Inefficient Information Intermediary and its Asset Pricing Implications: Evidence from the Corporate Bond Market *

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Abstract

Asset managers not only manage investment capital delegated by investors but also synthesize and disseminate information for investors' capital allocation. I argue that asset managers delay the information transmission to investors due to conflict of interests. Consequently, investors' capital allocation in response to information is delayed, resulting in market inefficiencies. I test this argument and its asset pricing implications in the corporate bond market. The main finding is that the delayed information transmission by corporate bond funds leads to price momentum in the corporate bond market. In addition, the delayed information transmission by corporate bond funds generates cross-bond return predictability among corporate bonds that are held by common fund owners. Finally, this paper sheds light on the over-valuation of high beta bonds relative to low beta bonds (beta anomaly) in the corporate bond market.

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1. Introduction

The asset management industry has experienced tremendous growth in the past four decades, and asset managers have become a vital player in the financial market. By the end of 2020, US mutual funds alone manage about $24 trillion of total assets, and they hold 22% of the US equity market and 18% of the US corporate bond market.[1] Given the giant size of the asset management industry, a large literature studies how asset managers impact asset prices. For example, prior research studies this topic from the perspectives of asset managers' preferences and demand (e.g., Gompers and Metrick, 2001), benchmark concerns (e.g., Baker, Bradley, and Wurgler, 2011), herding behavior (e.g., Wermers, 1999), etc. In this paper, I provide a new perspective on this topic. Specifically, I argue that asset managers are important information intermediaries for the capital allocation of investors. However, asset managers have incentives to delay the information transmission to investors, leading to market inefficiency.

Asset managers not only manage investment capital delegated by investors but also synthesize and disseminate information for investors' capital allocation decisions. In a frictionless financial market, asset managers disseminate the performance-relevant information to investors in a timely manner, and investors could immediately allocate capital (e.g., fund flows) in response to the information. However, conflict of interests distort incentives of asset managers to promptly report information to investors. As the performance of asset managers largely determines investors' capital allocation (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998), asset managers have incentives to smooth the reported performance in order to make their risk-return profile (e.g., Sharpe ratio) more attractive to investors.[2] By smoothing the reported performance, asset managers delay the transmission of performance-relevant information to investors, which in turn delays investors' capital allocation in response to information and ultimately leads to inefficiencies in financial markets.

To examine the above argument and its implications on market (in)efficiencies, I focus on US corporate bond mutual funds and study the implications on corporate bond prices.

[1] See the 2021 Investment Company Factbook.

[2] For instance, there is ample evidence showing that hedge funds tend to conduct return smoothing practice (e.g., Asness, Krail, and Liew, 2001; Bollen and Pool, 2008, 2009; Cao, Farnsworth, Liang, and Lo, 2017).

Corporate bond mutual funds have played an increasingly important role in the US corporate bond market. Their assets under management (AUM) have increased from $349 billion to $2,496 billion during 2000-2019, and they hold approximately 20% of the corporate bonds outstanding in 2019.[3] More importantly, two unique features of the corporate bond market make it an ideal empirical setting. First, corporate bond mutual funds act as essential information intermediaries for fund investors, distinct from equity mutual funds. Unlike the underlying assets of equity mutual funds, mainly stocks with easily accessible market prices, the underlying assets of corporate bond mutual funds are mainly bonds traded in the opaque over-the-counter (OTC) market. Investors of corporate bond mutual funds cannot easily obtain the pricing information of bonds and have to rely heavily on the pricing information reported by mutual funds (e.g., fund net asset values) for making capital allocation decisions. Second, corporate bond mutual funds have substantial discretion in marking their bond holdings (Cici, Gibson, and Merrick Jr, 2011), which enables them to delay updating pricing information into the fund net asset value (NAV) reported to investors (i.e., return smoothing).

Given the importance of fund performance in attracting investment capital, corporate bond mutual funds have both incentives and discretion to conduct return smoothing. As a result, corporate bond mutual funds would have stale NAVs. That is, their NAVs slowly adjust in response to the arrival of value-relevant information. Consistent with this argument, recent studies (e.g., Choi, Kronlund, and Oh, 2021) document severe staleness in NAVs among US bond mutual funds.[4]

The delay in updating information into NAVs could generate substantial information frictions for fund investors' capital allocation decisions and have significant implications on market (in)efficiency. The primary implication is on price momentum among corporate bonds. The price momentum pattern is well documented in equity markets, and it is arguably the biggest challenge to the efficient market hypothesis (Fama and French, 1996).[5] A recent

[3]See the 2021 Investment Company Factbook for the TNA of corporate bond funds. The figure of corporate bond fund ownership on corporate bonds is from Jiang, Li, Sun, and Wang (2021).

[4]By contrast, US equity funds, in general, do not suffer from stale pricing in NAVs in the recent two decades.

[5]An extensive literature is devoted to understanding the price momentum among stocks. See Section 2 for a list of empirical studies on price momentum among stocks.

study (Jostova, Nikolova, Philipov, and Stahel, 2013) finds that price momentum also exists in corporate bonds (dubbed by *corporate bond momentum*), but currently, there are no plausible explanations.

Intuitively, the delayed information transmission by corporate bond mutual funds leads to corporate bond momentum. When value-relevant news on bonds arrives, some sophisticated investors (e.g., hedge funds) respond and generate an initial price reaction to the news. However, the initial price movement is not far enough due to limits-to-arbitrage of these investors. Corporate bond mutual funds could play an important role in mitigating the limits-to-arbitrage. For example, if corporate bond mutual funds disseminate the news to fund investors without delay, fund investors would immediately allocate their capital into/out of the bond in the same direction as implied by the initial price reaction and push the bond price towards the information-efficient level quickly.[6] However, if corporate bond mutual funds delay the information transmission, fund investors slowly allocate capital into/out of the bonds, leading to price continuation that lasts for months (i.e., price momentum).

To test this implication, I start by investigating the extent to which corporate bond funds delay updating information to investors. In other words, I examine the corporate bond fund NAV staleness. As shown in Asness et al. (2001) and Getmansky, Lo, and Makarov (2004), a symptom of fund NAV staleness is that fund returns exhibit exposures on the lagged market factor returns. The rationale is, if funds delay updating information into NAVs, the market information will be slowly incorporated into fund NAVs, leading to a lagged relationship between fund returns and market factor returns. Based on a sample of 2,624 US corporate bond funds during 1998-2019, I indeed find a significant lagged relationship between fund returns and market factor returns. Specifically, in a monthly frequency panel regression, fund returns have a beta of 0.57 on contemporaneous corporate bond market return, and a beta of 0.12 on the one-month lagged corporate bond market return ($t = 2.72$).[7] In sharp

[6] The direction of fund investors' capital allocation and the initial price reaction would be in the same direction since prior studies on corporate bond mutual funds (e.g., Goldstein, Jiang, and Ng, 2017; Chen and Qin, 2017) document a positive flow-to-performance sensitivity.

[7] An alternative measure for the fund NAV staleness is fund return auto-correlation. However, the fund NAV staleness measured by the "lagged market exposure" approach of (Getmansky et al., 2004) have at least two unique advantages. First, the approach based on the lagged market exposure is immune from the contamination of fund manager skills. Specifically, one can think of fund returns as consisting of a factor-related component and a fund-specific component. Even without a stale pricing problem, a positive

contrast, I do not find such a pattern among US domestic equity funds, consistent with the argument that equity funds do not have such flexibility to delay updating their NAVs.

I further justify that the NAV staleness of corporate bond mutual funds manifests the funds' delay in updating information through return smoothing. Specifically, I conjecture that fund NAV staleness should be different between periods of upside returns and periods of downside returns. Specifically, since fund outflows are sensitive to bad performance more than fund inflows are sensitive to good performance (Goldstein et al., 2017), corporate bond fund managers should be more concerned with the capital flight in response to bad performance and thus have stronger incentive to smooth bad performance than good performance. In this sense, the NAV staleness should be more pronounced in periods of downside returns. Consistent with this conjecture, I find that corporate bond mutual funds' exposures on negative lagged market returns are larger than those on positive lagged market returns. Such asymmetric pattern of fund NAV staleness further supports the notion that the fund NAV staleness represents delayed information transmission by corporate bond funds.

Using the measure of fund NAV staleness by the exposure to the lagged market factor returns, I study the implications of delayed information transmission by corporate bond funds on corporate bond prices. To this end, I take two steps to construct a measure of bond-level latent fund staleness, which reflects the NAV staleness of a bond's fund owners. First, for each corporate bond mutual fund in each month, I measure fund-level staleness by the relative magnitude of a fund's exposure on the current and the lagged market factors which are estimated on a 36-month rolling basis.[8] Second, for each corporate bond at each quarter-end, I compute bond-level latent fund staleness as the weighted average of fund-level staleness across the bond's fund owners, where the weights are each fund's ownership on the bond. Intuitively, latent fund staleness can capture the effect of parent funds' delayed information transmission on individual bonds.

With this measure, I test the implication on corporate bond momentum by examining

auto-correlation in the fund returns can naturally arise from a persistent fund-specific return component that is due to managerial skills. Second, corporate bond market returns are largely i.i.d. across time. Thus, a positive lagged market exposure cannot be explained by persistence in market returns but rather by the funds' delay in updating NAVs.

