Valuations in the dark: When independent valuators influence corporate bond returns*

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Abstract

This paper extends the traditional microstructure models by introducing an additional agent, the independent valuator, whose sole objective is to provide accurate estimates of securities' fundamental value. As our agents operate in an opaque market, investors and valuators share information about their noisy estimates of the fundamental value. This in turn affects asset prices as both agents aim at correcting discrepancies between those. We document strong empirical support for this model in corporate bond markets and show it is helpful to understand various findings documented in the literature, such as the implementation shortfall of return-based strategies or the dependence structure across pricing sources. We find that distortions between traded prices and index valuations are a key factor driving the cross-section of contiguous future corporate bond returns, that can neither be explained by the risk of individual bond issues nor by widely accepted proxies for the microstructural noise embedded in traded prices.

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1. Introduction

Corporate bond markets are widely acknowledged to be illiquid markets.[a] Although this statement is bounded by notions of relativity, the simple fact that most corporate bonds don't trade at least once every day is probably the most outspoken illustration of this illiquidity.[b] Another feature of corporate bond markets is their opacity, which originates both from the limited post-trade transparency as well as the vivid lack of pre-trade transparency. Although investors have access to quote information, those are usually non-firm, updated infrequently and not distributed homogeneously to market participants. Moreover, contrary to equity markets, information about the best bids and asks, as well as the order book depth, is not available to investors.

The illiquidity and opacity of corporate bond markets pose challenges for investors. Beyond the difficulty to find a counterparty, the uncertainty around the fundamental value of securities is probably the most important one in the absence of an efficient price discovery mechanism. Indeed, even in the presence of post-trade transparency, market participants can't wait for demand and supply to meet in order to obtain a value for the assets they hold in portfolio or to form investment views. To palliate to the lack of transparent transaction-based price information, market participants have to rely on so-called 'valuation' models.

The early 1970s saw the first index providers entering fixed income markets, an innovation that paved the way for the progressive introduction of daily index valuations.[c] The rapid adoption of those benchmarks have made them an essential reference for market participants, not only because they are at the heart of relative performance and tracking error objectives, but also because they facilitate price discovery. The broad disclosure of index 'prices' has provided many investors with an anchor to what is generally accepted to be a sound estimate of the fundamental value of an instrument. Today, daily index 'prices' are the norm for fixed-income benchmarks. Nevertheless, we still on average observe index 'prices' at a higher frequency than traded prices, despite the increase in the liquidity of corporate bond markets over time. Given the inherent market illiquidity, index valuators face similar challenges as investors and do need to rely on proprietary models, that most often combine multiple inputs such as valuation models, dealers' quotes or past traded prices.

As investors anchor to index valuations and as those independent valuators incorporate information from past transactions, a natural question to ask is to what extent this reliance on each other's

[a] Bessembinder et al. (2020) provide a very detailed overview of the fixed income markets' microstructure, in which they discuss how these key market characteristics have evolved over time and provide a perspective on current developments.
[b] Edwards et al. (2007) report that transactions are highly clustered in time and that the median bond only trade about 48% of the days in their sample period, going as low as 2.7% for the first percentile of the distribution.
[c] Reilly et al. (1992) review and compare the major corporate bond benchmarks, including Lehman Brothers, Merrill Lynch and Salomon Brothers, going back to 1976.

information influences prices. The market microstructure literature has investigated at length the interaction between investors demanding immediacy and liquidity providers. Amongst others, it has shed light on the determinants of the costs of trading and their relationship with illiquidity, two inter-dependent notions that are highly relevant in corporate bond markets given their opacity. But, while the role of liquidity providers is well understood, the role of the valuators has received little attention in the literature.

In this paper, we propose a model that expands on the traditional market microstructure model, in which an investor engages with a dealer, by introducing an additional agent, being the independent valuator, whose aim is solely to provide accurate estimates of the fundamental value of securities. We focus specifically on the interaction between the investor and the valuator and its influence on prices. As we let the agents evolve in an opaque market, they have limited access to information and are forced to share noisy estimates of their past valuations. We show that this sharing of information has important implications for asset prices, that we test empirically. We leverage on our model to provide new insights on various empirical findings documented in the literature. Overall, this model helps in fostering our understanding of the role and influence of independent valuators in illiquid and opaque markets, of what drives pricing discrepancies between index valuations and traded prices and how those are resolved over time, but also, of the relevance that each pricing source should carry for investors.

Our paper contributes to various streams in the corporate bond asset pricing literature. First and foremost, we show that the pricing distortions between traded prices and index valuations are a key factor in explaining the cross-section of future contiguous corporate bond returns. While the information contained in those deviations has been studied in the context of the measurement of illiquidity by Jankowitsch et al. (2011), their impact of asset prices has remained largely undocumented in the literature. We find that this factor can neither be explained by the risk of individual bond issues nor by widely accepted proxies for the microstructural noise embedded into traded prices. Specifically, we show that these pricing distortions are a distinct phenomenon from the well documented bid-ask bounce effect, described in amongst others Roll (1984).

Next, we propose a minor adjustment to the return calculation methodology commonly used in the literature that relies on the record of transactions available in TRACE. Specifically, our enhancement guarantees an overlapping implementation lag in the cross-section, i.e. a common evaluation moment, which, although trivial in itself, is a crucial determinant of the ability to implement any strategy aiming at harvesting factor premia. This allows us to make a clear distinction between the 'explainability' and the 'harvestability' of factor premia. Our work contributes to the debate on 'harvestable' factor premia in illiquid markets. Specifically, we add to the findings of Dickerson et al. (2023b), who document large implementation shortfalls for return-based predictors, by providing insights into the drivers of this implementation shortfall. Consistent with the implication of our model, we show that the convergence across pricing sources drives to a large extent the instantaneous price adjustments that are behind the large drop in significance of factors, such as reversal, once properly accounting for an implementation lag. We confirm the results of Dickerson et al. (2023b) and show that the documented short-term reversal effect is explained by distortions across pricing sources and cannot be harvested in practice.

Moreover, this paper contributes to the market microstructure literature in various ways. First, as discussed above, by introducing an additional agent that interacts with investors by sharing information and influences traded prices. Second, our work also contributes to the debate on the relative importance of various costs resulting from the demand of immediacy of investors. Our paper shed light on the pervasive influence of dealer inventory imbalances on future corporate bond returns, which is found to be the sole market microstructure proxy to be significant after controlling for an implementation lag. This finding is consistent with those of Khang and King (2004) and a broader literature concerned with the capital commitment of dealers. We show that accumulated net positions by dealers lead to reversals in both pricing sources, a phenomenon distinct from the reversal driven by the convergence across pricing sources.

Finally, this paper contributes to the discussion on what the preferred choice of pricing source should be for both market participants and researchers. Amongst others, Kelly and Pruitt (2022), Bai et al. (2023) investigate the robustness of their results across pricing sources, while Andreani et al. (2023) compare the distributional properties of various sources to identify the potential presence of liquidity issues and market microstructure noise. The consensus seems to favor evaluated pricing sources from index providers such as ICE or Bloomberg, over the use of transaction prices from TRACE. This choice is either justified by the relevance of those index series for investors, as a large investor base follows and pays for those return series, or based on correlation motives, as those timeseries display lower negative serial correlation, indicating they are less contaminated by microstructural noise. In this paper, we show that both pricing sources carry relevant information for price discovery. While we confirm that traded prices are contaminated by microstructure effects to a much larger extent than index prices, we also shed light on the diffusion of information across pricing sources by showing that evaluated prices incorporate valuable market information contained in traded prices with a delay. To this aim, we extend the work of Andreani et al. (2023) by providing a more rigorous framework to investigate the lead-lag relationship across pricing sources. We show that once trades are matched and returns decomposed, the hypothesis that index prices lead traded prices is rejected. Moreover, our analysis highlights the importance of controlling for risk when investigating the dependence structure as cross-serial correlations are not robust to their inclusion.

The rest of the paper is organized as follows. Section 2 introduces our model focusing on the interaction between valuators and investors, and clarifies the implication for reversals. Section 3 covers the data and methodologies, and introduces our enhanced approach for return computation that correctly handles the introduction of an implementation lag. Section 4 sets the stage by reviewing some key empirical findings documented in the literature. Section 5 focuses on the empirical evaluation of the model implication for reversals. Finally, in Section 6, we conclude.

2. Modelling the role of the independent valuator

To better understand the interaction between the price at which securities trade in opaque and illiquid markets[d] and the independent valuations provided as a service by external agents, we propose a simple model that builds upon the work of amongst others Roll (1984)[e]. It introduces an additional agent in the traditional microstructure models that consider the interaction between liquidity providers and investors, namely the independent valuator, whose only role is to provide estimates of the unknown fundamental value of securities. This agent is external to the market in the sense that it neither provides nor demand liquidity. While the valuation services he provides play a key role in the trading behavior of market participants, they are by no means 'real' prices as no transaction ever takes place at those levels. Thus, they are not affected by trading frictions, or at least not directly as we will discuss below, while transaction prices are.[f] In our model, consistent with the market microstructure theory, those frictions present in 'realized' transaction prices emanate from the presence of a liquidity provider that accommodates investors' demand for immediacy and requires a compensation for the various risk and costs she faces, namely the inventory risk, the search costs and the risk of information asymmetry. With full knowledge of the exposed key differences between valuations and transaction prices, we will henceforth refer conveniently to both as 'pricing' sources, as in our model agents rely on that set of information for estimating the unknown fundamental value of securities.

2.1. Introducing the valuator

In our setting, all agents operate within an illiquid and opaque market which is characterized by a limited set of public information and the ability to rely on external valuation services to estimate the true unknown fundamental value of securities. More specifically, investors and valuators share noisy information about their past valuations that is processed together with the arrival of news to form estimates of the unknown fundamental value of securities. As they are allowed to process the

[d] Bessembinder et al. (2020) review the microstructure of fixed-income markets and contrast it with equity markets. They link the opacity in fixed income markets to, amongst others, the lower post- and pre-trade transparency and the lower market integration amongst venues. One determinant of market integration being regulation, they note that equity markets have faced higher regulatory pressure compared to the fixed income markets. Another determinant is the degree of competition, which in fixed-income markets is being impacted by the limited pre-trade transparency and the high search costs.

[e] The seminal work of Roll (1984) has implications beyond equity markets. Amongst others, Bao et al. (2011) leverage on the model developed by Roll (1984) to measure the illiquidity of corporate bonds.

[f] Moreover, valuations are usually expressed as bid prices.

information set differently, they do not have to agree in expectation on the unknown fundamental value of securities. Their expertise allows them to overcome the challenge of a limited information set and to form approximatively correct expectations about the true unobservable fundamental value, whereby the traded prices and independent valuations only deviate from the unknow true value due to respectively trading frictions or valuations errors. As a result, residual trading frictions and valuation errors lead valuations and traded prices to temporarily diverge. Moreover, past divergences contained in both trading prices and independent valuations are processed by agents to update their estimate of the asset fundamental value, which in turn affect their trading decisions and valuation adjustments. As at least one of the agent is concerned by the resolution of those distortions, both valuations and transaction prices are cointegrated and converge following the emergence of pricing source deviations. We present below the details of the model and discuss the key implications for the dynamics of both transaction prices and valuations.

We start by denoting P_t^T the clean price at which a security has been traded at time t, where the superscript T indicates that the source of the pricing information are transaction prices. For simplicity and without loss of generality, we assume that securities are zero-coupon bonds. This allows to define $p_t^T = lnP_t^T$ as the log price, such that Δp_t^T are the log returns. In the presence of alternative pricing information emanating from various independent valuators, such as index providers, we also denote P_t^I the evaluated price of that same security at time t, where the superscript I indicates that the source of the pricing information are index valuations, and $p_t^I = lnP_t^I$ is the log price. Following amongst others Roll (1984) and Bao et al. (2011), we assume that transaction prices consists of two components, one that captures the unknown fundamental value f_t of the security in the absence of trading frictions and a transitory component u_t^T originating from those frictions, uncorrelated with the fundamental value. We assume that the independent valuation follows a similar process, whereby it captures both the unknown fundamental value and some valuation error u_t^I.

$$p_t^T = f_t + u_t^T \tag{2-1}$$

$$p_t^I = f_t + u_t^I \tag{2-2}$$

As a result, the deviations of prices away from the true unknown fundamental value are solely driven by trading frictions or valuation errors. We refer to conveniently to both sources of deviations as noise. It is useful to rewrite the previous equations as the cumulative sum of changes in both the fundamental value and the noise terms to illustrate how potentially those accumulate into prices.

$$p_t^T = f_0 + \sum_{i=1}^{t} \Delta f_i + u_0^T + \sum_{i=1}^{t} \Delta u_i^T \tag{2-3}$$

$$p_t^I = f_0 + \sum_{i=1}^{t} \Delta f_i + u_0^I + \sum_{i=1}^{t} \Delta u_i^I \tag{2-4}$$

It follows from the above definitions that the noise accumulation can lead to and is the sole source of price distortions across pricing source D_t that we define as the difference between traded the prices p_t^T and the index valuations p_t^I. As such, small pricing distortions can accumulate over time, leading to the representation in equation (2-6).

$$D_t = p_t^T - p_t^I = (u_0^T - u_0^I) + \sum_{i=1}^{t} \left(\Delta u_i^T - \Delta u_i^I\right) \tag{2-5}$$

$$D_t = D_0 + \sum_{i=1}^{t} \left(\Delta D_i\right) \tag{2-6}$$

As an investor would trade up until the level at which it can transact p_t^T corresponds to her expectation $E_t^T[f_t]$ of the unknown fundamental value, we assume that in equilibrium both are equal. Likewise, the independent valuator would only agree to report a valuation level of p_t^I if it corresponds to its expectation $E_t^I[f_t]$ of the unknown fundamental value.

$$p_t^T = E_t^T[f_t] \tag{2-7}$$

$$p_t^I = E_t^I[f_t] \tag{2-8}$$

In our model, the market for this security is characterized by a high level of opacity, due e.g. to a lack of pre-trade transparency, and high illiquidity. The latter translates into sparse information emanating from transaction prices, which hinders the price discovery process and potentially forces market participants to rely on alternative information sources to estimate the fundamental value of the security. We further assume that market participants assess the security's fundamental value given a limited set of information that comprises past transaction prices p_{t-1}^T, past index valuations p_{t-1}^I and some new public information ε_t^T. We assume those innovations to have zero mean and to be uncorrelated to past prices, i.e. essentially being surprises. More specifically, investors and valuators estimate the unknown fundamental value as follows:

$$E_t^T[f_t] = (1 - \omega_t^T)\, p_{t-1}^I + \omega_t^T p_{t-1}^T + \varepsilon_t^T \tag{2-9}$$

$$E_t^I[f_t] = (1 - \omega_t^I)\, p_{t-1}^I + \omega_t^I p_{t-1}^T + \varepsilon_t^I \tag{2-10}$$

In such a setup, investors essentially assume that the most recent pricing information, coming both from transaction prices and from index valuations, contains valuable information about the fundamental value of the security and update it by some innovation term ε_t^T as new information is released. The ω_t^T

parameter characterizes the relative confidence investors have in the different pricing sources, allowing them to integrate explicitly the information contained in the price differential across pricing sources in the estimation of the fundamental value. The intensity at which investors incorporate information originating from the other agent is $(1-\omega_t^T)$ and can dynamically change over time.[g]

Such a specification nests some interesting cases and we thus review the implications of some parameters value. The case where $\omega_t^T=1$ represents the Martingale hypothesis in traded prices, whereby $E[p_t^T]=p_{t-1}^T$ and investors blindly take the past traded price as their estimate of the security's fundamental value in the absence of news. This hypothesis is amongst others used by Bartram et al. (2020). Alternatively, the case where $\omega_t^T=0$ corresponds to a setting in which investors assume that the past index valuations are unbiased estimates of the fundamental value. Under the Martingale hypothesis in index prices, whereby $E[p_t^I]=p_{t-1}^I$, this case is closely related to the work of Jankowitsch et al. (2011) who assume that index valuations capture the true fundamental value of securities and model the deviation of traded prices from the expected value to capture the inventory risk and search costs that affect traded prices. We will discuss later the interpretation of alternative parameter values.

It is important to note that assuming such functional form for the estimation of the fundamental value by investors conveniently allows both pricing sources to be cointegrated, within some reasonable intensity parameter values. Indeed, substituting equation (2-9) in equation (2-7), we can rewrite the process for traded prices as a function of past index and transaction prices, as well as the change in traded prices as a function of the past distance between the pricing sources D_{t-1}, which characterizes the error correction relationship[h].

$$p_t^T=(1-\omega_t^T)\,p_{t-1}^I+\omega_t^T\,p_{t-1}^T+\varepsilon_t^T \tag{2-11}$$

$$\Delta p_t^T=-(1-\omega_t^T)D_{t-1}+\varepsilon_t^T \tag{2-12}$$

While equation (2-12) describes the process by which past price distortions feed into future transaction prices, not all parameter values for ω_t^T ensure that the error correction process is well behaved. More specifically, for $\omega_t^T>1$ errors do not correct and transaction prices further diverge from index prices. When $\omega_t^T=1$, the change in traded prices is independent of deviations across pricing sources, while

[g] Note that in our model, a price observation is conveniently available at time $t-1$. This is also a requirement we impose in the empirical analysis conducted in this paper. In reality, corporate bonds trade on a very infrequent basis. In the case a price is not available, this might force investors to rely on older transaction prices (i.e., executed prior to $t-1$) and potentially put more weight on the external valuations. This extension of our model would constitute an interesting avenue of research as this introduce a potential additional driver for the intensity ω_t^T, namely the age of the transaction information.

[h] See Murray (1994) for an intuitive discussion, as well as Granger (1981) and Engle and Granger (1987) for a formal description.

$\omega_t^T < 1$ implies that traded prices converge toward index prices. We will discuss later the distribution of parameter values that ensures our system is well behaved.

Although no arbitrage activity can guarantee the cointegration relationship, as index valuations are not tradeable assets, we can provide additional strength to this relationship by further imposing that index valuations also approximate the true fundamental value of the asset using a similar estimation function. More specifically, we assume that independent valuators have access to the same information set as investors, namely past index valuations and traded prices, as well as to new information revealed over the period from $t-1$ to t. We allow those agents to process the information differently by introducing a coefficient ω_t^I that is specific to the valuators and allows them to weigh past price and valuation information differently from investors. The intensity at which valuators incorporate information originating from the other agent is ω_t^I and can also dynamically change over time. Likewise, the term ε_t^I allows them to process new information differently. Here as well, we assume those innovations to have zero mean and to be uncorrelated to past prices.

Following the same reasoning as for traded prices, we can substitute equation (2-10) in equation (2-8) to define the process of independent valuations as a function of the available information set. Deducting p_{t-1}^I on each side of equation (2-13) allows here as well to shed light on the error correction relationship that independent valuators enforce with intensity ω_t^I.

$$p_t^I = (1-\omega_t^I)\, p_{t-1}^I + \omega_t^I\, p_{t-1}^T + \varepsilon_t^I \quad (2\text{-}13)$$

$$\Delta p_t^I = \omega_t^I\, D_{t-1} + \varepsilon_t^I \quad (2\text{-}14)$$

So far we have shed light on how the sharing of information affects both traded prices and independent valuations, in respectively equations (2-11) and (2-13). We have also characterized how price discrepancies across pricing sources arise and build up over time, in equation (2-5), as well as by which mechanisms those errors are corrected, in respectively equations (2-12) and (2-14).

Another decomposition of returns, for both the traded prices and the independent valuations, is useful to consider and will serve as the basis for our empirical analysis in the remainder of this paper. To retrieve this alternative definition, we can simply take the difference in the log prices defined in equations (2-11) and (2-13) and their lagged versions. We then obtain the following decomposition of returns:

$$\Delta p_t^T = \Delta p_{t-1}^I + \omega_t^T \Delta D_{t-1} + \Delta\omega_t^T D_{t-2} + \Delta\varepsilon_t^T \quad (2\text{-}15)$$

$$\Delta p_t^I = \Delta p_{t-1}^I + \omega_t^I \Delta D_{t-1} + \Delta\omega_t^I D_{t-2} + \Delta\varepsilon_t^I \quad (2\text{-}16)$$

Both processes are similar with the same set of independent variables driving the returns of both the investors and the independent valuators. The first term on the right hand side is the previous month return in index prices. The implies that in the absence of price distortions and news, investors incorporate with delay into traded prices the information content of index valuations. This leads to positive cross-autocorrelation in returns between transaction price returns and past index returns. Likewise, valuation increments are serially correlated. The second term captures the contribution from the change in price distortions. Note the dependence on the investors and the independent valuators preferences, captured by respectively ω_t^T and ω_t^I, for the directionality and the degree to which they incorporate price distortions into prices, which might potentially differ. Finally, the third term reflects the contribution to returns from the marginal change in the agents' intensity to process the distortions.

Note that the above return decompositions shed light on the influence on asset prices of both the past levels and past changes in distortions. We will henceforth conveniently refer to any of those, or both, as 'pricing distortions'.

2.2. Well-behaved system

In our system both agents are assumed to be rational in the sense that they are concerned by the deviations of their transaction prices and index valuations away from fundamentals. This implies that at least one agent aims at correcting price distortions and that none of them exhibits an irrational behavior that would contribute to further increase the difference between traded prices and index valuations. Such behaviors ensure that the system is well-behaved and that distortions correct over time, i.e., that index valuations and transaction prices converge. Our assumptions effectively impose restrictions on the distribution of parameter values for the intensities ω_t^T and ω_t^I. To understand what those agent's behavior assumptions impose in terms of intensity, it is useful to consider equations (2-12) and (2-14).

To ensure a well-behaved system, investors should, on average, at worst disregard any price distortion and a best contribute to the resolution of those differences by setting limits on the price at which they are willing to trade. Likewise, valuators should, on average, at worst disregard those distortions and at best adjust their valuations. This implies that the price distortions should contribute to the reversal in at least one of the pricing source. This is one of the key implications of this model.

Such behaviors impose bounds on the expected value of the parameter values of the intensities ω_t^T and ω_t^I. Indeed, investors can disregard deviations by setting their intensity to 1 or contribute to the resolution of the distortions by imposing a lower than 1 intensity. This thus defines the upper bound of their intensities. At the same time, investors could overreact in their aim to close the gap between traded prices and index valuations, this would lead to a negative intensity. Would the intensity be below -1, the process would be explosive and the prices would not converge. We thus need to impose that the lower boundaries for the investors' intensities is set at -1, such that:

$$E[\omega_t^T] \in [-1,1] \tag{2-17}$$

Likewise, valuators can disregard distortions by setting their intensities to 0 or contribute to the resolution of the deviations by imposing a positive intensity. The latter results from the fact that distortions are here expressed from the view point of the investor. Any intensities above 1 would indicate that valuators overreact in their adjustment and a value of above 2 would lead valuations to never converge. We thus have to impose the following restriction on the expected parameter values of the valuators' intensities:

$$E[\omega_t^I] \in [0,2] \tag{2-18}$$

Note finally that as at least one of the agents needs to contribute to the convergence, both parties cannot on average set their intensities at the boundaries. Moreover, note that setting boundaries for the expected parameters values is less restrictive that forcing agent to continuously work toward a convergence of the prices. Temporary deviations from those bounds can easily be motivated when the arrival of news surprises randomly supports the price discrepancy.

2.3. Model implications

To summarize, our model introduces an additional agent in the traditional microstructure models, namely the independent valuator whose only role is to provide estimates of the unknown fundamental value of securities. The opacity and illiquidity of the market forces both investors and valuators to rely on a limited public information set containing past traded prices and index valuations. As they share with each other noisy information about their past estimates of the asset fundamental value, it introduces some serial dependence structure in returns, that takes the form of both serial auto- and cross-correlation between return series. In our model, distortions across pricing sources emanates from both trading frictions and valuation errors. Those are processed into valuations and transaction prices at a rate that is agent specific. Under some reasonable assumptions about the rationality of agents, agents adjust the price at which they are willing to trade and/or their valuations in a way as to resolve pricing source deviations such that those ultimately converge.

