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

Stacey Jacobsen[‡] Kumar Venkataraman[§] David X. Xu[¶]

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Abstract

This study examines whether AI-generated reference prices improve intraday price discovery in markets with infrequent trading. Using corporate bond transactions and CP+ reference quotes from MarketAxess, we find that CP+ quotes are generally more informative about future trade prices than the most recent trade. CP+ fills information gaps between trades by incorporating signals from bond, equity, and options markets, as well as bond-specific proprietary information. Coverage extends to most bonds on nearly all trading days, including less liquid issues. CP+'s added value to price discovery follows a bell-shaped pattern with respect to bond liquidity and increases during periods of elevated market uncertainty. Around block trades and rating downgrades, CP+ for less active bonds deviates more from trade prices and converges faster to post-event values. For active bonds, CP+'s strong reliance on trade data, even during large reversals, limits its independent contribution to price discovery.

Keywords: Artificial Intelligence, Corporate Bonds, Liquidity, Price Discovery

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[‡]Southern Methodist University. Email: staceyj@mail.cox.smu.edu

[§]Southern Methodist University. Email: kumar@mail.cox.smu.edu

[¶]Southern Methodist University. Email: davidxu@smu.edu

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 relevant market information made readily available to all participants, 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) bond markets.

We focus on the corporate bond market for several reasons. Unlike equities, the U.S. corporate bond market lacks a centralized quotation system ("pre-trade transparency") as indicative quotes are dispersed across dealers, requiring aggregation of fragmented information. To improve transparency, regulators have instead focused on 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, the effectiveness of post-trade transparency diminishes when trading activity is sparse.[2] In our sample from 2017 to 2023, the average corporate 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.

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

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 Composite+ (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 how AI-generated reference prices contribute to 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 CP+ quotes provide more accurate estimates of current trade prices 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 uncertainty, and around bond-specific events that often 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

[3]MarketAxess plays an important role in U.S. corporate bond trading. In March 2025, the platform facilitating 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.

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 autocorrelation for equally weighted bond portfolios constructed using time-weighted average trade prices and CP+ quote midpoints. The results show that trade-based portfolios exhibit greater pricing staleness than quote-based portfolios, as reflected in higher positive return autocorrelation. Cross-sectional analysis further reveals 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 just before the trade.

[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.

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.

We conduct a paired difference test to compare the absolute deviation between the current trade price and each benchmark. 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 CP+ quotes are generally more informative than the last observed trade price, even when that trade is relatively recent. The results are robust across several sub samples, including those restricted to trades with the same direction (e.g., both current and previous trades are buyer-initiated), which helps control for bid ask bounce. The results hold when we require trade size to be greater than $1 million, and also when we allow the previous trade to be a retail trade. We also find that CP+ can incorporate a substantial share of new information (30 to 60%) around large valuation shifts between trades.

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+ quote 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, they remain economically significant. For example, when more than five days have passed since the previous trade, the CP+ quote is closer to the current trade price than the adjusted previous trade price in 67% of cases, compared to 73% when using the unadjusted price.

We further show that CP+ quotes incorporate information not only from bond market signals 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 36.4%. Our results suggest that CP+ reflects not only broad market movements but also bond-specific proprietary information derived from activity on its platform.

Next, we examine the factors that influence CP+'s coverage for individual bonds. 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 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 examine the evolution of CP+ over a longer window surrounding bond-specific events that often result in large price movements. On the one hand, AI-algorithms may help stabilize markets by detecting information events and generating reference prices that speed convergence to fundamental value. However, CP+ is designed to estimate where the next trade is likely to occur, not necessarily the fundamental value. Further, during periods of higher uncertainty, trading activity often declines, and those transactions that do occur may reflect distressed sales or atypical conditions, which can disproportionately influence the CP+ reference price. If market participants rely on such estimates in subsequent negotiations, this may unintentionally amplify price discovery challenges rather than alleviate them.

We study CP+ pricing dynamics in two settings: large block transactions and credit rating downgrades. We study the trade and CP+ deviations over a [-10,+10] window surrounding the event, measured with respect to a long term fundamental value (day +10), where the deviation dynamics capture gradual adjustment or temporary mispricing. Our results suggest that CP+ does not appear to anticipate the information content of events with large, permanent price impact. Instead, CP+ quotes react similarly to trade prices observed in the market, especially in actively traded bonds. For events associated with meaningful return reversals (i.e., large temporary price impact), CP+ and trade-price series diverge more substantially for less actively traded bonds, with CP+ prices displaying smaller reversals and faster convergence to post-event values. For actively traded bonds, trades occur in close succession, and CP+ closely tracks the trade price series. Our results suggest that the algorithm's strong reliance on recent trades may limit its ability to adjust away from unrepresentative prices and independently contribute to price discovery beyond the next trade.

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 fixed income electronic trading marketplace for US corporate bonds. CP+ quotes are generated real-time based on current market conditions fed into the ML model that is trained using public (TRACE trade data) and proprietary data inputs. Proprietary data includes TRACE trade data completed on their platform, MarketAxess TraX market trading data across all asset classes, and the entire stack of RFQ inquiry responses between clients and dealers on their platform, regardless of whether the bond traded or not. The ML models are trained each night to "produce the price the market is most likely to trade at, without a rich or cheap bias" based on Minimized Absolute Deviation metric (Alexandre and Amalunweze, 2024). Signals related to time (more recent), trade side (spreads), trade size and type (institutional size customer trades in principal capacity), and pricing source (trade prices, RFQ responses) are used to calibrate the algorithm. 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.[7]

Next, we merge this sample of bonds with TRACE to obtain corporate bond transaction data. We link the FISD data to the TRACE data using the CUSIP identifier. We apply

[7]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.

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. A summary of the sample construction and resulting sample size is reported in Panel A of Table 1. Using this bond sample, we merge with MarketAxess CP+ data using the 9-digit CUSIP identifier. 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 consider the sample period between the first and last coverage dates of CP+ for the bond.

Our final sample includes 20,355 distinct CUSIPs, 24.8 million non-retail secondary market transactions, and 11.8 billion CP+ reference quotes. Of these, 3.3 billion are quote updates, defined as instances where the bid, ask, or both change relative to the prior quote. Panel B of Table 1 provides a breakdown of the sample by credit quality (investment grade versus high yield/unrated) and by issue size (small, medium, and large).[8] About 77% 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, 66% of all quotes, and 94% of quote updates, reflecting greater pricing activity in this segment of the market.

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 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

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

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.

Figure 3 displays the cross-sectional distribution of CP+ quote frequency across bonds over the sample period. For each trading day, Panel A reports the 1st, 10th, 50th, 90th, and 99th percentiles of the number of quotes per bond. Quoting frequency varies substantially across bonds. In 2023, the 99th percentile of daily quotes exceeded 5,000 quotes per day, while the median was above 1,000 and the 1st percentile exceeded 500 quotes per day.

Figure IA.1 in the Internet Appendix reports the total number of CP+ prices within every minute of the trading day, shown separately for each calendar year. In Panel A, CP+ quoting activity increased significantly from the year of CP+ introduction in 2017 (light gray line) over the sample period. In 2023 (black line), quoting activity remained relatively stable throughout the day, ranging from 3,000 to 4,000 quotes per minute. Panel B presents the same statistics using quote *updates*. Updates are more frequent during regular trading hours (8 AM to 5 PM), with CP+ providing about 1,500 updates per minute during this window in 2023, a threefold increase compared to 2017.

2. The Informativeness of CP+ Reference Prices

When traders seek to execute a trade at time t, they must estimate the bond's current value using available information. A common reference point is the price of the most recent trade, observed at time t-1. 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-relevant information has emerged. Institutional clients of MarketAxess observe the CP+ reference quotes, which are updated more frequently, often within minutes, as shown in Figure IA.1, and can provide a more timely estimate of 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. 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 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.

We focus on trades of at least $150,000 in par value, as large trades typically involve more sophisticated participants and better reflect fundamental values. Prior research shows that small trades are noisier and less informative: Goldstein, Hotchkiss, and Nikolova (2021) document greater price dispersion among retail-sized trades, while Bessembinder, Kahle, Maxwell, and Xu (2008) recommend excluding them from daily return calculations to improve statistical power. Smaller trades also carry significantly higher dealer markups, further reducing their informativeness (Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2007).

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 there 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 6pm, and (ii) the last standing quote just before the trade. Some recent studies in asset pricing research use the 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 literatures.

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.[9] 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.

Table 3, Panel A, presents statistics for trades with a time gap of at least one day from the previous trade. Trade deviations average $0.45 and range from $0.03 (10th percentile) to $1.13 (90th percentile), while CP+ deviations based on the prior day's closing quote average $0.40, ranging from $0.03 (10th percentile) to $0.96 (90th percentile). Deviations from the CP+ quote in the prior minute are lower, averaging $0.28, and ranging from $0.14 to $0.68. When trades occur on the same day, trade deviations average about $0.25, while CP+ prior-minute deviations are slightly lower, at $0.23.

We also study 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 by hours for same-day trades (Panel B). 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 1000 replications. Table 3, Panels B and C, 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. The same pattern holds, though the differences are smaller, when

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

the time between trades is one and five days. When the previous trade occurs on the same trading day, its price becomes more informative than prior day's closing CP+ 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+.

We examine robustness along three dimensions. First, in Table 4, Panel A, we restrict the sample to trades where the last and current trades are of the same direction (that is, both current and previous trades are buyer initiated), reducing deviations due to bid-ask bounce effects. Deviations decline slightly (by about $0.02) in comparison to those reported in Table 3, 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. Second, Panel B of Table 4 restricts the sample to round lot trades, 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. Third, Panel C calculates the deviations after allowing the last trade to be a retail-size trade (that is, smaller than $150,000). Results again are similar.

Overall, CP+ quotes are more accurate than past trades 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.

2.2.2. Economic Significance

The results thus far suggest that 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 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).[10] 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

[10] 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.