[8] I consider the alternative measure of the fund NAV staleness based on fund return auto-correlation and find that main results are robust.

whether cross-sectional variations in latent fund staleness drives variations in corporate bond momentum profits. Intuitively, when a corporate bond has high latent fund staleness, it is mainly held by stale funds that slowly update NAVs. Thus, information on this bond would be slowly updated to investors through sluggish adjustment in fund NAVs, which can delay investors' capital allocation activities on this bond and further lead to a pronounced momentum pattern. To test this argument, I first conduct a double-sorting portfolio analysis. Specifically, at each month-end, I sort corporate bonds into quintiles by past-six month returns (skipping the most recent month) and terciles by the most recent latent fund staleness.[9] I find strong evidence that latent fund staleness can largely drive the corporate bond momentum. That is, over a six-month holding period, the momentum long-short portfolio that buys the winner bonds and sells short the loser bonds generates a significant return of 0.44% per month ($t = 2.73$) among bonds in the highest tercile of latent fund staleness. By contrast, the momentum long-short portfolio only delivers an insignificant return -0.10% per month ($t = -0.79$) among bonds in the lowest tercile of latent fund staleness. This pattern remains after adjusting for risk exposures on common factors in bond (default and term premium factors) and stock markets (Fama and French (1993) three factors), and it is consistent in Fama-MacBeth regressions where a variety of bond characteristics (e.g., illiquidity and credit rating) are controlled for.

I conduct a battery of robustness checks. In particular, one may concern that latent fund staleness could be associated with the bond illiquidity, and the momentum effect is presumably stronger among corporate bonds with higher illiquidity (more limits-to-arbitrage). To address this concern, I first show that the correlation between latent fund staleness and Amihud illiquidity measure among corporate bonds is fairly low (0.066). Second, I compute residual latent fund staleness, which is orthogonal to bond characteristics. Specifically, in each month, I run cross-sectional regression of latent fund staleness on relevant bond characteristics (e.g., Amihud illiquidity and credit rating) and take the residuals from this regression as residual latent fund staleness. I find that variations in residual latent fund

[9] Jostova et al. (2013) also use past six-month returns as the sorting variable for corporate bond momentum long-short portfolio. My main findings are robust using past twelve-month returns as the sorting variable for momentum effect.

staleness still significantly drive variations in corporate bond momentum profits.

I further conduct several empirical tests to strengthen the link between the latent fund staleness and corporate bond momentum. As mentioned previously, latent fund staleness generates corporate bond momentum in the following steps: (i) corporate bond funds slowly disseminate value-relevant information of the bond to investors, and as a result, (ii) investors deploy investment capital sluggishly in response to the information. I find supporting evidence for this two-step channel in the data. First, based on the previous finding that funds tend to delay updating their NAVs to a larger extent following negative market returns than following positive market returns, I show that latent fund staleness exerts a larger impact on the corporate bond momentum profits following negative market returns. Second, I use flow-induced trading (FIT) from Lou (2012) to proxy for investors' capital allocation on each bond and examine whether is a sluggish capital allocation.[10] Through panel regressions, I find that FIT on bonds with high latent fund staleness exhibit much higher auto-correlation than FIT on bonds with low latent fund staleness. This implies that investors tend to sluggishly deploy investment capital on bonds with high latent fund staleness. Furthermore, I show that FIT can generate a significant contemporaneous price effect on corporate bonds. Taken together, delayed information transmission by corporate bond funds results in investors' sluggish capital allocation in response to information and further leads to price momentum.

In addition to the implication on price momentum, delayed information transmission by corporate bond funds has another important implication on cross-bond return predictability. That is, past information on one particular bond can predict future returns of other bonds commonly held by corporate bond mutual funds, particularly stale funds. To illustrate, suppose bond A and bond B are commonly held by a stale corporate bond mutual fund. When bad news on bond A arrives, it is only partially released to investors in the current fund NAVs, leading to predictable future redemption demand from fund investors. To pay for the redemption, funds without significant cash reserves have to liquidate its holdings on both bonds, so there is predictable short-term price pressure from mutual fund selling on bond B.

[10] In a nutshell, FIT captures mutual funds' aggregate buying or selling on individual bonds that are induced by investors' investment flows.

Moreover, as such short-term price pressure is not related to bond B's fundamentals, it will be followed by a reversal in the long term. Through connecting a corporate bond with other corporate bonds that are held by common corporate bond fund owners, I indeed find supporting evidence for my conjecture.[11] Moreover, I find such cross-bond return predictability with reversals is more pronounced among corporate bonds commonly held by stale funds. These findings suggest the delay in updating NAVs among corporate bond mutual funds can generate non-fundamental price effects on corporate bonds.

Finally, the fund NAV staleness also has implications on corporate bond valuations. Like the beta anomaly (high-risk-low-return) among stocks, corporate bonds with high betas or high credit risk underperform those with low betas or low credit risk (e.g., Frazzini and Pedersen, 2014). I argue that corporate bond mutual funds' NAV staleness can contribute to the beta anomaly in corporate bonds. Specifically, corporate bond funds with stale NAVs tend to hold more high beta bonds than other funds, presumably for return smoothing.[12] Meanwhile, as funds with stale NAVs appear to have better performance, investors will allocate excessively more capital into stale funds than their non-stale counterparts. In this sense, the corporate bonds with high betas or high credit risk experience excessively more capital allocation and thus have overvaluation relatively to corporate bonds with low betas or low credit risk. Through time-series regressions, I indeed find supporting evidence for this conjecture. That is, the excessive investment flows to stale corporate bond funds in a period can significantly and positively forecast future beta anomaly returns.[13]

[11] Connected bond momentum is a novel and unique price regularity in the corporate bond market, as I find a similar "connected stock" trading strategy based on US equity only earns insignificant monthly returns of 0.16% in the same sample period.

[12] Corporate bonds with high betas or high credit risk are harder to price and are more sparsely traded. Holding more such bonds gives fund managers larger room for return smoothing. In the data, I indeed find that funds with stale NAVs indeed hold more high-beta or high-credit-risk corporate bonds than their non-stale counterparts

[13] I follow Frazzini and Pedersen (2014) to construct beta anomaly long-short portfolio in the corporate bond market by taking long position in the Bloomberg Barclays US Corporate Aaa index and shot position in the Ca-D index.

2. Related Literature

This paper is related to a large literature on the influence of asset management on asset prices. Prior research finds evidence that the influence can arise from preferences and demand of asset managers (e.g., Harris and Gurel, 1986; Shleifer, 1986; Gompers and Metrick, 2001; Bennett, Sias, and Starks, 2003; Koijen and Yogo, 2019; Ben-David, Li, Rossi, and Song, 2021a), fund flows (e.g., Coval and Stafford, 2007; Frazzini and Lamont, 2008; Lou, 2012; Anton and Polk, 2014), benchmark concerns (e.g., Baker et al., 2011), herding behavior (e.g., Wermers, 1999; Nofsinger and Sias, 1999), and style investing (e.g., Teo and Woo, 2004; Froot and Teo, 2008). My paper contributes to this literature by providing a new angle that asset managers can delay the information transmission for investors' capital allocation and further generates delayed price response to information.

This paper is also related to the literature that attempts to explain the puzzling price momentum pattern.[14] After the seminal work by Jegadeesh and Titman (1993) which first document momentum, several subsequent papers (Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999) develop behavioral models in which the momentum phenomenon arises from investors' underreaction or overreaction to information.[15] Later empirical studies find that momentum in the equity market can be predicted or explained by trading volume (Lee and Swaminathan, 2000), analyst coverage and firm size (Hong, Lim, and Stein, 2000), anchoring bias (George and Hwang, 2004), prospect theory and mental accounting (Grinblatt and Han, 2005), liquidity risk (Sadka, 2006), information uncertainty (Zhang, 2006), earningns momentum (Chordia and Shivakumar, 2006), overconfidence and self-attribution bias (Chui, Titman, and Wei, 2010), fund flows-induced trading (Lou, 2012), information discreteness (Da, Gurun, and Warachka, 2014), and factor momentum (Ehsani and Linnainmaa, 2021). Momentum is also shown to be pervasive across different asset markets and diverse countries (e.g., Asness, Moskowitz, and Pedersen, 2013). In particular, Jostova et al. (2013) document significant momentum profitability in

[14] As argued in Fama and French (1996), momentum is perhaps the biggest embarrassment for the efficient market hypothesis.

[15] Some other contemporaneous papers provide rational explanations for momentum profitability (e.g., Conrad and Kaul, 1998; Chordia and Shivakumar, 2002).

the US corporate bond market. My paper contributes to this literature by providing a new channel for price momentum. Although my analysis is based on corporate bond market, the mechanism can also work in other asset markets where asset managers function inefficiently as information intermediaries.

This paper also adds to the literature on the stale pricing problem among mutual funds. Earlier studies mainly focus on the stale pricing and the resulting risk of dilution in international equity funds or illiquid domestic equity funds (e.g., Goetzmann, Ivković, and Rouwenhorst, 2001; Chalmers, Edelen, and Kadlec, 2001; Chandar and Bricker, 2002; Boudoukh, Richardson, Subrahmanyam, and Whitelaw, 2002; Greene and Hodges, 2002; Zitzewitz, 2003). Stale pricing is also pervasive among fixed income funds. Choi et al. (2021) show that bond mutual funds also suffer from stale pricing. While their focus is on the resulting risks of fragility and losses to long-term fund investors, my paper shows that stale pricing can generate market inefficiencies.

