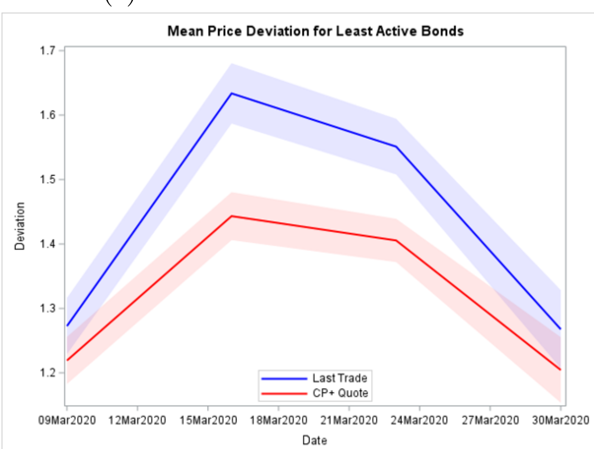
(a) Least Active Bonds: Feb to May



(b) Most Active Bonds: Feb to May



(c) Least Active Bonds: March



(d) Most Active Bonds: March

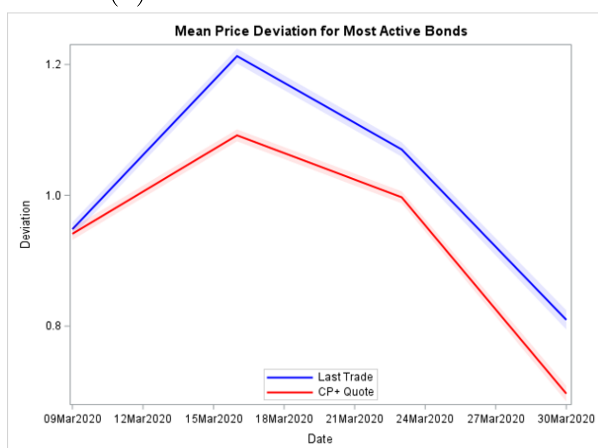


Figure 7: **Price Deviation Around Covid.**
This figure reports weekly average price deviations around Covid 19. For each week in the period, we report means and 95% confidence intervals. Blue indicates deviations using the last trade and red indicates deviations using CP+ quotes in the minute prior to the trade. Panels (a) and (c) report statistics for the least active bonds and Panels (b) and (d) for the most active bonds. The least active bonds are in the bottom quartile for number of trades in January 2020 and the most active bonds are in the top quartile for number of trades in January 2020. The first two panels report statistics from February 2020 to May 2020. The second two panels zoom in on the highest volatility period of the crisis from the second week of March to the end of March 2020.

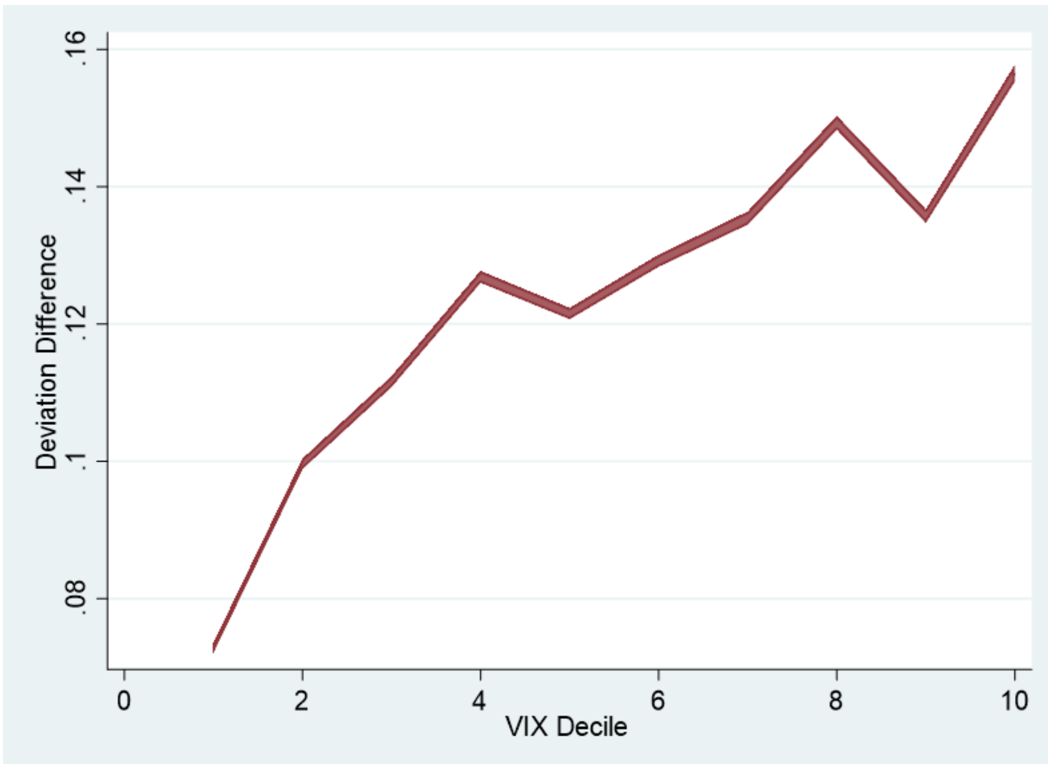
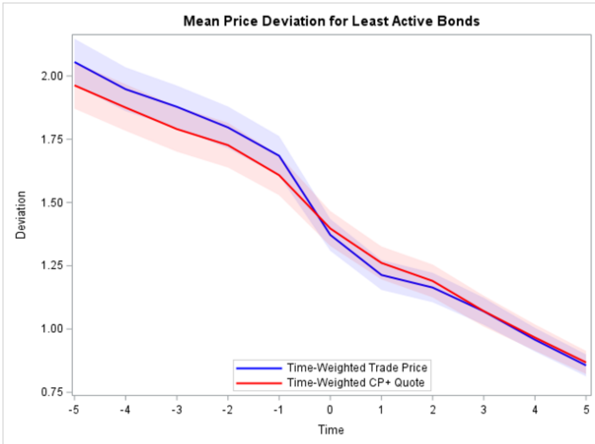
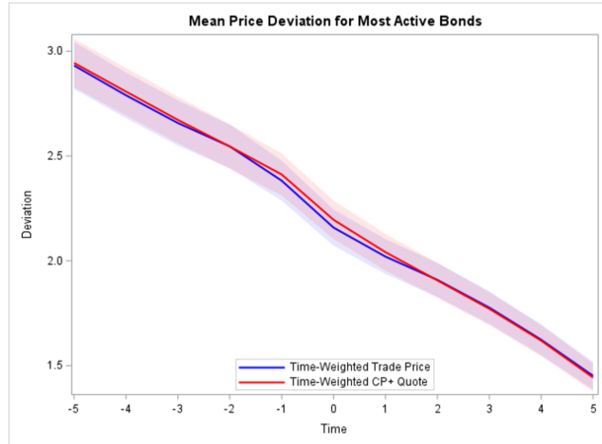