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 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 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 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. 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 trade to the prior day's close.[11] 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 begin with a deviation analysis, similar in design to Table 3, but now include comparisons with adjusted last trade prices. Table 5 reports absolute deviations, trade price versus CP+ benchmark, for each approach. For ease of comparison, Columns 1 and 3 replicate the unadjusted trade price comparisons in Table 3. 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 \$0.42 to \$0.29 when adjusting trade prices using Treasury returns until the minute prior to the current trade. However, CP+ still outperforms in 67% of cases, suggesting that it incorporates additional information beyond 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 \$0.29 to \$0.17 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.

[11] 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.

However, the prior-minute CP+ quote still exhibits smaller deviations when the last trade is 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 \$0.29 with no adjustments to \$0.24 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 elapsed time between trades is long.

2.4. Information Content of CP+ Reference Prices

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 with 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.[12] As the independent variables can only be measured 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 public market signals. In columns 1, 2 and 3, the contemporaneous return from the Treasury market, corporate bond market, and the stock market, all load significantly when entered individually, with R^2s for Treasury and bond index models around 26–28%. In columns 4 and 5, changes in credit spreads and VIX also exhibit negative and significant coefficients. When all factors are included, the R^2 rises to 36% in column 6. Combined, these results indicate that the updates to CP+ quotes incorporate 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.

[12] 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).

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 with CP+ sample (as shown in Table 1). Table 7 presents the results. All specifications include month fixed effects to absorb the improvement of CP+ coverage over time.

In column (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 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.[13]

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 characteristics and two piecewise-linear terms that split the prior month's trade count into low and high region. Table 8 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

[13]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.

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. In Panel B, the differences for more active bonds are smaller but remain statistically significant for most of the period, confirming that CP+ continues to outperform even when trading activity is relatively high. These results reinforce our earlier findings in Section 3: the benefits of CP+ are particularly pronounced when trading is sparse. 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.[14] 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

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

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 consider two measures: (i) the level of the VIX in the previous week, and (ii) the Corporate Bond Market Distress Index (CMDI) in the previous week.[15] In Figures 8 Panel A, 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. Similarly, Panel B, which reports mean deviations differences by CMDI decile, shows much higher value added for deciles 7-10.[16]

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. Analysis of Bond-Specific Information Events

In this section, we consider bond-specific events that often result in large, permanent changes in fundamental values, and in some instances, temporary dislocations from fundamentals. Our focus is on understanding how effectively CP+ responds to such shocks. Specifically, we study CP+ pricing dynamics in two settings: large block transactions and credit rating downgrades.[17] We examine episodes with large permanent and temporary price impacts.

On the one hand, AI-algorithms like CP+ may 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 a large weight

[15]This index is compiled by the Federal Reserve Bank of New York and aggregates dislocations across the primary and secondary corporate bond markets into a unified measure of market conditions. See https://www.newyorkfed.org/research/policy/cmdi.

[16]In regressions of value added on our two market uncertainty measures, controlling for bond fixed effects, we find a similarly positive relationship between CP+ valued added and each uncertainty proxy.

[17]The price effects surrounding large transactions and sustained customer imbalance in the corporate bond market has been examined by Cai, Han, Li, and Li (2019) and Anand, Jotikasthira, and Venkataraman (2021). Ellul, Jotikasthira, and Lundblad (2011) examine the price effects surrounding credit rating downgrades.

placed on realized trade data. Further, CP+ is designed to estimate the price of the *next trade*, not necessarily the bond's fundamental value. Around information events, liquidity often deteriorates, and the trades that occur may reflect distressed sales or atypical conditions. These outlier trades can disproportionately influence CP+ reference price. If market participants then rely on these references in subsequent negotiations, the algorithm's output may inadvertently exacerbate price discovery challenges rather than mitigate them.

4.1. Block Trades

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.[18] 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.

Results are presented in Figure 9. Because we are interested in the short period around

[18]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.

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 CP+ incorporates information primarily through realized trades.[19]

Overall, these findings suggest that while CP+ reflects value changes once trades occur, it does not appear to anticipate the information content of block trades with large permanent price impact. Instead, it reacts similarly to trade prices observed in the market, especially in actively traded bonds.

We next examine blocks associated with large temporary price impact. To identify such blocks, 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 B and C report the results. In the pre-block period, last trade price deviations are small. Following the block, deviations

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

increase, peaking on days 1 and 2, and gradually decline 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.

4.2. Credit Rating Downgrades

We conduct a parallel analysis for credit rating downgrades that result in large price movements. Specifically, we identify fallen angels, that is, bonds downgraded from investment grade to high yield ratings. If multiple downgrades occur in the same year (by different rating agencies), we retain only the first downgrade event. For each bond, we calculate time-weighted average trade prices and CP+ quotes over the 10 trading days before and after the downgrade announcement.

We identify a sample of downgrades with large permanent price impacts as follows. Permanent price impact is measured as the log difference between the time-weighted average trade prices on day –10 and day +10. We focus on downgrades with impacts in the top three deciles of this distribution. For each downgrade, we compute 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, using the time-weighted quote on day t relative to the day +10 trade price.

We also identify downgrades associated with large temporary price impacts. Here, we first calculate cumulative returns over both the pre-downgrade period (days –10 to –1) and the post-downgrade period (days +1 to +10). A downgrade is classified as temporary-impact if (i) the return signs in the two periods are opposite (e.g., a decline before the downgrade and a rebound after), and (ii) the absolute value of each cumulative return exceeds 0.5%.[20] Trade and CP+ quote deviations for this sample are again calculated relative to the day +10 trade price.

Figure 10, Panels A and B present results for downgrades with large permanent price impacts. We report average deviations for the five trading days before and after the downgrade, separately for less active and more active bonds following the earlier definition.

The results are similar to the block trade analysis. For less active bonds (Panel A), CP+ deviations are generally smaller than trade deviations in both the pre- and post-downgrade periods, but the differences are not statistically significant based on 95% confidence intervals. For actively traded bonds (Panel B), CP+ quotes track trade prices closely, and in some cases exhibit slightly larger deviations, though again without statistical significance.

Panels C and D report results for downgrades with large temporary price impacts. Since the post-downgrade period is of interest, we report statistics from day -1 to day +5. For both active and less active bonds, CP+ closely tracks the trade price series, as indicated by little differences in deviations. Overall, the algorithm's strong reliance on recent trade data potentially limits its ability to filter out noise or anticipate trade reversals when trade prices are distorted by stress.

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

[20]This approach differs from that used for block trades because price declines often precede rating downgrades, indicating partial anticipation (Goh and Ederington, 1993). Ellul, Jotikasthira, and Lundblad (2011) show that insurance companies often begin selling weeks before the official downgrade.

AI-generated reference prices made available by MarketAxess, a major electronic bond trading platform, contribute to 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 CP+ quotes are generally more informative about future 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. We show that CP+ incorporates movements in bond, equity, and options markets. 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.

These 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.

We examine CP+ quotes over a longer window surrounding bond specific events—block transactions and credit rating downgrades—that often result in large price movements. CP+ does not appear to anticipate the information content of events with large permanent price impact. For events associated with meaningful reversals, CP+ displays smaller reversals and faster convergence to post-event values in less actively traded bonds, while CP+ closely tracks the trade prices in actively traded bonds.

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. However, 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.

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. 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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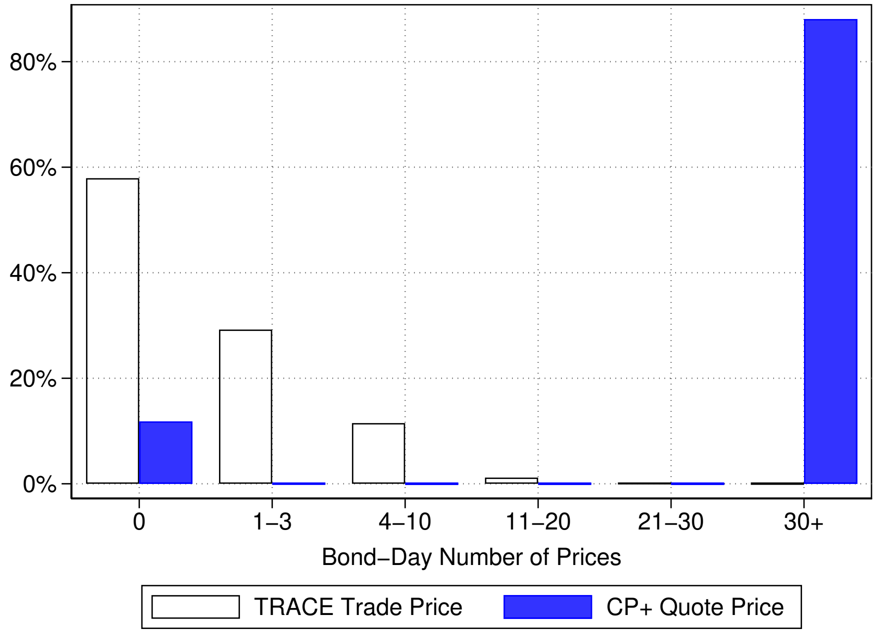
(a) All Bonds