Finally, this paper contributes to the literature that studies asset managers' strategic behavior. For example, prior studies document that asset managers deviate from their claimed investment policies (e.g., Chan, Chen, and Lakonishok, 2002; Wermers, 2012), misreport their portfolios (e.g., Bollen and Pool, 2009, 2012; Cici et al., 2011; Agarwal, Barber, Cheng, Hameed, and Yasuda, 2019; Chen, Cohen, and Gurun, 2020), manipulate prices of their holdings (e.g., Carhart, Kaniel, Musto, and Reed, 2002; Agarwal, Daniel, and Naik, 2011; Ben-David, Franzoni, Landier, and Moussawi, 2013), conduct data mining or incubation for raising new funds (e.g., Evans, 2010; Huang, Song, and Xiang, 2020), take excess risk to boost performance (e.g., Brown, Harlow, and Starks, 1996; Kaniel and Parham, 2017), and obfuscate fee structures and disclosures (e.g., Barber, Odean, and Zheng, 2005; Edelen, Evans, and Kadlec, 2012; deHaan, Song, Xie, and Zhu, 2020). My finding highlights that fund managers' strategic behavior in disseminating information to investors can result in inefficiencies in investors' capital allocation activities.

3. Data

3.1. Corporate Bonds

The corporate bond dataset is constructed by merging different databases. Bond prices are from Trade Reporting and Compliance Engine (TRACE) enhanced database and DataStream database. Specifically, TRACE provides transaction-level information for almost the entire US corporate bond market starting from July 2002.[16] To supplement TRACE data, I also obtain bond prices from DataStream, in which bond prices are mostly dealer quotes. I then merge corporate bond pricing data with the Mergent Fixed Income Securities (FISD) database, which covers a variety of bond characteristics, including offering date, offering amount, maturity date, bond type etc. After that, I apply several filters that are standard in the literature: (i) remove bonds issued under the 144A rule; (ii) remove bonds that do not trade in US dollars; (iii) require coupon type is fixed or zero; (iv) require bond type in US Corporate Debentures or US Corporate Medium Term Notes (Mergent FISD bond type in "CDEB," or "CMTN," or "CMTZ," or "CZ"); (v) exclude any remaining bonds that are convertible, asset backed, pay-in-kind, or part of unit deals. In addition, I exclude a bond-month observation with less than one year maturity in the empirical analysis.[17] Finally, unless otherwise mentioned, the sample period for the analysis on corporate bonds is from July 2002 to December 2019.

I use bond returns calculated from TRACE database and DataStream database. For TRACE data, I compute bond return in a month t as follows:

$$R_{i,t} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t} + AI_{i,t}} - 1. \tag{1}$$

$P_{i,t}$ is the bond clean price at month t end, $AI_{i,t}$ is accrued interest at month t end, and $C_{i,t}$ is any coupon payment between month $t-1$ end and month t end. Following Bessembinder, Kahle, Maxwell, and Xu (2008), daily clean price is computed as the volume-weighted average

[16] I follow Dick-Nielsen (2014) to clean the TRACE transaction data. The procedure in Dick-Nielsen (2014) mainly corrects for data errors such as cancellations, corrections, and reversals in the trade reports by dealers.

[17] As discussed in Bai, Bali, and Wen (2019), major corporate bond indices do not include corporate bonds with less than one year maturity. As a result, index-tracking investors will liquidate their holdings on these bonds, distorting the return calculation for bonds with less than one year maturity.

of intraday prices. Then, I follow Bai et al. (2019) to consider two scenarios for defining monthly returns: (i) returns from month $t-1$ end to month t end, and (ii) returns from month t beginning to month t end. In particular, a month end (beginning) refers to the latest (earliest) day with trading records within the last (first) five trading days of a month. If both types of returns are available for a bond-month, I use the first one in priority. For DataStream data, I compute monthly bond returns as the monthly percentage change in the total return index of each bond provided by DataStream. If both TRACE return and DataStream return are available for a bond-month, I use TRACE return in priority.[18]

To construct risk factors in the corporate bond market, I use corporate bond indices data from Bloomberg. Specifically, I use the total returns of Bloomberg Barclays US Corporate Bond Index as the market returns, and I define corporate bond market excess returns as the corporate bond market index returns minus one-month T-bill rate. I also construct a term premium factor (TERM) and a default premium factor (DEF). Specifically, TERM is the difference in the monthly long-term government bond return and one month T-bill returns. DEF is the difference in the monthly long-term investment-grade corporate bond returns and long-term government bond return. I use total returns on Bloomberg Barclays US Corp 10+ Years Index to proxy for monthly long-term investment-grade corporate bond returns, and I obtain long-term government bond return data from Amit Goyal's website.[19]

3.2. Corporate Bond Funds

Data on corporate bond funds is from CRSP Survivor-Bias-Free Mutual Fund database and Morningstar Direct. I follow Goldstein et al. (2017) to select sample corporate bond funds using the objective codes in CRSP database.[20] I obtain fund returns, total net assets (TNA), and other characteristics from CRSP. In this study, I use fund gross returns calculated as fund net returns plus 1/12 of annual fund expense ratio. For mutual funds

[18] To deal with outliers in bond returns, I follow Jostova et al. (2013) to eliminate bond-month observations with returns above 30%. The results are robust to other cut-offs.

[19] I thank Prof. Goyal for kindly sharing the updated dataset of Welch and Goyal (2008) on his website.

[20] I include mutual funds that have a: (i) first two-character CRSP objective code = "IC", or (ii) Lipper objective code in ("A", "BBB", "HY", "SII", "SID", "IID"), or (iii) Strategic Insight objective code in ("CGN","CHQ","CHY","CIM","CMQ","CPR","CSM"), or (iv) Wiesenberger objective code in ("CBD","CHY").

with multiple share classes, I combine the share classes into fund portfolio level based on the CRSP identifier *crsp_cl_grp*. Specifically, I sum the total net assets across share classes as the TNA of the fund, and I compute fund returns as the TNA-weighted average returns across share classes. The sample of corporate bond funds from CRSP consists of 2,624 distinct funds during 1998-2019.

For fund portfolio holdings, I employ data from Morningstar Direct, which includes the number of shares and reported holding value for each holding security during 2002-2019.[21] CRSP and Morningstar fund data are merged through CUSIP.[22]

I compute percentage fund flows of fund f in month t as monthly change in TNA after adjusting for portfolio returns:

$$flow_{f,t} = \frac{TNA_{f,t} - TNA_{f,t-1} \times (1 + Ret_{f,t})}{TNA_{f,t-1}}, \tag{2}$$

where $TNA_{f,t}$ is the total net assets of fund f at month t end, and $Ret_{f,t}$ is the fund gross return in month t. Fund flows are computed at fund portfolio level, and monthly fund flows are winsorized above at the value of 500%.

4. Stale Pricing in Corporate Bond Funds

In this section, I first examine the extent to which corporate bond funds exhibit staleness in updating NAVs. Then, I provide supporting evidence that fund NAV staleness is a manifestation of return smoothing. Finally, to capture the influence of fund NAV staleness on corporate bond prices, I construct a bond-level latent fund staleness measure by the average fund NAV staleness of the bond's fund owners.

4.1. Staleness in corporate bond fund NAVs

As shown in Asness et al. (2001) and Getmansky et al. (2004), a symptom of fund NAV staleness is that fund returns exhibit exposures on the lagged market factor. Intuitively,

[21] For holding reports, quarterly reporting frequency is mandatory, but some funds voluntarily report holdings at monthly frequency. To make the holding data balanced, I only use holdings reported at quarter-end.

[22] For analyses that do not require holding data, I use all the sample corporate bond funds from CRSP database. Only when holding data is required, I use the merged sample of funds from CRSP and Morningstar.

if there is a true equilibrium relationship between fund returns and market returns, when new market information arrives, the fund NAVs should also move. However, stale pricing in fund NAVs may prevent the move from fully showing up in the fund's reported returns in the same month. As a result, such market information may be slowly incorporated into fund NAV in subsequent months, leading to a lagged relationship between fund returns and market factor returns.

In this sense, I use the following regression specification to show the staleness in corporate bond fund NAVs:

$$\begin{aligned} ExRet_{f,t} =& \alpha_f + \beta_0 MktRf_t + \beta_1 MktRf_{t-1} + ... + \beta_k MktRf_{t-k} \\ &+ \gamma TNA_{t-1} + Fund\,FE + \epsilon_{f,t}, \end{aligned} \tag{3}$$

where $ExRet_{f,t}$ is the excess returns of corporate bond fund f in month t, $MktRf_{t-k}$ is the corporate bond market excess returns in month $t-k$, TNA_{t-1} is the fund total net assets at the end of month $t-1$, and fund fixed effects are included. I include three lags of market excess returns in the regression (i.e., k=4). If corporate bond fund returns are not fully synchronous with market returns due to stale pricing, then lagged market returns should also be correlated to current fund returns. In this case, the summed beta (i.e., β_0+β_1+...+β_k) represents a fund's actual market beta. Put it in another way, the ratio of the sum of lagged beta (i.e., β_1+...+β_k) over the actual beta measures the staleness of fund NAVs. Table 2 reports the regression results.

[Table 2 About Here]

Column (1) shows the regression results among corporate bond funds during the sample period of 1998.01-2019.12. As one can see, the coefficient on contemporaneous market excess returns (β_0) is 0.57 (t = 17.55). More importantly, the coefficient of the one-month lagged market excess returns (β_1) is 0.12 with a t-value of 2.72. Betas on the two-month and three-month lagged market returns are also positive with a magnitude of 0.04 and 0.03 respectively, but they are statistically insignificant. Based on these numbers, the sum of lagged betas is 0.19 (=0.12+0.04+0.03), and the actual beta is 0.76 (=0.59+0.12+0.04+0.03). Thus, 25% (=0.19/0.76) of the actual market beta are reflected by lagged relationships between corporate bond fund returns and corporate bond market returns, or in other words, only 75% of the market information is incorporated into fund NAVs in the current month. In columns (2)-(4), I sort corproate bond funds into terciles by their TNA in each month, and I find lagged betas enter the regression significantly across all size terciles. Specifically, the ratios of lagged beta to actual beta range from 25% to 27% and the t-value of the one-month lagged market returns range from 2.41 to 2.93.