By focusing on the interaction between valuators and investors, this model provides valuable insights on the relationship between traded prices and index valuations. While the literature has documented the presence of large deviations between transaction prices and composite valuations[i], as well as of a

[i] E.g., Jankowitsch et al. (2011) find deviations TRACE prices and composite valuations, from both Markit and Bloomberg, that are much larger than the bid-ask spread. They attribute those to trading frictions originating from the search costs faced by investors demanding liquidity and the inventory costs dealer charge for bearing price risk.

significant serial dependence structure in returns across pricing sources[j], little attention has been devoted to the dynamics of those distortions and their impact on asset prices. This model aim at partially filling this gap and provides a theoretical framework to understand some empirical findings documented in the literature as well as new insights presented in this paper.

The first implication of our model is that distortions across pricing sources is a key factor driving the contiguous future corporate bond returns. If agents jointly or independently force prices to converge, this leads to reversal in returns. In our model, this dynamic is distinct from the microstructure noise that can also be a source of serial correlation. The second insight is that this convergence does not have to occur solely in transaction prices but can also take place within index valuations. This results from the limited information set available to valuators, which forces them to rely on past transaction prices to estimate the unknown fundamental asset value.

This model elegantly offers concrete testable hypothesis that we will explore in the remainder of this paper. First and foremost, are agents concerned by deviation between valuation and traded prices? Do both investors and valuators care about those distortions? At which speed do agents aim at correcting those distortions? How important are those distortions in explaining the return dependence structure relative to other explanatory variables documented in the microstructure literature that aim at capturing the risks and costs that liquidity providers face? Do those deviations explain reversals in returns and the implementation shortfall of reversal strategies?

3. Data and methodology

3.1. Enhanced return methodology

To test the above hypotheses, we propose an improved methodology to investigate the 'harvestable' premium associated with predictors in illiquid markets. It palliates to a few shortcomings present in various approaches put forward in the literature that uses TRACE to compute bond returns, and is generalizable to any panel dataset with sparse price information due to infrequent trading.

Our approach is very simple. In a few words, it preserves the literature standard of using end-of-month prices to measure return-based signals but uses beginning-of-month prices for measuring the performance of return-based predictors.

This methodology leverages on a large body of literature that aims at cleaning the set of transactions reported in TRACE and at measuring corporate bond returns out of those. More specifically, we follow the Dick-Nielsen (2009, 2014) to clean the TRACE database and to select the subset of relevant

[j] E.g., Andreani et al. (2023) provide empirical evidence of a cross-autocorrelation structure between TRACE returns and index prices. They associate those correlation with the illiquidity of corporate bond markets.

transactions. Based on those, we construct volume-weighted average daily corporate bond prices in line with Bessembinder et al. (2008).[k] Finally, we follow the literature[l] and set a maximum search window around a common evaluation moment, fixed at 5 business days[m]. This allows us to define the end-of-month price as the last available price in the search window [T-4, T] and the beginning-of-month price as the first available price in the interval [T+1, T+5], where T is set to be the last business day of the month. We assign the time t with a superscript e or b, to indicate whether prices or returns are taken from the end- or beginning-of-month windows, respectively. This approach allows us to cleanly dissociate the measurement of return-based signals, evaluated on prices at t^e, the moment the trading decision is made (exactly at month end, t), and, their implementation, which then takes place in prices at t^b. More importantly, the difference between prices at t^e and t^b also allows us to measure precisely the implementation shortfall of the strategy, for which we denote this window as t^i. Figure 1 below illustrates what the proposed methodology entails for the selection of transactions within both the end-of-month (EOM) and beginning-of-month (BOM) search windows and the resulting implementation shortfall, where S, T and U refers to consecutive end of months and T+/-d corresponds to respectively the end-of-month date T plus or minus d business days.

While there is broad consensus in the literature on the how to clean the TRACE dataset, we observe large divergences in signal and return measurement across studies that relies on those transactions for that purpose. Below, we shed lights on some limitations that we have identified across various studies, with the aim to provide new standards for future researchers using not only this dataset but any dataset with infrequent pricing information. Our methodology brings forward a number of simple enhancements.[n]

First, it ensures that the strategy is implementable both at the individual bond level, by imposing an implementation lag[o], as well as across bonds (i.e. within a portfolio). This is a requirement for any strategy relying on full set of cross-sectional information to be implementable.[p] This guarantee is provided by a unique and common evaluation moment for the cross-section of bonds, in our case the

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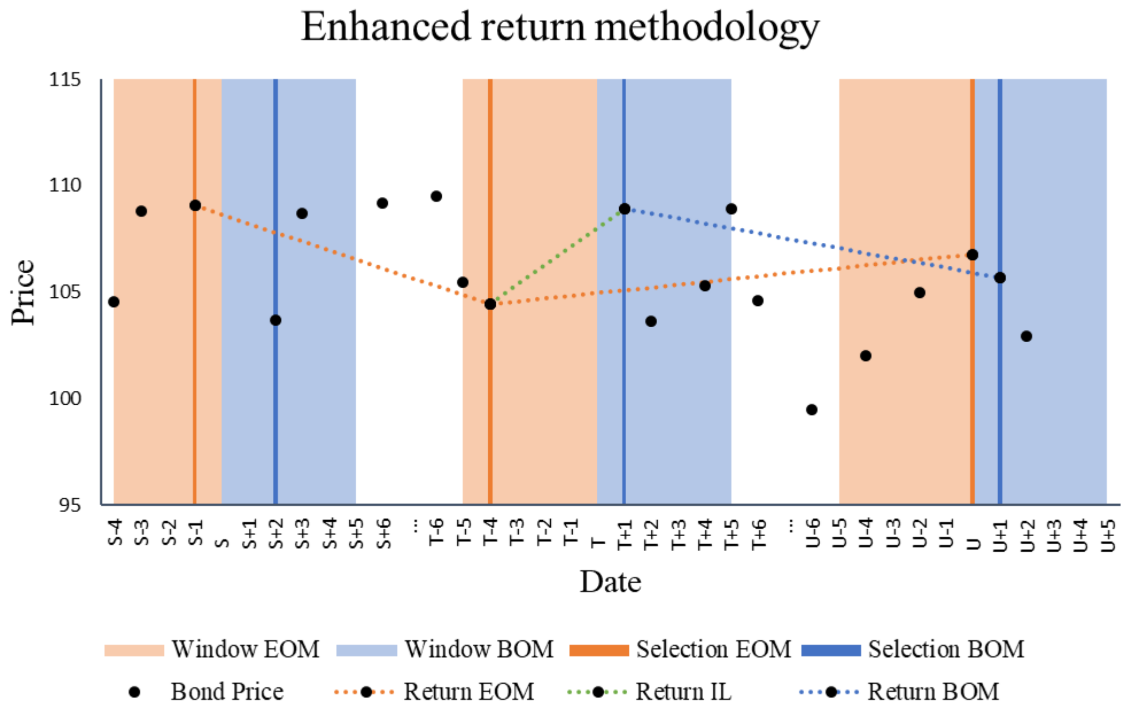
[k] To tackle concerns raised in Bessembinder et al. (2008) about the influence of small retail trades on the results, we will as a robustness check exclude all transactions below 100.000 USD.
[l] See e.g. Chordia et al. (2017) or Bai and al. (2019)
[m] Our results are robust to an increase in the search window, which leads to an increase in the number of observations especially in December and January months.
[n] In Appendix A.2, we provide a discussion on the limitations of the proposed methodology and the associated implications. The ambition is both to provide guidance for future work relying on sparse transaction datasets and to shed light on potential avenues of research.
[o] In the rest of this paper, we will interchangeably use the term trade lag, trade gap or implementation lag to refer to the time distance between the last observed transaction at t^e and t^b. We follow Bai and al. (2019) and search for the last/first transactions within a 5 business days window before/after the turn of the month to identify the exact day trading dates of t^e and t^b. This implies the length of the implementation lag differs per bond and depends on the availability of transactions in the TRACE sample, ranging between 1 and 9 business days.
[p] This is an implicit assumption in the sorting portfolio analysis that has long been standard in the literature to evaluate the performance of predictors, as well as their significance and monotonicity.

end-of-month, where all information is known. While Dickerson et al. (2023b) enforce an implementation lag by measuring the signal at least 1 day before the last trade of the month, the strategy does not impose a common evaluation moment. Specifically, an issue arises when the securities' implementation lag don't overlap, which renders any cross-sectional strategy unimplementable.

Figure 1



To illustrate this limitation, let's assume for simplicity the case of two securities for which we can observe two prices around the end-of-month, denoted T. Bond A has his last two trades on date T-1 and T, the signal can thus be measured on T-1 and the position taken at the price observed on T. Bond B has his last two trades on T-3 and T-2, the signal can thus be measured on T-3 and the position taken at the price observed on T-2. From this example, we can see that an investor cannot evaluate A against B and implement a cross-sectional view, as the bonds' implementation lags do not overlap. Indeed, on T-2 she only has information on B, while on T-1 she has information on A and B but cannot transact in B anymore. We solve this issue by separating measurement and implementation around a fixed moment, which we conveniently set at the turn of the month to keep return-based signal definitions in-line with the standard definition in the literature.[q] While the proposed methodology provides additional rigor to the evaluation framework by implicitly offering a conceptual enhancement over the Dickerson et al. (2023b) approach, it is unlikely to significantly affect their results as we reach similar conclusions on the impact of controlling for an implementation lag to reversal measured in TRACE.

[q] See Appendix A.2.1 for an illustration.

Another benefit of the proposed methodology is that it guarantees that the returns used in the performance evaluation can be chain-linked and capture the full information content of the bond price timeseries, thus preserving its distributional properties. Many studies have chosen to compute calendar month returns out of the first and last available trade within that month, often to increase coverage. Amongst other, Bartram et al. (2023) follows such an approach and Bai and al. (2019) use the first available trade of the month when no transaction occurred during the search window of the prior month. Such an approach suffers a few limitations. First, by discarding the information between the end of the prior month and the beginning of a month, it forgoes information about price developments within that window and only capture a fraction of the timeseries of prices. As a result, the chain-linking of returns cannot ensure the exact replication of the timeseries of prices. Second, discarding price information is likely to bias the estimation of moments for every individual securities, with a larger impact on the most illiquid securities. While the measurement of this bias and its impact on prior studies is beyond the scope of this paper, acknowledging this pitfall should help in providing guidance for future research.

A last benefit of this approach is that there is no need to project clean prices into the future as we are not bound to calendar month definitions. Returns are conditioned on the availability of trades and the common evaluation moment is guaranteed by the overlapping implementation lags across bonds. E.g., this relieves us from having to rely on the Martingale hypothesis, as invoked in Bartram et al. (2023). Acknowledging the fact that both the government bond yield curve and the issuer spread curve are on average not flat and that bond prices are mechanically pulled to par as time passes, the Martingale hypothesis might not hold empirically. Moreover, such adjustment have as side effects for return-based signals that it increases the contribution of the accrued interest, which benefits most to the high coupon bonds, thus potentially introducing a selection bias.

To compute returns based on source S over window $t^* \in \{t^e, t^i, t^b\}$, we follow the standard approach to calculate the bond i total return as the contribution from changes in the clean price P_{i,t^*}^S augmented by any accrued interest AI_{i,t^*}^S and received cashflow CF_{i,t^*}^S, over the relevant window t^*. Returns are computed for each pricing source and for consistency are always indexed to the timestamp of the last observed price. Note also that as a result of those price series using different windows, the AI and CF are indexed respectively to the price series and window definition.

$$R_{i,t^*}^S = \frac{P_{i,t^*}^S + AI_{i,t^*}^S + CF_{i,t^*}^S}{P_{i,t^*-1}^S + AI_{i,t^*-1}^S} - 1 \tag{3-1}$$

From the above definition, we understand that a strategy using as return-based predictor R_{i,t^e}^S is using information up to t^e of [T-4, T] in month t where T defines the last trading day of month t. It then invest based on that information in month $t+1$ and executes at the first available price in t^b of [T+1, T+5] in month $t+1$. The return in between those measurement and trading moments is identified by R_{i,t^i+1}^S

and the return earned by the strategy over the next monthly holding horizon is R^S_{i,t^b+1}. This does not only captures the return earned over month $t + 1$ but also including the first days of month $t + 2$, up until the position can be unwound at the beginning of that month. As we will discuss later, focusing on holding horizons has several advantages over the restrictive calendar month definitions.

3.2. Corporate bond data

In this paper, we study an extensive sample of USD denominated corporate bonds between July 2002 and December 2022 and analyze the intersection between two widely used datasets, namely the Enhanced TRACE database (henceforth $TRACE$) from FINRA and the daily Bloomberg (also BBG) database. Specifically, we focus on the constituents of the Bloomberg US Aggregate Corporate Investment Grade (IG) index and the Bloomberg US Corporate High Yield (HY) index. These indices cover a broad cross-section of publicly issued USD-denominated corporate bonds. By focusing on index constituents, we omit small and illiquid corporate bond issues.

To clean the record of transactions reported in TRACE, we leverage on a large body of literature. More specifically, we follow Dick-Nielsen (2009, 2014) to clean the TRACE database and to select the subset of relevant transactions. Based on those, we construct volume-weighted average daily corporate bond prices in line with Bessembinder et al. (2008).

The Bloomberg database contains information about index valuations, i.e. index prices, as well as bond issue characteristics such as its rating, time-to-maturity, amount outstanding, the bond age, the option-adjusted spread (OAS) and option-adjusted spread duration (OASD). The rating corresponds to the numerical value associated with the middle of the Moody's, S&P and Fitch ratings when all three are available, or the worst rating otherwise, where a rating of 1 corresponds to a AAA middle rating while a value of 18 corresponds to a CCC rating. We use the same cleaning procedure for the BBG dataset as for the $TRACE$ one (e.g., on minimum and maximum price exclusions). It is important to note that our sample is bounded by index membership rules, which impose amongst other things a minimum issue size and a minimum time-to-maturity.

To ensure no asynchronicity affects our comparison of returns across datasets, we match the measurement/trading dates in both $TRACE$ and Bloomberg. To define our final sample, we thus require that an index valuation from Bloomberg and a volume-weighted average price from $TRACE$ are both available, together with the bond characteristics mentioned above. Moreover, as the first leg of an end-of-month return is undefined in July 2002, we lose a month of observations. Likewise, the last leg of a beginning-of-month return is undefined in December 2022, and we lose another month of observations. As a result, our sample of returns is defined between August 2002 and November 2022.

Table 1: Descriptive statistics

This table reports the sample descriptive statistics for the sample period going from August 2002 to November 2022, when the sample is restricted to the availability of control variables. Statistics are reported for all returns used for evaluation of the model. For each of those, the table shows the number of bond-month observation (N) in the sample, the sample average (Mean) and median (Median), the sample standard deviation (SD), as well as various percentile values. The returns are expressed in percentage terms (%). Rating (RAT) corresponds to the numerical value associated with the middle of the Moody's, S&P and Fitch ratings when all three are available, or the worst rating otherwise, where a rating of 1 corresponds to a AAA middle rating while a value of 18 corresponds to a CCC rating. Maturities (MAT) are reported in years. The bond issue size (AO), the trading volumes over the last month (VOL) and the dealer inventory change over the last month (INV) are reported in millions USD. The imputed round-trip costs (IRTC) and bid-ask spreads (BAS) are expressed as a percentage of par value. Spreads (OAS) and the illiquidity measure (γ) are expressed in basis points.

					Percentiles					
	N	**Mean**	**Median**	**SD**	**1st**	**5th**	**25th**	**75th**	**95th**	**99th**
R^T_{i,t^e}	735,481	0.38	0.31	3.81	-9.63	-3.92	-0.54	1.37	4.65	9.95
R^T_{i,t^i}	735,481	-0.01	0.02	1.62	-3.74	-1.73	-0.31	0.35	1.46	3.22
R^T_{i,t^b}	735,481	0.39	0.31	3.85	-9.65	-3.85	-0.51	1.35	4.62	10.28
R^B_{i,t^e}	735,481	0.39	0.32	3.76	-9.68	-3.80	-0.45	1.32	4.52	9.88
R^B_{i,t^i}	735,481	0.00	0.02	0.96	-2.77	-1.11	-0.19	0.23	1.04	2.33
R^B_{i,t^b}	735,481	0.40	0.32	3.78	-9.61	-3.78	-0.46	1.32	4.59	10.31
OAS	735,481	223	138	347	18	37	80	249	641	1,451
OASD	735,481	6.16	4.87	4.35	0.81	1.38	2.98	7.67	15.53	18.13
DTS	735,481	1,265	796	1,372	28	74	302	1,823	3,817	6,280
Rating	735,481	8.74	8.00	3.53	1	4	6	10	16	18
Maturity	735,481	9.19	6.09	8.70	1.20	1.62	3.59	9.50	28.26	29.96
Amt. Out.	735,481	846	600	695	199	250	450	1,000	2,250	3,500
Age	735,481	3.94	3.02	3.55	0.14	0.36	1.44	5.42	10.22	18.08
IRTC	735,481	0.40	0.29	1.30	0.03	0.05	0.13	0.54	1.08	1.60
BIAS	735,481	0.50	0.08	12.36	0.00	0.00	0.02	0.28	1.73	5.15
γ	735,481	0.61	0.05	21.37	-0.61	-0.08	0.01	0.22	1.45	6.20
VOL	735,481	73	36	142	1	4	15	82	244	557
FREQ	735,481	111	68	153	12	19	38	130	334	682
INV	735,481	0.01	0.07	53.99	-49.61	-21.61	-4.19	4.54	22.11	49.07

By construction, our sample inherently focuses on the most liquid bonds but this preference does not diminishes its relevance. As of November 2022, our sample captures about 64% of the 6.9 trillion USD corporate debt outstanding and over 92% of the total traded volume reported in $TRACE$ over that same month. To ensure no asynchronicity affects our comparison of returns across datasets, we match the measurement/trading dates in both TRACE and Bloomberg. To define our final sample, we thus require that an index valuation from Bloomberg and a volume-weighted average price from TRACE are both available, together with the bond characteristics mentioned above. Moreover, as the first leg of an end-of-month return is undefined in July 2002, we lose a month of observations. Likewise, the last leg of a beginning-of-month return is undefined in December 2022, and we lose another month of observations. As a result, our sample of returns is defined between August 2002 and November 2022.

Table 1 above summarizes our sample by reporting the panel summary statistics for the various returns defined in the previous section. We see from this table that the sample contains 735,481 bond-month observations. The first row reports the key summary statistics for the bond total return over the end-of-month window t^e when computed from reported $TRACE$ transactions. On average, bonds have earned a total return of 38bps per month over our sample period, with a standard deviation of 3.81%. We observe from the percentiles the very large dispersion between the 1st and 99th percentiles of about 20%. The second row reports the returns over the implementation lag window. We see that those returns are of a much lower magnitude, which can be associated with the shorter measurement window. Note that the standard deviation of implementation lag return for TRACE is larger compared to that of Bloomberg, which indicates the impact of trading frictions. Note that Bloomberg prices are valued at the bid. The third row captures the return measured over the beginning-of-month window t^b. In line with expectations, those are very similar to those measured over t^e. The next three rows report the same results for returns measured from the Bloomberg index valuations. Overall the returns over both dataset are very similar on a monthly frequency.

3.3. Control variables

In section 4 and 5, we take our model to the data. In order to isolate the effects of pricing distortions from other factors known to affect corporate bond returns, we rely on an extensive set of control variables derived from both the asset pricing and market microstructure literatures.

To start with, we control for the risk of bonds. We use standard bond characteristics commonly associated with both their exposure to common risk factors and their idiosyncratic risk. We use the option-adjusted spread (OAS), the option-adjusted spread duration ($OASD$), the duration-times-spread (DTS) measure of Ben Dor et al. (2007)[r], the bond rating and maturity.

In our model, price distortions arise from the presence of market microstructure noise and valuations errors. It is thus important in our analysis to control for trading frictions. Following the market microstructure literature, those frictions present in 'realized' transaction prices emanate from the presence of a liquidity provider that accommodates the investor's demand for immediacy and requires a compensation for the various risk and costs she faces, namely the search costs, the inventory risk and the risk of information asymmetry.

Following the literature, we assume that search costs are higher when bonds are more illiquid and translate into higher transaction costs. We thus control for the illiquidity of corporate bonds, a key feature that characterizes the market in our model, with the autocovariance in bond price changes (γ) from Bao et al. (2011) and also consider standard bond characteristics associated with liquidity such as age, as suggested by Sarig and Warga (1989), or log issue size following Garbade and Silber (1976). To

[r] Ben Dor et al. (2007) show that the interaction between OAS and OASD captures the sensitivity to relative changes in spreads and is a better measure of the exposure to systematic changes in spreads.

control for transaction costs, we consider the imputed round trip cost ($IRTC$) of Feldhütter (2012) as well as bid-ask bias ($BIAS$) estimate of Blume and Stambaugh (1983), averaged over the last month.

While controlling for search costs is standard in the corporate bond asset pricing literature, the inventory and information asymmetry risk are often omitted. The first reason is that search frictions are usually perceived as the most prominent market microstructure noise affecting the pricing of bonds[s]. The second reason is that frictions originating from inventory and information asymmetry risks are difficult to measure[t]. Nevertheless, those frictions, especially those originating from inventory risk have been shown to have a large impact on the functioning of markets. Bessembinder et al. (2018) associate the capital committed by dealers to the order imbalances[u] and stress its relevance for the provision of liquidity, in particular in the presence of high search cost and the infrequent arrival of counterparties. They investigate the evolution of capital committed by dealers over time and document that for most transaction reported in TRACE dealers act as 'principal' investors whereby bonds are taken in inventory. Goldstein and Hotchkiss (2020) show that dealers' capital commitment varies with the risk and liquidity of securities, a finding that is consistent with a conscious management of inventory risk. Beyond the difficulty to measure the different frictions that affect the provision of liquidity, one additional complication in their identification is that those various costs are endogenously related. E.g., a lower capital commitment by dealer could also be associated with a greater information asymmetry risk. Hendershott et al. (2017) find that order imbalances are negatively associated with future bond returns and argue this is consistent with order flow causing price pressures that profit informed investors. In Ivashchenko (2022) the dealer willingness to commit capital is driven by the information content of trades.

In light of the relevance of inventory and information asymmetry risks, and despite the measurement and identification challenges, we attempt at controlling those by leveraging on measures proposed in the literature. For inventory risk, we rely on two metrics that aim at capturing the aggregate dealer inventory imbalances.[v] First, in the spirit of Bessembinder et al. (2018), we measure the inventory change (INV) over the last month as the net dealer buys, which are thus indicative of both the magnitude

[s] Duffie and al. (2005,2007) introduce a search and bargaining model in which transaction costs increase with the difficulty in finding a counterparty, i.e. they are inversely related to the search intensities in the model. Friewald and Nagler (2020) show that search and bargaining frictions have large explanatory power for the cross section of yield spread, in line with the predictions of Randall (2015) and Duffie and al. (2005, 2007). They find that search and bargaining frictions better explain the variance in yield spread than those originating from inventory risk.

[t] See Friewald and Nagler (2020) for a discussion and recent developments in the measurement of search and bargaining frictions.

[u] To capture the willingness of dealers to trade on a principal basis by using their own capital to absorb customer order imbalance, they define various measures of the changes in inventory, including a cumulative capital commitment over the past week with two variants that controls (or not) for the trading activity over that estimation window.

[v] The FINRA Enhanced TRACE database does not contain individual dealer identifiers. We thus define proxies of the aggregate dealer inventory risk per bond, which implicitly cumulates the risk across all dealers.

and the directionality of the imbalances and the capital commitment by dealers. Second, following Hendershott et al. (2017), we use the order imbalance (IMB) measure which essentially scales the inventory change by the total traded volume over the measurement period.

To control for the information asymmetry risk, we follow the literature and assume that trading activity is first and foremost information driven. E.g. Stoll (1989) uses past trading volumes as a proxy for the amount of informed trading. We use three trade-based measures, namely total traded volume (VOL), the volume in proportion of the issue size ($VOLS$), as well as the total number of trades ($FREQ$) over the past month.

Given the high correlation between some of those control variables, we select a subset of those variables to avoid multicollinearity issues in our analyses. When doing so, we confirm the robustness of our results by replacing the chosen correlated variables by its alternative in a second control group and report the results in the Internet Appendix in Section 1IA.1.