Figure 8: **CP+ Value Added and Market Uncertainty.**
In this figure, we report average daily differences in deviations by VIX, which proxies for periods of high uncertainty and volatility. We start with the trade-level deviations, then aggregate to daily deviations, resulting in a mean deviation for each bond-day using both unadjusted last trade and CP+ quotes in the previous minute. We then compute the daily deviation difference (trade deviation less CP+ quote deviation). We report average daily deviation differences by VIX decile in the previous week.

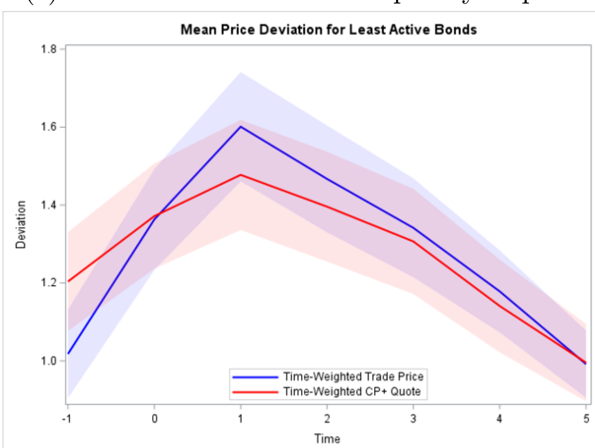
(a) Least Active Bonds: Permanent Impact



(b) Most Active Bonds: Permanent Impact



(c) Least Active Bonds: Temporary Impact



(d) Most Active Bonds: Temporary Impact

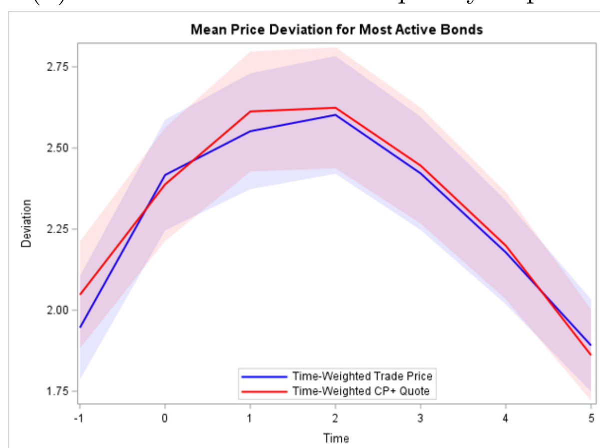


Figure 9: **Price Deviation Around Stress: Block Analysis.**
This figure reports average price deviations and 95% confidence intervals around block trades. Panels A and B report statistics for blocks with large permanent price impact. Permanent price impact is the log difference between day +10 and -10 trade prices (adjusted for buys or sells) and we focus on blocks with permanent price impact in the top 3 deciles. Trade deviation is the difference between the time-weighted (TW) average daily trade price on day t and the TW average daily trade price on day +10. CP+ quote deviations are computed analogously: we compare TW average daily quotes on day t to the TW average daily trade price on day +10. We report statistics for both less and more active bonds (bottom and top quartile of number of trades in the pre-block period). Panels C and D report statistics for blocks with large temporary price impact. We compute both the day 0 impact (log difference between the daily TW trade price on day 0 and day -1 adjusted for buys or sells) and the reversal over the post-block period (log difference between the daily TW trade price on day 0 and day +10 adjusted for buys or sells). To obtain meaningful temporary price impact, we require the day 0 impact to be in the top 3 deciles, for there to be a reversal (e.g., for a block buy, the time 0 price exceeds the time +10 price), and for the ratio of the reversal to impact to be at least 10%.

Table 1: **Sample Construction and Summary**

This table summarizes our corporate bond sample. Data on corporate bond trades are from Trade Reporting and Compliance Engine (TRACE). Bond descriptive data are from the Mergent Fixed Income Securities Database (FISD). Panel A reports details on the construction of our trade-level sample. Bond trades in this sample include non-retail (i.e., larger than $150,000) customer trades of CUSIPs in FISD on bond trading days between May 2017 and December 2023, with at least one prior trade within the last 250 trading days and an outstanding CP+ quote. Panel B summarizes the total number of trades, CP+ quotes, and CP+ quote updates for bond-trading days between the bond's first and last days of CP+ coverage. Investment Grade indicates the bond's current market segment in CP+ is investment grade. Small Issue, Medium Issue, and Large Issue indicate that the bond issue size is below $500 million, between $500 million and $1 billion, and above $1 billion, respectively. Panel C presents the cross-sectional distribution of bond-level average daily number of trades, CP+ quotes, and CP+ quote updates.

Panel A: Trade-Level Sample Construction

	CUSIPs	Trades
Corporate bonds in FISD and TRACE	22,505	93,088,653
Retain bonds in CP+	20,563	90,961,954
Retain trades larger than $150,000	20,501	25,647,083
Retain customer trades	20,496	16,632,064
Retain trades with past trade and quote	20,037	15,756,757

Panel B: Summary of Bond Trades, Quotes, and Quote Updates

	CUSIPs	Trades	CP+ Quotes	CP+ Updates
Full Sample	20,602	24,869,614	20,636,288,041	6,553,421,099
Investment Grade	16,245	16,506,280	14,533,741,403	6,266,818,520
Non-Investment Grade	7,101	8,363,334	6,102,546,638	286,602,579
Small Issue	7,313	2,971,373	4,929,042,359	1,655,942,228
Medium Issue	7,958	8,811,247	7,483,479,535	2,564,504,012
Large Issue	5,331	13,086,994	8,223,766,147	2,332,974,859

Panel C: Cross-Sectional Distribution of Daily Activity

	Mean	Median	p10	p25	p75	p90
Trades	2.9	2.4	1.7	1.9	3.2	4.5
CP+ Quotes	1,157.9	1,034.3	360.9	758.5	1,344.6	2,114.9
CP+ Quote Updates	335.0	302.2	4.3	35.2	574.2	683.8

Table 2: **Autocorrelation in Trade Prices and CP+ Quotes**

This table reports estimated autocorrelation coefficients of bond portfolio daily returns. Bond daily returns are computed with daily time-weighted average prices, where the weight is the time period a price observation lasts until the next price. These prices are computed separately for trade prices from TRACE and midpoint quote prices from CP+. Bonds are independently sorted into 6 portfolios by whether it is Investment Grade at the beginning of the year and by its issuance size group. Daily portfolio returns are equal weighted average returns across bonds in the portfolio.