For comparison, I also estimate the contemporaneous and lagged market betas for US domestic equity funds in the same sample period. In this regression, I use the CRSP value-weighted market return as the market return. Column (5) shows that while equity funds have a beta of 0.95 on contemporaneous market return ($t = 71.72$), their beta on the one-month lagged market return is only 0.02 and insignificant ($t = 1.51$). The comparison shows that stale pricing is particularly severe among corporate bond funds.

I also take alternative methods to show the staleness in corporate bond fund NAVs. First, to show that the results are not driven by the particular selection of benchmark factors, I replace the market model by a corporate bond two-factor model and re-perform the above analysis. The two-factor model consists of a bond default risk factor and a term premium factor, and I estimate fund exposures on the contemporaneous and lagged default/term factor returns. Table A.1 shows that corporate bond funds also load significantly on the one-month lagged default factor returns and term premium factor returns. Second, I follow Choi et al. (2021) to show the fraction of zero-return days and weekly return auto-correlation among corporate bond funds. A zero-return day means the NAV-based daily return of a fund is zero on a trading day. Since funds usually hold a well-diversified portfolio, a zero-return day may simply suggest that the fund does not update its NAV on that day. Table A.2 shows that the NAV-based daily returns of corporate bond funds are zero on 20.6% of the trading days. In comparison, US domestic equity funds only have zero-return days on 3.9% of the trading days. Another implication from fund NAV staleness is that fund returns should exhibit positive auto-correlation. Table A.3 shows that corporate bond fund returns exhibit significant auto-correlation up to two weeks.

Taken together, evidences here show that stale pricing is pervasive among corporate bond funds. In particular, the results emphasize "lagged market beta" as a symptom of fund NAV staleness.

4.2. Return smoothing and stale NAVs

In this section, I justify that fund NAV staleness is a manifestation of the funds' delay in updating NAVs under the motives of return smoothing. Since corporate bond fund outflows are sensitive to bad performance more than fund inflows are sensitive to good performance (Goldstein et al., 2017), corporate bond fund managers are more concerned with the capital flight in response to bad performance and thus have stronger incentives to smooth bad performance than good performance. In this sense, the NAV staleness should be more pronounced in periods of downside returns.

To test this conjecture, I estimate the following regression in subsamples of market upturns and downturns separately:

$$ExRet_{f,t} = \alpha_f + \beta_0 MktRf_t + \beta_1 MktRf_{t-1} + \gamma TNA_{t-1} + Fund\,FE + \epsilon_{f,t}. \tag{4}$$

The variable definitions follow equation 3. For an observation of fund f in month t, I classify it into market upturn (downturn) subsample if the corporate bond market return is positive (negative) in the month $t-1$. Under the conjecture of intentional smoothing, a fund manager who manage prices will report fund returns that exhibit higher lagged exposure to the market factor when market returns are negative than when they are positive. Table 3 reports the results.

[Table 3 About Here]

Column (1) shows that the one-month lagged market beta is only 0.08 ($t = 2.41$) following positive market returns. In comparison, column (2) shows that the lagged beta is 0.33 ($t = 2.44$) following negative market returns. In untabulated results, I find that the lagged beta is statistically significantly higher following down market than following up market. In a similar spirit as splitting samples by market returns, I form subsamples by the funds' own returns in the previous month. Columns (3)-(4) show that the lagged market beta is only 0.04 and insignificant ($t = 1.41$) following positive fund returns while that is 0.27 ($t = 2.14$) following negative fund returns. Results in this table clearly show that the lagged beta is asymmetrically larger following negative market returns or fund returns, consistent with the return smoothing hypothesis.

I conduct cross-sectional analyses to show that fund NAV staleness is more pronounced when funds have stronger incentives to conduct return smoothing. First, I conjecture that asset management companies (and corporate bond funds under their management) with more reputation concerns have less incentive to conduct purposeful return smoothing than those with fewer reputation concerns. To implement the test, I compute the average monthly total net assets of corporate bond funds managed by each asset management company during the sample period 1998-2019, and I classify the management companies into top 5 and non-top 5 groups by average monthly total net assets.[23] Intuitively, large asset management companies in the corporate bond market have accumulated more reputation capital than those small asset management companies, and they have weaker incentives to conduct return smoothing to attract investment flows. Second, I conjecture that institutional-oriented funds which face more sophisticated clients have less incentive to conduct return smoothing than retail-oriented funds. I follow Goldstein et al. (2017) for the classification of funds. Specifically, I use the institutional or retail share class flag in CRSP mutual fund database, and I define a fund as an institutional-oriented (retail-oriented) fund if more than 80% (less than 20%) of its TNA is from intutional share classes. Table A.4 shows that funds managed by top 5 asset management companies indeed have a smaller lagged beta than funds managed by non-top 5 companies (0.06 vs. 0.13) and institutional-oriented funds have a smaller lagged beta than retial-oriented funds (0.08 vs. 0.14).

To show evidence of return smoothing from the reported bond prices, I compare the fund-reported bond price with the traded bond price. Specifically, at a given reporting quarter-end, I compute the percentage difference between bond price reported in the holding data with the latest available daily traded price in TRACE database.[24] Then, I test whether funds are likely to mark their holding bonds above (below) latest traded price following bad (good) performance. Table A.5 shows that if the market returns or fund returns are negative

[23]In an average month during the sample period of 1998-2019, corporate bond funds managed by top 5 asset management companies account for about 41% of total net assets of all corporate bond funds.

[24]I compute daily traded price as the volume-weighted average traded price within a day, and I require the distance between the date of traded price and the date of reported price to be within 5 calendar days.

in a reporting quarter, funds tend to report holding prices that are higher than the traded prices at a reporting quarter-end.

Taken together, these findings suggest that fund NAV staleness is indeed a manifestation of funds' delay in updating NAVs under the return smoothing motive. These findings highlight that the conflict of interests between fund managers and investors generates information frictions for fund investors' capital allocation decisions.

4.3. Measuring bond-level latent fund staleness

Having shown that corporate bond funds have stale NAVs, I proceed to analyze the implications on corporate bond prices. In this regard, I hypothesize that staleness in corporate bond funds introduces latent staleness for their underlying corporate bonds. The rationale is, stale funds slowly incorporate value-relevant information into portfolio valuation; consequently, when a corporate bond is heavily held by stale funds, value-relevant information is only slowly incorporated into the reported bond price. This motivates a measure of bond-level staleness based on the staleness of their mutual fund owners.

Specifically, I take two steps to construct the measure of latent fund staleness. In the first step, for each corporate bond fund in each month I estimate the following regression:

$$ExRet_{f,t} = \alpha_f + \beta_{f,0} MktRf_t + \beta_{f,1} MktRf_{t-1} + ... + \beta_k MktRf_{t-k} + \epsilon_{f,t}. \tag{5}$$

$ExRet_{f,t}$ is the excess fund return in month t and $MktRf_{t-k}$ is the corporate bond market excess returns in month $t-k$. The estimation is conducted on a 36-month rolling basis, and I impose the constraints that parameters estimates of β_k are non-negative.[25] I then define fund-level staleness as:

$$\text{Fund staleness}_{f,t} = 1 - \sum_{j=0}^{k} (\frac{\beta_{f,j}}{\beta_f})^2, \quad \beta_f = \sum_{j=0}^{k} \beta_{f,j}. \tag{6}$$

As discussed earlier, the actual market beta (β_f) should be the sum of contemporaneous and lagged betas. $\beta_{f,k}/\beta_f$ reflects the fraction of market information in month $t-k$ that is incorporated into fund returns of month t. The fund staleness measure is constructed in a

[25]By imposing the non-negative constraints on β_ks, I assume that funds should positively load on the market factor and market information is only partially incorporated into fund NAVs.

Herfindahl index style. To interpret, fund staleness is minimized (=0) when $\beta_{f,0}/\beta_f = 1$, in which case a fund only has contemporaneous market exposure. As a fund exhibits positive current and lagged betas, fund staleness becomes positive, and it reaches the maximum when all betas have the same value: $\beta_{f,k} = 1/(k+1)$. For the main analysis, I estimate fund staleness only using the contemporaneous and one-month lagged market returns (k=0,1), since previous analyses show that corporate bond funds only have significant exposures on market returns in these two periods.

In the second step, I compute the latent fund staleness at each quarter-end as the weighted average fund-level staleness of the parent funds, and the weights are determined by each fund's relative holding amount on the bond:

$$\text{Latent Fund Staleness}_{i,q} = \frac{\sum_{f=1}^{F} \text{Hold\_Amt}_{f,i,q} \times \text{Fund staleness}_{f,q}}{\sum_{f=1}^{F} \text{Hold\_Amt}_{f,i,q}}. \tag{7}$$

$\text{Hold\_Amt}_{f,i,t}$ is the par value amount of bond i held by fund f at the end of quarter q, and Fund $\text{staleness}_{f,q}$ is the fund staleness measured at quarter q end following equation 6. To interpret, a high latent fund staleness means a corporate bond is mainly held by stale corporate bond funds, and thus value relevant information about the bond would be slowly transmitted to investors.