Table 1 also reports the summary statistics for all control variables identified above. Looking first at the risk controls, we see that the bonds in our sample exhibit an average spread of 223 bps and an average spread duration of 6.16, with large panel variations that elude to the large cross-sectional variation in bond rating and maturities. The interaction between OAS and OASD, i.e., the DTS, has a median value of 1,265 and percentiles range from 28 to 6,280 illustrating the large dispersion in risk in our panel data. We find that the median middle rating in our sample is BBB+ (equivalent to a middle rating value of 8), while the rating distribution goes from AAA to CCC. The median maturity is just above 6 years and ranges between 1 and 30 years.

Turning towards the various measures of illiquidity, we see that the median issue size is 600 million USD, and ranges between 200 million USD and 3.5 billion USD. The bond age is on average 3.94 years and ranges between 1 month and 18 years. We understand from the last two characteristics that although our sample focuses on the most liquid bonds, there is a large cross-sectional variation in the degree of liquidity. Next to that, we report two measures of transaction costs, the imputed round-trip transaction cost (IRTC) and the bid-ask spread (BAS), expressed in percentages of face value. The average IRTC is 40 bps and ranges between 3 bps to 160 bps. The bid-ask bias (BIAS) is a variance term that aims at capturing the contribution to return originating from the bid-ask bounce and is expressed in basis points. On average the BIAS is 0.50 bps and ranges from 0 bps to 515 bps. Finally, the illiquidity measure (γ) from Bao et al. (2011), expressed in basis points, shows with a mean of 0.61 bps that on average corporate bond returns exhibit negative serial correlation.

Focusing on the selected controls for the information asymmetry risk, we find that corporate bonds in our sample exhibit an average monthly trading volume of 73 million USD, which corresponds to about

9% of the average bond issue size. On average, bonds are traded about 111 times over a month and display a wide variation with as little as 12 times per month up to 682 times.

Finally, the inventory risk measures show that on average dealers do not carry inventory, with INV displaying a mean of 10.000 USD of net exposure accumulated over the past. We observe substantial variations in the exposures of dealers. Indeed, we see that the absolute net exposure can rise up to 49 million USD.

3.4. Methodology

The model developed in Section 2 suggests that pricing distortions across pricing sources are a key determinant of future corporate bond returns. Specifically, equations (2-12) and (2-14) relate future returns to the past level of the distance between the traded price in TRACE and the index valuation in Bloomberg, for respectively TRACE and Bloomberg returns. Moreover, equations (2-15) and (2-16) propose an alternative specification in which the future returns are explained by a lagged distortion level and its last change, for respectively TRACE and Bloomberg returns.

To investigate the cross-sectional relationship between future corporate bond returns and the explanatory variables put forward in our model, we leverage on the Fama-MacBeth (1973) methodology and run cross-sectional regressions between the future returns defined in Section 3.1 and the different measures of pricing distortions mentioned above. Those regressions are augmented by a number of control variables defined in Section 3.3. The regressions takes the following general form:

$$R_{i,t^*+1}^{S} = \alpha + \sum_{k=1}^{K} \beta_{k,t} Var_{i,t}^{k} + \sum_{l=K+1}^{K+L} \beta_{l,t} X_{i,t}^{l-K} + \varepsilon_{i,t+1} \tag{3-2}$$

R_{i,t^*+1}^{S} is any next-period return, $Var_{i,t}^{k}$ corresponds to one of the K explanatory variable put forward by the model, and $X_{i,t}^{l-K}$ is one of the control variable identified in the previous section. We report the timeseries average of the slope coefficients from those regressions, the Newey-West adjusted *t*-statistics and the average adjusted R^2 for various nested versions of this general specification.

4. Setting the stage

The presence of reversals in returns in corporate bond markets is well-established in the corporate bond literature. A first stream in this literature focuses directly on the identification and pricing of those reversals. Amongst others, Khang and King (2004) document strong short- and intermediate-term return reversals that are stronger in the early part of their sample. The authors relate the decrease in the reversal premium over time to the rise in liquidity and argue this sensitivity is consistent with the dealer inventory cost models. Chordia et al. (2017) find that past month returns significantly negatively explains future month returns and associate those dynamics with bond illiquidity. Bai et al. (2019), in their now retracted paper[w], find that one-month lagged bond returns have significant explanatory power for the cross-section of corporate bonds returns. While it is by far the strongest variable explaining the cross-sectional dispersion, they find that exposure to a reversal factor is not rewarded. Bali et al. (2021) identify economically and statistically significant long-term reversal patterns in corporate bonds. They find that those reversals are associated with the credit risk of bonds, their illiquidity, as well as to investors' constraints. More recently, Dickerson et al. (2023b) critically evaluate return-based anomalies and conclude that most of them do not survive once accounting for an implementation lag. Their results suggest that most of the return of those anomalies, including the short-term reversal, are earned over the implementation window and thus cannot be earned by investors in practice.

Another stream of literature relates to or is a derivative of the literature on market microstructure and builds on the implicit presence of reversal to address research questions that do not pertain directly to reversals. For example, Bao et al. (2011) uses the serial correlation in bond returns to estimate the illiquidity of bonds. Ivashchenko (2022) investigate dealers' response to the risk of information asymmetry by focusing on how the magnitude of price reversals changes in high and low volume environments. Andreani et al. (2023) rely on the serial correlation in bond returns to estimate the level of microstructure noise across different pricing sources.

Before diving into the core of our empirical investigation, it is important to illustrate some key empirical findings documented in the literature on short-term reversals. First, we investigate the robustness of the reversal factors across pricing sources and investment universes. Then, we assess the influence of imposing and implementation lag, using the enhanced return methodology proposed in Section 3.1, to corroborate the disappearance of the reversal factor premium after controlling for an implementation lag as documented in Dickerson et al. (2023b). Finally, we revisit the serial dependence structure across pricing sources identified by Andreani et al. (2023).

4.1. Reversal's robustness

In this section, we review the significance of past returns in explaining the cross-section of future returns using Fama-MacBeth regressions. To assess the robustness of the results, we evaluate the significance not only on the full sample, i.e. in the all-grade universe (AG), but also in the investment grade (IG) and high yield (HY) universes. This analysis is performed both using TRACE and Bloomberg as pricing source for both the signal measurement and the return evaluation.

[w] We find that those conclusions did not suffer from the issues identified by Dickerson et al. (2023b), that led to the retraction of their paper.

Table 2 reports the results when using TRACE or Bloomberg as the pricing source, without using an implementation lag in Panel A, evaluating using returns measured over t^e. The first specification (1) shows the main result documented in the literature. In the absence of an implementation lag, we find a negative coefficient on past returns. Specifications (2) and (3) perform the same cross-sectional regressions within respectively IG and HY. We see that the reversal factor documented in the literature is mostly present in IG but not significant in HY. The last three specifications perform the same analyses however changing the pricing source to Bloomberg index prices. Here, we find no reversal pattern, though a short-term momentum effect that predominantly stems from the HY market.

Panel B reports the results when imposing an implementation lag, evaluating returns over t^b. The table is in line with Dickerson et al. (2023b), which shows an absence of reversal in traded prices once accounting for an implementation lag. Consistent for both pricing sources, we find that in AG and HY markets past returns predict positively future returns, indicative of the presence of short-term momentum rather than reversal. In investment grade, there is no significant relationship between past and future returns.

Overall, we conclude that the reversal factor previously documented in the literature is not robust and specific to Investment Grade in transaction prices. Indeed, simply stressing the results on the universe definition or the pricing source leads to widely different conclusions. Those inconsistencies have so far remained undocumented in the literature and remind us of the influence of market segmentation in corporate bond markets and the importance to evaluate potential predictors separately in both IG and HY universes.

4.2. Dependence structure

To investigate the dependence structure across pricing source documented by Andreani et al. (2023), we introduce a simple return decomposition that aim at capturing the dynamics identified in our model and hopefully at shedding light on new insights with regards to the dependency structure across pricing sources. More specifically, for each pricing source S we decompose the returns R^S_{i,t^*} used for the signal measurement into two components being the return from the other pricing source and a differential term. This last term, that we denote R^D_{i,t^*}, follows from our model and aim at capturing the changes in pricing distortions over the measurement window.

$$R^T_{i,t^*} = R^D_{i,t^*} + R^B_{i,t^*} \tag{4-1}$$

It is important to mention that we are matching measurement/trading dates in both TRACE and Bloomberg which ensures no asynchronicity affect our analysis, when contrasting the returns of those different pricing sources.

Table 2

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022. The dependent variables are the future corporate bond returns measured both in of TRACE and Bloomberg. Results are displayed separately for All Grade (AG), Investment Grade (IG) and High Yield (HY) universes. The explanatory variables correspond to the short-term reversal signal. Panel A shows results without incorporating an implementation lag, i.e. future returns evaluated over t^e. Panel B includes an implementation lag to the explanatory variables, i.e. returns measured over t^b. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold.

Panel A: 'reversal' without implementation lag

Dependent return:	R^T_{i,t^e+1}			R^B_{i,t^e+1}		
Universe:	AG	IG	HY	AG	IG	HY
Constant	0.50	0.45	0.70	0.45	0.40	0.67
	3.83	***3.89***	***3.30***	***3.55***	***3.57***	***3.23***
R^T_{i,t^e}	-0.04	-0.13	-0.01			
	-1.96	***-5.06***	*-0.68*			
R^B_{i,t^e}				0.04	0.00	0.05
				2.31	*0.01*	***2.38***
R^2-adj	0.08	0.12	0.07	0.08	0.13	0.07
Bond-month obs	735,481	572,308	163,173	735,481	572,308	163,173

Panel B: 'reversal' with implementation lag

Dependent return:	R^T_{i,t^b+1}			R^B_{i,t^b+1}		
Universe:	AG	IG	HY	AG	IG	HY
constant	0.45	0.36	0.68	0.45	0.38	0.67
	3.60	***3.38***	***3.28***	***3.55***	***3.46***	***3.27***
R^T_{i,t^e}	0.04	0.03	0.04			
	2.25	*1.49*	***2.39***			
R^B_{i,t^e}				0.04	0.02	0.05
				2.17	*0.85*	***2.39***
R^2-adj	0.07	0.08	0.06	0.08	0.12	0.07
Bond-month obs	735,481	572,308	163,173	735,481	572,308	163,173

Equipped with those trivial rewriting of returns, we can now investigate how the decomposition of the short-term reversal signal, measured either from traded priced explains the cross-section of future corporate bond returns. Here, we evaluate future returns based on past month Bloomberg and differential returns, both with and without implementation lag.

In Table 3, the first specification (1) is the usual short-term reversal factor documented in the literature, which is based on TRACE transaction prices, uses returns measured over the past 1 month and earns the returns over the next 1 month, when no implementation lag is considered. The sole amendment we have brought to this standard setup is the decomposition of the past month returns according to equation (4-1). Note that this specification corresponds to a nested case of the reaction function of agents developed in Section 2 in equation (2-15). Comparing the results with specification (1) in Panel A of Table 2, the key insight is that the decomposition of the past month returns, to isolate the return associated with the change in pricing distortions across pricing sources, allows to identify that the reversal in traded prices exist as a result of differences in past month returns between pricing sources. The coefficient is negative at -0.29 and has a significant t-statistic of -16.22. It is interesting to see that the cross-autocorrelation is positive, suggesting short-term momentum, although it is not statistically significant.

Specification (2) regresses the index returns on past Bloomberg returns and changes in pricing distortions, according to the equations (2-16). A few interesting insights emerge from this regression. The first one is that index prices are influenced by past pricing distortions but have an opposite sign compared to the sensitivity of traded returns. This association is highly significant. A positive coefficient on R^D_{i,t^e} suggests Bloomberg prices converge towards TRACE prices and should thus be interpreted as a source of reversal. It is interesting to compare the statistical significance of the coefficients associated with the pricing distortions in specifications (1) versus (2). The lower significance for index returns, in specification (2), suggests that valuators process the distortions with lower intensity than investors. Another interpretation is that the valuation errors are of lower magnitude compared to trading frictions embedded in traded prices, and that each agent aims at correcting the fraction of the distortions that he associates to his own perturbation. While this is not a behavior explicitly modelled in our framework, this finding is consistent with the literature and the notion that transaction prices are most affected by trading frictions. E.g., Andreani et al. (2023) argue that traded prices are contaminated by microstructure effects to a much larger extent than index prices and as such are of lower quality and relevance for researchers.

Table 3: Revisiting short-term reversals in the presence of distortions across pricing sources
This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the future corporate bond returns from both TRACE and Bloomberg in the absence of an implementation lag, and after controlling for an implementation lag using beginning-of-month return series. The explanatory variables corresponds to the decomposition of the short-term reversal signal measured from either from traded priced, according to equation (4.2). The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold.

Specification: **Dependent return:**	(1) R^T_{i,t^e+1}	(2) R^B_{i,t^e+1}	(3) R^T_{i,t^b+1}	(4) R^B_{i,t^b+1}
constant	0.46	0.44	0.44	0.45
	3.72	***3.55***	***3.60***	***3.56***
R^B_{i,t^e}	0.03	0.06	0.05	0.05
	1.25	***2.96***	***2.33***	***2.49***
R^D_{i,t^e}	-0.29	0.17	0.01	0.09
	-16.22	***9.59***	*0.71*	***6.14***
R^2	0.11	0.09	0.08	0.09
Bond-month obs	735,481	735,481	735,481	735,481

The second interesting finding of specification (2) is the statistically significant positive serial correlation on past returns.[x] This result is in line with the findings from Sections 4.1. Moreover,

[x] We show in Appendix that those results hold irrespective the choice of pricing source as explanatory variable. Indeed, the coefficient values are the same in both specifications, when regressing on past TRACE or Bloomberg returns, supporting further the idea that both series are cointegrated and contain the same information, after controlling for pricing distortions.

comparing specifications (1) and (2), the stronger and significant (cross-) serial correlation suggests that index prices incorporate least swiftly all relevant market information than transaction prices do. This result differs from Andreani et al. (2023) who find that index returns tend to lead transaction-based returns. To understand why we reach different conclusions, we need to highlight the differences in setup. The first difference is that we match trade dates across pricing sources to remove any noise from asynchronicity. Nevertheless, this is unlikely to be the driver behind the difference in conclusions as their analysis is robust to various measurement windows for transaction-based returns[y]. The second difference is that the authors use jointly the past returns from both pricing sources as independent variables. In the presence of multicollinearity among pricing source, this affects the sign and significance of the coefficients[z]. Separating the different components affecting future returns allows to remove issues associated with confounding factors and provides a more rigorous framework to investigate the lead-lag relationship across pricing sources. This allows us to confirm that traded prices are contaminated by microstructure effects to a much larger extent than index prices, but also to shed light on the diffusion of information across pricing sources by showing that evaluated prices incorporate valuable market information contained in traded prices with a delay.

Turning now to specifications (3) and (4), which perform the same analyses discussed above but with the inclusion of an implementation lag, we find that the significance of the pricing distortions is gone for traded prices, and reduces for index prices. Moreover, we see that the (cross-) serial correlation is significantly positive for all specifications. Those results are consistent with the previous section and corroborate the findings of Dickerson et al. (2023b) who find that reversal disappears after the inclusion of an implementation lag, leaving place instead to short-term momentum.

Overall, this initial incursion into the reversal factor suggests that pricing distortions across sources are a indeed key driver of short-term reversals. At the same time, those distortions seem to have limited explanatory power beyond the implementation lag window, suggesting they are mostly helpful in explaining the instantaneous price adjustment over that time frame, but less so at predicting future harvestable returns beyond that short horizon. Consistent with the implications of our model, we find first that price distortions have an impact on asset prices and second that the discrepancies across pricing sources are also being closed by the independent valuator. Those early results thus provide empirical support to the theoretical framework proposed in Section 2.

As pricing sources converge towards another by incorporating this information with different intensities, it is interesting to take a closer look at the empirical estimates of those intensities. Given equation (2-15), and assuming $\Delta\omega_t^T = 0$, specification (1) shows that ω_t^T is on average -0.29, a value

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[y] See Table 4 in Andreani et al. (2023).

[z] We confirm this intuition by running the regression with the same specification as Andreani et al. (2023) and find similar results as reported in their paper. Results are reported in Appendix.

consistent with a well-behaved system according to the boundaries defined in equation (2-17). This value has a few important interpretations. First, according to our definition of the valuation function of investors in equation (2-9), this value suggests that investors overweight the information content of past index valuations, which corroborates their anchoring to this important reference point. Second, this value allows to reflect on some of the assumptions made in the literature for return estimation. Specifically, as $\omega_t^T \neq 1$ the Martingale hypothesis in traded prices used in amongst others in Bartram et al. (2020) is rejected. Likewise the assumption in Jankowitsch et al. (2011) that the index prices captures the fundamental value of securities, while more in line with how investors weigh this information empirically, does not hold as $\omega_t^T \neq 0$.

Given equation (2-16), specification (2) shows that ω_t^I is on average 0.17, a value consistent with a well-behaved system according to the boundaries defined in equation (2-18). This confirms empirically that independent valuators also react to pricing distortions and contribute to their resolution. While our model does not impose such a behavior, this opportunity is available to them. Also interesting to note is that their contribution to the resolution is of lower magnitude than the one of investors.

Having set the stage, we now turn towards providing further insights on the implementation shortfall of reversal strategies and the persistence of those pricing distortions in explaining the cross-section of future corporate bond returns.

5. The drivers of reversal

As presented in Section 2.3, our model has implications for the cross-section of future corporate bonds returns. The first implication is that price distortions across pricing sources is a key factor driving the reversal in returns, as agents jointly or independently force prices to converge. The second insight is that this convergence does not have to occur solely in transaction prices but can also take place within index valuations. In this section, we investigate empirically whether agents are concerned by deviation between valuation and traded prices. More specifically, we assess the extent to which those deviations explain both the implementation shortfall of reversal strategies as well as the cross-section of future harvestable corporate bond returns. By evaluating the influence of the pricing distortions independently on each pricing source, we are able to analyze whether both investors and valuators care about those distortions and whether they aim at correcting those with the same intensity.

5.1. Implementation shortfall

Dickerson et al. (2023b) associate the disappearance of the reversal's returns, and other return-based strategies, to the presence of high market microstructure noise in corporate bond markets. While the authors suggest this finding might be related to the elevated bid-ask bias, they do not explicitly evaluate what effectively drives the implementation shortfall of those strategies.

Given the implication of our model for reversals, we aim in this section at filling this void. The first question we want to address is whether distortions across pricing sources can explain the sharp reversal in prices over the implementation lag window. Indeed, the intuitive reason behind the failure of reversals is that prices adjust instantaneously at the next trade, such that when the investor enters the position the expected return has just vanished. In the presence of distortions across pricing source, it is fair to expect that next time demand meets supply, the parties to the trade aim at correcting the mispricing. To illustrate this dynamic, let's assume party S is interested in selling a security. She starts searching for a counterparty and meets a potential buyer B. Once they meet, they start negotiating the price at which they would be both willing to complete the trade. The last information available to both parties is that the last trade occurred at a price p_{t-1}^{T} far above the last index valuation p_{t-1}^{I}. It is likely that B is interested in buying the security at price p_{t-1}^{I} while the seller would like to get p_{t-1}^{T}. Nevertheless, if both parties want to trade, they will agree on a price that aims at correcting the mispricing. In the absence of news, whether they trade closer to p_{t-1}^{I} or p_{t-1}^{T} depends on how both party evaluate the share of valuation errors relative to the amount of trading frictions that is currently embedded in this price discrepancy. The instantaneous price adjustment that takes place upon agreement should thus occur irrespective of the illiquidity of the bond or the time elapsed since the last trade. Moreover, distortions across pricing sources should be predictive of the instantaneous reversal that occurs over the implementation lag window.

As a side step, it is interesting to discuss who earns the return over the implementation lag window. Indeed, if the expected return of the reversal strategy has just vanished, some party must have earned that return. Assuming in our example that prices do correct, i.e. if $p_{t-1}^{I} < p_{t}^{T} < p_{t-1}^{T}$, then S makes a loss. In an economy with two agents, an investor that demands immediacy and a dealer providing liquidity, S can only trade with B. We then have to assume that B was also the counterparty to the trade at time $t-1$. Let's further assume that S is initiating all trades, thus demanding liquidity, and B acts as the dealer by providing liquidity. Assuming the fundamental value has not changed over the implementation window then the loss $p_{t}^{T} - p_{t-1}^{T}$ corresponds to the cost for demanding immediacy. Although the dealer did not hold the security over that period, he earns the opposite return which can thus be interpreted as the return for providing liquidity. Having acknowledged the nature of the returns over the implementation window, it is only a short step to make the parallel with the investor aiming at harvesting the returns of a reversal strategy. The implementation shortfall of the strategy is associated with his demand for immediacy.

Although we can characterize this return, we still do not know what drives the cost of immediacy. Our model suggests that pricing distortions should be a driver of the implementation shortfall. At the same time, the market microstructure literature identifies that liquidity providers require a compensation for facing search costs, inventory and information asymmetry risks. Thus, the second question we aim at addressing in this section is whether the potential explanatory power of pricing distortions is sensitive to the inclusion of controls that capture those required compensations. Given that in our model the price discrepancies originate in part from trading frictions, we would expect that upon controlling for those the potential significance of pricing distortions would decrease or disappear. One difference though is that the pricing distortions essentially contains the cumulative sum of valuation errors and trading frictions, as opposed to estimates of single period trading frictions for most of the control variables that we consider and introduced in Section 3.3.

To assess whether the implementation shortfall of the short-term reversal strategy is indeed driven by those distortions we regress the implementation lag return R^T_{i,t^i+1} on the drivers of the transaction-based returns identified in our model, according to equation (2-15). More specifically, in this setup the terms Δp^I_t, ΔD_{t^e} and D_{t^e} in equation (2-15) correspond respectively to the index price return R^B_{i,t^e}, to the return contribution from the change in distortions across pricing sources R^D_{i,t^e} over that same window, and to the level of the distortions at the beginning of the EOM window, denoted D_{i,t^e-1} going forward. To evaluate whether traditional microstructure compensation measures can also explain the implementation shortfall, we add as controls the set of variables defined in Section 3.3. Table 4 shows the results of the Fama-MacBeth regressions.

Specification (1) corroborates further the implications brought forward by our model that price distortions matter for explaining the cross-section of future corporate bond returns. We see that the reversal driven by past index returns is statistically significant, but to a much lower extent than the negative coefficients associated with both the past level and change in price distortions. Following equation (2-15), our results suggest that on average investors aim at correcting the past change in pricing distortions with an average intensity ω^T_t of -0.52. This means that half of the past month distortion change instantaneously corrects at the next trade. This value is consistent with a well-behaved system according to the boundaries defined in equation (2-17).

In specification (2), we consider the control variables that capture the risk of the underlying securities and see that only the bond spread duration is statistically significant. Specifications (3) to (5) capture the different categories of microstructure compensations that dealers are expected to require in exchange for providing liquidity.

We see in specification (3) that within the search costs' proxies related to illiquidity only the Bao et al. (2011) γ measure is insignificant. Amongst the significant drivers of the implementation lag returns, we find that bond characteristics traditionally associated with illiquidity, namely the bond issue size and age, lead to an instantaneous reversal, while measures of the bid-ask bounce such as the imputed round trip costs or the bid-ask bias push prices upward. This captures the markup in price that dealers request as compensation for providing liquidity to investor. Note that the positive coefficient for the BIAS suggests that it does not contribute to the explaining the implementation shortfall of the reversal factor, contrary to what is suggested by Dickerson et al. (2023b).