(b) Small Issue Bonds

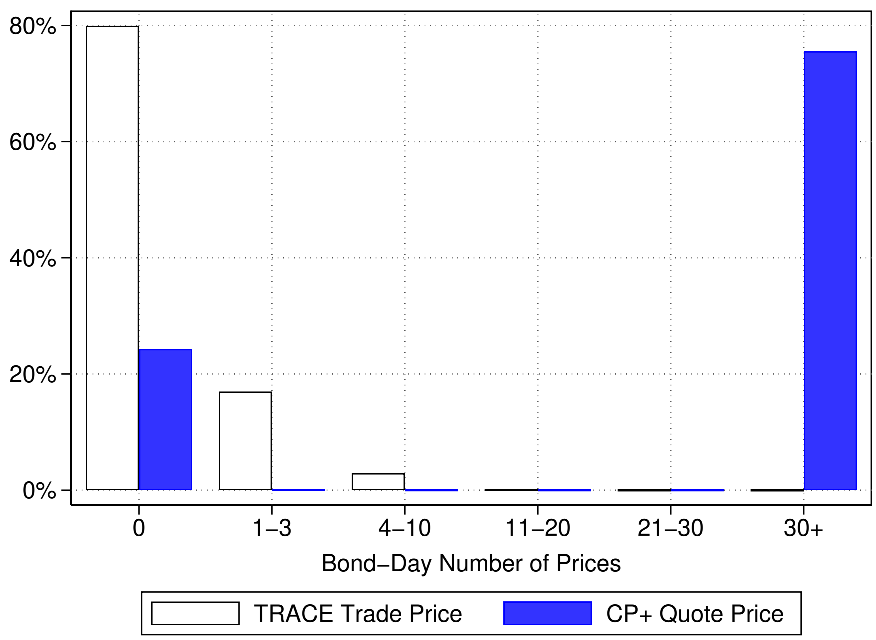


Figure 1: **Distribution of the Number of Prices Per Bond-Day.**
This figure presents the distribution of the numbers of trade prices and CP+ quote prices at the bond-day level. In Panel A, the sample includes all bonds in FISD and TRACE and their trading days between the bond's first and last days in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

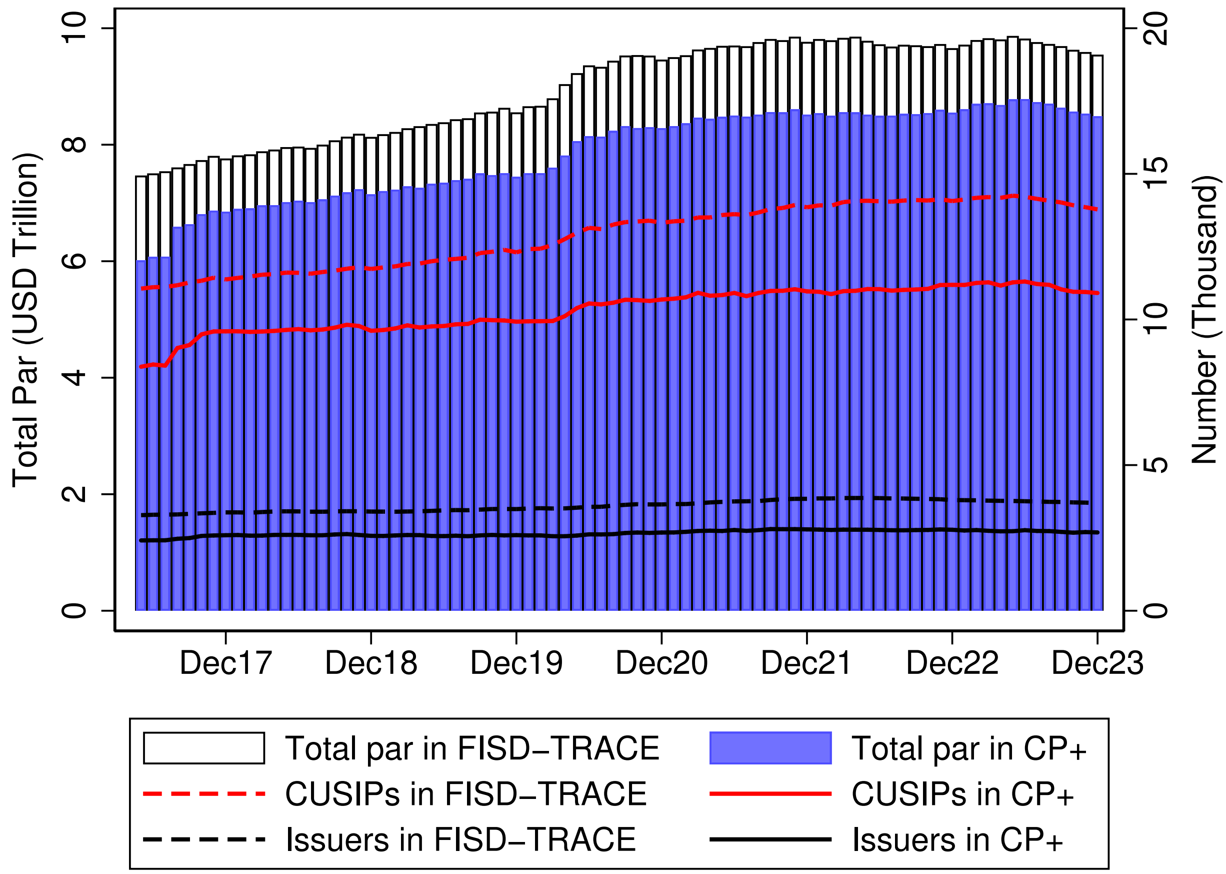
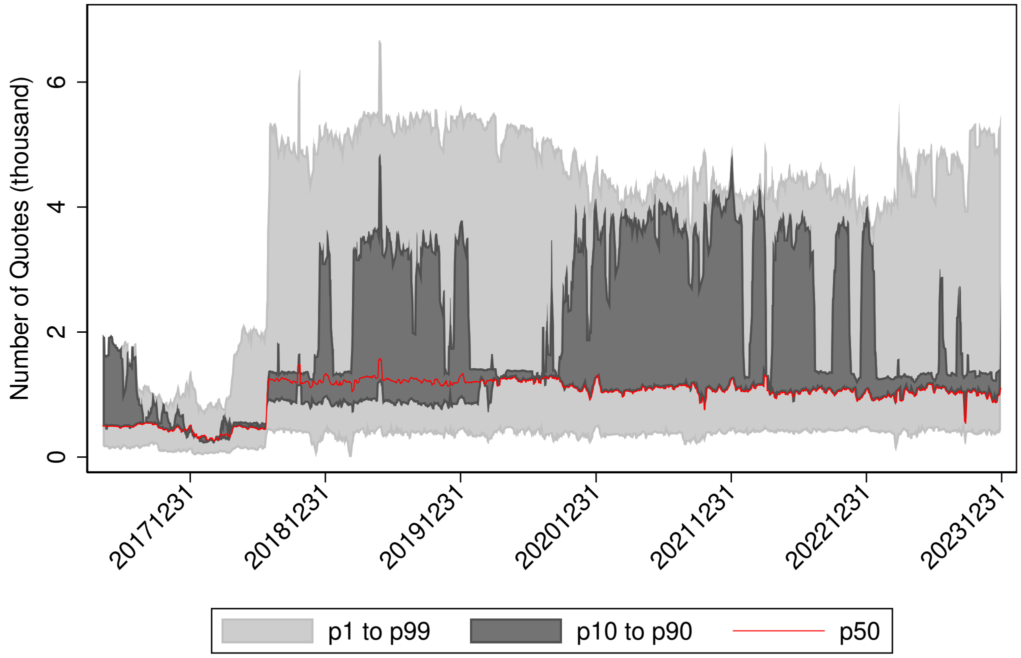


Figure 2: **CP+ Coverage of Corporate Bonds by Month.**
This figure presents the monthly coverage of CP+ among corporate bonds in FISD and TRACE. Blue and white bars indicate the total bond par values (USD trillion) in CP+ and in FISD-TRACE, respectively. Solid and dashed red lines indicate the number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

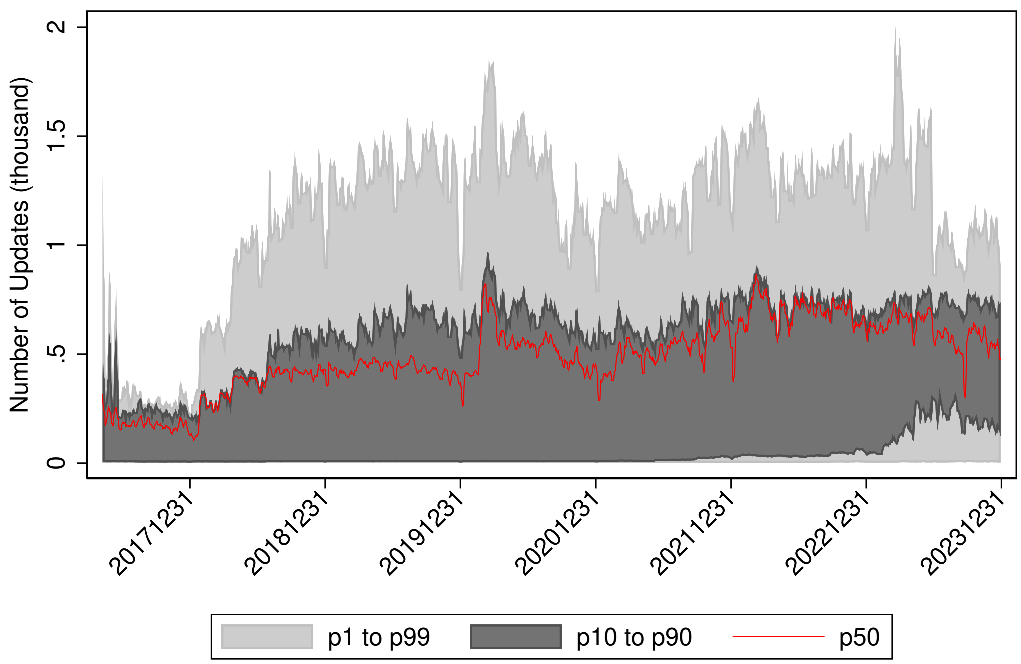


Figure 3: **Daily Cross-Sectional Distribution of the Number of CP+ Prices.** This figure presents daily cross-sectional distribution of the number of CP+ reference prices. Panel A presents the distribution of the number of quotes. Panel B presents the distribution of the number of updates. Red line 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.