	Full Sample		IG-Small		IG-Large		HY-Small		HY-Large	
	Trade	CP+	Trade	CP+	Trade	CP+	Trade	CP+	Trades	CP+
Lag	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	0.86	0.52	0.91	0.39	0.80	0.47	0.87	0.78	0.76	0.70
2	0.62	0.32	0.77	0.17	0.47	0.25	0.71	0.68	0.46	0.45
3	0.43	0.21	0.67	0.13	0.23	0.13	0.61	0.55	0.27	0.24
4	0.30	0.13	0.58	0.10	0.11	0.05	0.51	0.41	0.12	0.07
5	0.21	0.08	0.51	0.11	0.04	0.01	0.45	0.32	0.04	-0.01
6	0.14	0.03	0.44	0.09	-0.01	-0.03	0.39	0.26	0.01	-0.05
7	0.12	-0.02	0.40	0.03	-0.03	-0.06	0.35	0.23	0.04	-0.01
8	0.12	-0.04	0.37	0.01	-0.03	-0.07	0.32	0.20	0.08	0.04
9	0.11	0.02	0.34	0.09	-0.01	-0.02	0.28	0.20	0.10	0.09
10	0.09	0.02	0.32	0.08	0.00	-0.01	0.23	0.17	0.08	0.06
11	0.06	0.01	0.29	0.05	0.00	-0.01	0.20	0.14	0.01	0.01
12	0.02	-0.01	0.25	0.01	-0.01	-0.01	0.16	0.12	-0.05	-0.04
13	-0.01	0.00	0.22	0.00	-0.02	-0.01	0.11	0.06	-0.09	-0.08
14	-0.02	0.03	0.19	0.04	-0.03	0.02	0.08	0.03	-0.11	-0.08
15	-0.04	-0.02	0.16	0.03	-0.05	-0.02	0.06	-0.01	-0.12	-0.11
16	-0.05	-0.02	0.13	0.01	-0.07	-0.04	0.03	-0.03	-0.10	-0.08
17	-0.05	-0.04	0.11	0.01	-0.06	-0.05	0.02	-0.06	-0.06	-0.06
18	-0.05	-0.05	0.11	0.03	-0.06	-0.04	0.01	-0.04	-0.04	-0.04
19	-0.06	-0.06	0.11	0.02	-0.06	-0.05	-0.01	-0.06	-0.04	-0.06
20	-0.07	-0.05	0.10	0.01	-0.06	-0.03	-0.04	-0.10	-0.08	-0.09

Table 3: **Deviation Analysis**

This table presents the results of deviation analysis. For each trade, we compute the trade deviation as the absolute difference between the trade price and last trade price and the CP+ quote deviation as the absolute difference between the trade price and CP+ outstanding quote in the previous minute. Difference in deviations is trade deviation less CP+ deviation. *> 5 days*, *1-5 days*, *1 hour - 1 day*, and *< 1 hour* indicate subsamples where the last trade is more than 5 days ago, between 1 and 5 days, more than 1 hour within the same day, and within the same hour, respectively. Difference: Same Signed indicates a subsample for trades restricted to be the same sign (e.g., both the last and current trades are buys) and compute CP+ deviations using the bid or ask rather than the midpoint. Standard errors for the mean and median differences in deviations are clustered at the date of the trade level. For medians, standard errors are obtained via cluster-level bootstrapping with 1000 replications. *** indicates that the difference in deviations is statistically different at the 1% level.

	N	Mean	Median	p10	p25	p75	p90
		All Trades					
Trade Deviation	15,756,757	0.34	0.18	0.02	0.06	0.40	0.81
CP+ Deviation (m-1)	15,756,757	0.25	0.13	0.02	0.05	0.30	0.60
Difference	15,756,757	0.08***	0.03***	-0.18	-0.05	0.16	0.41
Difference: Same-signed	5,279,563	0.08***	0.02***	-0.16	-0.05	0.14	0.41
		> 5 days					
Trade Deviation	416,308	0.93	0.55	0.06	0.19	1.46	2.74
CP+ Deviation (m-1)	416,308	0.48	0.24	0.03	0.09	0.61	1.35
Difference	416,308	0.44***	0.21***	-0.22	-0.01	0.74	1.68
Difference: Same-signed	136,559	0.44***	0.21***	-0.21	-0.01	0.73	1.67
		1-5 days					
Trade Deviation	6,254,291	0.42	0.24	0.03	0.09	0.53	1.03
CP+ Deviation (m-1)	6,254,291	0.27	0.14	0.02	0.05	0.32	0.65
Difference	6,254,291	0.15***	0.06***	-0.16	-0.03	0.25	0.59
Difference: Same-signed	2,238,071	0.15***	0.06***	-0.14	-0.03	0.25	0.58
		1 hour - 1 day					
Trade Deviation	4,547,393	0.27	0.16	0.02	0.06	0.33	0.63
CP+ Deviation (m-1)	4,547,393	0.22	0.12	0.02	0.05	0.26	0.51
Difference	4,547,393	0.05***	0.02***	-0.15	-0.05	0.12	0.28
Difference: Same-signed	1,514,323	0.03***	0.01***	-0.15	-0.05	0.10	0.25
		< 1 hour					
Trade Deviation	4,538,765	0.24	0.13	0.01	0.05	0.28	0.53
CP+ Deviation (m-1)	4,538,765	0.25	0.13	0.02	0.05	0.28	0.56
Difference	4,538,765	-0.01***	0.00***	-0.21	-0.08	0.09	0.21
Difference: Same-signed	1,390,610	-0.02***	0.00***	-0.20	-0.07	0.06	0.18

Table 4: **Difference in Deviations: Additional Analyses**

This table presents additional analyses of difference in deviations. All variables are the same as in Table 3. Panel A reports the results of robustness tests, where we separately restrict the sample to trades that are at least $1 million in par value (i.e., both the current and the last trade exceed $1 million), exclude prearranged riskless principal (PRP) trades, and allow the last trade to be smaller than $150,000. Panel B reports subsample analyses where divide the sample of trades by bond credit ratings, by issue size, and by the issuer's exchange listing status, respectively.