Table 4: Explaining the implementation shortfall of reversals

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables is the TRACE returns over the implementation lag window as defined in equation (3-2). It captures the implementation shortfall of strategies relying on predictors known in the EOM window. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-15), together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent return:			R^T_{i,t^i+1}			
constant	13.50	0.47	75.07	20.17	13.53	85.73
	6.74	*0.15*	***4.12***	***2.53***	***6.74***	***4.66***
R^B_{i,t^e}	-0.01	-0.04	-0.01	-0.01	-0.01	-0.04
	-2.35	***-7.34***	***-2.87***	***-2.42***	***-2.39***	***-7.86***
R^D_{i,t^e}	-0.52	-0.55	-0.54	-0.52	-0.52	-0.56
	-28.07	***-32.70***	***-30.02***	***-28.16***	***-28.08***	***-32.99***
$D_{i,t-1}$	-0.42	-0.45	-0.44	-0.42	-0.42	-0.47
	-20.79	***-24.20***	***-21.93***	***-20.80***	***-20.79***	***-23.92***
OAS		0.02				0.02
		1.86				*1.79*
OASD		1.73				1.48
		1.85				*1.70*
DTS		0.00				0.00
		0.66				*0.40*
Amt. Out.			-3.17			-3.59
			-3.63			***-4.55***
Age			-1.16			-1.21
			-6.53			***-7.02***
IRT			13.28			8.90
			6.16			***4.49***
BIAS			3.71			1.57
			4.20			***2.77***
γ			0.73			0.44
			0.82			*0.64*
VOL				-0.43		-0.60
				-0.99		*-1.72*
FREQ				0.01		0.01
				3.44		***4.19***
INV					-0.07	-0.07
					-9.88	***-11.12***
R^2	0.22	0.29	0.24	0.22	0.22	0.31
Bond-month obs	735,481	735,481	735,481	735,481	735,481	735,481

Specification (4) reports the results for the control variables capturing the risk of information asymmetry. We find that past trade counts are significantly associated with a positive return over the implementation lag window. Although the economic significance of this relationship is limited, it suggests that informed trading can exercise upward pressure on bond prices, in line with Stoll (1989) assumption. Specification (5) considers the influence of dealers' inventory changes, and we find that this variable is also highly significant. The finding that dealers' stock accumulation has a negative impact on the implementation lag returns is consistent with the work of Khang and King (2004). The authors evaluate various competing explanations for the existence of a reversal factor and conclude that dealer inventory imbalances are the most likely candidate. In their paper, though, the evidence relies mostly on the rejection of competing hypothesis and the observation that the reversal's returns diminished over the sample period. This dynamic is in turn coincident with an increase in liquidity and lower bid-ask spread, which in the Stoll (1989) model should be associated with amongst other lower inventory risks. Our analysis provides additional support for this conclusion by introducing a direct measure of dealer inventory imbalances as control variable, which allows to isolate that effect from other potential drivers of reversals.

Comparing the R^2 of the various specifications discussed above we see that pricing distortions from specification (1) have by far the largest explanatory power for the cross-sectional variation of future implementation lag returns, with a R^2 of 22%, The addition of the bond risk variables increases the R^2 by 7% and then the search cost group adds 2%.

Finally specification (6) combines the price distortions measures with all control variables. This specification is able to explain on average 31% of the cross-sectional variations in the implementation lag returns. We see that the significance of the divergence in prices across pricing sources is robust to the inclusion of all controls of market microstructure noise. Combining all variables leaves the significance of microstructure control variables unchanged compared to the previous specifications.

Overall, this analysis extend the work of Dickerson et al. (2023b) by providing new insights on the determinants of the reversal strategy's implementation shortfall. First and foremost, it shows that the implementation shortfall is significantly affected by past deviations across pricing sources. This is by far the most dominant factor driving the returns over the implementation lag. We argue that this phenomenon is consistent with the lack of transparency in corporate bond markets, i.e., the opacity of what the true fundamental value of a security is, which leads prices from different pricing source to converge towards another. Those sharp price adjustments occur instantaneously, i.e., at the next transaction post signal measurement, and lead to a significant erosion in the expected returns of the reversal strategy. Our findings can neither be explained by bond risk characteristics nor by various control variables that aim at capturing the search cost, the inventory risk and the information asymmetry risk. Taken together, those controls have relatively limited additional explanatory power.

Our results are robust to various degrees of freedom and the inclusion of control variables. More specifically, our findings are invariant in the definition of the divergence across pricing sources.[aa] Moreover, the results cannot be explained by the subset on bid transactions, the presence of small (retail) trades, different search windows in the construction of returns, the separation of credit returns from

[aa] We consider as an alternative proxy for the price distortion the EOM price difference across pricing source, according to equation (2-12) and (2-14).

interest rate returns, the length of the implementation lag, the investment universe, the choice of controls, as well as the sample period. Some of these results are reported in the Internet Appendix IA.1.1.

5.2. Implementable reversal

Having shown that price discrepancies across pricing sources are a key driver of the returns over the implementation lag window, it is natural to wonder whether those fully disappear over this window or whether they have explanatory power beyond that narrow horizon. In our model, agents can vary the intensity at which they aim to correct the distortions and there is no requirement for the price discrepancies to fully correct from one trade to another. The results in section 4.2 suggested that controlling for an implementation lag diminished their significance. In Table 5 below, we reevaluate those findings by including now the same controls considered in section 4.2, together with the drivers of the return over the implementation lag window.

In specification (1), we find back the result we had in Table 3 for the specification (3) where we evaluated the sensitivity of future corporate bond returns measured out of TRACE, after controlling for an implementation lag, on the past return decomposition. We find that this decomposition explains about 9% of the cross-sectional variation and that the coefficient on past index returns is statistically positively significant, suggesting the presence of short-term momentum once prices have adjusted over the implementation lag window. This finding is consistent with those of Dickerson et al. (2023b). We also see that the price distortions are not leading to reversals and are not significant anymore, suggesting that distortions have corrected sufficiently over the implementation window, to a level at which they don't influence anymore future corporate bond returns. It is important to note though that this specification, by omitting information on the dynamics of the pricing distortions over the implementation lag window, does not correspond anymore to return decomposition put forward by our model in equation (2-15). We address this in specification (7) by including the return drivers when measured not only over the end-of-month window but also over the implementation lag window.

In specifications (2) to (5), we evaluate the additional explanatory power of the various control groups. The results for specification (2) are mostly consistent with what we found in the previous section as risk characteristics are not significant. What is worth noting is the very high explanatory power reached when adding the risk control variables with a R^2 of 30%, which is much larger than when our model return predictors from the end-of-month window are used as base case in specification (1). This would be consistent with a larger contribution to returns from exposures to systematic credit risk exposures over longer holding horizons[bb]. We also note that controlling for risk allows to reveal the role of past

[bb] van Binsbergen et al. (2023) show that the CAPM prices corporate bonds once the contribution from interest rate exposures is stripped out of corporate bonds total return. Dickerson et al. (2023a) find strong empirical support for a bond and equity CAPM model. Those findings suggest the systematic exposure to credit risk is priced and is a key determinant of the cross-sectional variance in returns.

distortion changes and levels as reversal drivers. Also, we find that the short-term momentum is not robust to the inclusion of risk controls.

Table 5: Evaluating the persistence of price distortions in explaining reversals

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of TRACE. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent return:				R^T_{i,t^b+1}			
constant	42.88	19.65	37.50	-25.89	42.91	2.97	70.44
	(3.71)	***(3.05)***	*(0.54)*	*(-0.93)*	***(3.71)***	*(0.05)*	*(1.21)*
R^B_{i,t^e}	0.05	-0.01	0.03	0.05	0.05	-0.01	-0.03
	(2.26)	*(-0.48)*	*(1.78)*	***(2.53)***	***(2.23)***	*(-0.50)*	***(-2.36)***
R^D_{i,t^e}	0.02	-0.03	0.01	0.02	0.02	-0.03	0.36
	(1.08)	***(-2.21)***	*(0.41)*	*(1.03)*	*(1.02)*	***(-2.98)***	*(1.39)*
$D_{i,t-1}$	0.01	-0.03	0.00	0.01	0.01	-0.03	0.42
	(0.50)	***(-2.39)***	*(-0.02)*	*(0.50)*	*(0.48)*	***(-2.81)***	*(1.63)*
OAS		0.01				0.00	0.01
		(0.32)				*(0.28)*	*(0.74)*
OASD		0.00				0.34	1.20
		(0.00)				*(0.15)*	*(0.52)*
DTS		0.01				0.01	0.02
		(1.73)				*(1.81)*	*(1.81)*
Amt. Out.			0.02			-1.25	-4.02
			(0.01)			*(-0.39)*	*(-1.25)*
Age			0.36			0.71	-0.14
			(1.08)			***(2.01)***	*(-0.39)*
IRT			11.28			1.45	6.19
			(1.74)			*(0.46)*	*(2.00)*
BIAS			-4.75			-5.27	-3.85
			(-0.68)			***(-2.80)***	***(-2.18)***
γ			-1.12			-0.08	1.17
			(-0.48)			*(-0.06)*	*(0.87)*
VOL				3.86		2.20	1.66
				(1.77)		***(2.38)***	*(1.80)*
FREQ				0.01		0.01	0.02
				(0.79)		*(1.13)*	***(2.08)***
INV					-0.12	-0.15	-0.18
					(-4.94)	***(-7.72)***	***(-8.78)***
R^B_{i,t^i}							-0.18
							(-8.98)
R^D_{i,t^i}							-0.59
							(-29.43)
$D_{i,t}$							-0.77
							(-3.04)
R^2	0.09	0.31	0.13	0.10	0.09	0.34	0.40
Bond-month obs	735,481	735,481	735,481	735,481	735,481	735,481	735,481

Specification (3) shows that none of the search costs' proxies are significant beyond the implementation lag window. Similarly, in specification (4) we find that the control variables capturing the risk of information asymmetry have no explanatory power for the returns over t^b. Specification (5) considers the influence of dealers' inventory changes, and we find that this variable remains highly significant after controlling for an implementation lag.

In specification (6), we pull together all control variables to revisit the conclusions reached in specification (2). Dealer inventory imbalances remain significant and by far the most significant driver of reversal after controlling for an implementation lag. The observation that this measure is significant both over the implementation window and afterwards suggests that the results are robust and it is an important explanatory variables for the cross-section of future corporate bond returns over multiple horizons.

Specification (7) further controls for the drivers of returns in our model over the implementation lag window. These additions affect the conclusion reached in specification (6), i.e. the coefficient for the level of the pricing distortions at the start of the end-of-month window which loses its negative sign and becomes insignificant.

The high significance of the pricing distortions over t^i is consistent with the results obtained in Section 5.1 and illustrates for the beginning-of-month returns as well that those discrepancies across pricing sources are the main driver of reversals in 'contiguous' returns. As for our analysis of the implementation shortfall, we find the results to be robust to various degrees of freedom and the inclusion of control variables. More specifically, our findings are invariant in the definition of the divergence across pricing sources. Moreover, the results cannot be explained by the subsetting on bid transactions, the presence of small (retail) trades, different search windows in the construction of returns, the separation of credit returns from interest rate returns, the investment universe, the choice of controls, as well as the sample period.

The 'contiguous' qualification used above is an important detail as it effectively implies that this information is not available to investors at the time of making their investment decisions. So while the distortions over t^i are key explanatory variables for the reversal present in the cross-section of future corporate bond returns, they cannot be used to harvest the reversal premium associated with those distortions. Cognizant of the importance of imposing an implementation lag when investigating the performance of portfolio strategies in illiquid markets, we have to rely on the information available over t^e. We find that the predictive power of those distortions beyond the implementation lag is greatly diminished. Over the full sample, end-of-month pricing distortions still predict significantly reversals, but we find that those results are not robust. The results reported in the Internet Appendix 1IA.1.2 show that the predictive power of the end-of-month information is insignificant in the recent sample period and in HY. We thus conclude that while price distortions are helpful in understanding the dynamics of corporate bond returns, the expected return associated with those cannot be harvested in practice. This is consistent with the findings of Dickerson et al. (2023b).

5.3. Subsetting on bids only

From Table 5 we have noted the highly significant negative coefficient on the implementation lag return contribution from price distortions R^D_{i,t^i+1}, which suggests that following the steep correction of prices over the implementation window, prices adjust back in the other direction. This finding is consistent with an AR(1) process that would characterize the bid-ask bounce. Still, we control for proxies of the bid-ask bounce, such as the imputed round-trip costs or the bid-ask bias, and find that those do not explain the significance of the implementation shortfall return.

This finding could be interpreted in various ways. First, it could suggest that this distortion-driven price adjustment and the following reversal is a distinct phenomenon. Second, an alternative explanation could be that the dispersion across pricing sources is essentially a better measure of the bid-ask bounce in corporate bonds, such that it would span all other proxies and render them insignificant in the analysis conducted above. Finally, a third explanation could be that the measures we use to proxy bid-ask bounce fail to accurately capture those dynamics. Having considered a variety of widely accepted proxies from the literature, it seems unlikely that adding alternative metrics is going to be change the picture. The numerous robustness checks conducted in the Internet Appendix IA.1 support this hypothesis.

Ultimately, the question thus remains whether the dispersion across pricing sources contains unique information beyond the one contained in the various proxies of the bid-ask bounce we control for, or, whether it is just a better measure of the bid-ask bounce. This question is highly relevant given the difference between the pricing sources. Indeed, index prices are quoted at the bid while we aggregate buy and sell transactions on a volume-weighted average basis to define the traded prices in TRACE. There is thus by definition a pricing gap that on average should equal the bid-mid spread, i.e., half the bid-ask spread, under the assumption of equal traded buy and sell volumes, as well as equal bid-mid and mid-ask spreads. Intuitively, if the index price doesn't change over the estimation window then the returns of the price distortions is solely driven by the bid-ask bounce, even in the case of a structural level difference in bids between index and traded prices.

To answer this question, we subset the record of TRACE transactions to contain solely sell transaction executed at the bids and compute the volume-weighted average "bids only" traded price. This allows to remove any bid-ask noise from the return estimated out of transaction data, and thus to focus on the information content of distortions across pricing sources beyond the bid-ask bounce. We then rerun the same analysis as in Table 5 but when returns are estimated from "bids only" for transaction prices. The results are reported in Table 6. Overall, we observe a marginal drop in the significance of most coefficient but the conclusions are unchanged. We can thus confidently conclude that dispersions across pricing sources are unrelated to the bid-ask bounce and contain unique information that drives the 'contiguous' reversal effect in corporate bond markets.

Table 6: Evaluating the persistence of price distortions in explaining reversals – bid price only

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the t^b returns defined in equation (3-3) measured out of TRACE. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-15), when measured over both t^e and t^i, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent return:				R^T_{i,t^b+1}			
constant	43.12	16.29	27.02	-8.40	43.17	-34.55	-66.30
	3.46	***2.35***	*0.33*	*-0.31*	***3.46***	*-0.53*	*-1.02*
R^B_{i,t^e}	0.04	-0.01	0.02	0.04	0.04	-0.01	-0.03
	1.80	*-0.77*	*1.23*	***2.06***	*1.77*	*-0.87*	***-2.13***
R^D_{i,t^e}	-0.02	-0.03	-0.02	-0.03	-0.02	-0.03	0.36
	-1.24	***-2.73***	*-1.02*	*-1.33*	*-1.27*	***-3.16***	*1.17*
$D_{i,t-1}$	-0.06	-0.05	-0.04	-0.07	-0.06	-0.05	0.41
	-2.38	***-2.92***	*-1.80*	***-2.59***	***-2.37***	***-3.31***	*1.32*
OAS		0.01				0.01	0.02
		0.69				*0.60*	*0.78*
OASD		0.20				0.36	0.57
		0.10				*0.16*	*0.24*
DTS		0.01				0.01	0.01
		1.57				*1.68*	*1.65*
Amt. Out.			0.46			1.59	2.42
			0.12			*0.44*	*0.69*
Age			0.00			0.32	-0.93
			0.00			*0.93*	***-2.42***
IRT			13.89			2.63	1.87
			2.03			*0.63*	*0.43*
BIAS			-4.54			-6.73	-8.15
			-0.42			*-1.90*	***-2.42***
γ			0.26			2.03	2.21
			0.07			*0.85*	*0.91*
VOL				2.76		0.89	1.80
				1.28		*0.87*	*1.87*
FREQ				0.02		0.01	0.00
				1.26		*1.08*	*0.61*
INV					-0.14	-0.16	-0.19
					-3.97	***-6.01***	***-7.10***
R^B_{i,t^i}							-0.15
							-6.90
R^D_{i,t^i}							-0.57
							-19.45
$D_{i,t}$							-0.80
							-2.53
R^2	0.09	0.31	0.15	0.11	0.09	0.35	0.40
Bond-month obs	551,538	551,538	551,538	551,538	551,538	551,538	551,538

5.4. Index prices' dynamics

Although index prices are not actual tradeable prices, they are highly relevant for investors for two reasons. First, as most fixed income investors track an index, their prices are determining the relative performance and tracking error that result from the trading decisions of both active and passive investors. Second, in opaque and illiquid markets, index prices provide on a daily basis a reference valuation for tradeable securities. They thus contribute indirectly to the price discovery when market transparency is limited. This is the case in corporate bond markets where pre-trade transparency is essentially non-existent. Indeed, although investors have access to quote information, those are usually non-firm, are updated infrequently and are not distributed homogeneously to market participants. Moreover, contrary to equity markets, the best bids and asks, as well as the order book depth, are not available to investors.

Nevertheless, independent valuators face similar challenges as investors when it comes to determining the fair-value of securities in such illiquid and opaque markets. Namely, in the presence of very limited pre-trade transparency, they need to rely on post-trade record of transactions, when available, and on valuation models to determine the index prices. Given the illiquidity of corporate bond markets, valuators have to deal with the infrequent arrival of transaction information and potentially outdated traded prices when the market has moved. E.g., Bloomberg, which is our data source for index prices, values most fixed-income securities using their proprietary valuation algorithm BVAL[cc]. For corporate bonds, BVAL relies on information from both TRACE and their own relative valuation models[dd]. The contribution of traded prices to the index valuation depends amongst others on the recency of the transactions, whereby more weight is being given to recently observed transactions compared to alternative valuation mechanisms.

Such methodological choices from index providers, consistent with the model we introduced in Section 2, are likely to introduce cross-serial dependence across pricing sources. Table 3 already provided early empirical support for this intuition. In this section, we further explore the dynamics of index prices over the implementation lag window as well as over the subsequent month, after controlling for the implementation lag. Although the latter is less relevant for index prices, as they are non-tradeable prices, this alignment with the previous analyses allows to compare directly the results obtained from index prices with those from TRACE prices.

In Table 7 below we report the results of the Fama-MacBeth regressions of the Bloomberg returns over the implementation lag window $R^{B}_{i,t^{i}+1}$ on the same set of explanatory variables as for the TRACE returns in Table 4. Overall, we find mostly the same results as for transaction prices and the key finding is that distortions across pricing sources not only affect traded prices but also index valuations, in line with our expectation.

A few noteworthy differences should be discussed though. First, as mentioned earlier, the sign of the coefficient on the contribution to returns from price distortions $R^{D}_{i,t^{e}}$ is of opposite sign when we consider index returns. This results from the fact that this contribution is expressed as the difference between TRACE returns and index returns, such that a positive coefficient indicates that index prices converge toward traded prices and identifies reversals in index prices. The finding is consistent with the

[cc] See Bloomberg (2023) index methodology for fixed-income indices.
[dd] See Bloomberg (2018a, 2018b) for more information on the BVAL index methodology.

index valuation methodologies, whereby the evaluated prices dynamically incorporate traded prices as new information becomes available, putting more weight on recent transaction and thus inducing cross-serial correlation.

Table 7: Explaining the implementation shortfall of reversal – index prices

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BBG returns over the implementation lag window as defined in equation (3-2). It captures the implementation shortfall of strategies relying on predictors known in the EOM window. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-16), together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent return:			R^B_{i,t^i+1}			
constant	-5.02	-1.14	-20.89	-16.10	-5.02	-28.99
	-3.28	*-0.72*	*-1.06*	***-2.58***	***-3.27***	*-1.91*
R^B_{i,t^e}	0.01	-0.01	0.01	0.01	0.01	-0.01
	1.21	***-3.09***	*1.17*	*1.14*	*1.18*	***-3.25***
R^D_{i,t^e}	0.14	0.13	0.15	0.15	0.14	0.14
	16.69	***16.81***	***17.47***	***16.60***	***16.65***	***17.02***
$D_{i,t-1}$	0.13	0.12	0.14	0.13	0.13	0.13
	14.95	***15.63***	***15.53***	***14.74***	***14.95***	***15.74***
OAS		0.00				0.00
		-0.66				*-0.75*
OASD		-0.82				-0.80
		-1.11				*-1.07*
DTS		0.00				0.00
		0.93				*1.14*
Amt. Out.			0.78			0.94
			0.81			*1.52*
Age			0.22			0.16
			2.70			*1.71*
IRT			-2.24			-1.67
			-1.74			***-2.24***
BIAS			-0.90			-1.13
			-1.05			*-1.97*
γ			-1.64			-1.15
			-1.85			***-2.06***
VOL				0.64		0.54
				1.75		*1.85*
FREQ				0.00		0.00
				0.80		*-1.79*
INV					-0.03	-0.04
					-5.04	***-7.57***
R^2	0.08	0.20	0.11	0.09	0.08	0.22
Bond-month obs	735,481	735,481	735,481	735,481	735,481	735,481

Second, the significance of those distortions, although they remain by far the most significant explanatory variable over the implementation lag window, is only a fraction of what we found for transaction prices. While this could be interpreted as index prices being less sensitive to trading frictions, we have shown in the previous section that distortions across pricing sources are unrelated to trading frictions. A more likely explanation is the larger reliance of index providers on valuation models such that post-trade information is of lower relevance for valuators than for investors.

This smaller importance is also reflected in the much smaller R^2 obtained for specification (1) compared to Table 4. On the opposite, we observe in specification (2) a much larger contribution from risk measures, although none of the variables are statistically significant, with the R^2 more than doubling relative to specification (1). Assuming valuators' models focus mostly on the pricing of the key bond characteristics, their high contribution further supports the hypothesis that index providers put more emphasis on valuation models than in the sparse information coming from the record of transactions.

Third, we find that none of the trading friction proxies are significant except for the dealers inventory imbalances which remain a key driver of future corporate bond returns. This result comes as no surprise as non-traded index valuations should not be affected by market microstructure noise. At the same time, the strong significance of the dealers' inventory imbalances suggests this affects all pricing sources. Our model offers a potential explanation on the transmission channel through which those imbalances feed into index valuations. Indeed, as dealers unwinds their positions traded prices adjust, which in turn feeds into the valuators' expectations.

In Table 8, we further explore the persistence of pricing distortions on index valuations. The results are very much in line with those for transaction-based returns in Table 5, as we find that dispersions across pricing sources are also a key determinant of reversals in the cross-section of contiguous future corporate bond index returns. This result is in line with the predictions of our model in which valuators also aim at closing the price distortion by adjusting their valuation towards past traded prices. One key difference though is that the forecasting power of past price distortions measured over the end-of-month window extends beyond the implementation lag in t^b. This is of course of limited relevance for investors who cannot transact at those prices, but is highly informative about the valuation process of index providers as this suggests independent valuators incorporate slowly those distortions into index prices. This is consistent with a valuation function that combines to proprietary models not only the last pricing distortions but also multiple lags of those dispersions.

Table 8 also confirms that dealer inventory imbalances have predictive power for index returns beyond the implementation lag window, which testifies of the pervasive influence the unwinding of dealers positions have in illiquid markets. It is interesting to note that the coefficient sign is similar for both Bloomberg and TRACE returns which shows it is not a source of convergence across pricing source but rather a common driver of reversal. This confirms that the unwinding by dealers of their large accumulated net positions leads to selling pressures that drive price reversals in both pricing sources, a phenomenon unrelated to the dynamics of reversals between pricing sources.