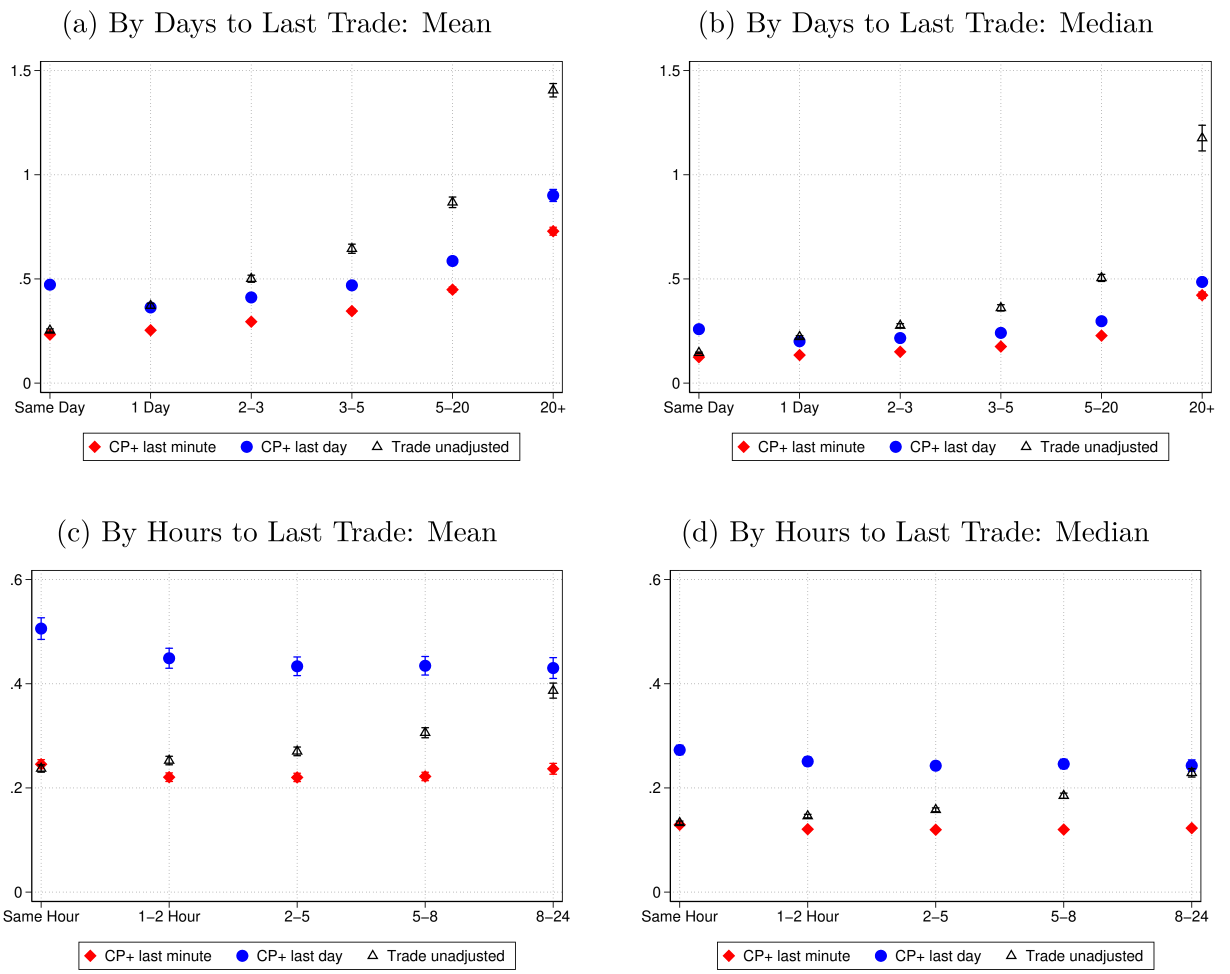
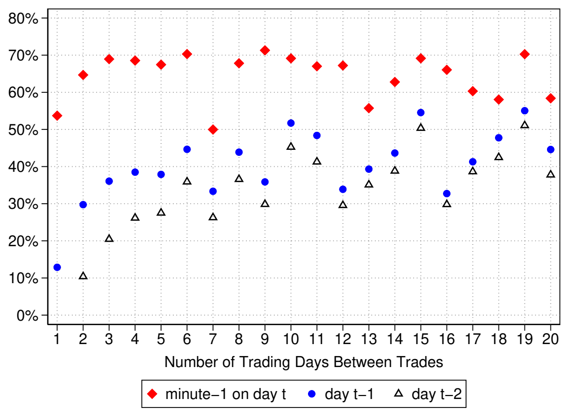
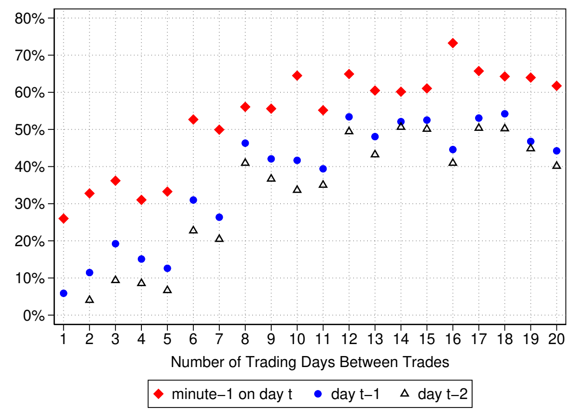


Figure 4: **Bond Price Deviations: CP+ vs Last Trade Price.**
This figure presents the means and medians of trade deviation and CP+ deviation. In Panels (a) and (b), the sample includes all trades. In Panels (c) and (d), the sample consists of trades for which the last trade is within the same day. Red 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.

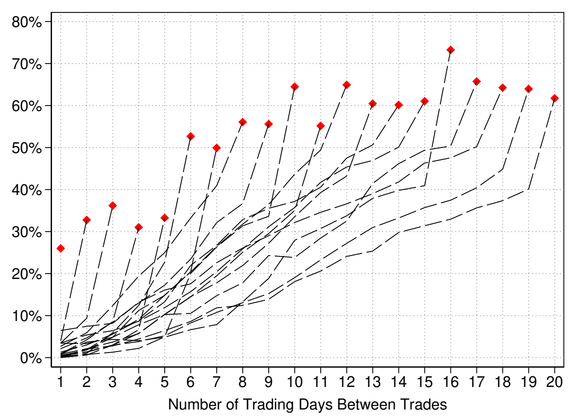
(a) $1\% \leq |ret| < 3\%$: Daily



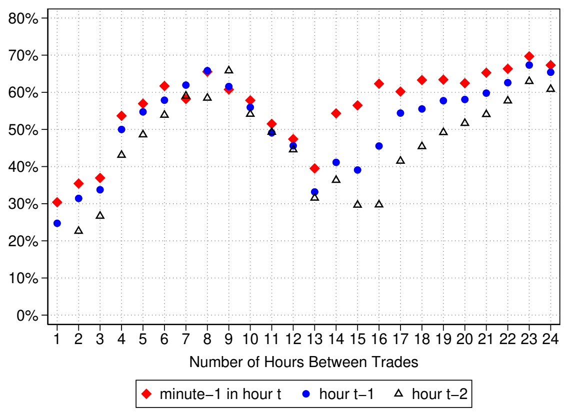
(b) $|ret| \geq 3\%$: Daily



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



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



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

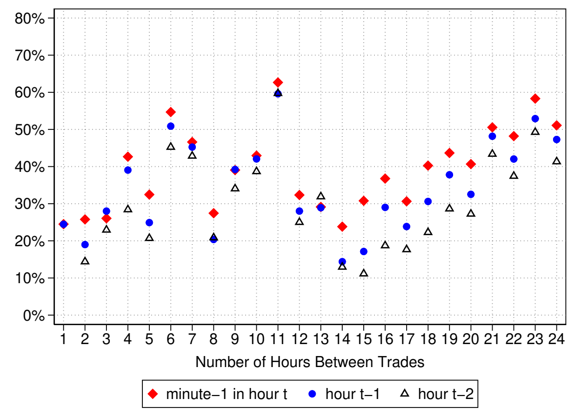


Figure 5: **CP+ Price Discovery Between Successive Trades. (Continued)**
This figure presents R^2s from regressions of bond trade return on the return from last trade price to CP+ price before trade. Panels (a), (c) include trades with an absolute trade return between 1% and 3%. Panels (b) and (d) include 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.