5. Implication on Corporate Bond Momentum

In this section, I examine whether delayed information transmission by corporate bond funds can lead to price momentum among corporate bonds. Specifically, I use latent fund staleness to capture the effect of delayed information transmission by corporate bond funds on individual bonds. Then I examine whether cross-sectional variations in latent fund staleness can drive variation in corporate bond momentum profits through portfolio sorting and Fama-MacBeth regressions. After that, I examine the underlying mechanism for latent fund staleness to influence corporate bond momentum profits.

5.1. Portfolio analysis

I start the analysis by replicating the corporate bond momentum documented in prior studies (e.g., Jostova et al., 2013). In each month, I sort corporate bonds into decile portfolios based on their past six-month cumulative returns (skip the most recent month). The portfolios are held over the next six months, and equal-weighted average portfolio returns are computed. To deal with overlapping portfolios in each holding period, I follow Jegadeesh and Titman (1993) to take the average returns across portfolios formed in different months. Table A.7 shows the performance of the corporate bond momentum decile portfolios from July 2002 to December 2019. As one can see, the top decile outperforms the bottom decile by 36 bps raw returns per month ($t = 2.35$) in the six-month holding period. In terms of five-factor alpha which adjusts for exposures on Fama and French (1993) stock market three factors and corporate bond term and default factors, the top-minus-bottom decile spread is 45 bps per month ($t = 3.09$). [26] The magnitude of corporate bond momentum long-short spread is similar to that of Jostova et al. (2013). This result confirms that the well-known price momentum in the stock market also exists in the corporate bond market.

Next, I examine whether cross-sectional variation in latent fund staleness can drive variation in the corporate bond momentum profits. To this end, I conduct a portfolio double-sorting analysis based on the past bond returns and latent fund staleness.[27] In each month, I sort corporate bonds into quintiles by their past six month returns with the most recent month skipped (PRET), and I independently sort corporate bonds into terciles by their latent fund staleness (dubbed by Staleness; see equation 7 for definition). The two-way sorted portfolios are held over the next six months, and equal-weighted portfolio returns are computed. If latent fund staleness is a key driving factor of corporate bond momentum, the momentum profitability (i.e., the difference in returns between top PRET quintile and bottom PRET quintile) should concentrate on the group of bonds with high latent fund staleness. Table 4 reports the results.

[26] In untabulated results, I find that corporate bond momentum strategies with formation periods of 3/6/12 months and holding periods of 1/3/6 months (skip the most recent month) can generate economically and statistically significant alphas. In the main analysis, I focus on the momentum strategy with a formation period of 6 months and a holding period of 6 months , since this specification is widely used in the analysis on momentum. I also use the momentum strategy with a formation period of 12 months and holding period of 1 month for robustness check.

[27] In my sample, the correlation between latent fund staleness and past six-month returns is -0.002 (see Table A.8). This ensures that the independent sorting by past returns and latent fund staleness is not a further sort on past returns, and this also alleviates the concern that the two-way sorted portfolios would be too thin.

[Table 4 About Here]

Panel A shows that, among the top Staleness tercile, momentum winner portfolio earns a monthly excess returns of 45 bps while that is 1 bps for momentum loser portfolio. Momentum long-short portfolio that goes long (short) in the winner (loser) portfolio earns 44 bps per month with a t-value of 2.73. By comparison, among bottom and medium staleness terciles, momentum long-short portfolio only earn monthly returns of -10 bps and 1 bps, respectively. The difference in momentum long-short returns between the top and bottom Staleness tercile is 54 bps per month ($t = 4.13$). Panel B and Panel C reports the risk-adjusted portfolio performance under a two-factor model and a five-factor model model, respectively.[28] The results are similar with Panel A. For instance, in the top Staleness tercile, momentum long-short alpha is 50 bps (57 bps) per month on a two-factor (five-factor) adjusted basis with a t-value of 3.28 (3.63); In the bottom Staleness tercile, momentum long-short alpha is -6 bps (-6 bps) per month on a two-factor (five-factor) adjusted basis with a t-statistic of -0.60 (-0.51). In sum, corporate bond momentum strategy is only profitable among corporate bonds with high latent fund staleness.

It's also worth noting that the effect of latent fund staleness on momentum mainly works through the momentum loser portfolio (PRET 1 portfolio). For instance, within the bottom PRET quintile, the highest staleness tercile underperforms the lowest staleness tercile by 59 bps five-factor alpha per month ($t = 3.34$); whereas, within the top PRET quintile, the highest staleness tercile outperforms the lowest staleness tercile by only 4 bps five-factor alpha per month ($t = 0.49$). This asymmetric effect of latent fund staleness on momentum loser and winner portfolios is consistent with results in Table 3 that corporate bond funds are more likely to conduct return smoothing and withhold negative information when faced with negative market returns or fund returns.

Overall, the results here show that variation in latent fund staleness can largely drive variation in corporate bond momentum profits and corporate bond momentum only exists among corporate bonds with high latent fund staleness. In addition, the effect of latent fund

[28] Two factor model includes corporate bond default and term premium factors. Five-factor model includes Fama and French (1993) stock-market three factors augmented with corporate bond default and term premium factors.

staleness mainly works through the momentum loser portfolio. These findings collectively suggest that delayed information transmission by corporate bond funds leads to corporate bond momentum.

5.2. Robustness checks

One may be concerned that latent fund staleness can capture certain bond characteristics which are also associated with future corporate bond returns or cross-sectional variation in momentum profitability. For example, credit rating has been documented to be associated with both corporate bond returns and the corporate bond momentum profitability (e.g., Jostova et al., 2013). To ensure that the findings on the staleness effect are not contaminated by other bond characteristics that might correlate with latent fund staleness and drive the variation in corporate bond momentum, I compute residual latent fund staleness from cross-sectional regressions of latent fund staleness on a set of relevant bond characteristics:

$$\begin{aligned} Staleness_{i,t} = \beta_0 + \beta_1 Rating_{i,t} + \beta_2 Age_{i,t} + \beta_3 Illiquidity_{i,t} \\ + \beta_4 Offering\_amt_{i,t} + \beta_5 PRET_{i,t} + \epsilon_{i,t}. \end{aligned} \tag{8}$$

The characteristics on the right-hand side include numerical rating, age, amihud illiquidity, offering amount, and past six-month cumulative returns of the bonds. I take the residual terms from the cross-sectional regression ($\epsilon_{i,t}$) as the residual latent fund staleness for a given bond i in month t. By definition, residual latent fund staleness is orthogonal to the bond characteristics controlled in the above regression.

I re-perform the portfolio analysis in Table 4 by replacing latent fund staleness with residual latent fund staleness. Table A.9 reports the results. On a five-factor-adjusted basis, corporate bond momentum profits are 2 bps and 39 bps in the lowest and highest residual latent fund staleness terciles, respectively (t-values are 0.19 and 2.69, respectively). This evidence confirms latent fund staleness can explain cross-sectional differences in momentum after controlling for relevant bond characteristics such as credit rating.

In addition, I conduct several robustness checks for the portfolio analysis in Table 4. (i) Instead of using corporate bond returns calculated based on both TRACE transaction data and Datastream quote data, I re-examine the results by only using bond returns from

TRACE data. This is to address the concern that dealer quotes from Datastream data may fail to reveal infrequent trading or stale prices, which are important for implementing momentum strategy. Table A.10 shows that the return patterns associated with PRET and latent fund staleness are almost unchanged. (ii) Instead of equal-weighted portfolio returns, I compute value-weighted portfolio returns in Table A.11, and the results are similar. (iii) I examine the staleness effect on corporate bond momentum in both the first-half and second-half of my sample period, and I find the results are robust in both sub-periods (Table A.13. (iv) I investigate the staleness effect on corporate bond momentum among investment-grade bonds and high-yield bonds separately, and the results are in Table A.14. First, I find that momentum profits are unconditionally higher among high-yield bonds, and this is consistent with prior literature. Moreover, I find a significant staleness effect on momentum profits among both investment-grade and high-yield bonds. Specifically, on a five-factor adjusted basis, the difference in momentum profits between the lowest and the highest staleness tercile of bonds is 27 bps per month ($t = 2.58$) among investment-grade bonds, and that is 43 bps per month ($t = 2.53$) among non-investment-grade bonds.

5.3. Fama-MacBeth regression

To examine the interaction effect between latent fund staleness and past returns in predicting future corporate bond returns after controlling for other bond characteristics that are known to be related to bond performance, I conduct the following Fama-MacBeth return predictive regression:

$$\begin{aligned} Ret_{i,t+1:t+6} = \beta_0 + \beta_1 PRET_{i,t-6:t-1} + \beta_2 PRET_{i,t-6:t-1} \times Staleness_{i,t} \\ + \beta_3 Staleness_{i,t} + \gamma Controls_{i,t} + \epsilon_{i,t+1:t+6}, \end{aligned} \tag{9}$$

where the dependent variable is cumulative bond returns over the next six months [29], $PRET_{i,t-6:t-1}$ is cumulative stock returns in the past six months (skip the most recent month), and $Staleness_{i,t}$ is the most recent latent fund staleness. Control variables include bond maturity in months (Maturity), numerical credit rating (Rating), natural logarithm of offering amount (Ln(Size)), fraction of zero-return day in the most recent quarter

[29]Standard errors in this regression are with Newey-West correction for five lags to correct for the autocorrelation in the error term.

(ZRD Ratio), natural logarithm of amihud illiquidity measure in the most recent quarter (Ln(Amihud)), and bond age in months (Age). Momentum literature suggests that β_1 should be positive, and a positive estimate of β_2 for the interaction term $PRET_{i,t-6:t-1} \times Staleness_{i,t}$ would suggest that higher latent fund staleness results in stronger momentum than lower latent fund staleness. Table 5 reports the regression results.