Table 8: Evaluating the persistence of price distortions in explaining reversals – index prices

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of BBG. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-16), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent return:				R^B_{i,t^b+1}			
constant	42.88	19.65	37.50	-25.89	42.91	2.97	70.44
	(3.71)	***(3.05)***	*(0.54)*	*(-0.93)*	***(3.71)***	*(0.05)*	*(1.21)*
R^B_{i,t^e}	0.05	-0.01	0.03	0.05	0.05	-0.01	-0.03
	(2.26)	*(-0.48)*	*(1.78)*	***(2.53)***	***(2.23)***	*(-0.50)*	***(-2.36)***
R^D_{i,t^e}	0.02	-0.03	0.01	0.02	0.02	-0.03	0.36
	(1.08)	***(-2.21)***	*(0.41)*	*(1.03)*	*(1.02)*	***(-2.98)***	*(1.39)*
$D_{i,t-1}$	0.01	-0.03	0.00	0.01	0.01	-0.03	0.42
	(0.50)	***(-2.39)***	*(-0.02)*	*(0.50)*	*(0.48)*	***(-2.81)***	*(1.63)*
OAS		0.01				0.00	0.01
		(0.32)				*(0.28)*	*(0.74)*
OASD		0.00				0.34	1.20
		(0.00)				*(0.15)*	*(0.52)*
DTS		0.01				0.01	0.02
		(1.73)				*(1.81)*	*(1.81)*
Amt. Out.			0.02			-1.25	-4.02
			(0.01)			*(-0.39)*	*(-1.25)*
Age			0.36			0.71	-0.14
			(1.08)			***(2.01)***	*(-0.39)*
IRT			11.28			1.45	6.19
			(1.74)			*(0.46)*	*(2.00)*
BIAS			-4.75			-5.27	-3.85
			(-0.68)			***(-2.80)***	***(-2.18)***
γ			-1.12			-0.08	1.17
			(-0.48)			*(-0.06)*	*(0.87)*
VOL				3.86		2.20	1.66
				(1.77)		***(2.38)***	*(1.80)*
FREQ				0.01		0.01	0.02
				(0.79)		*(1.13)*	***(2.08)***
INV					-0.12	-0.15	-0.18
					(-4.94)	***(-7.72)***	***(-8.78)***
R^B_{i,t^i}							-0.18
							(-8.98)
R^D_{i,t^i}							-0.59
							(-29.43)
$D_{i,t}$							-0.77
							(-3.04)
R^2	0.09	0.31	0.13	0.10	0.09	0.34	0.40
Bond-month obs	735,481	735,481	735,481	735,481	735,481	735,481	735,481

6. Conclusion

This paper proposes a model that expands on the traditional market microstructure model, in which an investor engages with a dealer, by introducing a third agent, being the independent valuator, whose aim is solely to provide accurate estimates of the fundamental value of securities. We focus specifically on the interaction between the investor and the valuator and its influence on prices. As we let the agents evolve in an opaque market, they have limited access to information and are forced to share noisy estimates of their past valuations. We show that this sharing of information has important implications for asset prices.

More specifically, we show that the pricing distortions between traded prices and index valuations are a key factor in explaining the cross-section of contiguous future corporate bond returns. While the information contained in those deviations has been studied in the context of the measurement of illiquidity by Jankowitsch et al. (2011), their impact of asset prices has remained largely undocumented in the literature. We find that this factor can neither be explained by the risk of individual bond issues nor by widely accepted proxies for the microstructural noise embedded in traded prices. We show that these pricing distortions are a distinct phenomenon from the well documented bid-ask bounce effect, described in amongst others Roll (1984).

This paper also extends the work of Dickerson et al. (2023b), who document large implementation shortfalls for return-based predictors, by providing insights into the drivers of this implementation shortfall. Consistent with the implication of our model, we show that the convergence across pricing sources drives to a large extent the instantaneous price adjustments that are behind the large drop in significance of reversal, once properly accounting for an implementation lag. We confirm the results of Dickerson et al. (2023b) and show that the documented short-term reversal effect is explained by distortions across pricing sources and cannot be harvested in practice. Indeed, while pricing distortions have large explanatory power for contiguous returns, their predictive power beyond the implementation lag window is not robust and varies over universes, time periods the choice of control variables.

Beyond documenting the substantial influence independent valuators have on corporate bond returns, our paper shed additional light on the pervasive influence of dealer inventory imbalances on future corporate bond returns, which is found to be the sole market microstructure proxy to be significant after controlling for an implementation lag. This finding is consistent with those of Khang and King (2004) and a broader literature concerned with the capital commitment of dealers. We show that accumulated net positions by dealers lead to reversals in both pricing sources, a phenomenon distinct from the reversal driven by the convergence across pricing sources.

Finally, we show that both pricing sources carry relevant information for price discovery. While we confirm that traded prices are contaminated by microstructure effects to a much larger extent than index prices, we also shed light on the diffusion of information across pricing sources by showing that evaluated prices incorporate valuable market information contained in traded prices with a delay. Specifically, distortions across pricing sources are found to have predictive power for the cross-section of valuation-based returns beyond the implementation lag window.

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Appendix

A.1. Additional model insights

Having characterized in Section 2.1 the returns of both transaction prices and index valuations as a function of past index returns and changes in price distortions, it is important to highlight that our model does not strictly impose this (cross-) serial correlation with index prices. Rather, it enforces a dependence structure on past returns independent of the pricing source. Indeed, the fundamental value estimation functions for both agents can be expressed as a function of past traded prices. This allows to rewrite the returns of both pricing sources as a function of past returns in traded prices. What changes between those formulations is essentially the processing of the distortions. To provide intuition for this equivalence, it is useful to think about the limiting case where traded prices and index valuations are perfectly cointegrated in the absence of trading frictions and valuation errors. Then, pricing sources are perfect substitutes and the dependence structure on past returns is independent of the choice of pricing source.

$$E_t^T[f_t\ ] = p_{t-1}^T - (1 - \omega_t^T)\, D_{t-1} + \varepsilon_t^T \tag{A-1}$$

$$E_t^I[f_t\ ] = p_{t-1}^T - (1 - \omega_t^I)\, D_{t-1} + \varepsilon_t^I \tag{A-2}$$

$$\Delta p_t^T = \Delta p_{t-1}^T - (1 - \omega_t^T)\Delta D_{t-1} + \Delta\omega_t^T D_{t-2} + \Delta\varepsilon_t^T \tag{A-3}$$

$$\Delta p_t^I = \Delta p_{t-1}^T - (1 - \omega_t^I)\Delta D_{t-1} + \Delta\omega_t^I D_{t-2} + \Delta\varepsilon_t^I \tag{A-4}$$

A.2. Enhanced return methodology

A.2.1. Common evaluation moment illustration

Figure 2 and Figure 3 below illustrate respectively the issue present in the Dickerson et al. (2023b) return calculation methodology that prevents the implementation of cross-sectional strategy and how our enhanced return methodology allows to address this issue.

Figure 2

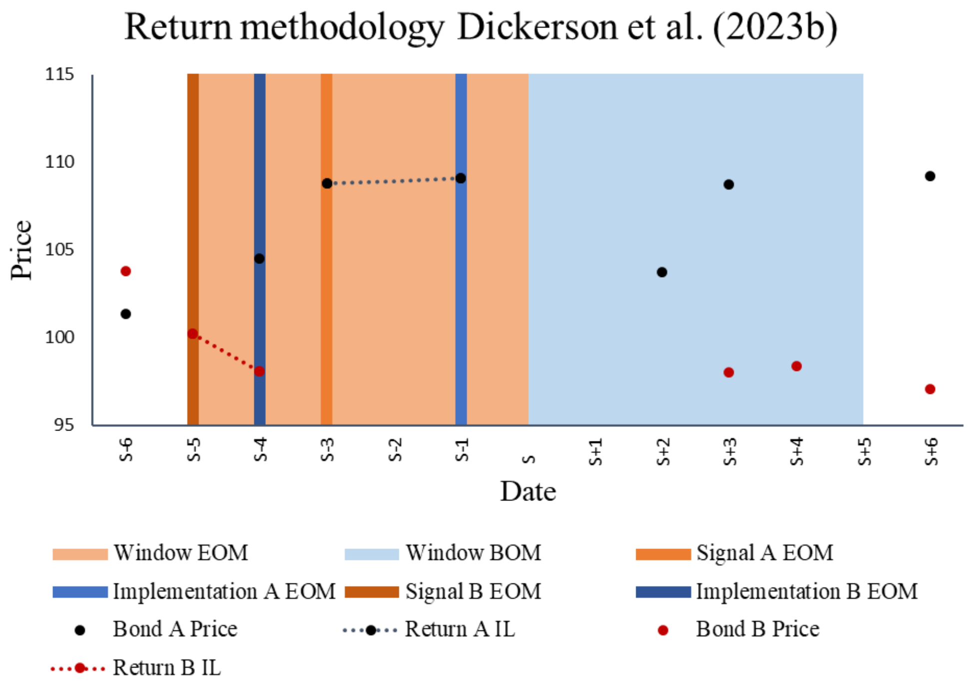
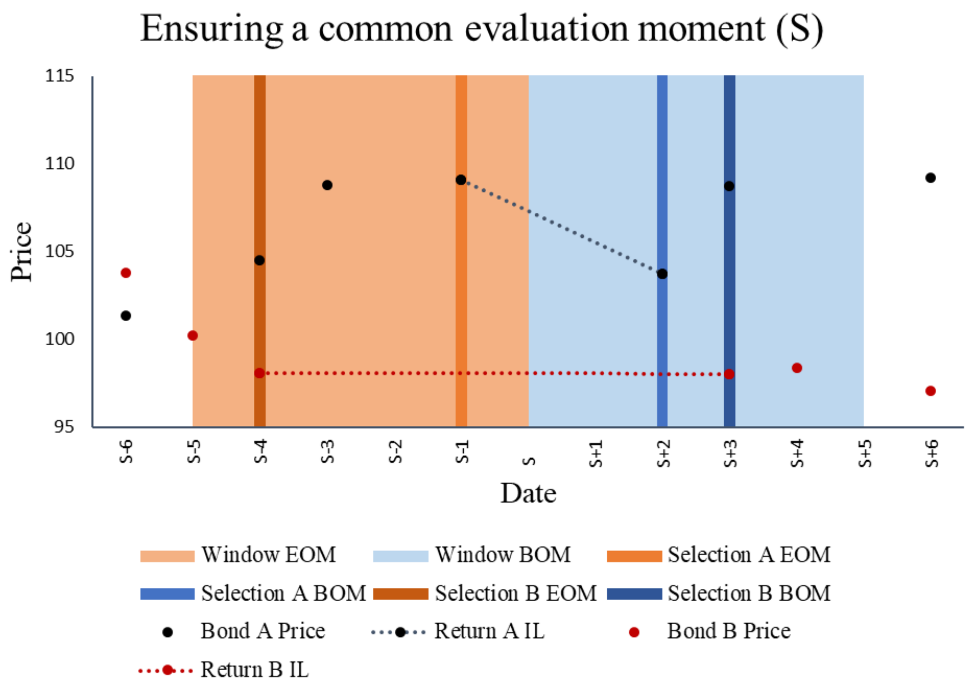


Figure 3



A.2.2. Discussion on the improvements

Having presented in Section 3.1 our methodology and the enhancements it brings over other approaches used in the literature, we want to raise awareness on the influence of the single degree of freedom available in this approach, the length of the search window, once having cleaned the transaction dataset and having computed returns. While this might be obvious for most of the interested reader versed to conducting research on the TRACE transaction dataset, it is important to highlight that this limited search window introduces a selection bias towards the most liquid bonds[ee] and decrease coverage. While we conveniently borrow the 5 business days limit from the literature, the fact is that researchers are left with an important degree of freedom when it comes to fixing the maximum look-back or look-forward window, for respectively the EOM and BOM prices.

In one of the most extreme case, being an unbounded search window within a month, researchers can essentially get coverage for the whole universe, including the most illiquid bonds, as long as any bond is traded at least one a month. E.g., this allows Bartram et al. (2023) to benefit from a large increase in coverage, with about 30% more bond-month observations than other studies relying on the same sample data. This is achieved by allowing to measure returns out of a single transaction within a month. It goes without saying that such returns could never be earned and only contains accrued interest and paid cashflows. One could argue that this could be the return earned from holding a bond purchased prior and sold after the performance evaluation window. As accounting standards usually require the mark-to-market of assets, i.e. are not grounded in the Martingale hypothesis, independent valuators are required to estimate the fair-value of untraded assets, such that the contribution to portfolio returns of holding this bond is unlikely to solely contain accrued interest and coupons payments. Also, note that including such bond-month return observation in any sorting portfolio analysis, aimed at creating long-short factor portfolio, would violate the implicit assumption that the asset can be traded at the chosen rebalancing frequency. This matters only when the asset migrates across quantile-based portfolios and will have larger influence on factors associated with high transition probabilities.

Moreover, would this return be used as predictor, it would most likely be driven by the coupon rate for the most illiquid bonds and induce time-varying selection biases, whereby liquid bonds are essentially preferred (or disliked) over illiquid ones solely because no transaction occurred and past prices would not capture actual market conditions. It is worth mentioning that this issue is exacerbated for the approaches that uses both beginning-of-month and end-of-month prices, as is described in the case above.

On the back of the large influence such a degree of freedom potentially introduces, we suggest following the standard convention within the literature of using as default a 5 business days search window, which

[ee] Bessembinder et al. (2020) highlight the risk that estimates weighing infrequent reported transactions will essentially only capture information about the most liquid segment of the market.

seems qualitatively reasonable, but do recommend to stress the results on wider/narrower search windows as a way to evaluate the sensitivity to the implicit liquidity sampling.

A.2.3. Discussion on the limitations

While our methodology provides both improvements over other approaches documented in the literature and hopefully guidance for future research, it is important to fully disclose and acknowledge its limitations and the associated potential implications.

The main limitation of the approach is that it introduces a hindsight bias in any sorting portfolio analysis. Being the asset pricing literature's workhorse, it is needless to say that this has broad-based impact. The hindsight bias originates from missing observations induced by an absence of trading activity. This leads portfolios to drop bonds without any trading activity over the evaluation window and to potentially buy them back upon the recording of future transactions in TRACE. This is likely to induce noise in portfolio return estimates and introduce an upward bias in turnover. To tackle this issue, one would need a methodology that retains illiquid bonds within portfolios until the arrival of a new transaction. The implication of such an adjustment would be that the portfolios would start losing exposure to the targeted factor as a result of liquidity constraints. This also suggests that the top factor portfolios are unachievable ideals that suffers hindsight bias in illiquid markets, and, that the resulting estimated factor premia should be interpreted as an upper bound for the 'harvestable' premium, even after accounting for an implementation lag.

The second limitation comes from the assumptions that liquidity is infinite. While the daily price estimates account for relative trade sizes over the day, any analysis that focuses solely on returns assumes that they are scalable (i.e., independent of the traded volume). The reality is that there is a finite market depth associated with each transaction in TRACE. This implies that returns do not scale with portfolio size. For large portfolios targeting factor exposures, this involves trading-off an increase in the number of holdings, in the case of a pure liquidity taker that simply engages in all transactions related to bonds belonging to the target portfolio, against higher liquidity search costs, in case of constraints on the minimum position size or weight. For small portfolios, assuming traded quantities are non-negotiable, this leads to an opportunity cost as the investor needs to forgo potentially attractive exposure when the traded notional is too high. In all case, accounting for finite liquidity is likely to result in a factor exposure dilution, which in turn will affect the 'harvestable' factor premium.

Another related assumption is the absence of competition for liquidity. Indeed, by considering all transaction records one essentially assumes a market in which a single risk taker faces a single liquidity provider. Relaxing this assumption, whereby multiple risk takers compete for liquidity, implies any single market participant can only consume a fraction of the aggregate liquidity. Akin to the impact of relaxing the previous assumption for small portfolios, this will lead to missed trades. This opportunity cost will affect the targeting of exposures and reduce the 'harvestable' premium.

As counterargument to the previous limitations, one might argue that the record of transactions in TRACE does not capture the full liquidity available to market participants. Indeed, as any transaction requires the matching of interests and an agreement on the price, we only observe instances where supply met demand, at the right moment. While it is fair to assume that liquidity might be continuously available, i.e. trading is not restricted to the arrival and size of trades in TRACE, it is also reasonable to assume that in such case the search for liquidity will lead to higher transaction costs[ff]. Notwithstanding the challenge of evaluating the equilibrium price at which supply and demand would meet[gg], for strategies assuming trading moments outside the set of transaction records, the additional search cost are likely to also impair the 'harvestable' net factor premium.

Finally, another limitation of such methodology is that while it guarantees a common evaluation moment, the trading possibilities are conditioned on the arrival and directionality of trades within the search window. This poses practical challenges for any investor with leverage, cash or funding constraints. Assuming portfolio rebalancing needs to be fully funded, meaning that a sell needs to happen prior to a buy, such that cash is raised before being reinvested, the random arrival of transaction acts as a constraints on the implementation. Traditional sorting portfolio analysis disregard the ordering of transaction, a complexity which in practice leads to a similar drop in factor exposure as the above limitations.

[ff] Market microstructure theory relates transaction costs to the various risks born by dealers, namely the inventory risk, the risk of information asymmetry, but also the search risk. As argued in Bessembinder et al. (2020), the latter is likely higher in decentralized and opaque markets such as the over-the-counter market for corporate bonds. Understanding the impact of search costs on bid-ask spread and asset prices has received considerable attention in the literature. Duffie and al. (2005,2007) introduce a search and bargaining model in which transaction costs increase with the difficulty in finding a counterparty, i.e. they are inversely related to the search intensities in the model. Jankowitsch et al. (2011) document sizeable deviations between TRACE prices and Markit composite quotations, that are substantially larger than the bid-ask spread. They motivates the existence of large transaction price deviations from fundamental values by the presence of inventory and search costs. They introduce a price dispersion measure that captures jointly the impact of inventory and search costs which impact the liquidity of corporate bonds. They show that this metric is highly related to common proxies of liquidity. Feldhutter (2012) extend the search model of Duffie et al. (2005) to show that large investors characterized by a high search intensity manage to negotiate larger price discounts relative to small investors, a difference that is exacerbated when buying in the presence selling pressure, thanks to their ability to easily identify new alternative counterparties. Friewald and Nagler (2020) provide empirical evidence that when search frictions relax the intermediation premium required by dealers diminishes. They introduce three measures capturing the intensity of the search frictions and estimate that those explain about 4% of the systematic variation in yield spread changes, which is slightly below the contribution from dealer inventory imbalances at 5% and similar to frictions originating from bargaining power.

[gg] We document in this paper large pricing differences between the TRACE transaction prices and BBG index prices and show that index prices do not incorporate all information available in markets. While in the absence of transactions only index composite pricing can provide information about the expected equilibrium price, those are likely noisy estimates.

The discussed challenges are not particular to our proposed methodology and more generally extends to the literature that has been using TRACE to compute returns and form portfolios. Addressing them is beyond the scope of this paper. This discussion mostly aimed at raising awareness and at suggesting future avenues of research to take into account important dimensions affecting the expected 'harvestable' net factor premium.

A.3. Sample and variable definitions

A.3.1. Sample definition

In the below table we report in Panel A the impact of the key cleaning steps on the final sample of transaction in TRACE. To clean the record of transactions reported in TRACE, we leverage on a large body of literature. More specifically, we follow Dick-Nielsen (2009, 2014) to clean the TRACE database and to continue selecting the subset of relevant transactions. Panel B reports the influence of the sample definition on the final sample size in terms of the number of bond-month observations and the number of unique bonds in our sample, where we require that all the past month EOM returns are available as well as the EOM, IS and BOM returns for both return sources. Our sample is restricted to USD denominated corporate bonds between July 2002 and December 2022 that are constituents of the Bloomberg US Aggregate Corporate Investment Grade (IG) index and the Bloomberg US Corporate High Yield (HY) index. Finally, we impose that all control variables are available.

Table A-1

This table reports in Panel A the impact of the key cleaning steps on the final sample of transaction in TRACE. To clean the record of transactions reported in TRACE, we leverage on a large body of literature. More specifically, we follow Dick-Nielsen (2009, 2014) to clean the TRACE database and to select the subset of relevant transactions. Panel B reports the influence of the sample definition on the final sample size in terms of the number of bond-month observations and the number of unique bonds in our sample. Our sample is restricted to USD denominated corporate bonds between July 2002 and December 2022 that are constituents of the Bloomberg US Aggregate Corporate Investment Grade (IG) index and the Bloomberg US Corporate High Yield (HY) index. Moreover, we require that all the past month EOM returns are available as well as the EOM, IS and BOM returns for both return sources. Finally, we impose that all control variables are available.

Panel A: Cleaning TRACE

Description	Transactions	Bond-Month	Bonds
All transactions with a CUSIP in TRACE (after Dick-Nielsen filters)	321,574,937	4,403,400	323,683
Matched trades to Bloomberg database	251,504,369	2,104,754	39,522
Country is US, Currency is USD and Flag144A is False	224,410,540	1,779,229	32,100
Remove Structured Notes, MBS, ABS, Agency-backed, Equity-Linked and Convertibles	219,264,409	1,707,663	30,825
Remove prices below 5 USD and above 1.000 USD	219,091,028	1,700,285	30,706
Remove floaters	211,025,271	1,601,212	28,015
Remove below 1 year maturity	193,674,851	1,486,392	27,232
Remove special transactions	190,610,520	1,486,049	27,230
Remove days to settlement above 3 business days	190,393,444	1,485,505	27,223
Remove transactions below 10.000 USD	141,444,710	1,463,645	27,182
Remove agency and double dealer trades	96,785,357	1,462,946	27,178

Panel B: Sample definition

Description	Bond-Month	Bonds
Returns available over required windows	877,887	21,696
Bloomberg index constituents	809,914	19,906
Sample restricted to the availability of all control variables	735,481	19,409

A.3.2. Variable definitions

In this section, we provide the exact definitions used for the control variables that are not readily available and require to be calculated. Starting with the bond illiquidity measure (γ) from Bao et al. (2011), it is defined as the negative of the autocovariance in daily log returns over a 22 business days window, where prices are the daily volume-weighted average price $\bar{p}$ computed from our final sample of TRACE transactions. We follow the authors and compute the autocovariance under the conditions that there are at least 10 return observations, that the maximum distance between returns is a week and that the bond is trading on at least 16 of the 22 business days.

$$\gamma_{i,t} = -Cov_{i,s:s-21}\left(\Delta\bar{p}_{i,s}, \Delta\bar{p}_{i,s-1}\right) \quad \text{(A-5)}$$

The imputed round trip cost ($IRTC$) of Feldhütter (2012) is defined as the maximum minus the minimum price p for transactions with similar traded amount and executed within a 15 minutes window during the same day. For each set j of matched transactions, with similar traded amounts within a 15 minutes window, we refer to $p_{i,s,j}^{max}$ and $p_{i,s,j}^{min}$ as respectively the maximum and minimum price within that set, where the subscripts i, s and j refer respectively to the bond i, the day s, and to the set j of matched transactions. We further take the average of the computed autocovariance over the past month in order to limit the shrinkage of our sample size when constraining our sample on the availability of all control variables.[hh]

$$IRTC_{i,t} = \frac{1}{22}\sum_{s=t-21}^{t}\frac{1}{J}\sum_{j=1}^{J} p_{i,s,j}^{max} - p_{i,s,j}^{min} \quad \text{(A-6)}$$

The bid-ask spread (BAS) is defined as the difference between the daily volume-weighted average of ask and bid prices, denoted respectively as $\bar{p}_{i,s}^{ask}$ and $\bar{p}_{i,s}^{bid}$, computed from our final sample of TRACE transactions. Similar to the imputed round trip cost ($IRTC$), we take the average over the past month.

$$BAS_{i,t} = \frac{1}{22}\sum_{s=t-21}^{t}\bar{p}_{i,s}^{ask} - \bar{p}_{i,s}^{bid} \quad \text{(A-7)}$$

The bid-ask bias ($BIAS$) estimate of Blume and Stambaugh (1983), is defined as the square of the bid-ask spread divided by the sum of the bid and ask prices. Similar to the imputed round trip cost ($IRTC$), we take the average over the past month.

$$BIAS_{i,t} = \frac{1}{22}\sum_{s=t-21}^{t}\left(\frac{\bar{p}_{i,s}^{ask} - \bar{p}_{i,s}^{bid}}{\bar{p}_{i,s}^{ask} + \bar{p}_{i,s}^{bid}}\right)^2 \quad \text{(A-8)}$$

[hh] This adjustment assumes implicitly that the illiquidity of bonds is a stable property over the past month. This allows to keep more bonds within our sample.