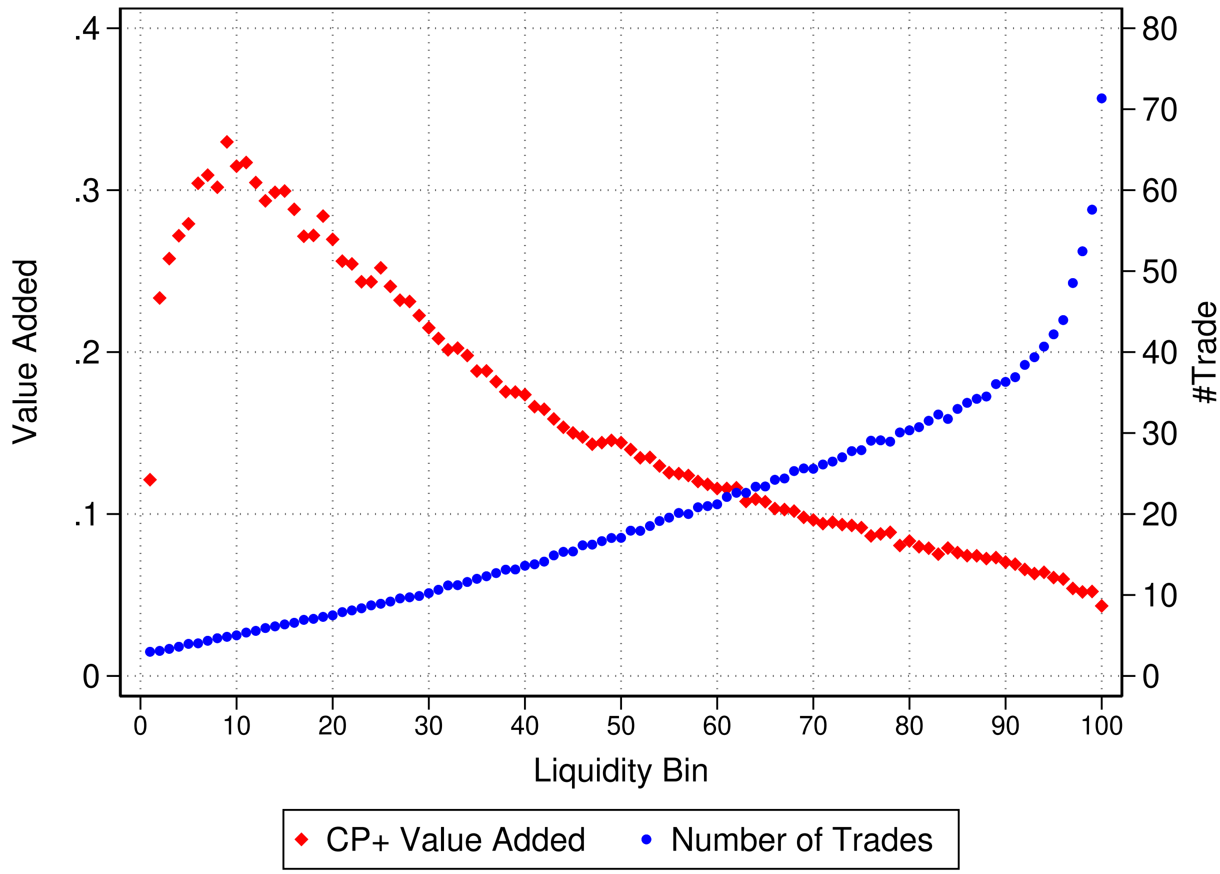
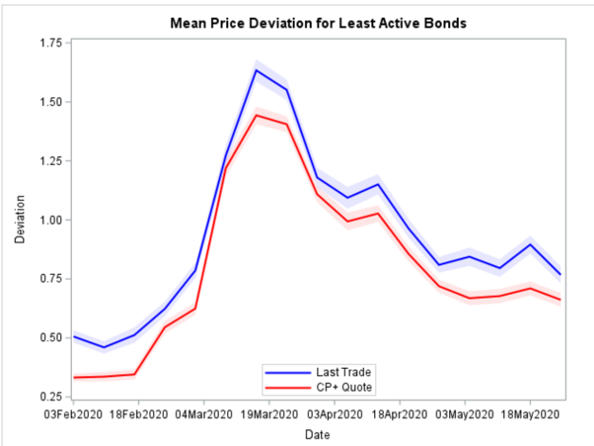
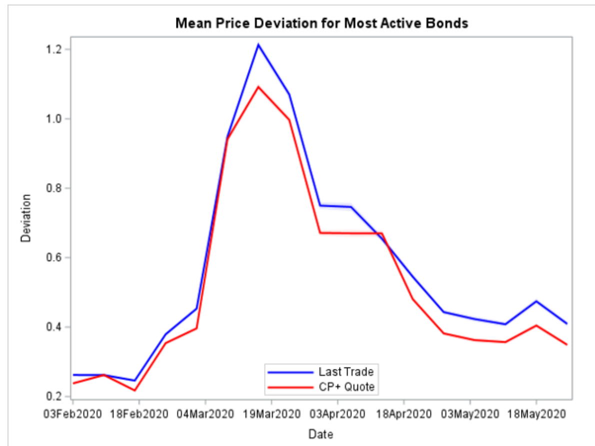


Figure 6: **Bond Liquidity and CP+ Value Added.**
This figure presents the relationship between bond liquidity and CP+ value added. For each trade, CP+ value added is defined as last trade price deviation minus CP+ (m-1) price deviation. Bond-month value added is the average of its trade-level values. 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.

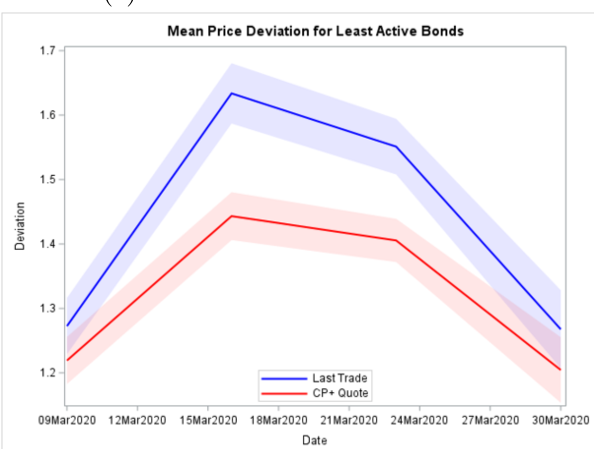
(a) Least Active Bonds: Feb to May



(b) Most Active Bonds: Feb to May



(c) Least Active Bonds: March



(d) Most Active Bonds: March

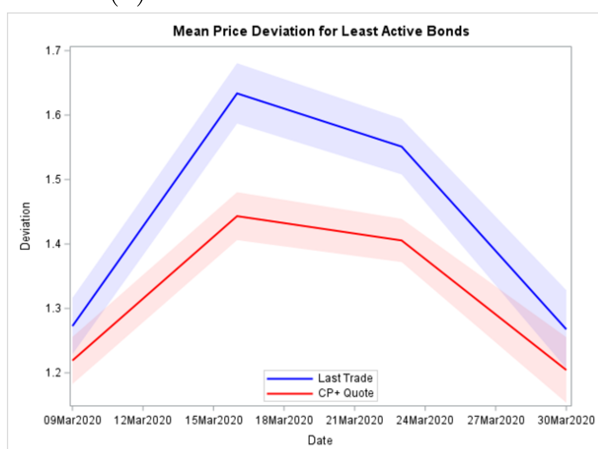


Figure 7: **Price Deviation Around Covid.**
This figure reports weekly mean trade-level price deviations around Covid 19. We start with deviations at the trade-level then aggregate to a weekly level. For each week in the period, we report means and 95% confidence intervals. Blue indicates deviations using the last trade and red indicates deviations using CP+ quotes in the minute prior to the trade. We report statistics for less active and more 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 figures report statistics from February 2020 to May 2020. The second two figures zoom in on the highest volatility period of the crisis from the second week of March to the end of March 2020.

(a) Value Added and VIX (b) Value Added and CMDI

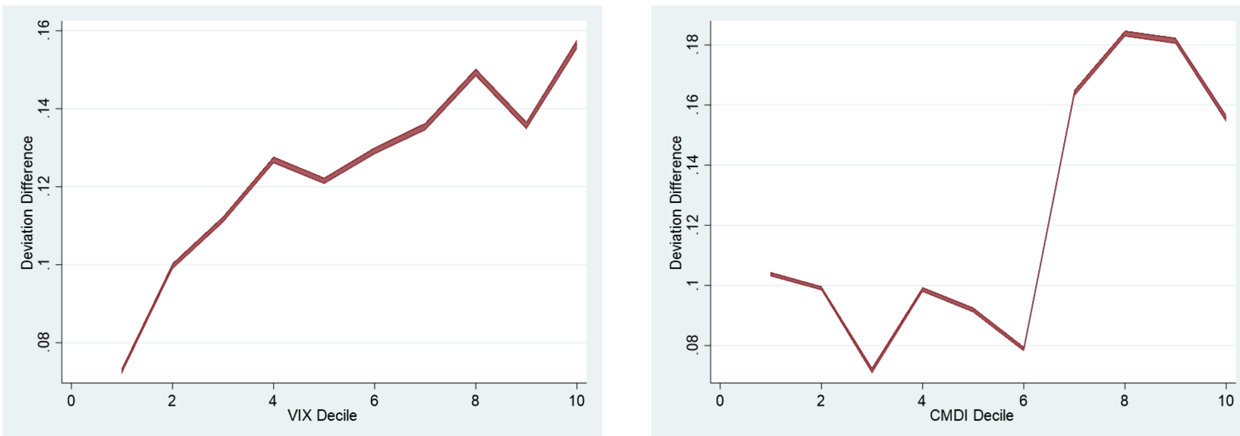
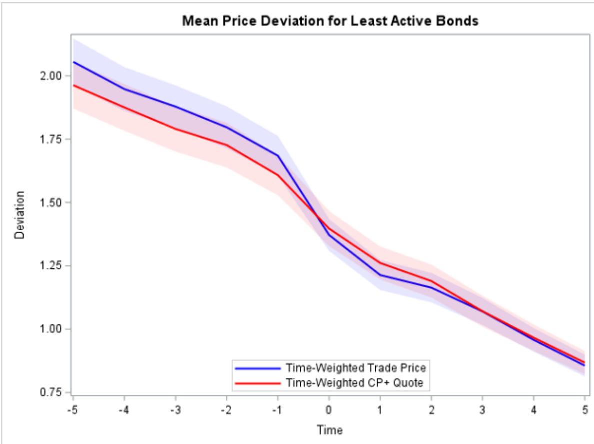
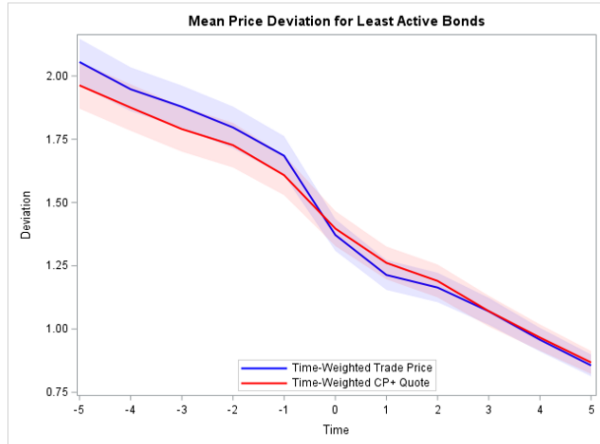


Figure 8: **CP+ Value Added and Market Uncertainty.**
In this figure, we report differences in deviations by proxies for periods of high uncertainty and volatility. We start with the trade-level deviations, then aggregate to daily deviations, resulting in a mean deviation for each bond-day using both 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 mean daily deviation differences by previous week VIX decile in Panel A and by Corporate Bond Market Distress Index (CMDI) decile in Panel B.