Panel A: Robustness

	Time Since Last Trade							
	> 5 days		1-5 days		1 hour - 1 day		< 1 hour	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Exclude Trades <$1M	0.38	0.16	0.11	0.04	0.02	0.02	-0.04	0.00
Exclude PRP Trades	0.45	0.22	0.15	0.06	0.05	0.02	-0.01	0.00
Include Retail Trades	0.28	0.11	0.11	0.05	0.11	0.04	0.04	0.01

Panel B: Subsample Analysis

	Time Since Last Trade							
	>5 days		1-5 days		1 hour - 1 day		< 1 hour	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
By Credit Rating								
Investment Grade	0.51	0.28	0.19	0.07	0.06	0.03	0.00	0.00
Non-Investment Grade	0.17	0.06	0.07	0.03	0.02	0.02	-0.03	0.00
By Issue Size								
Small Issue	0.43	0.22	0.13	0.05	0.02	0.02	-0.08	-0.01
Medium Issue	0.47	0.22	0.15	0.06	0.04	0.02	-0.02	0.00
Large Issue	0.42	0.18	0.15	0.06	0.06	0.02	0.00	0.00
By Issuer Listing Status								
Private Issuer	0.49	0.25	0.17	0.07	0.06	0.03	0.01	0.01
Public Issuer	0.44	0.21	0.15	0.06	0.05	0.02	-0.01	0.00

Table 5: **Deviation Horse Race: Adjusting for Treasury and Credit Index Returns**

This table reports differences in deviations between trades and CP+ quotes. We compute trade deviations using unadjusted trades, trades adjusted for treasury returns, and trades adjusted for investment grade and high yield credit index returns. For each trade, we compute the difference between each version of the trade deviation and CP+ quote deviation. In columns 1 and 3, we use the unadjusted trade price, in column 2 the treasury adjusted (as of one minute prior to the trade) trade price, in column 4 the treasury adjusted (as of one day prior to the trade) trade price, and in column 5 the index adjusted (as of one day prior to the trade) trade price. In columns 1-2 we use the CP+ quote outstanding as of the minute prior to the trade and in columns 3-5 the quote outstanding at the end of previous day. *All Trades, %Difference > 0* indicates the percentage of observations with a trade deviation that exceeds the quote deviation. *Trades with Same Signs, Mean* indicates subsample analysis for trades restricted to be the same sign (e.g., both the last and current trades are buys) and compute CP+ deviations using the bid or ask rather than the midpoint. *Trades ≥ $1M, Mean* indicates results for large trades (both the current and the last trade are at least $1 million).

CP+ Last Trade	m-1 Unadjusted	m-1 Treasury (m-1)	d-1 Unadjusted	d-1 Treasury (d-1)	d-1 Index (d-1)
	(1)	(2)	(3)	(4)	(5)
			All Trades, Mean		
> 5 days	0.44	0.29	0.33	0.18	0.29
1-5 days	0.15	0.11	0.05	0.04	0.04
< 1 day	0.05	0.04	-0.16	-0.16	-0.16
< 1 hour	-0.01	-0.01	-0.26	-0.26	-0.26
			All Trades, Median		
> 5 days	0.21	0.16	0.14	0.10	0.22
1-5 days	0.06	0.04	0.02	0.02	0.02
< 1 day	0.02	0.02	-0.06	-0.06	-0.06
< 1 hour	0.00	0.00	-0.10	-0.10	-0.10
			All Trades, %Difference > 0		
> 5 days	74%	71%	68%	64%	67%
1-5 days	66%	64%	57%	56%	57%
< 1 day	60%	58%	36%	36%	36%
< 1 hour	51%	51%	30%	30%	30%
			Trades with Same Signs, Mean		
> 5 days	0.44	0.28	0.32	0.18	0.25
1-5 days	0.15	0.10	0.04	0.03	0.03
< 1 day	0.03	0.02	-0.18	-0.18	-0.18
< 1 hour	-0.02	-0.02	-0.29	-0.29	-0.29
			Trades ≥ $1M, Mean		
> 5 days	0.38	0.23	0.26	0.13	0.22
1-5 days	0.11	0.08	0.02	0.01	0.01
< 1 day	0.02	0.01	-0.22	-0.22	-0.22
< 1 hour	-0.04	-0.04	-0.35	-0.35	-0.35

Table 6: **CP+ and Public Information Incorporation**

This table reports regressions of CP+ returns on returns of other markets. Every observation is a trade between May 2017 and December 2023 where the bond's last trade is at least 2 trading days ago. CP+ returns are computed with bond daily time-weighted average quote midpoint prices. All independent variables are measured from the day of the last trade and the trading day prior to the current trade. Treasury, Credit Index, and SP500 are the returns of the bond's benchmark Treasury security, corresponding corporate bond index, and S&P 500 index, respectively. ΔCredit Spread is the change in yield difference between Baa bond index and 10-year constant maturity Treasury. ΔVIX is the change in VIX index level. Panel A presents contemporaneous regressions, where the dependent variable is CP+ return from the day of the last trade and the trading day prior to the current trade. Panel B presents predictive regressions, where the dependent variable is 5-day CP+ return from the day of the current trade. Standard errors, two-way clustered at the issuer CUSIP and current trade date levels, are reported in parentheses.