In the spirit of Bessembinder et al. (2018), the inventory change (INV) over the last month is measured as the cumulative net dealer buys over the last month, where $q_{i,s}^{bid}$ and $q_{i,s}^{ask}$ refer respectively to the total quantities bought and sold by dealers in security i over day s.

$$INV_{i,t} = \sum_{s=t-21}^{t} q_{i,s}^{bid} - q_{i,s}^{ask} \tag{A-9}$$

Following Hendershott et al. (2017), the order imbalance (IMB) scales the inventory change by the total traded volume over the measurement period.

$$IMB_{i,t} = \frac{\sum_{s=t-21}^{t} q_{i,s}^{bid} - q_{i,s}^{ask}}{\sum_{s=t-21}^{t} q_{i,s}^{bid} + q_{i,s}^{ask}} \tag{A-10}$$

We use three trade-based measures, namely total traded volume (VOL), the volume in proportion of the issue size ($VOLS$), where $ao_{i,s}$ denotes the bond amount outstanding, as well as the total number of trades ($FREQ$) over the past month, where $n_{i,s}$ corresponds to the number of reported trades in TRACE for bond i over day s.

$$VOL_{i,t} = \sum_{s=t-21}^{t} q_{i,s}^{bid} + q_{i,s}^{ask} \tag{A-11}$$

$$VOLS_{i,t} = \frac{\sum_{s=t-21}^{t} q_{i,s}^{bid} + q_{i,s}^{ask}}{ao_{i,t}} \tag{A-12}$$

$$FREQ_{i,t} = \sum_{s=t-21}^{t} n_{i,s} \tag{A-13}$$

A.4. Dependence structure across pricing sources

We replicate in Table A-2 below the analysis conducted in Table 4 of Andreani et al. (2023) where they investigate the lead-lag relationship across pricing sources. Specifically, they regress next month returns for both pricing sources independently on the past month returns of both pricing sources jointly. While in their study they use ICE/BAML as index valuations source, we can replicate their main finding using Bloomberg data. That is, we find back the predictive power of one source for another, as well as the stronger predictability from index valuations than traded prices. Likewise, our data also displays stronger negative serial correlation in traded prices.

Table A-2: Replication of table 4 in Andreani et al. (2023)

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the future corporate bond returns measured both out of TRACE and Bloomberg in the absence of an implementation lag, and after controlling for an implementation lag using our BOM return series. The explanatory variables corresponds to the EOM return series of both sources. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold.

Specification: **Dependent return:**	(1) R^T_{i,t^e+1}	(2) R^B_{i,t^e+1}	(3) R^T_{i,t^b+1}	(4) R^B_{i,t^b+1}
constant	0.46	0.44	0.44	0.45
	3.72	***3.55***	***3.60***	***3.56***
R^B_{i,t^e}	0.32	-0.11	0.04	-0.04
	16.39	***-6.44***	***2.16***	***-2.42***
R^T_{i,t^e}	-0.29	0.17	0.01	0.09
	-16.22	***9.59***	*0.71*	***6.14***
R^2	0.11	0.10	0.08	0.09
Bond-month obs	735,481	735,481	735,481	735,481

Following Section 4.2, we revisit those findings while addressing the multicollinearity concern in the above specifications when pricing sources are cointegrated. Once appropriately tackling this issue using the proposed trivial decomposition, we show in Table A-3 that no pricing source is more informative than another as the coefficients for the serial correlation (i.e., the betas to the past returns from the same pricing source) and for the cross-autocorrelation (i.e., the betas to the past returns from the other pricing source) are equal.

We see in the below table that across specifications we alternate between R^B_{i,t^e} and R^T_{i,t^e} for each dependent return variable. The key insight is that the coefficients measuring these (cross-) serial dependences are equal when we change the pricing source of the past return (e.g., in specification 1 vs 2). This suggests that both return sources are cointegrated and carry the same information content, as long as pricing distortions are adequately controlled for. The key implication, is that no single pricing source is more informative than another for predicting the cross-section of future returns.

Table A-3: revisiting short-term reversals in the presence of distortions across pricing sources

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the future corporate bond returns measured both out of TRACE and BBG in the absence of an implementation lag, and after controlling for an implementation lag using our BOM return series. The explanatory variables corresponds to the decomposition of the short-term reversal signal measured from either from traded priced, according to equation (4.2), or from index prices, according to equation (4.3). The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold.

Specification:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent return:	R^T_{i,t^e+1}		R^B_{i,t^e+1}		R^T_{i,t^b+1}		R^B_{i,t^b+1}	
constant	0.46	0.46	0.44	0.44	0.44	0.44	0.45	0.45
	3.72	***3.72***	***3.55***	***3.55***	***3.60***	***3.60***	***3.56***	***3.56***
R^B_{i,t^e}	0.03		0.06		0.05		0.05	
	1.25		***2.96***		***2.33***		***2.49***	
R^T_{i,t^e}		0.03		0.06		0.05		0.05
		1.25		***2.96***		***2.33***		***2.49***
R^D_{i,t^e}	-0.29	-0.32	0.17	0.11	0.01	-0.04	0.09	0.04
	-16.22	***-16.39***	***9.59***	***6.44***	*0.71*	***-2.16***	***6.14***	***2.42***
R^2	0.11	0.11	0.10	0.10	0.08	0.08	0.09	0.09
Bond-month obs	735,481	735,481	735,481	735,481	735,481	735,481	735,481	735,481

This result differs from Andreani et al. (2023) who find that index returns tend to lead transaction-based returns, when using jointly the past returns from both pricing sources as independent variables. In the presence of multicollinearity amongst pricing source, this affects the sign and significance of the coefficients. Separating the different components affecting future returns allows to remove issues associated with confounding factors and provides a more rigorous framework to investigate the lead-lag relationship across pricing sources.

Internet Appendix

Valuations in the dark: When independent valuators influence corporate bond returns

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March 2024

Abstract

The Internet Appendix reports additional tables and figures that provide support to the results and conclusions presented in the main paper.

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IA.1. Robustness Checks

In this section, we report a number of additional analyses we have conducted to ensure our results are robust to various degrees of freedom. Below, we show that our findings are invariant in the definition of the divergence across pricing sources and cannot be explained by the subsetting on bid transactions, the presence of small (retail) trades, the separation of credit returns from interest rate returns, as well as the sample period. Section IA.1.1 investigates the robustness of the results over the implementation lag window while Sections IA.1.2 and IA.1.3 report similar robustness checks for the BOM window, for respectively the TRACE and BBG returns.

IA.1.1. Implementation shortfall

In Table IA- 1, specification (1) corresponds to specification (6) in Table 4 and is the base case. In specification (2) we test whether the results are robust to changing the set of control variables, while specification (3) adds as control variable the length of the implementation lag as additional control variable. Specifications (4) to (6) perform the same analyses when we consider alternative return drivers suggested by our model being the level of pricing distortions at the end of the EOM window, which follows from equation (2-12), instead of the return drivers identified in equation (2-15) and used in the specification (1) to (3).

Table IA- 2 stresses the results of Table IA- 1 by investigating the robustness of the results over sub-sample periods when the sample period is split in halves. Table IA- 3 conducts the standard robustness checks of Table IA- 1 on TRACE returns computed out of bids-only. Table IA- 4 and Table IA- 5 reiterate the analyses conducted in Table IA- 1 for respectively the IG and HY universes, while Table IA- 6 analyses the results on the AG universe when considering credit returns.

Overall, our key results are robust. In all tables, the sign and significance of R^D_{i,t^e}, $D_{i,t-1}$ and $D_{i,t}$ remains unchanged, indicating that distortions across pricing sources are key explanatory factors of the cross-section of future contiguous corporate bond returns, leading to reversals over the implementation lag window. Likewise $INV_{i,t}$ and $IMB_{i,t}$, the two proxies for inventory risk, are both significant drivers of reversal over the implementation lag window. As we are using information from the end of the EOM window, this return drivers cannot be harvested.

Table IA- 1 – Alternative measures

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the TRACE returns over the implementation lag window as defined in equation (3-2). It captures the implementation shortfall of strategies relying on predictors known in the EOM window. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent return:			$R^{T}_{i,t^{i}+1}$			
constant	85.73	96.40	104.34	87.77	113.24	107.24
	4.66	***5.04***	***5.32***	***4.66***	***6.28***	***5.21***
$R^{B}_{i,t^{e}}$	-0.04	-0.03	-0.04			
	-7.86	***-5.61***	***-7.72***			
$R^{D}_{i,t^{e}}$	-0.56	-0.55	-0.56			
	-32.99	***-30.29***	***-33.06***			
$D_{i,t-1}$	*-0.47*	*-0.46*	*-0.47*			
	-23.92	***-22.48***	***-23.97***			
$D_{i,t}$				-0.53	-0.52	-0.53
				-29.84	***-27.75***	***-29.90***
OAS	0.02		0.02	0.02		0.02
	1.79		*1.82*	***2.03***		***2.07***
OASD	1.48		1.55	1.38		1.44
	1.70		*1.76*	*1.70*		*1.76*
DTS	0.00		0.00	0.00		0.00
	0.40		*0.40*	*0.69*		*0.67*
Rating		0.48			0.46	
		0.97			*1.07*	
Maturity		0.44			0.42	
		2.69			***2.41***	
Amt. Out.	-3.59	-4.58	-4.18	-3.20	-5.38	-3.82
	-4.55	***-5.73***	***-4.92***	***-4.18***	***-6.90***	***-4.50***
Age	-1.21	-1.07	-1.22	-1.48	-1.30	-1.48
	-7.02	***-5.06***	***-7.07***	***-7.00***	***-5.70***	***-7.02***
IRT	8.90	9.34	8.83	9.88	9.89	9.80
	4.49	***4.08***	***4.45***	***5.16***	***4.48***	***5.10***
BAS		***3.44***			***4.37***	
		4.23			***5.06***	
BIAS	1.57		1.36	1.83		1.63
	2.77		***2.47***	***3.35***		***3.03***
γ	0.44	1.02	0.50	0.47	1.09	0.52
	0.64	*1.56*	*0.74*	*0.68*	*1.69*	*0.78*
VOL	-0.60		-0.82	-1.21		-1.44
	-1.72		***-2.74***	***-2.99***		***-3.95***
VOLS		0.03			0.03	
		0.84			*0.90*	
FREQ	0.01	0.01	0.01	0.01	0.02	0.01
	4.19	***4.71***	***3.97***	***5.47***	***5.29***	***5.31***
INV	-0.07		-0.07	-0.05		-0.05
	-11.12		***-11.13***	***-7.84***		***-8.02***
IMB		-0.04			-0.02	
		-2.97			*-1.60*	
DAYS			-1.14			-1.15
			-2.06			*-1.99*
R^2	0.31	0.28	0.32	0.29	0.27	0.30
Bond-month obs	735,481	735,481	735,481	735,481	735,481	735,481

Table IA- 2 – Subsample period analysis

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the TRACE returns over the implementation lag window as defined in equation (3-2). It captures the implementation shortfall of strategies relying on predictors known in the EOM window. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent return:			R^T_{i,t^i+1}			
constant	85.73	72.62	99.38	113.24	119.68	106.52
	4.66	***2.17***	***7.42***	***6.28***	***3.74***	***7.02***
R^B_{i,t^e}	-0.04	-0.06	-0.02			
	-7.86	***-7.99***	***-4.54***			
R^D_{i,t^e}	-0.56	-0.52	-0.60			
	-32.99	***-24.35***	***-25.62***			
$D_{i,t-1}$	*-0.47*	*-0.40*	*-0.54*			
	-23.92	***-20.27***	***-20.01***			
$D_{i,t}$				-0.52	-0.47	-0.58
				-27.75	***-18.95***	***-24.31***
OAS	0.02	0.03	0.00			
	1.79	***2.05***	*-0.11*			
OASD	1.48	2.95	-0.04			
	1.70	*1.88*	*-0.08*			
DTS	0.00	0.00	0.00			
	0.40	*-0.19*	***2.07***			
Rating				0.46	0.83	0.09
				1.07	*1.07*	*0.24*
Maturity				0.42	0.56	0.26
				2.41	*1.99*	*1.39*
Amt. Out.	-3.59	-3.52	-3.67	-5.38	-5.79	-4.95
	-4.55	***-2.42***	***-6.75***	***-6.90***	***-4.25***	***-7.14***
Age	-1.21	-2.01	-0.38	-1.30	-2.19	-0.37
	-7.02	***-8.54***	***-4.92***	***-5.70***	***-6.21***	***-3.97***
IRT	8.90	10.20	7.54	9.89	12.16	7.52
	4.49	***2.73***	***7.34***	***4.48***	***2.95***	***6.35***
BAS				***4.37***	***3.20***	***5.60***
				5.06	***2.11***	***7.86***
BIAS	1.57	1.53	1.61			
	2.77	***2.32***	*1.74*			
γ	0.44	0.60	0.29	1.09	1.10	1.08
	0.64	*0.93*	*0.23*	*1.69*	*1.75*	*0.94*
VOL	-0.60	-0.17	-1.04			
	-1.72	*-0.32*	***-2.60***			
VOLS				0.03	0.06	0.00
				0.90	*1.51*	*0.03*
FREQ	0.01	0.01	0.01	0.02	0.02	0.01
	4.19	***2.84***	***3.62***	***5.29***	***4.38***	***3.73***
INV	-0.07	-0.06	-0.07			
	-11.12	***-6.01***	***-12.51***			
IMB				-0.02	-0.01	-0.03
				-1.60	*-0.37*	***-6.46***
Start	Aug'02	Aug'02	Jan'13	Aug'02	Aug'02	Jan'13
End	Nov'22	Dec'12	Nov'22	Nov'22	Dec'12	Nov'22
R^2	0.31	0.29	0.32	0.27	0.24	0.29
Bond-month obs	735,481	246,255	489,226	735,481	246,255	489,226

Table IA- 3 – Bids only

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the TRACE returns over the implementation lag window as defined in equation (3-2). It captures the implementation shortfall of strategies relying on predictors known in the EOM window. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent return:			R^T_{i,t^i+1}			
constant	-31.06	-41.70	-91.60	-46.56	-39.67	-113.35
	-1.90	*-1.91*	***-5.79***	***-2.63***	*-1.90*	***-6.39***
R^B_{i,t^e}	-0.03	-0.02	-0.03			
	-6.21	***-4.53***	***-5.88***			
R^D_{i,t^e}	-0.54	-0.54	-0.54			
	-28.64	***-27.32***	***-28.78***			
$D_{i,t-1}$	*-0.46*	*-0.46*	*-0.47*			
	-20.09	***-20.09***	***-20.22***			
$D_{i,t}$				-0.52	-0.52	-0.52
				-26.82	***-25.80***	***-27.02***
OAS	0.01		0.01	0.01		0.01
	1.58		*1.58*	*1.72*		*1.72*
OASD	0.37		0.28	0.23		0.14
	0.39		*0.30*	*0.27*		*0.17*
DTS	0.00		0.00	0.00		0.00
	0.88		*0.86*	*1.16*		*1.13*
Rating		0.88			0.88	
		1.49			*1.51*	
Maturity		0.12			0.08	
		0.68			*0.44*	
Amt. Out.	1.31	2.05	3.42	2.37	1.97	4.66
	1.90	***2.16***	***4.97***	***3.44***	***2.12***	***5.97***
Age	-2.13	-2.05	-2.04	-2.50	-2.35	-2.39
	-8.75	***-8.30***	***-8.84***	***-8.37***	***-7.96***	***-8.46***
IRT	0.64	1.69	1.18	0.52	1.79	1.09
	0.43	*1.15*	*0.82*	*0.36*	*1.21*	*0.77*
BAS		*1.40*			*0.87*	
		1.43			*0.89*	
BIAS	-1.90		-1.73	-2.39		-2.16
	-2.04		*-1.86*	***-2.60***		***-2.34***
γ	-1.26	-1.12	-1.38	-1.78	-1.58	-1.92
	-1.46	*-1.29*	*-1.60*	***-2.08***	*-1.78*	***-2.25***
VOL	0.47		0.84	0.08		0.55
	0.89		*1.74*	*0.15*		*1.09*
VOLS		0.13			0.13	
		2.68			***2.61***	
FREQ	-0.01	-0.01	0.00	-0.01	-0.01	0.00
	-2.40	***-2.13***	*-1.03*	***-2.07***	*-1.86*	*-0.65*
INV	-0.10		-0.10	-0.09		-0.09
	-9.47		***-9.60***	***-9.49***		***-9.65***
IMB		-0.15			-0.13	
		-12.33			***-11.97***	
DAYS			2.26			2.54
			3.15			***3.43***
R^2	0.28	0.25	0.30	0.27	0.23	0.28
Bond-month obs	551,538	551,538	551,538	551,538	551,538	551,538

Table IA- 4 – Investment Grade

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the TRACE returns over the implementation lag window as defined in equation (3-2). It captures the implementation shortfall of strategies relying on predictors known in the EOM window. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent return:			R^T_{i,t^i+1}			
constant	104.54	109.03	120.06	120.73	128.51	136.13
	5.55	***5.59***	***5.93***	***6.06***	***6.94***	***6.31***
R^B_{i,t^e}	-0.12	-0.09	-0.11			
	-13.88	***-12.03***	***-13.65***			
R^D_{i,t^e}	-0.59	-0.57	-0.59			
	-33.40	***-30.69***	***-33.48***			
$D_{i,t-1}$	*-0.45*	*-0.44*	*-0.45*			
	-21.60	***-19.98***	***-21.69***			
$D_{i,t}$				-0.54	-0.52	-0.54
				-27.64	***-25.81***	***-27.72***
OAS	0.05		0.05	0.06		0.07
	5.42		***5.69***	***6.92***		***7.21***
OASD	0.32		0.36	-0.41		-0.36
	0.37		*0.43*	*-0.61*		*-0.53*
DTS	0.01		0.01	0.01		0.01
	1.85		*1.87*	***3.20***		***3.18***
Rating		0.48			0.43	
		1.51			*1.39*	
Maturity		0.56			0.49	
		3.13			***2.75***	
Amt. Out.	-4.05	-5.05	-4.58	-4.60	-6.04	-5.14
	-4.77	***-5.71***	***-5.28***	***-5.21***	***-7.11***	***-5.66***
Age	-1.53	-1.46	-1.53	-1.92	-1.75	-1.91
	-6.60	***-6.50***	***-6.62***	***-6.80***	***-6.81***	***-6.82***
IRT	2.81	6.06	2.73	2.53	6.68	2.48
	3.07	***5.54***	***3.07***	***2.75***	***6.42***	***2.77***
BAS		***4.75***			***5.80***	
		9.06			***10.62***	
BIAS	3.80		3.63	4.13		3.97
	6.32		***6.30***	***6.75***		***6.77***
γ	1.21	1.96	1.24	1.15	2.29	1.18
	1.78	***2.80***	*1.93*	*1.67*	***3.21***	*1.77*
VOL	-0.89		-1.05	-1.24		-1.39
	-3.29		***-4.02***	***-4.06***		***-4.63***
VOLS		-0.08			-0.05	
		-2.18			*-1.65*	
FREQ	0.01	0.02	0.01	0.01	0.02	0.01
	3.07	***5.11***	***3.23***	***3.43***	***5.79***	***3.57***
INV	-0.07		-0.07	-0.03		-0.03
	-11.48		***-11.04***	***-7.77***		***-7.67***
IMB		-0.02			-0.01	
		-2.82			*-0.76*	
DAYS			-0.93			-0.89
			-1.50			*-1.33*
R^2	0.32	0.30	0.33	0.29	0.27	0.31
Bond-month obs	572,308	572,308	572,308	572,308	572,308	572,308

Table IA- 5 – High Yield

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the TRACE returns over the implementation lag window as defined in equation (3-2). It captures the implementation shortfall of strategies relying on predictors known in the EOM window. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent return:			R^{T}_{i,t^i+1}			
constant	-6.27	40.91	7.36	3.25	59.57	18.13
	-0.12	*0.95*	*0.11*	*0.06*	*1.54*	*0.28*
R^{B}_{i,t^e}	-0.01	-0.01	-0.01			
	-2.86	*-1.89*	***-2.72***			
R^{D}_{i,t^e}	-0.58	-0.57	-0.58			
	-31.85	***-28.81***	***-31.79***			
$D_{i,t-1}$	-0.52	-0.52	-0.53			
	-27.71	***-24.05***	***-27.66***			
$D_{i,t}$				-0.57	-0.55	-0.57
				-31.10	***-27.61***	***-31.06***
OAS	0.03		0.03	0.03		0.03
	2.84		***2.85***	***2.94***		***2.94***
OASD	4.41		4.51	4.26		4.34
	2.07		***2.07***	***2.08***		***2.09***
DTS	0.00		0.00	0.00		0.00
	-0.71		*-0.69*	*-0.54*		*-0.53*
Rating		1.19			1.22	
		1.43			*1.57*	
Maturity		0.41			0.31	
		2.27			*1.57*	
Amt. Out.	-1.21	-2.63	-1.62	-1.14	-3.56	-1.62
	-0.52	*-1.25*	*-0.61*	*-0.49*	*-1.81*	*-0.61*
Age	-0.09	0.57	0.02	-0.19	0.43	-0.08
	-0.25	*0.67*	*0.06*	*-0.58*	*0.48*	*-0.22*
IRT	13.98	16.24	13.20	14.71	16.92	13.90
	2.20	***2.18***	***2.04***	***2.32***	***2.28***	***2.16***
BAS		*-1.66*			*-1.06*	
		-0.52			*-0.32*	
BIAS	-0.24		-0.55	-0.16		-0.46
	-0.22		*-0.51*	*-0.15*		*-0.44*
γ	0.33	1.33	0.46	0.38	1.46	0.52
	0.36	*1.53*	*0.50*	*0.41*	*1.69*	*0.55*
VOL	0.87		0.55	0.15		-0.15
	0.79		*0.53*	*0.16*		*-0.19*
VOLS		0.13			0.13	
		1.97			***2.15***	
FREQ	-0.01	0.00	-0.01	-0.01	0.00	-0.01
	-0.94	*0.13*	*-0.88*	*-0.85*	*0.17*	*-0.76*
INV	-0.14		-0.14	-0.11		-0.11
	-6.64		***-6.57***	***-4.51***		***-4.36***
IMB		-0.09			-0.08	
		-1.71			*-1.45*	
DAYS			-0.94			-1.01
			-0.99			*-1.02*
R^2	0.34	0.30	0.34	0.32	0.28	0.33
Bond-month obs	163,173	163,173	163,173	163,173	163,173	163,173

Table IA- 6 – Credit returns

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the TRACE returns over the implementation lag window as defined in equation (3-2). It captures the implementation shortfall of strategies relying on predictors known in the EOM window. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent return:			R^T_{i,t^i+1}			
constant	104.54	109.03	120.06	120.73	128.51	136.13
	5.55	***5.59***	***5.93***	***6.06***	***6.94***	***6.31***
R^B_{i,t^e}	-0.03	-0.02	-0.03			
	-6.28	***-4.29***	***-6.31***			
R^D_{i,t^e}	-0.56	-0.56	-0.57			
	-32.78	***-30.22***	***-32.84***			
$D_{i,t-1}$	*-0.47*	*-0.47*	*-0.47*			
	-23.63	***-22.29***	***-23.77***			
$D_{i,t}$				-0.54	-0.53	-0.54
				-29.66	***-27.63***	***-29.73***
OAS	0.02		0.02	0.02		0.02
	1.87		*1.97*	***2.10***		***2.18***
OASD	1.82		1.98	1.72		1.87
	3.53		***3.74***	***3.60***		***3.80***
DTS	0.00		0.00	0.00		0.00
	0.38		*0.35*	*0.63*		*0.59*
Rating		0.37			0.41	
		0.79			*0.96*	
Maturity		0.61			0.57	
		5.26			***4.91***	
Amt. Out.	-2.07	-2.97	-3.97	-1.80	-3.69	-3.73
	-2.46	***-3.56***	***-4.74***	***-2.07***	***-4.45***	***-4.45***
Age	-1.19	-1.11	-1.22	-1.45	-1.34	-1.47
	-6.94	***-5.25***	***-6.99***	***-6.97***	***-5.88***	***-6.99***
IRT	9.08	9.19	8.58	10.17	9.83	9.62
	4.67	***4.07***	***4.38***	***5.40***	***4.51***	***5.05***
BAS		***4.08***			***5.00***	
		4.94			***5.67***	
BIAS	1.89		1.48	2.15		1.73
	3.41		***2.76***	***3.94***		***3.28***
γ	0.44	1.00	0.57	0.45	1.07	0.58
	0.68	*1.61*	*0.90*	*0.69*	*1.74*	*0.89*
VOL	-0.40		-0.90	-0.94		-1.45
	-1.15		***-2.98***	***-2.30***		***-4.02***
VOLS		0.04			0.05	
		1.28			*1.34*	
FREQ	0.01	0.02	0.01	0.02	0.02	0.01
	5.10	***6.34***	***4.37***	***6.27***	***7.21***	***5.74***
INV	-0.06		-0.06	-0.05		-0.05
	-10.76		***-10.82***	***-7.99***		***-8.18***
IMB		-0.03			-0.02	
		-2.66			*-1.52*	
DAYS			-3.06			-3.10
			-5.80			***-5.74***
R^2	0.30	0.27	0.30	0.29	0.26	0.29
Bond-month obs	735,481	735,481	735,481	735,481	735,481	735,481

IA.1.2. Implementable reversal

Table IA- 7 specifications (1) and (3) correspond to respectively specification (6) and (7) in Table 5 and constitute the base cases. The first one investigates the predictive power of pricing distortions measured over the EOM window on the BOM window TRACE returns while the second one also includes contiguous information about those distortions from the implementation lag window. In specification (2) and (4) we test whether the results are robust to changing the set of control variables. Specifications (5) to (6) perform the same analyses when we consider alternative return drivers suggested by our model being the level of pricing distortions at the end of the EOM window, which follows from equation (2-12), instead of the return drivers identified in equation (2-15) and used in the specification (1) to (3). Specification (7) to (8) add as controls the distortion information from the implementation lag window.