[Table 5 About Here]

Columns (1) and (2) show that PRET predicts future corporate bond returns with marginally significant t-values ranging from 1.72 to 1.87. A positive but weakly significant coefficient on PRET is not surprising, since results in Table 4 show that corporate bond momentum concentrates on the one-third of sample bonds with the highest latent fund staleness. The sign of the control variables are in general consistent with prior studies. For example, higher maturity, credit rating, and illiquidity are associated with higher expected bond returns. More important, column (3) shows that the interaction term between PRET and Staleness is positive and significant with a t-statistic of 2.20. This confirms that higher latent fund staleness results in stronger momentum than lower latent fund staleness. To better understand the difference in momentum profits between high and low staleness bonds, in each month I sort corporate bonds into terciles by latent fund staleness and I generate a dummy variable, Dummy_Stale, which equals one for the top staleness tercile and zero elsewhere. In column (4), I replace $Staleness_{i,t}$ in equation 9 by $Dummy\_Stale_{i,t}$ and find that coefficient of PRET is indifferent from zero while the interaction term between $PRET_{i,t-6:t-1} \times Dummy\_Stale_{i,t}$ is significant with a t-statistic of 3.25. This is consistent with the findings in Table 4 that corporate bond momentum only exists among bonds with high staleness. Next, I split the sample into a high staleness subsample consisting of bonds in the top staleness tercile in each month and a low staleness subsample consisting of bonds in the bottom and medium staleness tercile, and I investigate the return predictability of PRET in the high and low staleness subsample separately. Columns (5)-(8) shows that the coefficient of PRET is positive and significant among high staleness bonds while it is close to zero among low staleness bonds.

I conduct two additional analyses in the regression approach. First, I replace latent fund staleness by residual latent fund staleness estimated through equation 8 and re-perform the regression analysis. This approach is essentially to control for the interaction effect between other bond characteristics and PRET and re-examine the interaction effect between Staleness and PRET on bond returns. Table A.16 shows that the results based on residual latent fund staleness are robust. Second, to rule out the possibility that the interaction between PRET and Staleness may capture the flow-induced trading channel of momentum (Lou, 2012), I control for the expected flow-induced trading in Table A.17 and find the coefficient estimates for the interaction term between PRET and Staleness are almost unchanged.

Taken together, results from Fama-MacBeth regressions confirm the findings from portfolio analysis that higher latent fund staleness results in stronger corporate bond momentum and the momentum profits concentrate on the tercile of bonds with the highest latent fund staleness.

5.4. Mechanism tests

I conduct several empirical tests to strengthen the link between the latent fund staleness and corporate bond momentum. As introduced previously, latent fund staleness drives corporate bond momentum in the following steps: (i) corporate bond funds slowly disseminate value relevant information of the bond to investors, and as a result, (ii) investors deploy investment capital sluggishly in response to the information. In this section, I provide supporting evidence for this two-step mechanism.

For the first step of the mechanism, I show that the effect of latent fund staleness on corporate bond momentum is more pronounced when corporate bond funds have stronger incentives to delay the information transmission to investors, and I conduct two sets of tests in this regard. First, I exploit the previous finding that fund managers have a stronger tendency to delay the information transmission following market downturns than upturns. If the delayed information transmission channel is key to momentum profits, momentum profits should be larger following market downturns; in addition, variation in latent fund staleness should exert a stronger effect on generating variation in momentum profits following market downturn. To implement the test, I focus on the momentum strategy that is studied in the previous section. For each month t, I compute the past six-month market return as average monthly corporate bond market returns during the month $t-7$ to $t-2$, and I classify a momentum holding month into market downturn (upturn) if the past six-month market return is below (above) the sample median. After that, I examine the momentum profitability and staleness effect on momentum within market upturns or downturns separately. Table 6 reports the results.

[Table 6 About Here]

Panel A shows that corporate bond momentum profits are much larger following market downturns than market upturns. Specifically, the momentum long-short return is 32 bps per month following market downturn while it is only 7 bps per month following market upturn. Similar patterns are found on a five-factor alpha basis. Based on the double sorting analysis in Table 4, Panel B further examines the staleness effect on momentum following market downturns and upturns separately. Following market downturns, the momentum profit is 64 bps five-factor alpha per month among stale bonds, while that is only -5 bps among non-stale bonds. By comparison, following market upturns, the momentum profit is 9 bps five-factor alpha per month among stale bonds, and that is -32 bps among non-stale bonds. In sum, Panel B shows that latent fund staleness generates a stronger momentum following market downturns.

Second, I exploit the heterogeneity across funds in their incentives to conduct return smoothing. To this end, I classify corporate bond funds into subsamples based on their asset management companies' sizes or based on the target clients of the funds. The idea is that larger asset management companies have more reputation concerns for return smoothing practices than smaller asset management companies, and institutional-oriented funds face with more sophisticated fund investors that can detect their return smoothing practices than retail-oriented funds. I indeed find that the effect of latent fund staleness on corporate bond momentum profits are weaker for the funds managed by top 3 asset management companies in the corporate bond mutual fund industry and funds that are institutional-oriented (see Table A.18 and Table A.19).

To verify the second step of the mechanism, I use flow-induced trading (FIT) from Lou (2012) to proxy for investors' capital allocation on each bond. In a nutshell, FIT captures mutual funds' aggregate buying or selling on individual bonds that are induced by investors' investment flows. If latent fund staleness indeed leads to investors' sluggish capital allocations into the bonds, one should observe FIT on high staleness bonds to be persistent over time.

To begin with, I examine whether stale corporate bond funds experience more persistent fund flows than non-stale funds. In each month, I classify corporate bond funds into stale funds and non-stale funds based on the median fund staleness. Then, I regress monthly fund flows on one-month lagged fund flows in panel regressions. Panel A of Table 7 shows that fund flows exhibit a higher auto-correlation among stale funds than non-stale funds (0.06 vs. 0.03). This suggests that, due to staleness in fund NAVs, investors gradually allocate their investment capitals into the funds. Next, I sort corporate bonds into terciles by their latent fund staleness in each month and classify the top tercile of bonds into a stale group and the rest of bonds into a non-stale group. Panel B of Table 7 shows that flow-induced trading has a significantly positive auto-correlation of 0.25 among stale bonds, while that is only 0.04 and insignificant among non-stale bonds. Panel C of Table 7 examines the flow-induced price pressure on corporate bonds. In each month, I sort corporate bonds into deciles by their FIT in the month, and I compute the equal-weighted portfolio returns in the same month. The top FIT decile outperform the bottom FIT decile by 40 bps in terms of raw returns (t = 5.00) and 48 bps on a five-factor alpha basis (t = 4.88).

[Table 7 About Here]

6. Other Implications

In this section, I proceed to examine two other asset pricing implications arising from the delayed information transmission by corporate bond funds. In Section 6.1, I examine a cross-bond return predictability pattern which reflects non-fundamental price effects. In Section 6.2, I show that fund NAV staleness can lead to overvaluation on high beta corporate bonds, which potentially contributes to the beta anomaly in the corporate bond market.

6.1. *Connected Bond Momentum*

Another important asset pricing implication arising from delayed information transmission by corporate bond funds is cross-bond return predictability (also dubbed by connected bond momentum). Specifically, past information on one bond creates return predictability on other bonds that are connected through common ownership by stale funds. To illustrate, suppose bond A and bond B are commonly held by a stale corporate bond fund. When good news on bond A arrives, it is only partially updated to investors in the current fund NAVs, leading to predictable future capital allocation into the fund portfolio. As the fund will expand its holdings with investment capital in the future, there is predictable and non-fundamental price pressure on bond B. I test this prediction in this section.

To implement the test, I connect each corporate bond with other corporate bonds that are held by common corporate bond fund owners based on quarterly fund holdings. Specifically, for a pair of corporate bond i and j at a given quarter q end, I define common mutual fund ownership as:

$$COWN_{i,j,q} = \sum_{f=1}^{F} (S_{i,q}^{f} P_i + S_{j,q}^{f} P_j)/(S_i P_i + S_j P_j), \tag{10}$$

where $S_{i,q}^{f}$ is the shares of bond i held by fund f with a par value P_i, and $S_{i,q}P_i$ is the par value offering amount of bond i. At the end of quarter q, for each bond I compute connected bond returns as the COWN-weighted average of its connected bonds' returns in quarter t:

$$CBRet_{i,q} = \frac{\sum_{j=1}^{J} COWN_{i,j,t} \times Ret_{j,q}}{\sum_{j=1}^{J} COWN_{i,j,t}}. \tag{11}$$

I construct a connected bond momentum trading strategy using connected bond returns. In each quarter I sort corporate bonds into quintiles based on the connected bond returns. Corporate bonds with more than 20 mutual fund owners are excluded at the portfolio formation, since these bonds are essentially connected through a corporate bond market portfolio. The quintile portfolios are held over the next quarter and equal-weighted average portfolio returns are computed. Table 8 reports the results.

[Table 8 About Here]

Panel A shows that corporate bond portfolio returns monotonically increase with past connected bond returns. Specifically, the top CBR quintile earns a monthly five-factor alpha of 41 bps, while the bottom CBR quintile earns a monthly five-factor alpha of −0.16 bps. A long-short strategy that goes long in the top CBR quintile and short in the bottom CBR quintile yields a monthly five-factor alpha of 58 bps (t-statistic = 3.66).[30]

For comparison, I also examine the performance of a similar trading strategy among US equities. The rationale behind this test is that, if connected bond staleness is the driving factor for the connected bond momentum pattern, we should not observe a similar "connected momentum" pattern when switching to non-stale assets such as US equity. To implement, I follow Anton and Polk (2014) to compute connected stock returns for common stocks traded on NYSE, AMEX, or NASDAQ with market capitalization above NYSE median value. At each quarter-end, I sort stocks into quintiles based on the connected stock returns. I long the top quintile and short the bottom, and I track equal-weighted portfolio returns over the next quarter. Panel B shows that such a connected stock trading strategy only earns an insignificant monthly alpha of 10 bps (t-statistic = 0.58) after adjusting for the risk exposures on Fama and French (2015) five factors and stock market momentum factor.