Panel A: CP+ Return Between Trades

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treasury	0.559***					0.621***	
	(0.016)					(0.011)	
Credit Index		0.693***					0.759***
		(0.016)					(0.016)
SP500			0.079***			0.027***	-0.056***
			(0.010)			(0.005)	(0.006)
ΔCredit Spread				-1.956***		-3.357***	
				(0.365)		(0.230)	
ΔVIX					-0.016***		
					(0.006)		
Intercept	-0.008	-0.045***	-0.039***	-0.027**	-0.025**	-0.013**	-0.037***
	(0.008)	(0.005)	(0.011)	(0.010)	(0.011)	(0.006)	(0.005)
N	2,098,954	2,098,954	2,098,954	2,098,954	2,098,954	2,098,954	2,098,954
R^2	0.284	0.261	0.022	0.022	0.002	0.360	0.270

Panel B: CP+ 5-Day Return From Current Trade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treasury	-0.012					0.027	
	(0.042)					(0.037)	
Credit Index		0.312***					0.219***
		(0.045)					(0.038)
SP500			0.119***			0.084***	0.080***
			(0.023)			(0.021)	(0.023)
ΔCredit Spread				-2.740***		-1.732***	
				(0.599)		(0.518)	
ΔVIX					-0.085***		
					(0.017)		
Intercept	-0.020	-0.028	-0.040	-0.022	-0.019	-0.034	-0.039
	(0.024)	(0.023)	(0.024)	(0.023)	(0.022)	(0.024)	(0.024)
N	2,091,082	2,091,082	2,091,082	2,091,082	2,091,082	2,091,082	2,091,082
R^2	0.000	0.023	0.022	0.019	0.026	0.027	0.031

Table 7: **Differences in Deviations and RFQ Information**

This table reports differences in deviations when RFQs are observed between trades. Panel A reports results using the CP+ quote outstanding as of the minute prior to the trade and Panel B reports results using the CP+ quote outstanding as of the day prior to the trade. Column 2 in Panel A identifies did-not-trade RFQs that are submitted after the last trade and at least 15 minutes prior to the current trade. Column 2 in Panel B identifies did-not-trade RFQs after the last trade and at least a trading day prior to the current trade. Column 5 in Panel A identifies delayed spot RFQs that have been negotiated after the last trade and at least 15 minutes prior to the current trade. Column 5 in Panel B identifies delayed RFQs after the last trade and at least a trading day prior to the current trade. Columns 1 and 4 report differences for trades with no did-not-trade and no delayed spot RFQ. Columns 3 and 6 report the differences between columns.

	Did-Not-Trade RFQ		(2)-(1)	Delayed Spot RFQ		(5)-(4)
	No	Yes		No	Yes	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: CP+ Quote Outstanding at m-1						
N	12,483,574	3,277,388		14,835,282	925,680	
All Trades, Mean						
$>$ 5 days	0.35	0.51	0.16	0.40	0.70	0.30
1-5 days	0.13	0.20	0.07	0.14	0.28	0.14
$<$ 1 day	0.01	0.06	0.04	0.02	0.09	0.07
All Trades, Median						
$>$ 5 days	0.12	0.31	0.19	0.18	0.45	0.28
1-5 days	0.05	0.10	0.05	0.05	0.15	0.09
$<$ 1 day	0.01	0.03	0.02	0.01	0.04	0.03
All Trades, %Difference $>$ 0						
$>$ 5 days	0.72	0.75	0.04	0.73	0.80	0.08
1-5 days	0.65	0.68	0.03	0.65	0.74	0.09
$<$ 1 day	0.55	0.60	0.05	0.55	0.65	0.10
Trades with Same Signs, Mean						
$>$ 5 days	0.35	0.51	0.16	0.40	0.71	0.31
1-5 days	0.13	0.20	0.07	0.14	0.29	0.15
$<$ 1 day	0.00	0.04	0.04	0.01	0.08	0.08
Trades $\geq$ \$1M, Mean						
$>$ 5 days	0.28	0.47	0.19	0.34	0.64	0.30
1-5 days	0.09	0.16	0.07	0.10	0.25	0.14
$<$ 1 day	-0.02	0.03	0.05	-0.02	0.07	0.09
Panel B: CP+ Quote Outstanding at d-1						
N	14,266,439	1,494,523		15,599,967	160,995	
All Trades, Mean						
$>$ 5 days	0.26	0.38	0.12	0.30	0.57	0.27
1-5 days	0.04	0.10	0.06	0.05	0.19	0.14
All Trades, Median						
$>$ 5 days	0.08	0.20	0.12	0.12	0.40	0.28
1-5 days	0.01	0.04	0.03	0.02	0.09	0.07

Table 8: **Cross-Sectional Determinants of CP+ Coverage, Quotes, and Updates**

This table reports panel regressions of CP+ activities on bond characteristics. Every observation is a bond-month between May 2017 and December 2023 for CUSIPs in both FISD and TRACE. In columns (1)-(3), the dependent variable is a dummy that equals one if the bond has any CP+ quote prices in the month. In columns (4)-(6), the dependent variable is the natural log of the number of CP+ quotes for the bond during the month. In columns (7)-(9) the dependent variable is the natural log of the number of CP+ quote updates for the bond during the month. Issue Size is the bond's par amount at issuance. Age is the number of months since bond issuance. Maturity is the number of months before the bond's contractual maturity date. Public Issuer is a dummy that equals one if the bond's issuer is currently publicly traded. IG is a dummy that equals one if the bond currently has an investment grade rating. #Trade is the bond's number of trades during the past month. Standard errors, two-way clustered at the issuer CUSIP and month levels, are reported in parentheses.

	1(Covered by CP+)			Log(Number of Quotes)			Log(Number of Quote Updates)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(Issue Size)	0.107***	-0.015		0.472***	0.280***		0.530***	0.329***	
	(0.008)	(0.015)		(0.011)	(0.009)		(0.053)	(0.071)	
Log(Age)	-0.041***	-0.011***	0.008***	-0.123***	-0.106***	-0.045***	-0.084***	-0.066***	0.132***
	(0.003)	(0.003)	(0.002)	(0.005)	(0.004)	(0.007)	(0.013)	(0.013)	(0.012)
Log(Maturity)	0.006*	0.022***	0.015***	-0.059***	-0.020***	-0.067***	0.387***	0.427***	0.957***
	(0.003)	(0.003)	(0.004)	(0.006)	(0.004)	(0.010)	(0.021)	(0.021)	(0.066)
IG	0.090***	0.070***	-0.002	-0.357***	-0.301***	-0.351***	2.735***	2.793***	1.794***
	(0.012)	(0.010)	(0.009)	(0.018)	(0.018)	(0.023)	(0.105)	(0.107)	(0.105)
Public Issuer	0.021	-0.018	0.036	0.013	-0.025	0.251***	0.042	0.002	0.517**
	(0.027)	(0.021)	(0.042)	(0.021)	(0.020)	(0.085)	(0.044)	(0.044)	(0.219)
Log(#Trade)		0.149***	0.111***		0.214***	0.226***		0.224***	0.190***
		(0.003)	(0.002)		(0.005)	(0.006)		(0.016)	(0.010)
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bond FEs	N	N	Y	N	N	Y	N	N	Y
N	1,008,250	1,008,250	1,008,132	804,777	804,777	804,492	804,777	804,777	804,492
R^2	0.094	0.450	0.802	0.440	0.524	0.661	0.600	0.614	0.815