Table IA- 8 stresses the results of Table IA- 7 by investigating the robustness of the results over sub-sample periods when the sample period is split in halves. Table IA- 9 conducts the standard robustness checks of Table IA- 7 on TRACE returns computed out of bids-only Table IA- 10 and Table IA- 11 reiterate the analyses conducted in Table IA- 7 for respectively the IG and HY universes, while Table IA- 12 analyzes the results on the AG universe when considering credit returns.

Overall, our key results are robust. In all tables, the sign and significance of R^D_{i,t^i}, $D_{i,t-1}$ and $D_{i,t}$ (bottom part of the table) remains unchanged, indicating that distortions across pricing sources are key explanatory factors of the cross-section of future contiguous corporate bond returns, leading to reversals over the implementation lag window. But while contiguous information has consistently large explanatory power, the predictive power of those distortions beyond the implementation lag window varies across universes, time periods and the choice of control variables. E.g. looking at the sign and significance of R^D_{i,t^e}, $D_{i,t-1}$ and $D_{i,t}$ (upper part of the table), we find that past distortions predicts reversals in both IG and HY, but it is only significant in the high-grade universe.

Finally, we find that $INV_{i,t}$ and $IMB_{i,t}$, the two proxies for inventory risk, are both significant drivers of reversal over the BOM window. As we are using information from the end of the EOM window, this return drivers can be harvested.

Table IA- 7 – Alternative measures

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of TRACE. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent return:				R^T_{i,t^b+1}				
constant	2.97	-78.63	70.44	-8.68	5.44	-63.17	69.09	7.01
	0.05	*-1.12*	*1.21*	*-0.12*	*0.09*	*-0.88*	*1.12*	*0.09*
R^B_{i,t^e}	-0.01	0.02	-0.03	0.00				
	-0.50	*1.18*	***-2.36***	*0.07*				
R^D_{i,t^e}	-0.03	-0.01	0.36	0.41				
	-2.98	*-0.90*	*1.39*	*1.38*				
D_{i,t^e-1}	*-0.03*	*-0.02*	*0.42*	*0.46*				
	-2.81	*-1.21*	*1.63*	*1.56*				
D_{i,t^e}					-0.03	-0.02	0.13	0.14
					-3.31	*-1.25*	***10.61***	***8.38***
OAS	0.00		0.01		0.01		0.02	
	0.28		*0.74*		*0.32*		*0.85*	
OASD	0.34		1.20		0.43		1.46	
	0.15		*0.52*		*0.20*		*0.66*	
DTS	0.01		0.02		0.01		0.01	
	1.81		*1.81*		*1.71*		*1.76*	
Rating		4.11		4.09		4.47		4.53
		1.83		*1.77*		*1.86*		*1.86*
Maturity		1.22		1.64		1.11		1.47
		2.10		***2.79***		*1.90*		***2.53***
Amt. Out.	-1.25	3.29	-4.02	0.09	-0.97	2.54	-3.47	-0.67
	-0.39	*1.05*	*-1.25*	*0.03*	*-0.28*	*0.81*	*-1.00*	*-0.21*
Age	0.71	0.82	-0.14	-0.01	0.62	0.80	-0.30	-0.13
	2.01	***2.16***	*-0.39*	*-0.02*	*1.80*	***2.15***	*-0.86*	*-0.32*
IRT	1.45	6.39	6.19	10.61	2.04	8.06	7.37	12.70
	0.46	*1.86*	*2.00*	***3.05***	*0.70*	***2.43***	***2.54***	***3.71***
BAS		*-0.80*		*1.41*		*-0.90*		*1.83*
		-0.32		*0.56*		*-0.31*		*0.64*
BIAS	-5.27		-3.85		-4.94		-3.59	
	-2.80		***-2.18***		***-2.73***		*-2.00*	
γ	-0.08	0.37	1.17	2.22	0.44	0.66	1.32	1.77
	-0.06	*0.20*	*0.87*	*1.22*	*0.31*	*0.32*	*0.94*	*0.83*
VOL	2.20		1.66		1.78		1.15	
	2.38		*1.80*		*1.81*		*1.16*	
VOLS		0.33		0.31		0.31		0.31
		1.50		*1.45*		*1.17*		*1.15*
FREQ	0.01	0.01	0.02	0.02	0.01	0.01	0.02	0.02
	1.13	*1.41*	***2.08***	***2.15***	*1.07*	*1.26*	***2.19***	***2.06***
INV	-0.15		-0.18		-0.15		-0.16	
	-7.72		***-8.78***		***-6.61***		***-6.92***	
DAYS		-0.15		-0.16		-0.15		-0.15
		-8.55		***-8.95***		***-7.78***		***-7.75***
R^B_{i,t^i}			-0.18	-0.10				
			-8.98	***-4.33***				
R^D_{i,t^i}			*-0.59*	*-0.55*				
			-29.43	***-24.64***				
D_{i,t^e}			*-0.77*	*-0.79*				
			-3.04	***-2.67***				
D_{i,t^i}							-0.54	-0.52
							-27.01	***-23.67***
R^2	0.34	0.26	0.40	0.33	0.32	0.23	0.37	0.27
Bond-month obs	735,481	735,481	735,481	735,481	735,481	735,481	735,481	735,481

Table IA- 8 – subsample analysis

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of TRACE. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent return:			R^T_{i,t^b+1}			
constant	70.44	75.96	64.69	69.32	144.88	17.73
	1.21	*1.04*	*0.70*	*0.68*	***2.33***	*0.14*
R^B_{i,t^e}	-0.03	-0.02	-0.05			
	-2.36	*-0.91*	***-2.49***			
R^D_{i,t^e}	0.36	0.10	0.63			
	1.39	*0.45*	*1.36*			
D_{i,t^e-1}	*0.42*	*0.20*	*0.65*			
	1.63	*0.86*	*1.41*			
D_{i,t^e}				0.14	0.18	0.10
				8.38	***8.87***	***4.11***
OAS	0.01	0.02	0.00			
	0.74	*0.95*	*0.07*			
OASD	1.20	2.37	-0.01			
	0.52	*0.65*	*0.00*			
DTS	0.02	0.02	0.01			
	1.81	*1.51*	*1.01*			
Rating				4.53	6.76	2.20
				1.86	*1.65*	*0.91*
Maturity				1.47	2.02	0.90
				2.53	***3.05***	*0.95*
Amt. Out.	-4.02	-4.68	-3.34	-0.67	2.70	-4.19
	-1.25	*-1.19*	*-0.65*	*-0.21*	*0.48*	*-1.46*
Age	-0.14	-0.41	0.14	-0.13	-0.68	0.44
	-0.39	*-0.65*	*0.44*	*-0.32*	*-0.95*	*1.41*
IRT	6.19	4.30	8.16	12.70	9.50	16.03
	2.00	*1.03*	*1.78*	***3.71***	***2.60***	***2.77***
BAS				*1.83*	*1.78*	*1.89*
				0.64	*0.45*	*0.45*
BIAS	-3.85	-1.97	-5.81			
	-2.18	*-1.51*	*-1.76*			
γ	1.17	-0.51	2.93	1.77	-0.61	4.25
	0.87	*-0.47*	*1.22*	*0.83*	*-0.28*	*1.21*
VOL	1.66	2.32	0.97			
	1.80	*1.60*	*0.87*			
VOLS				0.31	0.23	0.39
				1.15	*0.69*	*0.93*
FREQ	0.02	0.01	0.02	0.02	0.03	0.02
	2.08	*1.14*	*1.81*	***2.06***	*1.82*	*1.12*
INV	-0.18	-0.15	-0.20			
	-8.78	***-4.58***	***-9.70***			
IMB				-0.15	-0.17	-0.13
				-7.75	***-5.43***	***-5.90***
R^B_{i,t^i}	*-0.18*	*-0.17*	*-0.19*			
	-8.98	***-6.56***	***-6.24***			
R^D_{i,t^i}	*-0.59*	*-0.61*	*-0.57*			
	-29.43	***-19.51***	***-23.96***			
D_{i,t^e}	*-0.77*	*-0.53*	*-1.02*			
	-3.04	***-2.34***	***-2.24***			
D_{i,t^i}				*-0.52*	*-0.53*	*-0.51*
				-23.67	***-15.53***	***-19.00***
Start	Aug'02	Aug'02	Jan'13	Aug'02	Aug'02	Jan'13
End	Nov'22	Dec'12	Nov'22	Nov'22	Dec'12	Nov'22
R^2	0.40	0.38	0.41	0.27	0.26	0.29
Bond-month obs	735,481	246,255	489,226	735,481	246,255	489,226

Table IA- 9 – Bids only

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of TRACE. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent return:				R^T_{i,t^b+1}				
constant	-34.55	-88.17	-66.30	-116.95	-36.09	-86.07	-75.79	-110.11
	-0.53	*-1.21*	*-1.02*	*-1.58*	*-0.53*	*-1.12*	*-1.11*	*-1.43*
R^B_{i,t^e}	-0.01	0.01	-0.03	0.00				
	-0.87	*0.80*	***-2.13***	*0.13*				
R^D_{i,t^e}	-0.03	-0.02	0.36	0.20				
	-3.16	*-1.72*	*1.17*	*0.63*				
D_{i,t^e-1}	*-0.05*	*-0.04*	*0.41*	*0.24*				
	-3.31	***-2.33***	*1.32*	*0.76*				
D_{i,t^e}					-0.04	-0.03	0.11	0.12
					-3.23	*-1.92*	***7.86***	***6.13***
OAS	0.01		0.02		0.01		0.02	
	0.60		*0.78*		*0.62*		*0.95*	
OASD	0.36		0.57		0.28		0.69	
	0.16		*0.24*		*0.13*		*0.32*	
DTS	0.01		0.01		0.01		0.01	
	1.68		*1.65*		*1.66*		*1.59*	
Rating		4.14		4.17		4.76		4.78
		1.93		*1.89*		***2.04***		***2.03***
Maturity		1.15		1.33		1.02		1.16
		1.92		***2.17***		*1.69*		*1.92*
Amt. Out.	1.59	3.67	2.42	5.22	2.04	3.43	3.62	4.78
	0.44	*1.11*	*0.69*	*1.56*	*0.54*	*1.00*	*0.96*	*1.39*
Age	0.32	0.47	-0.93	-0.70	0.28	0.52	-1.13	-0.81
	0.93	*1.18*	***-2.42***	*-1.64*	*0.83*	*1.31*	***-2.96***	*-1.80*
IRT	2.63	9.95	1.87	9.30	3.48	11.94	2.33	11.70
	0.63	***2.36***	*0.43*	***2.30***	*0.91*	***2.97***	*0.60*	***2.91***
BAS		*0.09*		*-1.02*		*0.34*		***-2.01***
		0.02		*-0.26*		*0.08*		*-0.45*
BIAS	-6.73		-8.15		-6.34		-8.45	
	-1.90		***-2.42***		*-1.84*		***-2.46***	
γ	2.03	3.37	2.21	3.58	2.57	4.33	1.59	3.01
	0.85	*1.04*	*0.91*	*1.07*	*1.07*	*1.12*	*0.67*	*0.78*
VOL	0.89		1.80		0.48		0.97	
	0.87		*1.87*		*0.43*		*0.91*	
VOLS		0.19		0.20		0.20		0.22
		0.82		*0.87*		*0.67*		*0.74*
FREQ	0.01	0.02	0.00	0.01	0.01	0.02	0.01	0.01
	1.08	*1.73*	*0.61*	*1.49*	*1.00*	*1.44*	*0.68*	*1.32*
INV	-0.16		-0.19		-0.15		-0.17	
	-6.01		***-7.10***		***-5.59***		***-6.05***	
DAYS		-0.18		-0.22		-0.17		-0.20
		-8.63		***-10.89***		***-7.46***		***-8.47***
R^B_{i,t^i}			-0.15	-0.07				
			-6.90	***-3.12***				
R^D_{i,t^i}			*-0.57*	*-0.53*				
			-19.45	***-18.05***				
D_{i,t^e}			*-0.80*	*-0.61*				
			-2.53	*-1.89*				
D_{i,t^i}							-0.53	-0.51
							-18.23	***-17.32***
R^2	0.35	0.27	0.40	0.33	0.33	0.24	0.37	0.27
Bond-month obs	551,538	551,538	551,538	551,538	551,538	551,538	551,538	551,538

Table IA- 10 – Investment Grade

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of TRACE. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent return:				R^T_{i,t^b+1}				
constant	6.00	-34.40	86.66	45.92	26.91	-19.47	109.36	66.32
	0.16	*-0.60*	*1.99*	*0.75*	*0.65*	*-0.33*	**2.33**	*1.06*
R^B_{i,t^e}	-0.02	0.00	-0.08	-0.04				
	-2.10	*0.15*	**-7.12**	**-2.22**				
R^D_{i,t^e}	-0.04	-0.02	0.02	0.16				
	-5.26	*-1.53*	*0.15*	*0.71*				
D_{i,t^e-1}	-0.03	-0.01	0.13	0.25				
	-3.58	*-1.22*	*0.77*	*1.14*				
D_{i,t^e}					-0.04	-0.02	0.18	0.20
					-4.68	*-1.70*	**15.71**	**13.89**
OAS	0.01		0.05		0.01		0.05	
	0.25		*0.89*		*0.16*		*0.90*	
OASD	0.55		0.96		0.78		1.15	
	0.28		*0.45*		*0.40*		*0.58*	
DTS	0.01		0.02		0.01		0.01	
	1.52		*1.86*		*1.37*		*1.81*	
Rating		2.07		2.07		2.50		2.46
		1.59		*1.49*		*1.76*		*1.66*
Maturity		1.05		1.60		1.02		1.46
		1.73		**2.60**		*1.71*		**2.48**
Amt. Out.	-0.05	1.87	-3.32	-1.82	-0.87	1.09	-4.15	-2.83
	-0.02	*0.67*	*-1.39*	*-0.62*	*-0.38*	*0.39*	*-1.63*	*-0.95*
Age	0.13	0.48	-0.92	-0.51	0.09	0.35	-1.13	-0.80
	0.63	*1.48*	**-3.23**	*-1.37*	*0.40*	*1.01*	**-3.92**	**-2.07**
IRT	1.64	7.63	3.94	11.73	1.63	7.94	4.43	12.37
	0.91	**2.17**	*1.98*	**3.20**	*0.91*	**2.17**	**2.57**	**3.39**
BAS		*0.27*		**3.67**		*0.86*		**4.55**
		0.12		*1.66*		*0.38*		**2.00**
BIAS	-2.56		0.28		-2.37		0.55	
	-1.97		*0.22*		*-1.88*		*0.45*	
γ	1.89	1.15	2.65	2.55	2.13	2.99	3.15	4.59
	1.02	*0.69*	*1.48*	*1.61*	*0.91*	*0.83*	*1.35*	*1.27*
VOL	0.46		-0.15		0.29		-0.46	
	0.82		*-0.27*		*0.47*		*-0.74*	
VOLS		0.28		0.20		0.30		0.25
		2.63		*1.86*		**2.34**		*1.93*
FREQ	0.02	0.02	0.02	0.03	0.02	0.01	0.02	0.03
	2.25	*1.98*	**3.34**	**3.25**	**2.21**	*1.49*	**3.35**	**2.82**
INV	-0.15		-0.18		-0.14		-0.15	
	-6.38		**-7.00**		**-5.59**		**-5.60**	
DAYS		-0.10		-0.11		-0.10		-0.10
		-6.62		**-7.20**		**-5.95**		**-6.03**
R^B_{i,t^i}			-0.28	-0.22				
			-17.49	**-11.39**				
R^D_{i,t^i}			-0.68	-0.65				
			-39.46	**-34.37**				
D_{i,t^e}			-0.52	-0.60				
			-3.11	**-2.78**				
D_{i,t^i}							-0.62	-0.59
							-33.03	**-30.84**
R^2	0.37	0.30	0.48	0.41	0.35	0.27	0.45	0.36
Bond-month obs	572,308	572,308	572,308	572,308	572,308	572,308	572,308	572,308

Table IA- 11 – High Yield

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of TRACE. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent return:				R^T_{i,t^b+1}				
constant	-96.93	-230.32	-49.74	-161.50	-95.04	-201.36	-54.70	-145.31
	-0.65	*-1.45*	*-0.34*	*-1.09*	*-0.65*	*-1.23*	*-0.37*	*-0.90*
R^B_{i,t^e}	0.00	0.02	-0.02	0.01				
	-0.27	*1.20*	*-1.26*	*0.64*				
R^D_{i,t^e}	-0.03	-0.02	0.45	0.54				
	-1.44	*-0.72*	*1.37*	*1.44*				
D_{i,t^e-1}	*-0.04*	*-0.04*	*0.48*	*0.56*				
	-1.51	*-0.96*	*1.47*	*1.50*				
D_{i,t^e}					-0.04	-0.03	0.07	0.07
					-1.87	*-0.91*	***3.24***	***2.50***
OAS	-0.02		0.00		-0.02		0.00	
	-0.78		*-0.17*		*-0.65*		*-0.20*	
OASD	-3.41		-2.59		-3.19		-2.72	
	-0.77		*-0.58*		*-0.68*		*-0.58*	
DTS	0.02		0.02		0.02		0.02	
	1.56		*1.54*		*1.45*		*1.50*	
Rating		6.18		6.80		6.51		7.04
		1.29		*1.44*		*1.22*		*1.33*
Maturity		1.80		2.04		1.70		1.83
		1.88		***2.08***		*1.80*		*1.85*
Amt. Out.	-3.31	9.01	-4.96	5.41	-2.50	7.53	-4.50	4.62
	-0.45	*1.34*	*-0.70*	*0.87*	*-0.33*	*1.12*	*-0.61*	*0.70*
Age	3.66	2.06	2.80	1.34	3.25	1.94	2.62	1.45
	2.56	*1.93*	***2.07***	*1.19*	***2.66***	*1.95*	***2.12***	*1.30*
IRT	9.22	15.13	13.22	17.49	8.02	19.22	13.72	24.78
	1.51	***2.23***	***2.29***	***2.70***	*1.30*	***2.26***	***2.30***	***2.89***
BAS		***-6.18***		***-4.50***		***-9.18***		***-7.94***
		-1.10		*-0.82*		*-1.22*		*-1.08*
BIAS	-8.93		-6.93		-8.39		-6.89	
	-2.47		***-2.06***		***-2.44***		***-2.07***	
γ	1.85	4.01	4.13	6.34	2.36	4.09	2.74	5.11
	0.71	*1.20*	*1.54*	*1.85*	*0.88*	*1.22*	*1.07*	*1.55*
VOL	10.85		10.09		9.86		9.93	
	3.76		***3.94***		***3.67***		***3.74***	
VOLS		0.84		0.76		0.85		0.84
		2.11		***2.09***		*1.68*		*1.75*
FREQ	-0.04	-0.05	-0.03	-0.03	-0.04	-0.06	-0.04	-0.04
	-1.83	*-1.13*	*-1.50*	*-0.80*	*-1.93*	*-1.20*	*-1.79*	*-0.96*
INV	-0.14		-0.17		-0.06		-0.06	
	-1.44		*-1.71*		*-0.53*		*-0.57*	
DAYS		-0.32		-0.34		-0.27		-0.28
		-5.44		***-5.06***		***-4.20***		***-3.76***
R^B_{i,t^i}			-0.06	0.00				
			-2.06	*0.08*				
R^D_{i,t^i}			*-0.48*	*-0.44*				
			-18.76	***-13.12***				
D_{i,t^e}			*-0.83*	*-0.87*				
			-2.55	***-2.31***				
D_{i,t^i}							-0.45	-0.42
							-17.55	***-12.28***
R^2	0.31	0.22	0.36	0.28	0.28	0.17	0.31	0.20
Bond-month obs	163,173	163,173	163,173	163,173	163,173	163,173	163,173	163,173

Table IA- 12 – Credit returns

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of TRACE. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent return:				R^T_{i,t^b+1}				
constant	-12.12	-88.34	58.13	-13.13	-9.96	-76.63	55.80	-3.98
	-0.21	*-1.30*	*1.00*	*-0.18*	*-0.16*	*-1.09*	*0.91*	*-0.05*
R^B_{i,t^e}	-0.01	0.02	-0.03	0.00				
	-0.44	*1.03*	***-2.26***	*-0.07*				
R^D_{i,t^e}	-0.03	-0.02	0.34	0.35				
	-2.99	*-1.22*	*1.35*	*1.19*				
D_{i,t^e-1}	*-0.03*	*-0.02*	*0.40*	*0.40*				
	-2.92	*-1.38*	*1.59*	*1.36*				
D_{i,t^e}					-0.03	-0.02	0.14	0.14
					-3.33	*-1.45*	***10.64***	***8.46***
OAS	0.01		0.02		0.01		0.02	
	0.45		*0.91*		*0.46*		*0.98*	
OASD	-2.04		-1.12		-1.90		-0.87	
	-1.53		*-0.86*		*-1.49*		*-0.68*	
DTS	0.01		0.01		0.01		0.01	
	1.75		*1.73*		*1.63*		*1.68*	
Rating		4.28		4.19		4.62		4.68
		1.96		*1.86*		*1.97*		*1.97*
Maturity		0.37		0.81		0.30		0.66
		0.87		*1.84*		*0.77*		*1.70*
Amt. Out.	-1.21	2.79	-4.05	-0.63	-0.94	2.25	-3.51	-1.08
	-0.38	*0.94*	*-1.28*	*-0.20*	*-0.27*	*0.75*	*-1.02*	*-0.35*
Age	0.83	1.19	-0.02	0.34	0.74	1.17	-0.19	0.23
	2.33	***3.16***	*-0.05*	*0.86*	***2.13***	***3.25***	*-0.54*	*0.60*
IRT	0.78	3.76	5.50	8.01	1.42	5.34	6.86	10.10
	0.25	*1.06*	*1.81*	***2.24***	*0.50*	*1.61*	***2.47***	***2.97***
BAS		*-1.33*		*0.99*		*-1.46*		*1.37*
		-0.50		*0.37*		*-0.48*		*0.45*
BIAS	-5.52		-3.82		-5.29		-3.88	
	-3.04		***-2.30***		***-3.04***		***-2.28***	
γ	-0.31	0.07	1.04	2.06	0.27	0.51	1.17	1.66
	-0.23	*0.04*	*0.78*	*1.10*	*0.19*	*0.24*	*0.84*	*0.78*
VOL	2.28		1.65		1.88		1.22	
	2.46		*1.79*		*1.91*		*1.23*	
VOLS		0.32		0.30		0.31		0.31
		1.47		*1.39*		*1.16*		*1.14*
FREQ	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.02
	1.10	*1.79*	***2.09***	***2.65***	*1.03*	*1.48*	***2.19***	***2.41***
INV	-0.15		-0.17		-0.15		-0.16	
	-7.79		***-8.71***		***-6.75***		***-7.07***	
DAYS		-0.15		-0.16		-0.15		-0.15
		-8.97		***-9.19***		***-8.26***		***-8.26***
R^B_{i,t^i}			-0.09	-0.02				
			-5.20	*-1.14*				
R^D_{i,t^i}			*-0.59*	*-0.56*				
			-29.60	***-24.84***				
D_{i,t^e}			*-0.77*	*-0.74*				
			-3.05	***-2.54***				
D_{i,t^i}							-0.55	-0.54
							-27.87	***-24.08***
R^2	0.29	0.22	0.36	0.29	0.28	0.18	0.33	0.23
Bond-month obs	735,481	735,481	735,481	735,481	735,481	735,481	735,481	735,481

IA.1.3. Index prices' dynamics

Table IA- 13 specifications (1) and (3) correspond to respectively specification (6) and (7) in Table 8 and constitute the base cases. The first one investigates the predictive power of pricing distortions measured over the EOM window on the BOM window Bloomberg returns while the second one also includes contiguous information about those distortions from the implementation lag window. In specification (2) and (4) we test whether the results are robust to changing the set of control variables. Specifications (5) to (6) perform the same analyses when we consider alternative return drivers suggested by our model being the level of pricing distortions at the end of the EOM window, which follows from equation (2-12), instead of the return drivers identified in equation (2-15) and used in the specification (1) to (3). Specification (7) to (8) add as controls the distortion information from the implementation lag window.Table IA- 14 stresses the results of Table IA- 13 by investigating the robustness of the results over sub-sample periods when the sample period is split in halves. Table IA- 15 and Table IA- 16 reiterate the analyses conducted in Table IA- 13 for respectively the IG and HY universes, while Table IA- 17

analyzes the results on the AG universe when considering credit returns.