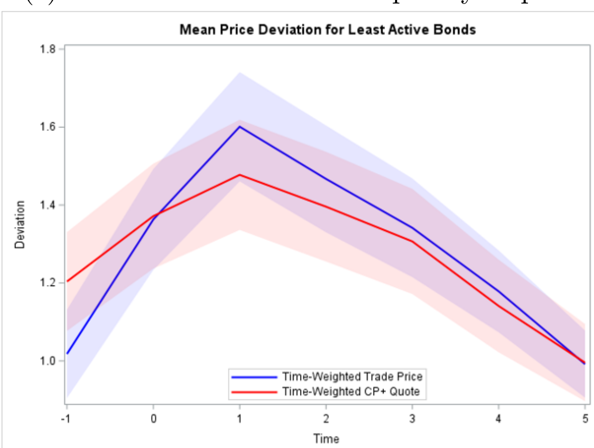
(a) Least Active Bonds: Permanent Impact



(b) Most Active Bonds: Permanent Impact



(c) Least Active Bonds: Temporary Impact



(d) Most Active Bonds: Temporary Impact

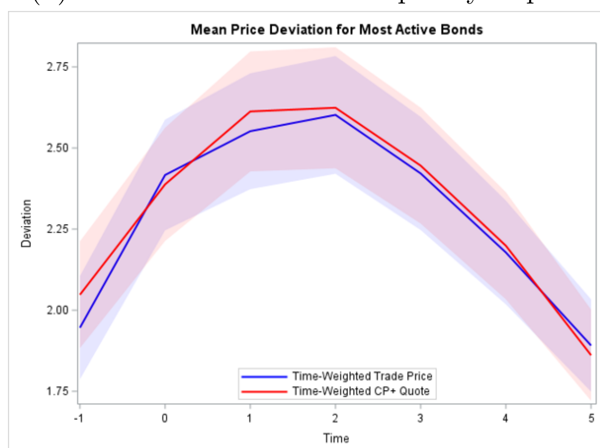
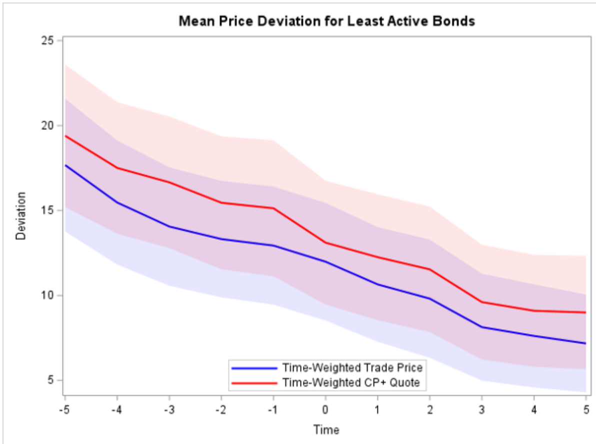
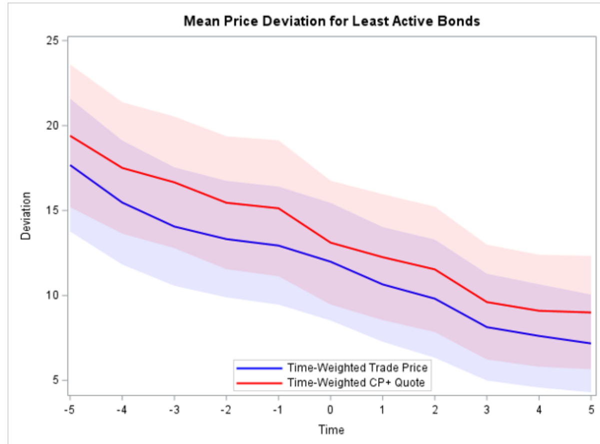


Figure 9: **Price Deviation Around Stress: Block Analysis.**
This figure reports mean price deviations and 95% confidence intervals around block trades. In Panel A and B, we report statistics for blocks with large permanent price impact. We compute time-weighted (TW) daily trade prices and TW daily CP+ quotes. 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 deviations are the difference between the TW daily price on day t and the TW daily price on day +10. CP+ quote deviations are computed analogously: we compare TW daily quotes on day t to the TW 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). In Panel C and D, we 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%. Trade deviations are the difference between the TW daily price on day t and the TW daily price on day +10. CP+ quote deviations are computed analogously.

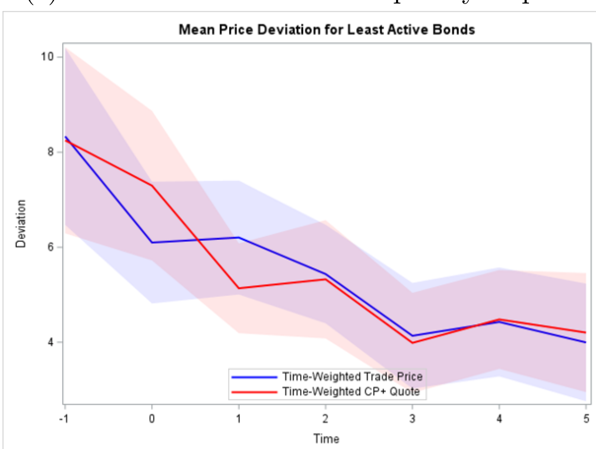
(a) Least Active Bonds: Permanent Impact



(b) Most Active Bonds: Permanent Impact



(c) Least Active Bonds: Temporary Impact



(d) Most Active Bonds: Temporary Impact

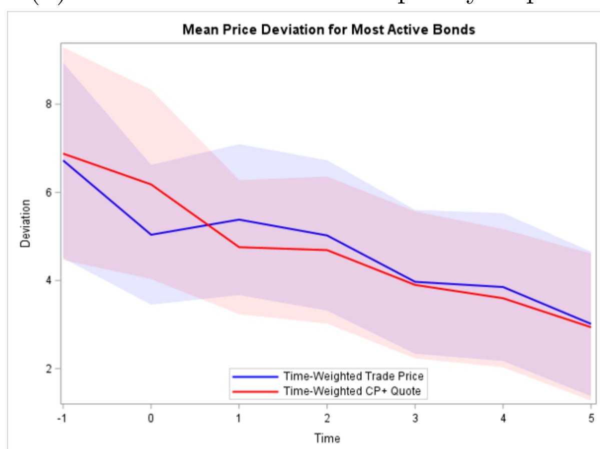


Figure 10: **Price Deviation Around Stress: Downgrade Analysis.**
This figure reports mean price deviations and 95% confidence intervals around large downgrades. In Panel A and B, we report statistics for downgrades with large permanent price impact. For the 10 trading days prior/subsequent to the downgrade, we compute time-weighted (TW) daily trade prices and TW daily CP+ quotes. Permanent price impact is the log difference between day -10 and +10 trade prices and we focus on downgrades with permanent price impact in the top 3 deciles. Trade deviations are the difference between TW daily price on day t and TW daily price on day +10. CP+ quote deviations are computed analogously: the difference between TW daily quotes on day t and TW 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-downgrade period). In Panel C and D, we report statistics for downgrades with large temporary price impact. We cumulate returns over both the pre- (days -10 to -1) and post-downgrade period (+1 to +10) and require the downgrade to generate a reversal (pre-downgrade cumulative returns are negative and post-downgrade cumulative returns are positive). To obtain meaningful temporary price impact, we require both pre- and post-downgrade cumulative returns to be at least 0.5%. Trade deviations are the difference between TW daily price on day t and TW daily price on day +10. CP+ quote deviations are computed analogously. We report statistics for both less and more active bonds (below and above median number of trades in the pre-downgrade period).

Table 1: **Sample Construction and Composition**

This table summarizes our corporate bond sample. Data on corporate bond trades are from TRACE (Trade Reporting and Compliance Engine). Bond descriptive data are from the Mergent Fixed Income Securities Database (FISD). Panel A reports sample construction. Bond trades in our sample include non-retail trades (e.g., larger than $150,000) of CUSIPs in FISD on bond trading days between May 2017 and December 2023. Panel B reports the composition of our sample. 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 A: 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 bond-days within CP+ coverage	20,355	24,869,614

Panel B: Sample Composition

	CUSIPs	Trades	CP+ Quotes	CP+ Updates
Full Sample	20,355	24,869,614	11,806,247,558	3,267,380,073
Investment Grade	15,741	16,506,280	7,832,423,101	3,074,071,336
Non-Investment Grade	6,597	8,363,334	3,973,824,457	193,308,737
Small Issue	7,152	2,971,373	1,388,410,174	372,588,313
Medium Issue	7,920	8,811,247	3,946,264,868	1,167,112,586
Large Issue	5,283	13,086,994	6,471,572,516	1,727,679,174

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 weights the time period a price observation lasts until the next price. These prices are computed separately for trade prices from TRACE and 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 deviation analysis results. Panel A reports deviations statistics. 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. We consider both the CP+ quotes outstanding in the previous minute (m-1) and previous day (d-1). Panels B and C report differences in deviations, i.e., trade deviation less CP+ deviation. In Panel B, we report differences using the CP+ quote outstanding in the previous minute (m-1) and in Panel C, we report differences using the CP+ quote outstanding in the previous day (d-1). In Panels B and C, standard errors are clustered at the trade date 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.