Table 9: **Bond Liquidity and CP+ Value Added**

This table reports regressions of CP+ value added on bond characteristics. Every observation is a bond-month between May 2017 and December 2023. The dependent variable is bond-month average CP+ value added, defined as last trade price deviation minus CP+ price (m-1) deviation. Issue Size is the bond's par amount at issuance. Age is the number of months since bond issuance. Maturity is the number of months before the bond's contractual maturity date. Public Issuer is a dummy that equals one if the bond's issuer is currently publicly traded. IG is a dummy that equals one if the bond currently has an investment grade rating. #Trade is the bond's number of trades during the past month. Standard errors, two-way clustered at the issuer CUSIP and month levels, are reported in parentheses.

Dependent Variable: CP+ Value Added

	(1)	(2)	(3)
Log(Issue Size)	-0.058***	-0.025***	
	(0.005)	(0.003)	
Log(Age)	0.032***	0.032***	-0.003
	(0.002)	(0.002)	(0.004)
Log(Maturity)	0.092***	0.085***	0.093***
	(0.005)	(0.005)	(0.008)
Public Issuer	-0.000	0.008	-0.011
	(0.006)	(0.006)	(0.023)
IG	0.125***	0.117***	0.034***
	(0.007)	(0.006)	(0.007)
Log(Min(#Trade, 10))		0.068***	0.033***
		(0.007)	(0.006)
Log(Max(#Trade, 10))		-0.048***	-0.033***
		(0.003)	(0.003)
Month FEs	Y	Y	Y
Bond FEs	N	N	Y
N	736,230	736,230	735,840
R^2	0.190	0.206	0.297

Table 10: **CP+ Adjustments Around Trades**

This table reports mean and median CP+ quote deviations before and after a trade. Quote deviation is the absolute difference between the current trade price and the outstanding CP+ quote midpoint price at the respective time cutoffs.

	Time Since Last Trade							
	> 5 days		1-5 days		1 hour - 1 day		< 1 hour	
Time From Trade	Mean	Median	Mean	Median	Mean	Median	Mean	Median
-1 day	0.60	0.30	0.37	0.20	0.43	0.24	0.50	0.27
-1 minute	0.48	0.24	0.27	0.14	0.22	0.12	0.25	0.13
+1 minute	0.46	0.23	0.25	0.13	0.21	0.11	0.23	0.12
+5 minutes	0.28	0.13	0.18	0.09	0.17	0.10	0.20	0.11
+10 minute	0.26	0.13	0.17	0.09	0.17	0.10	0.19	0.11
+30 minutes	0.26	0.13	0.17	0.09	0.17	0.10	0.20	0.11
+60 minutes	0.26	0.13	0.18	0.10	0.18	0.10	0.20	0.11
+120 minutes	0.27	0.13	0.19	0.11	0.18	0.11	0.21	0.12
+1 day	0.42	0.22	0.38	0.21	0.39	0.22	0.45	0.26

Internet Appendix

“Illiquidity Meets Intelligence: AI-Driven Price Discovery in Corporate Bonds”

This appendix contains the details of empirical analyses and additional empirical results that are discussed but not reported in the paper.

IA.1. Minute-Level Maturity-Matched Treasury Prices

For each corporate bond, we infer the minute-level maturity-matched treasury prices from its CP+ quotes as follows.

We begin with the universe of CP+ quotes. For each quote observation, we infer the maturity-matched treasury yield by subtracting the credit spread from the corporate bond’s yield, both of which are reported in the CP+ quote. This calculation is performed separately for the bid yield and spread, and for the ask yield and spread. We use the average of the inferred yields from the bid-side and ask-side as the current yield of the treasury security, which is uniquely identified by its International Securities Identification Number (ISIN).

Second, we aggregate the inferred treasury yields by taking the average across all CP+ quotes to the ISIN-minute level, where the minute is based on the timestamp of each quote.

Finally, we convert the treasury yields to ISIN-minute treasury prices. To do so, we use information on the ISIN’s issuance date, maturity date, issue size, coupon rate, and payment schedule from the CRSP Treasuries database. We compute the ISIN’s current clean price as the difference between its dirty price (i.e., present value of future cash flows, discounted at the current yield) and its accrued interest.