I next examine whether bond staleness can explain the connected bond momentum. To this end, I construct a measure of connected bonds staleness. For a bond i and a connected bond j at quarter t end, I define common owner staleness as the average fund-level staleness across mutual funds that commonly hold bond i and j. Then, for a bond i at quarter t end, I define connected bond staleness (CB Staleness) as the COWN-weighted average common owner staleness across the connected bonds of bond i. In each quarter, I sort corporate bonds into quintiles based on their connected bond returns in the quarter, and I further independently sort corporate bonds into two groups based on the median connected bond staleness. I then track the equal-weighted portfolio returns over the next 12 quarters. Table 9 reports the results.

[Table 9 About Here]

[30] In Appendix table, I examine the long-horizon performance of connected bond momentum strategy, and I find that returns of the strategy revert during the 6th-8th quarter after portfolio formation.

Panel A, B, and C reports average monthly excess returns, two-factor alpha, and five-factor alphas. As shown in Panel C, for the stale group, the difference in five-factor alpha between top and bottom CB Ret quintile is 66 bps per month ($t = 3.76$) in the first post-formation quarter; while the alphas are indistinguishable from zero during quarter 2 to 5, the alpha spread turns -19 bps per month ($t = -2.09$) during quarter 6 to 8. For the non-stale group, the five-factor alpha spread between top and bottom CB Ret quintile is only 24 bps per month ($t = 1.84$) in the quarter 1, and the return spread is indistinguishable from zero in the following quarters. This comparison shows that connected bond momentum mainly arises from bonds that are connected through stale funds (i.e., the stale group). Moreover, one can observe from the stale group that positive return spread in the first quarter is followed by a significant return reversal during quarters 6-8. This is consistent with the conjecture that connected bond momentum reflects non-fundamental price pressure.

6.2. Investors' ignorance of fund staleness and its implication on beta anomaly

Previous analysis is established on the assumption that investors do not understand fund staleness so that mutual funds' delayed information transmission leads to investors' delayed capital allocation. To verify this assumption in data, I examine whether investors take into account the staleness in fund NAVs when making capital investments across corporate bond funds. Specifically, I use a revealed preference approach of Berk and van Binsbergen (2016) and perform a flow-performance horse race test to infer whether corporate bond investors consider the effect of staleness on fund performance when making capital allocation decisions. In the second part of this section, I study the implication of investors' ignorance of fund staleness on the beta anomaly in corporate bond market. If investors do not attend to the staleness effect on fund performance, they will allocate more capital into stale funds which disproportionately hold high beta bonds. As a result, investors' disproportionate capital allocation into high beta bonds can temporarily push the bond price away from the fundamental value, leading to lower returns of high beta bonds in the future. I construct a measure of investors' excessive capital allocation into stale funds and examine whether it can forecast beta anomaly returns in the corporate bond market.

6.2.1. *Do investors understand staleness?*

In the presence of stale NAVs, if investors only take into account the contemporaneous relationship between fund returns and factor realization, fund returns will exhibit lower factor exposures, which results in upward biased estimation of fund alphas (see Asness et al. (2001) and Getmansky et al. (2004)). To correct for the staleness effect in fund performance, one should include the lagged factor returns when calculating fund alphas, as shown in equation 5. If performance-chasing investors do not understand fund staleness, their investment flows are more sensitive to the fund alpha estimated in a naive "contemporaneous regression approach" than the fund alpha estimated in a "lagged regression approach."

Specifically, I take the following approach to estimate fund monthly alphas. In each month, I estimate the fund exposures on corporate bond market factors on a 36-month rolling basis:

$$ExRet_{f,t} = \alpha_f + \beta_0 MktRf_t + \beta_1 MktRf_{t-1} + +... + \beta_k MktRf_{t-k} + \epsilon_{f,t}. \tag{12}$$

$ExRet_{f,t}$ and $MktRf_t$ are fund excess returns and corporate bond market excess returns in month t, respectively. Then, I compute the fund alpha in a given month as:

$$\hat{\alpha_{f,t}} = ExRet_{f,t} - (\hat{\beta_0} MktRf_t + \hat{\beta_1} MktRf_{t-1} + +... + \hat{\beta_k} MktRf_{t-k}), \tag{13}$$

where the $\hat{\beta_k}$ is the coefficient estimate of β_k from equation 12. I set the k=0 to estimate the fund alpha without taking into account fund staleness, and I denote the fund alpha under such a "non-stale model" by $\alpha^{NS}_{f,t}$. To correct for the staleness effect, I let $k = 1$ in the above equations, and I denote the fund alpha under such a "stale model" by $\alpha^{S}_{f,t}$.

To test whether investment flows are more sensitive to fund alphas under stale or non-stale model, I follow the empirical methodology of Berk and van Binsbergen (2016).[31] I start from a simple regression of fund flows on one-month lagged fund alphas:

$$\Phi(Flow_{f,t}) = a + b \times \Phi(\alpha_{f,t-1}) + \epsilon_{f,t}, \tag{14}$$

[31] Barber, Huang, and Odean (2016) also proposes a methodology to compare different fund performance evaluation model based on flow-to-performance relationship. However, Ben-David, Li, Rossi, and Song (2021b) criticize that the methodology in Barber et al. (2016) may under-estimate the flow sensitivity to market-related component of fund returns. The methodology of Berk and van Binsbergen (2016) is immune from this issue.

where $\Phi(Flow_{f,t})$ is the sign of the fund flow in monbth t and $\Phi(\alpha_{f,t-1})$ is the sign of fund alpha in month $t-1$.[32] Standard errors are two-way clustered by fund and time. The regression is estimated using the fund alpha under either stale or non-stale model. I report coefficient estimates and t-statistics associated with b in columns (1) and (2) of Table 10, respectively. While fund flows are significantly and positively related to fund alphas estimated in both models, the magnitude is larger for fund alphas estimated in a naive non-stale model than fund alphas estimated in stale model (0.041 vs. 0.034).

[Table 10 About Here]

To test whether the flow-performance relationship under non-stale model is statistically higher than that under stale model, I conduct the following regression:

$$\Phi(Flow_{f,t}) = c + d \times (\frac{(\Phi(\alpha^{NS}_{f,t-1})}{Var(\Phi(\alpha^{NS}_{f,t-1}))} - \frac{(\Phi(\alpha^{S}_{f,t-1})}{Var(\Phi(\alpha^{S}_{f,t-1}))}) + \epsilon_{f,t}, \tag{15}$$

where $\alpha^{S}_{f,t-1}$ and $\alpha^{NS}_{f,t-1}$ are the fund alphas in month $t-1$ computed based on stale model and non-stale model respectively, and $Var(\Phi(\alpha^{S}_{f,t-1}))$ is the variance of the sign of the fund alpha computed based on stale model. Standard errors are two-way clustered by fund and time. A positive significant estiamte of d would imply that non-stale model, which do not correct for the staleness effect, is a better approximation to the performance evaluation model adopted by investors. Column (3) of Table 10 shows that d is positive with a t-statistic of 2.49, suggesting that non-stale model is more likely to be the true model than the stale model. In Appendix Table A.21, I replace the market model by the two-factor model consisting of corporate bond default and term factors, and I find the results are robust.

In sum, this subsection shows that investors tend to rely on simple contemporaneous relationship between fund returns and market returns to evaluate fund performance, while not correcting for the effect of staleness. This evidence supports the key assumption that investors in general do not attend to fund staleness when making capital allocation decisions.

[32] I estimate the flow-to-performance relationship in one-month horizon, since the flow-to-performance sensitivity is strongest at the one-month horizon

6.2.2. Implication on beta anomaly

In this subsection, I relate investors' ignorance of fund staleness to the beta anomaly in the corporate bond market. Evidence in the previous subsection suggests that investors tend to evaluate fund performance simply based on the contemporaneous relationship between fund returns and market returns. In these investors' minds, even if two funds have the same actual fund alpha, the fund with more stale NAV exhibits a lower factor exposure and a higher fund alpha than the fund with less stale NAV. As a result, stale funds will receive relatively more investment capital than non-stale funds, holding all else being equal. I refer to this pattern as "misallocation of flows." Meanwhile, as stale funds usually hold more high beta bonds than their non-stale counterparts[33], the misallocated capital flows will be disproportionately deployed into high beta bonds. Thus, the misallocation of flows can temporarily push the bond price away from the fundamental value, leading to lower returns of high beta bonds in the future.

To set the stage, I follow Frazzini and Pedersen (2014) to construct a beta arbitrage strategy in the corporate bond market. Specifically, I use the Bloomberg Barclays corporate bond credit indices as the testing assets.[34] In each month, I long the Bloomberg Barclays US Corporate Aaa index and short the Bloomberg Barclays US Corporate Ca-D index and compute the long-short return as the beta arbitrage return.