Panel A: Deviation Statistics

	N	Mean	Median	p10	p25	p75	p90
	1+ Days Since Last Trade						
Trade Deviation	6,709,913	0.45	0.25	0.03	0.09	0.56	1.13
CP+ Deviation (m-1)	6,709,913	0.28	0.14	0.02	0.06	0.34	0.68
CP+ Deviation (d-1)	6,709,913	0.40	0.21	0.03	0.08	0.49	0.96
	<1 Day Since Last Trade						
Trade Deviation	9,053,040	0.25	0.15	0.01	0.05	0.30	0.58
CP+ Deviation (m-1)	9,053,040	0.23	0.12	0.02	0.05	0.27	0.53

Panel B: Difference in Deviation, Last Trade vs CP+ (m-1)

	N	Mean	Median	p10	p25	p75	p90
> 5 days	414,781	0.42***	0.21***	-0.22	-0.01	0.75	1.68
1-5 days	6,295,132	0.15***	0.06***	-0.17	-0.03	0.13	0.35
< 1 day	9,053,040	0.02***	0.01***	-0.18	-0.06	0.11	0.25
< 1 hour	4,461,458	-0.01***	0.00***	-0.21	-0.08	0.09	0.21

Panel C: Difference in Deviation, Last Trade vs CP+ (d-1)

	N	Mean	Median	p10	p25	p75	p90
> 5 days	414,781	0.30***	0.12***	-0.44	-0.06	0.62	1.43
1-5 days	6,295,132	0.04***	0.01***	-0.24	-0.08	0.13	0.35
< 1 day	9,053,040	-0.22***	-0.08***	-0.79	-0.34	0.04	0.19
< 1 hour	4,461,458	-0.27***	-0.10***	-0.89	-0.39	0.02	0.17

Table 4: **Deviation Analysis: Robustness**

This table presents results of robustness tests for the deviations analysis. All variables are the same as in Table 3. In Panel A, we restrict the sample to trades for which the current and last trade have the same sign (e.g., both the last and current trades are buys). We also compute CP+ deviations using the bid or ask (depending on the trade sign) rather than the midpoint. In Panel B, we restrict the sample to trades that are at least $1 million in par value (e.g., both the current and the last trade exceed $1 million). In Panel C, we allow the last trade to be smaller than $150,000.

Panel A: Same-Signed Last Trades

	N	Mean	Median	p10	p25	p75	p90
	1+ Days Since Last Trade						
Trade Deviation	3,411,679	0.43	0.23	0.02	0.08	0.54	1.09
CP+ Deviation (m-1)	3,411,679	0.25	0.12	0.02	0.05	0.30	0.62
CP+ Deviation (d-1)	3,411,679	0.38	0.20	0.03	0.07	0.47	0.92
	<1 Day Since Last Trade						
Trade Deviation	4,485,631	0.23	0.12	0.01	0.04	0.27	0.53
CP+ Deviation (m-1)	4,485,631	0.21	0.11	0.01	0.04	0.24	0.49

Panel B: Trades $\geq$ $1M

	N	Mean	Median	p10	p25	p75	p90
	1+ Days Since Last Trade						
Trade Deviation	2,488,139	0.41	0.25	0.02	0.08	0.50	1.00
CP+ Deviation (m-1)	2,488,139	0.29	0.15	0.02	0.06	0.34	0.69
CP+ Deviation (d-1)	2,488,139	0.40	0.21	0.03	0.08	0.48	0.95
	<1 Day Since Last Trade						
Trade Deviation	4,193,781	0.22	0.14	0.00	0.05	0.25	0.50
CP+ Deviation (m-1)	4,193,781	0.24	0.13	0.02	0.05	0.28	0.53

Panel C: Include Retail Trades

	N	Mean	Median	p10	p25	p75	p90
	1+ Days Since Last Trade						
Trade Deviation	2,404,485	0.41	0.25	0.02	0.09	0.52	1.02
CP+ Deviation (m-1)	2,404,485	0.30	0.16	0.02	0.06	0.36	0.71
CP+ Deviation (d-1)	2,404,485	0.40	0.22	0.03	0.08	0.49	0.96
	<1 Day Since Last Trade						
Trade Deviation	13,358,468	0.32	0.17	0.02	0.06	0.38	0.77
CP+ Deviation (m-1)	13,358,468	0.25	0.13	0.02	0.05	0.29	0.58

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

This table reports differences in deviations between trades and CP+ quotes. We report differences 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 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	0.42	0.29	0.29	0.17	0.24
1-5 days	0.15	0.11	0.04	0.03	0.03
< 1 day	0.05	0.04	-0.17	-0.17	-0.17
< 1 hour	0.00	0.00	-0.26	-0.26	-0.26
			All Trades, Median		
> 5 days	0.20	0.15	0.15	0.11	0.23
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	73%	67%	69%	63%	64%
1-5 days	66%	62%	56%	55%	55%
< 1 day	59%	57%	36%	36%	36%
< 1 hour	51%	50%	30%	30%	30%
			Trades with Same Signs, Mean		
> 5 days	0.41	0.26	0.27	0.15	0.19
1-5 days	0.13	0.08	0.02	0.01	0.01
< 1 day	0.02	0.01	-0.20	-0.20	-0.20
< 1 hour	-0.03	-0.03	-0.28	-0.28	-0.28
			Trades ≥ \$1M, Mean		
> 5 days	0.36	0.25	0.24	0.14	0.19
1-5 days	0.11	0.08	0.01	0.00	0.00
< 1 day	0.03	0.02	-0.23	-0.23	-0.23
< 1 hour	-0.03	-0.03	-0.34	-0.34	-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***					0.615***	
	(0.016)					(0.011)	
Credit Index		0.693***					0.761***
		(0.016)					(0.016)
SP500			0.079***			0.061***	-0.019**
			(0.010)			(0.009)	(0.008)
ΔCredit Spread				-1.956***		-3.366***	0.466***
				(0.365)		(0.221)	(0.154)
ΔVIX					-0.016***	0.030***	0.024***
					(0.006)	(0.008)	(0.006)
Intercept	-0.008	-0.045***	-0.039***	-0.027**	-0.025**	-0.019***	-0.043***
	(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	0.364	0.273

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treasury	-0.012					0.038	
	(0.042)					(0.036)	
Credit Index		0.312***					0.218***
		(0.045)					(0.035)
SP500			0.119***			0.015	-0.021
			(0.023)			(0.025)	(0.027)
ΔCredit Spread				-2.740***		-1.714***	-1.075**
				(0.599)		(0.491)	(0.513)
ΔVIX					-0.085***	-0.060***	-0.068***
					(0.017)	(0.021)	(0.021)
Intercept	-0.020	-0.028	-0.040	-0.022	-0.019	-0.022	-0.022
	(0.024)	(0.023)	(0.024)	(0.023)	(0.022)	(0.023)	(0.022)
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	0.033	0.041

Table 7: **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 8: **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

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

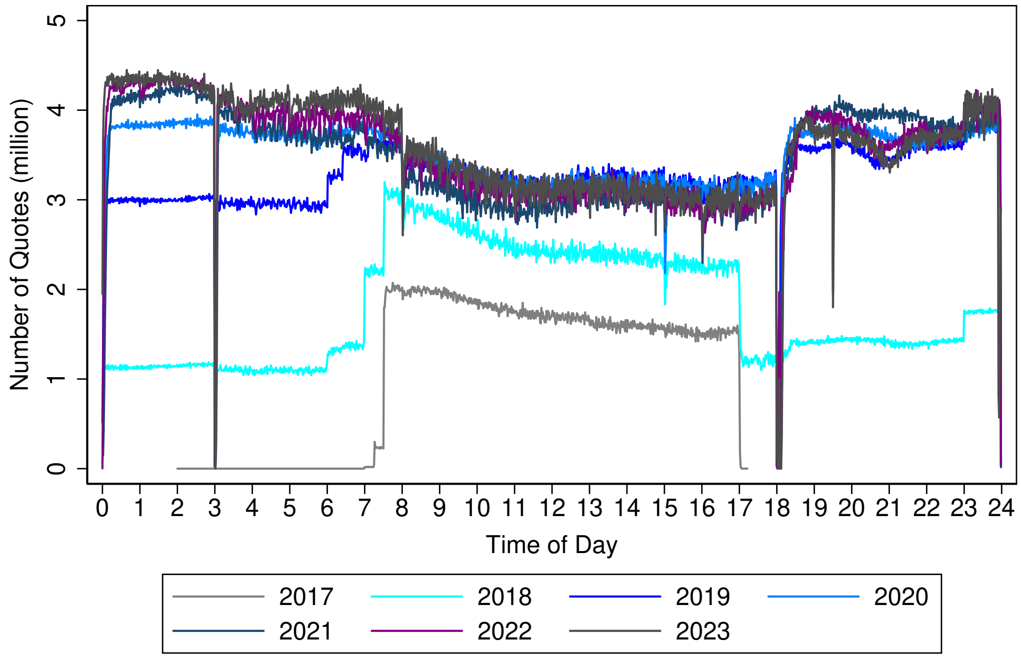
For each corporate bond, we infer the minute-level maturity-matched treasury prices from its CP+ quotes as follows.

We begin with the universe of CP+ quotes. For each quote observation, we infer the maturity-matched treasury yield by subtracting 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.