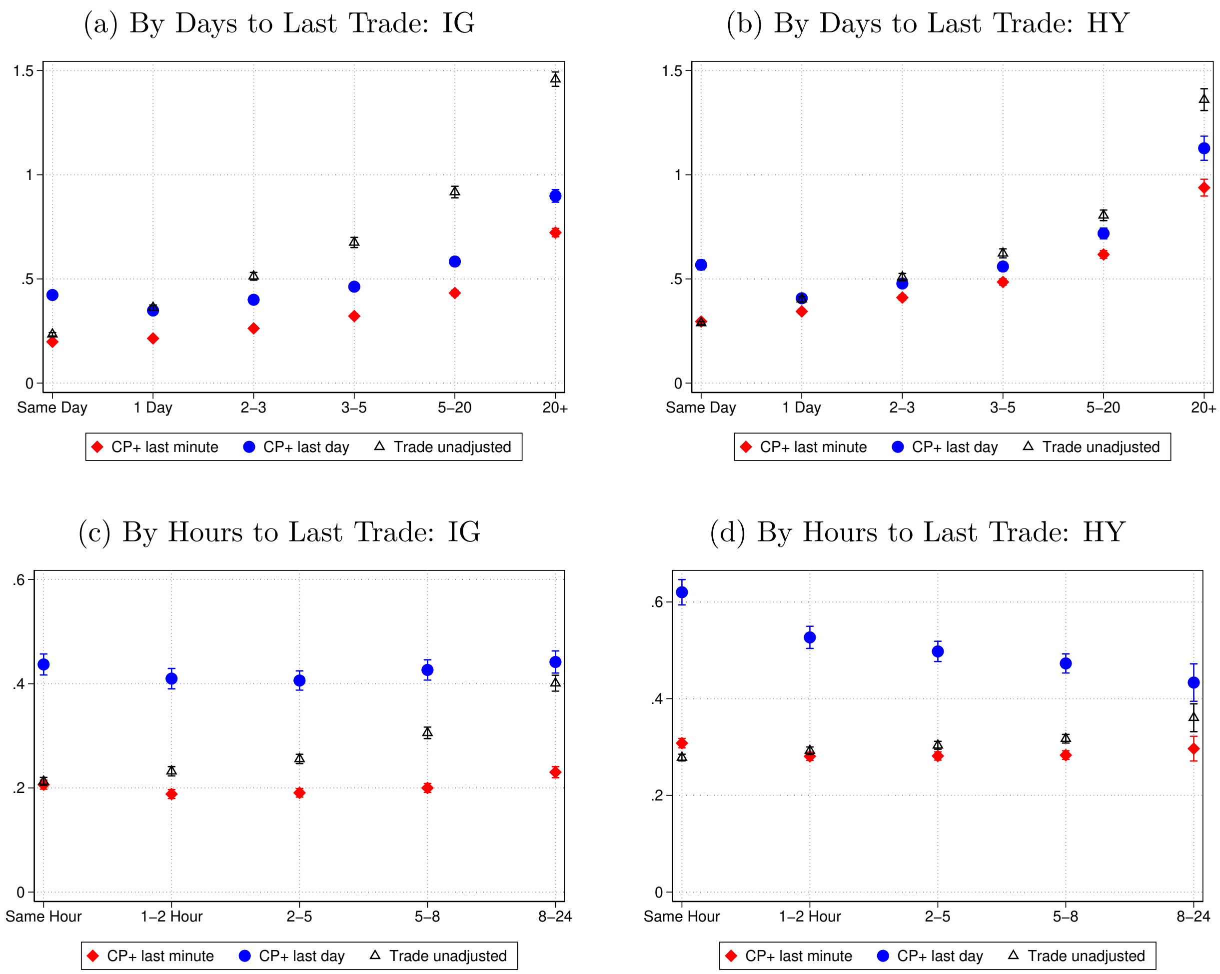


Figure IA.1: **Bond Price Deviations: Investment Grade and High Yield.**
This figure presents the means of trade deviation and CP+ deviation, separately for investment grade and high yield bonds. In Panels (a) and (b), the sample includes all trades. In Panels (c) and (d), the sample consists of trades for which the last trade is within the same day. Red diamonds indicate CP+ deviation using the previous minute quote (m-1), blue circles indicate using the previous day quote (d-1), and black triangles indicate trade deviation. Upper and lower bars around each marker are 99% confidence intervals. Standard errors are clustered at the trade date level.