Overall, our key results are robust. Contrary to what we find for transaction prices, we find that distortions have predictive power beyond the implementation lag window, indicating that this information is only progressively incorporated into valuations. In all tables, the sign and significance of R^D_{i,t^e}, $D_{i,t-1}$ and $D_{i,t}$ (upper part of the table) remains unchanged, indicating that distortions across pricing sources are key explanatory factors of the cross-section of future valuation-based returns, leading to reversals not only over the implementation lag window, but also over the BOM window.

Finally, as for TRACE returns, we find that $INV_{i,t}$ and $IMB_{i,t}$, the two proxies for inventory risk, are both significant drivers of reversal over the BOM window.

Table IA- 13 – alternative measures

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of Bloomberg. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent return:				R^B_{i,t^b+1}				
constant	-31.97	-107.60	-69.48	-154.82	-33.44	-94.94	-82.81	-153.01
	-0.53	*-1.56*	*-1.13*	***-2.16***	*-0.53*	*-1.33*	*-1.25*	***-2.04***
R^B_{i,t^e}	-0.01	0.02	-0.01	0.02				
	-0.81	*1.10*	*-0.84*	*1.31*				
R^D_{i,t^e}	0.13	0.15	0.45	0.52				
	11.67	***9.72***	*1.68*	*1.64*				
D_{i,t^e-1}	*0.13*	*0.14*	*0.43*	*0.49*				
	8.99	***6.83***	*1.58*	*1.53*				
D_{i,t^e}					0.13	0.15	0.03	0.04
					11.36	***7.59***	***3.32***	***2.41***
OAS	0.00		0.00		0.00		0.00	
	0.08		*-0.23*		*0.06*		*-0.16*	
OASD	-0.05		-0.89		-0.13		-0.79	
	-0.02		*-0.39*		*-0.06*		*-0.37*	
DTS	0.01		0.02		0.01		0.01	
	1.88		*1.89*		*1.82*		*1.77*	
Rating		3.95		3.84		4.23		4.18
		1.78		*1.77*		*1.78*		*1.78*
Maturity		1.06		0.88		0.92		0.68
		1.82		*1.49*		*1.57*		*1.16*
Amt. Out.	0.78	4.51	2.03	6.63	1.18	3.91	2.95	6.56
	0.24	*1.48*	*0.64*	***2.09***	*0.34*	*1.27*	*0.84*	***2.02***
Age	0.76	0.99	1.17	1.47	0.73	1.00	1.22	1.55
	2.23	***2.77***	***3.07***	***3.85***	***2.06***	***2.81***	***3.06***	***3.91***
IRT	1.82	6.79	-1.40	3.57	2.48	8.45	-1.03	5.14
	0.58	***2.02***	*-0.44*	*1.05*	*0.85*	***2.56***	*-0.33*	*1.54*
BAS		*-1.02*		***-3.37***		*-1.16*		***-3.63***
		-0.42		*-1.40*		*-0.41*		*-1.31*
BIAS	-5.19		-6.07		-4.85		-5.74	
	-2.90		***-3.45***		***-2.79***		***-3.21***	
γ	0.11	0.45	0.10	0.78	0.76	0.74	0.30	0.32
	0.08	*0.23*	*0.07*	*0.43*	*0.55*	*0.35*	*0.22*	*0.15*
VOL	1.59		2.15		1.26		1.90	
	1.58		***2.03***		*1.16*		*1.68*	
VOLS		0.31		0.32		0.29		0.28
		1.36		*1.49*		*1.04*		*1.05*
FREQ	0.01	0.01	0.00	0.01	0.01	0.01	0.00	0.01
	1.17	*1.41*	*0.44*	*0.94*	*1.04*	*1.15*	*0.28*	*0.66*
INV	-0.17		-0.17		-0.17		-0.16	
	-8.20		***-8.52***		***-7.18***		***-7.15***	
DAYS		-0.16		-0.15		-0.15		-0.15
		-10.10		***-10.03***		***-9.42***		***-8.70***
R^B_{i,t^i}			-0.15	-0.08				
			-7.49	***-3.30***				
R^D_{i,t^i}			*0.30*	*0.33*				
			17.08	***15.58***				
D_{i,t^e}			*-0.09*	*-0.13*				
			-0.34	*-0.41*				
D_{i,t^i}							0.32	0.34
							19.16	***16.92***
R^2	0.37	0.29	0.40	0.33	0.35	0.25	0.37	0.27
Bond-month obs	735,481	735,481	735,481	735,481	735,481	735,481	735,481	735,481

Table IA- 14 – subsample analysis

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of Bloomberg. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent return:			R^B_{i,t^b+1}			
constant	-94.94	-82.81	-153.01	-49.51	62.19	-81.40
	-1.33	*-1.25*	***-2.04***	*-0.44*	*0.98*	*-0.69*
R^B_{i,t^e}	-0.01	0.01	-0.04			
	-0.84	*0.66*	*-1.84*			
R^D_{i,t^e}	0.45	0.23	0.69			
	1.68	*0.98*	*1.41*			
D_{i,t^e-1}	*0.43*	*0.21*	*0.65*			
	1.58	*0.90*	*1.33*			
D_{i,t^e}				0.04	0.04	0.03
				2.41	***2.90***	*1.13*
OAS	0.00	0.00	-0.01			
	-0.23	*0.00*	*-0.35*			
OASD	-0.89	-0.23	-1.57			
	-0.39	*-0.06*	*-0.58*			
DTS	0.02	0.02	0.01			
	1.89	*1.57*	*1.07*			
Rating				4.18	6.16	2.12
				1.78	*1.56*	*0.89*
Maturity				0.68	1.15	0.19
				1.16	*1.65*	*0.20*
Amt. Out.	2.03	1.87	2.19	6.56	10.16	2.80
	0.64	*0.47*	*0.44*	***2.02***	*1.80*	*0.96*
Age	1.17	1.74	0.57	1.55	2.07	1.01
	3.07	***2.68***	*1.67*	***3.91***	***2.95***	***3.20***
IRT	-1.40	-2.64	-0.11	5.14	2.67	7.71
	-0.44	*-0.61*	*-0.02*	*1.54*	*0.70*	*1.40*
BAS				***-3.63***	***-3.28***	***-3.99***
				-1.31	*-0.91*	*-0.94*
BIAS	-6.07	-3.71	-8.54			
	-3.45	***-2.72***	***-2.64***			
γ	0.10	-0.21	0.42	0.32	-0.47	1.15
	0.07	*-0.19*	*0.17*	*0.15*	*-0.21*	*0.32*
VOL	2.15	1.93	2.38			
	2.03	*1.11*	***2.02***			
VOLS				0.28	0.15	0.42
				1.05	*0.45*	*0.99*
FREQ	0.00	-0.01	0.01	0.01	0.00	0.01
	0.44	*-0.66*	*1.28*	*0.66*	*0.17*	*0.74*
INV	-0.17	-0.15	-0.19			
	-8.52	***-4.40***	***-9.72***			
IMB				-0.15	-0.18	-0.12
				-8.70	***-6.61***	***-6.13***
R^B_{i,t^i}	*-0.15*	*-0.12*	*-0.18*			
	-7.49	***-5.54***	***-5.44***			
R^D_{i,t^i}	*0.30*	*0.25*	*0.34*			
	17.08	***10.70***	***15.51***			
D_{i,t^e}	*-0.09*	*0.07*	*-0.26*			
	-0.34	*0.32*	*-0.54*			
D_{i,t^i}				*0.34*	*0.30*	*0.38*
				16.92	***10.33***	***15.17***
Start	Aug’02	Aug’02	Jan’13	Aug’02	Aug’02	Jan’13
End	Nov’22	Dec’12	Nov’22	Nov’22	Dec’12	Nov’22
R^2	0.40	0.39	0.42	0.27	0.26	0.29
Bond-month obs	735,481	246,255	489,226	735,481	246,255	489,226

Table IA- 15 – Bids only

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of Bloomberg. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent return:				R^B_{i,t^b+1}				
constant	-4.78	-70.85	9.62	-68.84	-8.54	-66.81	5.81	-60.20
	-0.08	*-0.97*	*0.16*	*-0.93*	*-0.13*	*-0.87*	*0.09*	*-0.77*
R^B_{i,t^e}	-0.01	0.01	-0.02	0.01				
	-0.95	*0.74*	*-1.26*	*0.76*				
R^D_{i,t^e}	0.12	0.14	0.44	0.33				
	10.54	***9.17***	*1.52*	*1.10*				
D_{i,t^e-1}	*0.12*	*0.12*	*0.41*	*0.30*				
	6.92	***5.88***	*1.39*	*0.97*				
D_{i,t^e}					0.13	0.14	0.02	0.02
					9.71	***7.69***	*1.74*	*1.38*
OAS	0.01		0.01		0.01		0.01	
	0.60		*0.28*		*0.57*		*0.40*	
OASD	0.26		-0.44		0.12		-0.38	
	0.12		*-0.19*		*0.06*		*-0.18*	
DTS	0.01		0.02		0.01		0.01	
	1.75		*1.95*		*1.70*		*1.85*	
Rating		4.20		4.20		4.71		4.78
		1.98		***2.02***		***2.06***		***2.11***
Maturity		1.10		1.01		0.94		0.83
		1.84		*1.65*		*1.55*		*1.37*
Amt. Out.	0.23	2.70	-0.67	2.41	0.84	2.42	0.21	1.90
	0.07	*0.82*	*-0.20*	*0.73*	*0.23*	*0.72*	*0.06*	*0.56*
Age	0.70	0.78	1.36	1.54	0.67	0.83	1.45	1.67
	2.07	***2.05***	***3.43***	***3.69***	*1.92*	***2.17***	***3.69***	***3.92***
IRT	4.10	10.09	4.59	9.94	5.24	12.38	5.81	12.69
	1.05	***2.65***	*1.13*	***2.64***	*1.50*	***3.33***	*1.63*	***3.44***
BAS		***3.03***		***4.30***		***3.12***		***4.27***
		0.80		*1.18*		*0.72*		*1.01*
BIAS	-4.78		-3.35		-4.45		-2.73	
	-1.28		*-0.98*		*-1.21*		*-0.78*	
γ	3.21	4.82	4.71	6.91	3.78	5.59	4.33	6.53
	1.35	*1.52*	*1.90*	***2.06***	*1.60*	*1.45*	*1.82*	*1.68*
VOL	0.70		0.84		0.22		0.07	
	0.71		*0.86*		*0.20*		*0.06*	
VOLS		0.20		0.19		0.19		0.18
		0.81		*0.79*		*0.62*		*0.60*
FREQ	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.02
	1.50	*1.85*	*1.46*	*1.81*	*1.37*	*1.54*	*1.45*	*1.55*
INV	-0.17		-0.17		-0.16		-0.15	
	-6.21		***-6.36***		***-5.83***		***-5.73***	
DAYS		-0.20		-0.17		-0.19		-0.17
		-9.36		***-9.09***		***-7.95***		***-7.22***
R^B_{i,t^i}			-0.14	-0.07				
			-6.73	***-3.07***				
R^D_{i,t^i}			*0.31*	*0.34*				
			14.28	***14.80***				
D_{i,t^e}			*-0.08*	*0.05*				
			-0.27	*0.17*				
D_{i,t^i}							0.35	0.36
							16.08	***15.93***
R^2	0.37	0.29	0.41	0.33	0.35	0.26	0.37	0.27
Bond-month obs	551,538	551,538	551,538	551,538	551,538	551,538	551,538	551,538

Table IA- 16 – Investment Grade

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of Bloomberg. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent return:	R^B_{i,t^b+1}							
constant	-52.62	-76.50	-73.89	-108.14	-34.98	-61.31	-68.77	-101.84
	-1.43	*-1.42*	*-1.98*	***-2.05***	*-0.94*	*-1.12*	*-1.81*	*-1.87*
R^B_{i,t^e}	-0.04	-0.01	-0.04	-0.01				
	-3.80	*-0.55*	***-3.77***	*-0.35*				
R^D_{i,t^e}	0.13	0.16	0.04	0.17				
	13.02	***11.59***	*0.22*	*0.70*				
D_{i,t^e-1}	*0.14*	*0.16*	*0.04*	*0.15*				
	12.22	***9.90***	*0.22*	*0.65*				
D_{i,t^e}					0.14	0.16	0.05	0.07
					14.13	***11.24***	***8.75***	***7.26***
OAS	0.02		0.01		0.02		0.00	
	0.45		*0.20*		*0.35*		*0.05*	
OASD	0.44		-0.23		0.61		0.32	
	0.22		*-0.11*		*0.31*		*0.16*	
DTS	0.01		0.01		0.01		0.01	
	1.49		*1.59*		*1.30*		*1.24*	
Rating		2.04		2.08		2.41		2.33
		1.58		*1.63*		*1.71*		*1.70*
Maturity		0.94		0.82		0.84		0.66
		1.54		*1.32*		*1.40*		*1.09*
Amt. Out.	3.21	3.71	3.94	5.07	2.42	2.91	3.76	4.78
	1.68	*1.41*	***2.10***	*1.97*	*1.23*	*1.12*	*1.96*	*1.84*
Age	0.41	0.83	0.68	1.20	0.36	0.72	0.69	1.10
	1.69	***2.43***	***2.42***	***3.18***	*1.43*	*1.99*	***2.56***	***2.91***
IRT	-0.11	5.80	-1.57	3.79	-0.28	6.07	-1.38	3.94
	-0.05	*1.49*	*-0.60*	*0.96*	*-0.12*	*1.52*	*-0.55*	*0.99*
BAS		*-0.18*		*-1.50*		*0.26*		*-1.34*
		-0.08		*-0.69*		*0.12*		*-0.60*
BIAS	-2.24		-3.39		-2.14		-3.36	
	-1.75		***-2.56***		*-1.73*		***-2.57***	
γ	1.74	1.21	1.12	0.50	2.12	3.11	1.60	2.30
	0.98	*0.79*	*0.67*	*0.36*	*0.92*	*0.88*	*0.70*	*0.66*
VOL	-0.35		0.01		-0.39		-0.07	
	-0.57		*0.01*		*-0.61*		*-0.11*	
VOLS		0.20		0.21		0.24		0.27
		1.81		*1.94*		*1.84*		***2.07***
FREQ	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01
	2.16	***2.18***	*1.74*	*1.80*	***2.06***	*1.56*	*1.61*	*1.05*
INV	-0.16		-0.17		-0.15		-0.15	
	-6.78		***-6.88***		***-5.96***		***-6.04***	
DAYS		-0.10		-0.10		-0.10		-0.10
		-9.01		***-9.81***		***-7.50***		***-7.49***
R^B_{i,t^i}			-0.24	-0.18				
			-15.32	***-9.82***				
R^D_{i,t^i}			*0.20*	*0.23*				
			16.17	***15.28***				
D_{i,t^e}			*0.23*	*0.15*				
			1.20	*0.65*				
D_{i,t^i}							0.24	0.26
							16.83	***16.73***
R^2	0.46	0.38	0.49	0.41	0.44	0.34	0.46	0.36
Bond-month obs	572,308	572,308	572,308	572,308	572,308	572,308	572,308	572,308

Table IA- 17

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of Bloomberg. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent return:				$R^{B}_{i,t^{b}+1}$				
constant	-129.97	-248.92	-153.74	-263.39	-115.58	-217.12	-177.10	-267.37
	-0.89	*-1.55*	*-1.11*	*-1.89*	*-0.81*	*-1.34*	*-1.26*	*-1.72*
$R^{B}_{i,t^{e}}$	-0.01	0.02	-0.01	0.03				
	-0.40	*1.22*	*-0.45*	*1.46*				
$R^{D}_{i,t^{e}}$	0.11	0.13	0.65	0.75				
	5.67	***4.30***	*1.91*	*1.86*				
$D_{i,t^{e}-1}$	*0.09*	*0.10*	*0.61*	*0.70*				
	3.18	***2.40***	*1.82*	*1.75*				
$D_{i,t^{e}}$					0.11	0.12	0.01	0.00
					5.18	***3.63***	*0.39*	*0.08*
OAS	-0.02		-0.03		-0.02		-0.03	
	-0.93		*-1.18*		*-0.91*		*-1.24*	
OASD	-3.95		-4.76		-3.99		-4.76	
	-0.88		*-1.04*		*-0.84*		*-1.01*	
DTS	0.02		0.02		0.02		0.02	
	1.56		*1.45*		*1.54*		*1.46*	
Rating		5.38		4.71		5.40		4.62
		1.12		*1.05*		*1.03*		*0.90*
Maturity		1.66		1.69		1.52		1.56
		1.73		*1.68*		*1.62*		*1.57*
Amt. Out.	-1.25	10.22	0.66	10.99	-1.24	8.77	2.41	11.36
	-0.18	*1.54*	*0.10*	*1.88*	*-0.17*	*1.35*	*0.33*	*1.82*
Age	3.12	1.70	3.08	1.61	2.93	1.71	3.25	2.01
	2.47	*1.75*	***2.73***	***2.03***	***2.61***	*1.84*	***3.00***	***2.39***
IRT	11.88	17.59	7.27	11.35	11.07	21.83	7.51	18.06
	2.15	***2.72***	*1.39*	*1.92*	*1.93*	***2.42***	*1.35*	***2.14***
BAS		***-5.49***		***-7.00***		***-8.61***		***-10.76***
		-1.00		*-1.36*		*-1.13*		*-1.50*
BIAS	-8.74		-8.38		-8.15		-8.04	
	-2.23		***-2.23***		***-2.26***		***-2.25***	
γ	2.58	4.73	3.77	5.40	3.31	5.02	2.76	4.47
	1.03	*1.40*	*1.35*	*1.54*	*1.29*	*1.46*	*1.05*	*1.31*
VOL	10.33		9.36		9.46		8.72	
	3.09		***2.99***		***2.98***		***3.00***	
VOLS		0.89		0.72		0.88		0.71
		2.14		***2.05***		*1.71*		*1.53*
FREQ	-0.05	-0.06	-0.04	-0.04	-0.05	-0.07	-0.04	-0.06
	-2.12	*-1.28*	*-1.72*	*-1.24*	***-2.08***	*-1.37*	*-1.95*	*-1.43*
INV	-0.15		-0.17		-0.06		-0.07	
	-1.42		*-1.63*		*-0.55*		*-0.68*	
DAYS		-0.38		-0.36		-0.33		-0.31
		-6.10		***-6.28***		***-5.51***		***-5.21***
$R^{B}_{i,t^{i}}$			-0.03	0.02				
			-1.22	*0.66*				
$R^{D}_{i,t^{i}}$			*0.42*	*0.46*				
			15.15	***12.68***				
$D_{i,t^{e}}$			*-0.19*	*-0.25*				
			-0.57	*-0.62*				
$D_{i,t^{i}}$							0.44	0.46
							15.44	***12.01***
R^2	0.32	0.22	0.36	0.28	0.29	0.18	0.31	0.20
Bond-month obs	163,173	163,173	163,173	163,173	163,173	163,173	163,173	163,173

Table IA- 18 – Credit returns

This table reports the Fama-MacBeth regression results for the sample period going from August 2002 to November 2022 when the universe is restricted on the availability of all control variables defined in Section 3.3. The dependent variables are the BOM returns defined in equation (3-3) measured out of Bloomberg. The explanatory variables correspond to the drivers of future returns in our model according to equation (2-12) or (2-15), when measured over both the EOM and the IL windows, together with the set of controls defined in Section 3.3. The numbers in parenthesis correspond to the t-statistic of the coefficient value, reported above, where the significant coefficients are identified in bold. Returns are expressed in basis points.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent return:				R^B_{i,t^b+1}				
constant	-47.05	-117.32	-81.79	-159.27	-48.84	-108.40	-96.10	-163.99
	-0.79	*-1.76*	*-1.34*	***-2.29***	*-0.77*	*-1.56*	*-1.46*	***-2.23***
R^B_{i,t^e}	-0.01	0.02	-0.01	0.02				
	-0.75	*0.95*	*-0.71*	*1.19*				
R^D_{i,t^e}	0.13	0.15	0.44	0.46				
	11.56	***9.53***	*1.64*	*1.46*				
D_{i,t^e-1}	*0.13*	*0.14*	*0.41*	*0.42*				
	9.01	***6.82***	*1.55*	*1.35*				
D_{i,t^e}					0.13	0.15	0.04	0.04
					11.14	***7.45***	***3.58***	***2.50***
OAS	0.00		0.00		0.00		0.00	
	0.25		*-0.04*		*0.20*		*-0.02*	
OASD	-2.43		-3.21		-2.47		-3.11	
	-1.89		***-2.67***		***-2.05***		***-2.64***	
DTS	0.01		0.01		0.01		0.01	
	1.81		*1.80*		*1.73*		*1.69*	
Rating		4.12		3.95		4.38		4.34
		1.91		*1.87*		*1.89*		*1.89*
Maturity		0.22		0.04		0.11		-0.13
		0.49		*0.10*		*0.27*		*-0.32*
Amt. Out.	0.82	4.01	2.00	5.90	1.21	3.62	2.91	6.15
	0.26	*1.39*	*0.64*	*1.96*	*0.35*	*1.23*	*0.84*	*1.97*
Age	0.88	1.35	1.29	1.82	0.86	1.38	1.33	1.91
	2.56	***3.93***	***3.33***	***4.78***	***2.39***	***3.94***	***3.27***	***4.78***
IRT	1.15	4.16	-2.09	0.96	1.86	5.73	-1.53	2.54
	0.37	*1.18*	*-0.65*	*0.27*	*0.65*	*1.72*	*-0.50*	*0.75*
BAS		*-1.55*		***-3.79***		*-1.72*		***-4.09***
		-0.60		*-1.50*		*-0.58*		*-1.40*
BIAS	-5.44		-6.04		-5.20		-6.03	
	-3.15		***-3.64***		***-3.12***		***-3.53***	
γ	-0.11	0.15	-0.03	0.61	0.59	0.60	0.15	0.22
	-0.08	*0.08*	*-0.03*	*0.33*	*0.43*	*0.28*	*0.11*	*0.10*
VOL	1.66		2.14		1.36		1.97	
	1.64		***2.01***		*1.24*		*1.73*	
VOLS		0.30		0.31		0.29		0.28
		1.34		*1.43*		*1.04*		*1.04*
FREQ	0.01	0.02	0.00	0.01	0.01	0.01	0.00	0.01
	1.14	*1.80*	*0.43*	*1.25*	*1.00*	*1.37*	*0.26*	*0.82*
INV	-0.17		-0.17		-0.17		-0.16	
	-8.23		***-8.39***		***-7.30***		***-7.27***	
DAYS		-0.16		-0.15		-0.15		-0.15
		-10.60		***-10.36***		***-10.05***		***-9.27***
R^B_{i,t^i}			-0.06	0.00				
			-3.56	*0.21*				
R^D_{i,t^i}			*0.30*	*0.32*				
			17.19	***15.56***				
D_{i,t^e}			*-0.09*	*-0.08*				
			-0.33	*-0.26*				
D_{i,t^i}							0.31	0.32
							18.75	***16.11***
R^2	0.32	0.24	0.35	0.28	0.30	0.21	0.32	0.22
Bond-month obs	735,481	735,481	735,481	735,481	735,481	735,481	735,481	735,481