(a) CP+ Quote Prices



(b) CP+ Quote Updates

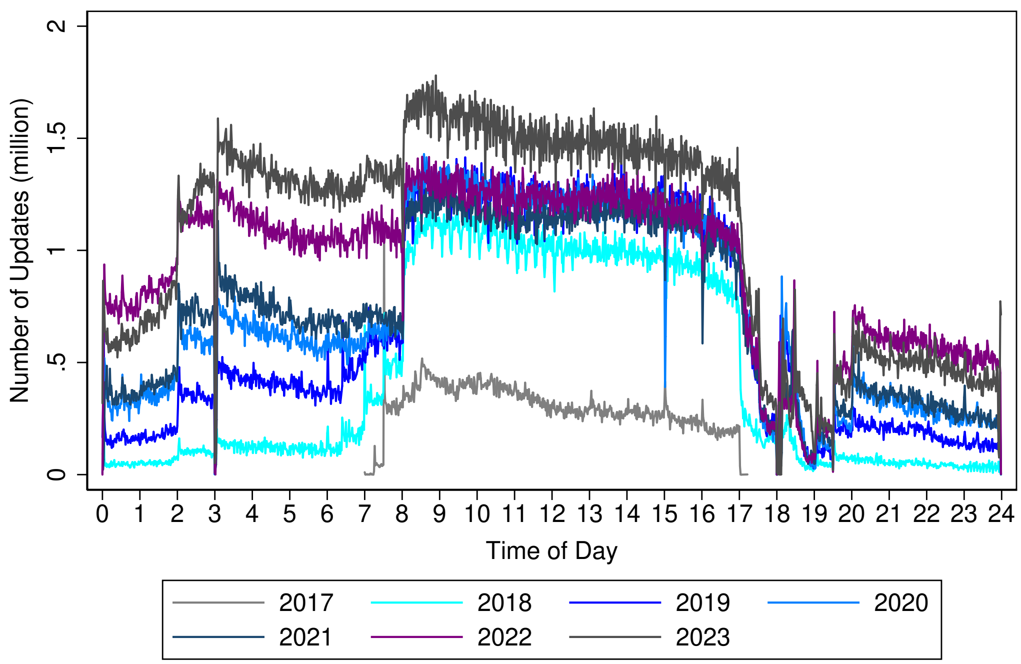


Figure IA.1: **Total Number of CP+ Prices by Minute of Day**
This figure presents the total number of CP+ prices displayed within every minute of the day across all trading days of the year, separately for each year between 2017 and 2023. Panel A presents the number of quotes, and Panel B presents the number of updates. Ticks in the horizontal axis shows the hour of the day.

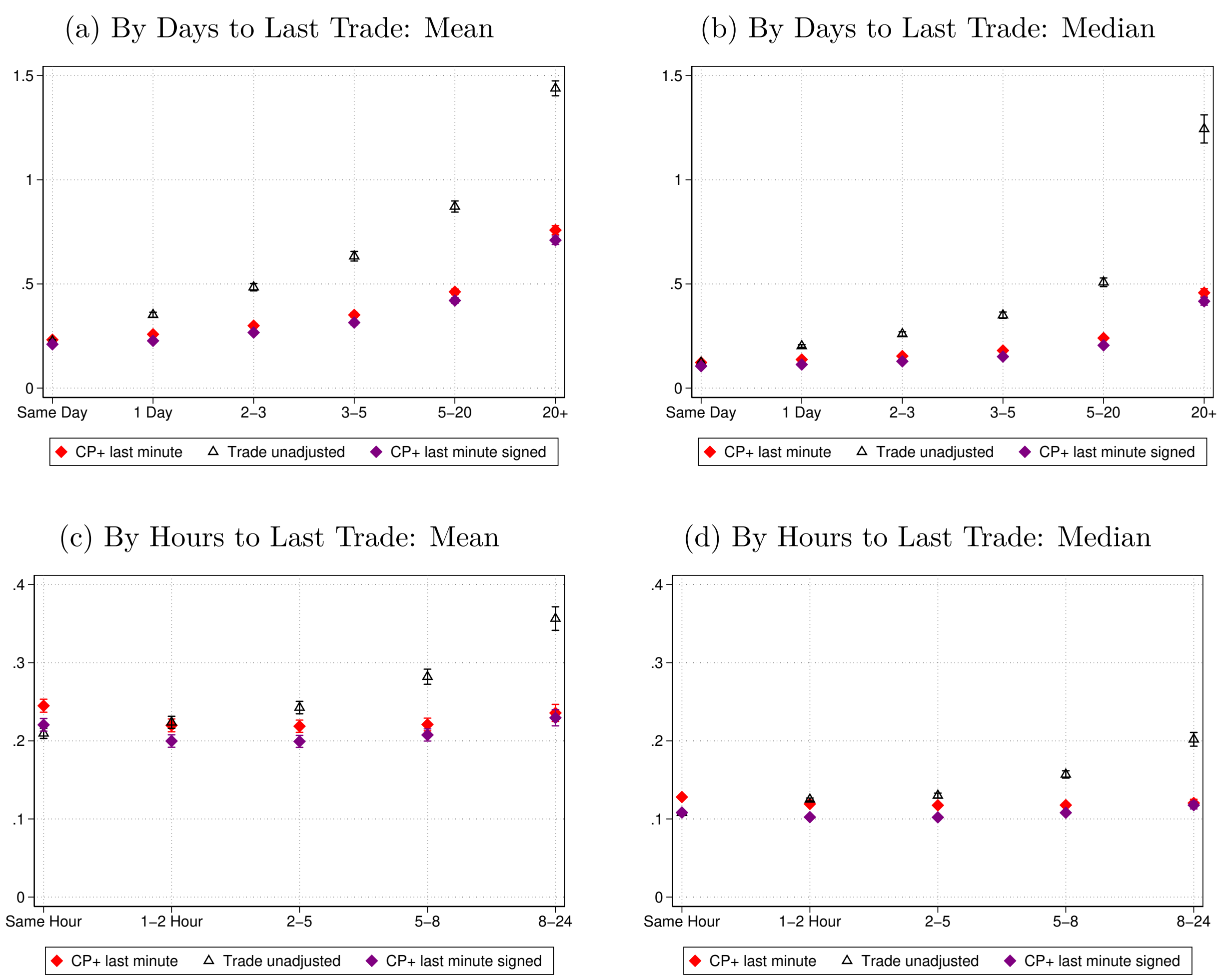


Figure IA.2: **Bond Price Deviations: Adjusting for Bid-Ask Spreads.**
This figure presents the means and medians of trade deviation and CP+ deviation for the sample for which the current and last trade have the same sign (e.g., both the current and last trades are buys). CP+ deviations are computed 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.

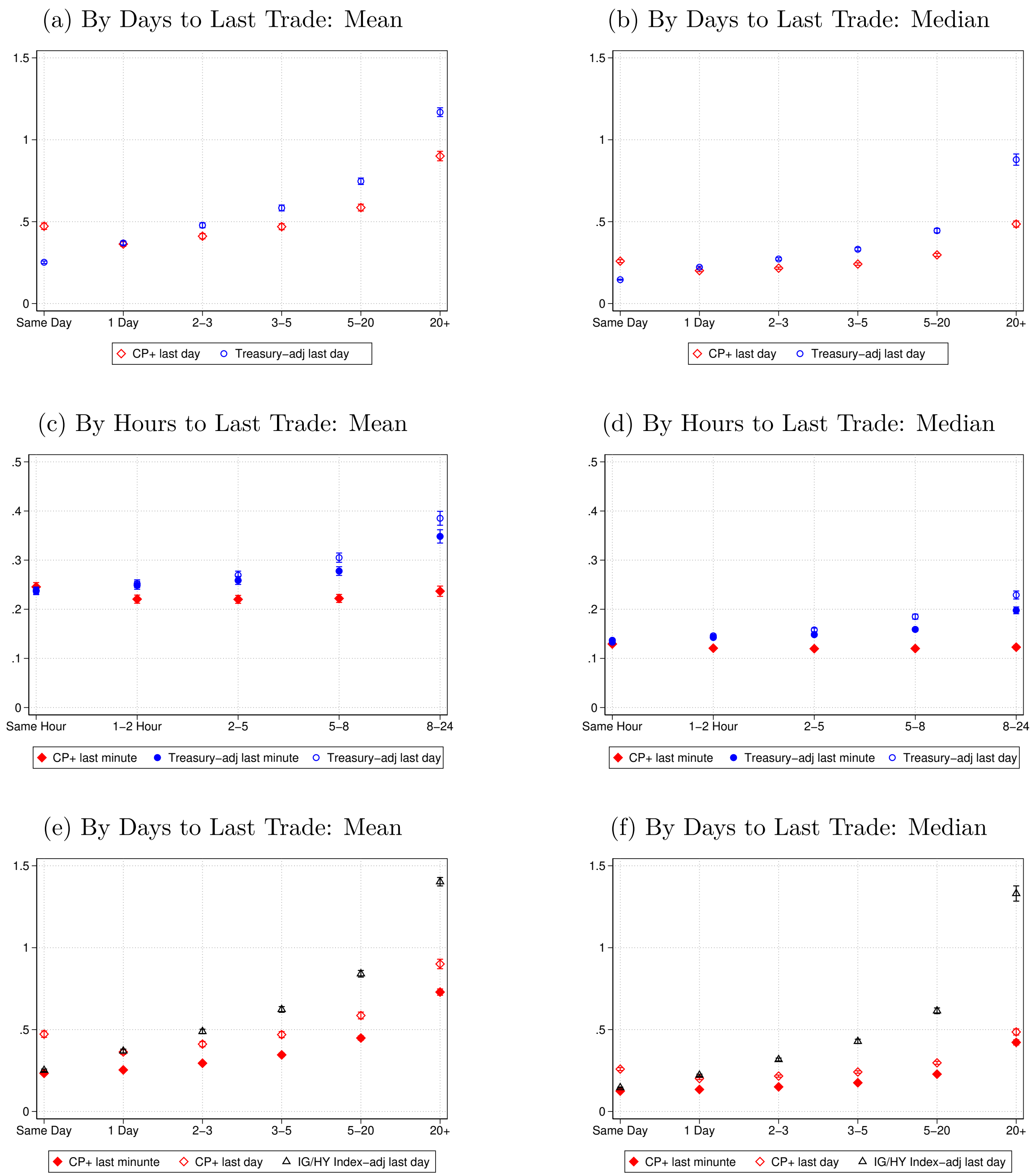


Figure IA.3: **Bond Price Deviations: CP+ vs Last Trade Price Adjusted.**
This figure presents the means and medians of trade deviation and CP+ deviation. In Panels (a), (b), (e), and (f), the sample includes all trades. In Panels (c) and (d), the sample consists of trades for which the last trade is 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.