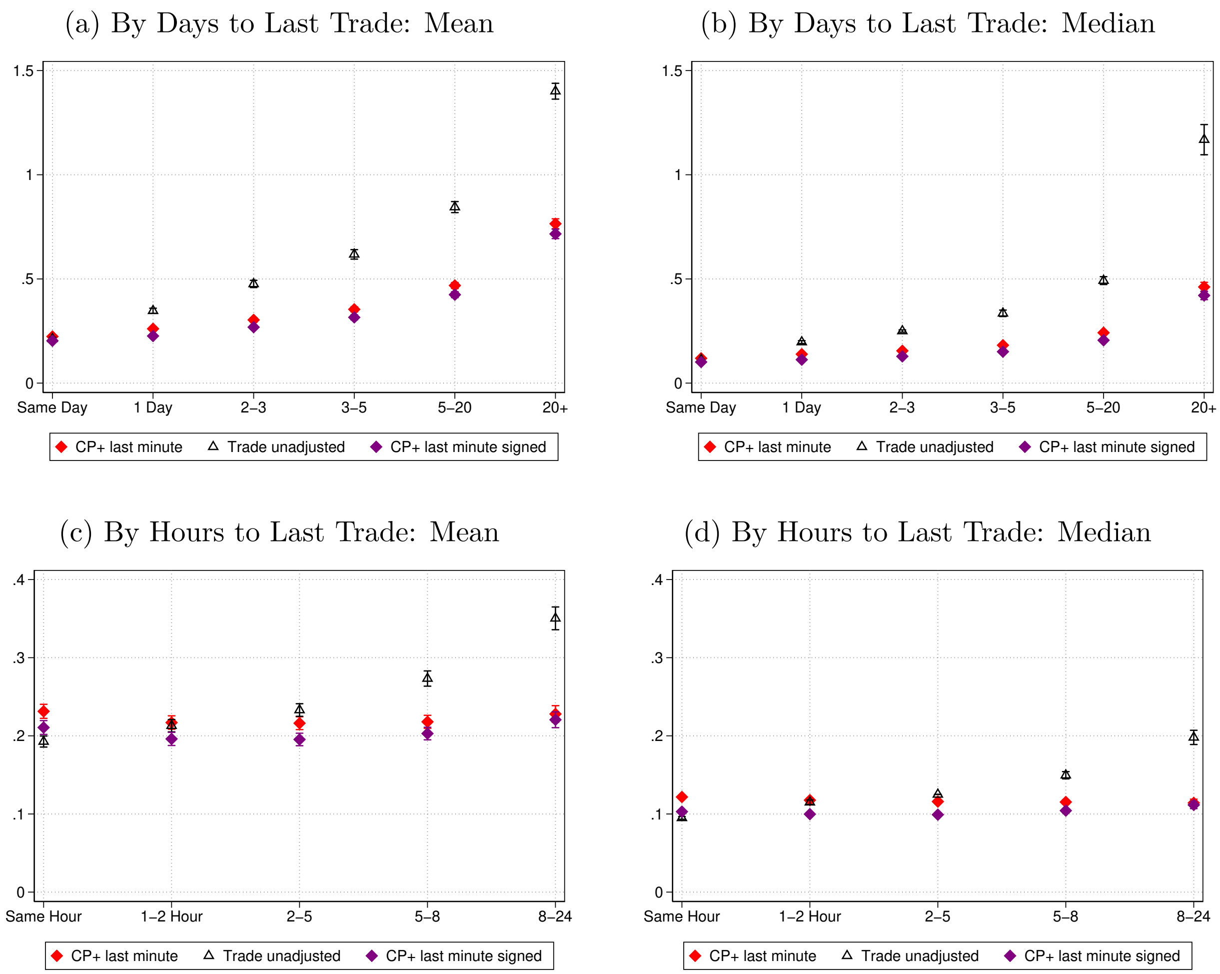


Figure IA.2: **Bond Price Deviations: Adjusting for Bid-Ask Spreads.**
This figure presents the means and medians of trade deviation and CP+ deviation for the sample for which the current and last trade have the same sign (e.g., both the current and last trades are buys). CP+ deviations are computed using the bid or ask (depending on trade sign) rather than the midpoint. In Panels (a) and (b), the sample includes all trades. In Panels (c) and (d), the sample consists of trades for which the last trade is within 24 hours. Red diamonds indicate CP+ deviation using the previous minute quote midpoint (m-1), black triangles indicate trade deviation, and purple diamonds indicate CP+ deviation using the previous minute quote of the same sign (m-1). Upper and lower bars around each marker are 99% confidence intervals. Standard errors are clustered at the trade date level. For medians, standard errors are obtained via cluster-level bootstrapping with 1000 replications.

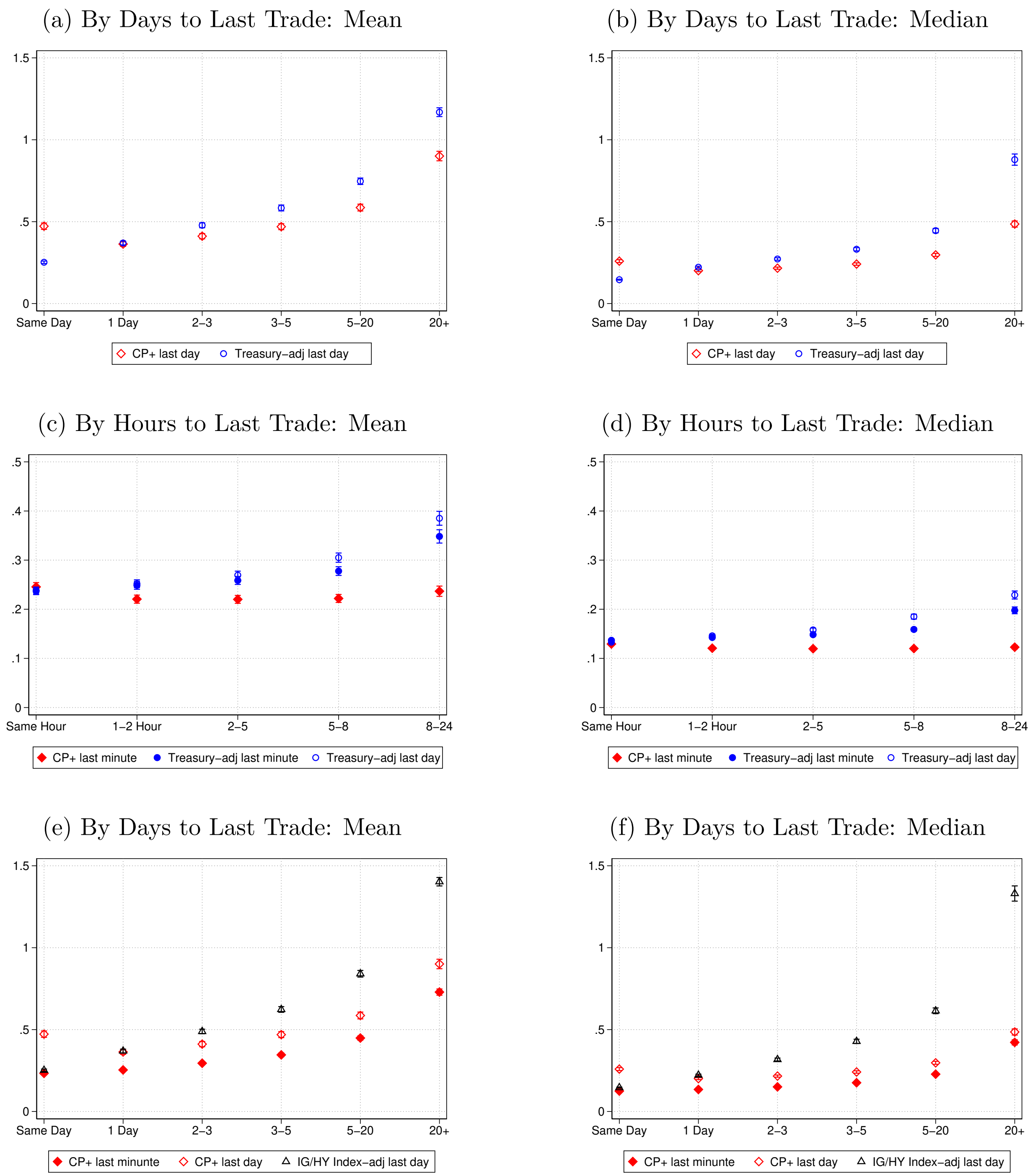


Figure IA.3: **Bond Price Deviations: CP+ vs Last Trade Price Adjusted.**
This figure presents the means and medians of trade deviation and CP+ deviation. In Panels (a), (b), (e), and (f), the sample includes all trades. In Panels (c) and (d), the sample consists of trades for which the last trade is within 24 hours. Red diamonds indicate CP+ deviation using the previous minute quote midpoint (m-1), hollow red diamonds indicate CP+ deviation using the previous day quote midpoint (d-1), blue circles indicate last trade price adjusted using Treasury price up to the prior minute (m-1), hollow blue circles indicate last trade price adjusted using Treasury price up to the prior day (d-1), black triangles indicate adjusted last trade price using corporate bond index up to the prior day (d-1). Upper and lower bars around each marker are 99% confidence intervals. Standard errors are clustered at the trade date level. For medians, standard errors are obtained via cluster-level bootstrapping with 1000 replications.