In order to get a pure credit version of beta arbitrage portfolio, I follow Frazzini and Pedersen (2014) to hedge away the interest rate risks. Specifically, in each month, I regress credit index excess returns on the excess returns of Bloomberg Barclays US government bond index to obtain the interest risk exposure θ. Then, I compute interest rate risk-hedged returns for each credit index as:$ExRet_{i,t}^{Hedged} = ExRet_{i,t} - \theta \times ExRet_{govt,t}$, where $ExRet_{i,t}$ and $ExRet_{govt,t}$ are the excess returns of a credit index i and the excess returns of the government index in month t, respectively. Hedged beta arbitrage returns is the difference in hedged

[33]Summary statistics

[34]Frazzini and Pedersen (2014) also use credit indices instead of individual corporate bonds to form beta arbitrage portfolio. A major advantage of using credit indices offered by professional pricing agencies (e.g., Bloomberg) is that they can use the most timely updated bond prices to calculate the returns of high beta or high credit risk bond portfolio. If one attempts to calculate returns of high beta bonds using TRACE transaction data, the infrequent trading problems or default events will make this task extremely difficult.

returns between Bloomberg Barclays US Corporate Aaa index and Bloomberg Barclays US Corporate Ca-D index.

I then construct a market-level measure of misallocation of flows due to the effect as follows. First, I adopt the methodology described in Section 6.2.1 to compute the fund monthly alpha with or without correcting for the staleness effect, which are denoted by $\alpha^{S}_{f,t}$ and $\alpha^{NS}_{f,t}$ respectively. Next, I estimate the flow-to-performance sensitivity (denoted by γ) from the Fama-MacBeth regressions of one-month-ahead fund flows on fund alphas in the current month.[35] After that, for each fund in each month, I compute the misallocation of flows due to ignorance of fund staleness as $\gamma \times (\alpha^{NS}_{f,t} - \alpha^{S}_{f,t})$. Finally, I compute the market-level misallocation of flows as the TNA-weighted average of fund-level misallocation of flows across corporate bond funds in my sample.

In Table 11, I conduct a time-series regression of one-month-ahead (hedged) beta arbitrage returns on the average monthly market-level misallocation of flows in the previous 12 months. Column (1) shows that misallocation of flows indeed positively and significantly forecast future beta arbitrage returns. In columns (2) and (3), I control for the contemporaneous realization of stock and corporaet bond market factors or several variables related to macroeconomic conditions, the results are robust. In columns (4)-(6), I replace the dependent variable by the hedged beta arbitrage returns, and I find misallocation of flows still positively forecasts the hedged beta arbitrage returns though the statistical significance is weaker.[36]

Overall, the findings in this section is consistent with the hypothesis that investors' ignorance of fund staleness leads to excessive capital allocation into high beta corporate bonds, which further results in lower future returns of high beta bonds relative to low beta bonds.

[Table 11 About Here]

[35] For the estimation of flow-to-performance regression, I use the fund alpha that is not corrected for staleness effect, since Table 10 suggests that investors do not take into account fund staleness.

[36] One may argue that the effect of misallocation of flows should mainly work through the high beta bonds (short-leg of the beta arbitrage portfolio). In Appendix Table A.22, I find that misallocation of flows can positively and significantly predict future short-leg returns alone.

7. Conclusion

In this paper, I provide a new perspective on how asset managers can impact asset prices. Specifically, I argue that asset managers are important information intermediaries for investors' capital allocation. However, asset managers have incentives to delay the information transmission to investors, and this could delay investors' capital allocation in response to information and lead to market inefficiency.

I test this argument and its asset pricing implications in the context of corporate bond mutual funds. Consistent with the argument, I find that the delayed information transmission by corporate bond mutual funds can largely explain the price momentum in corporate bonds. In addition, I find that the delayed information transmission by corporate bond funds can generate cross-firm return predictability; that is, past information on one bond can predict future returns of other corporate bonds that are held by common mutual fund owners. Finally, I show that corporate bond funds tend excessively hold high risk corporate bonds for return smoothing, and this can lead to sub-optimal capital allocation on corporate bonds with high beta and contribute to the beta anomaly in the corporate bond market.

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Table 1 **Summary Statistics on Corporate Bonds and Corporate Bond Funds.** This table reports summary statistics on corporate bonds and corporate bond funds during the sample period of July 2002 - December 2019. Panel A reports the distribution of variables at corporate bond-by-month level. Monthly Return is the monthly corporate bond return, which combines the return calculated using TRACE data and returns from Datastream database. Returns calculated from TRACE data are used in priority. Numerical rating is the median value of S&P, Moody's, and Fitch rating (1=AAA, 2=AA+,..., 21=C, 22=D). IG is a dummy variable that equals one if numerical rating is loIr than or equal to 11 (BB+). Maturity is the number of months to maturity. Age is the number of months since issuance. ZRD Ratio is the fraction of trading days with zero or missing return in the most recent quarter. Amount Outstanding is the market value of outstanding bonds in $ million. Staleness is the bond-level staleness measure defined as the shares-weighted average of fund-level staleness across corporate bond funds that hold the bond (see section 4.3). Panel B reports the distribution of variables at corporate bond fund-by-month level, where variables are aggregated at fund portfolio level. TNA is total net assets in $ million. Expense ratio is the annual percentage expense ratio across share classes. Monthly Fund Return is the monthly gross return of corporate bond funds. For funds with multiple share classes, TNA is the sum of total net assets across share classes and fund expense ratios and returns are computed as the TNA-weighted average values across share classes. # Share Classes is the number of share classes of a fund. Fund Staleness measures the staleness in fund NAV based on the lagged relation betIen fund returns and corporate bond market returns (see section 4.3).

Panel A: Summary statistics at bond-level					
Variable	Mean	SD	P25	P50	P75
Monthly Return	0.49%	4.08%	−0.29%	0.42%	1.44%
Numerical rating	8.43	3.73	6.00	8.00	10.00
IG	0.79	0.41	1.00	1.00	1.00
Maturity (month)	98.70	107.18	31.00	63.00	112.00
Age (month)	65.79	63.65	21.00	47.00	90.00
ZRD Ratio	0.43	0.32	0.13	0.42	0.72
Amount Outstanding ($ million)	533.13	639.98	159.48	354.06	672.70
Latent Fund Staleness	0.13	0.14	0.01	0.07	0.19
Panel B: Summary statistics at fund-level					
Variable	Mean	SD	P25	P50	P75
TNA ($ million)	1690.95	8347.85	67.90	260.30	947.10
Expense Ratio	0.74%	0.38%	0.49%	0.70%	0.94%
Monthly Fund Return	0.43%	1.71%	−0.10%	0.39%	1.05%
# Share Classes	2.65	2.24	1.00	2.00	4.00
Fund Staleness	0.17	0.19	0.00	0.09	0.35

Table 2 **Staleness of Corporate Bond Funds: Lagged Market Betas.** This table reports panel regressions of fund returns on contemporaneous and lagged market factor returns. I estimate fund market beta through regressing monthly fund excess returns on the contemporaneous market excess returns ($MktRf_t$) and three lags of monthly market excess returns. In columns (1)-(4), the sample consists of corporate bond funds, and the market excess return is defined as the excess return of the Bloomberg Barclays US Corporate Bond Index. Column (1) reports the regression results in the full sample. In columns (2)-(4), in each month I sort the corporate bond funds into terciles by fund TNA, and I report the regression results for each tercile of corporate bond funds separately. In column (5), I report the regression results for US domestic equity funds for comparison. The market excess return for equity funds is the CRSP value-weighted market excess returns. For all regressions, I control for the one-month lagged fund TNA. Fund fixed effects are included. t-statistics are computed based on standard errors two-way clustered by fund and time. The sample period is from January 1998 to December 2019. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	Corporate Bond Funds				Equity Funds
	All	Small-Size	Medium-Size	Large-Size	
$MktRf_t$	0.57***	0.55***	0.56***	0.61***	0.95***
	(17.55)	(17.54)	(18.18)	(16.21)	(71.72)
$MktRf_{t-1}$	0.12***	0.13***	0.12***	0.12**	0.02
	(2.72)	(2.93)	(2.80)	(2.41)	(1.51)
$MktRf_{t-2}$	0.04	0.04	0.04	0.05	−0.01
	(1.02)	(0.98)	(0.91)	(1.17)	(−0.54)
$MktRf_{t-3}$	0.03	0.03	0.03	0.04	−0.02
	(1.36)	(1.52)	(1.13)	(1.46)	(−1.65)
TNA_{t-1}	−0.00***	−0.00	−0.00**	−0.00***	−0.00**
	(−2.83)	(−1.56)	(−2.58)	(−3.02)	(−2.13)
Fund FE	Y	Y	Y	Y	Y
No. Obs.	195,006	64,844	65,077	64,997	970,850
Adj. R^2	0.295	0.314	0.246	0.350	0.446

Table 3 **Staleness of Corporate Bond Funds: Asymmetric Betas.** This table reports panel regressions of fund returns on contemporaneous and lagged market factors in the subsamples classified by market returns and fund returns. The dependent variable is fund excess returns in month t and the key independent variables are market excess returns in month t and month $t-1$. In columns (1)-(2), subsamples are formed based on the sign of market return in month $t-1$. In columns (3)-(4), subsamples are formed based on the sign of fund return in month $t-1$. In all regressions, fund TNA at the end of month $t-1$ is controlled, and fund fixed effects are included. t-statistics are computed based on standard errors two-way clustered by fund and time. The sample period is from January 1998 to December 2019. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Subsample by:	Market Return		Fund Return	
	Positive	Negative	Positive	Negative
$\mathrm{MktRf_t}$	0.56***	0.57***	0.57***	0.57***
	(23.26)	(7.91)	(23.82)	(7.10)
$\mathrm{MktRf_{t-1}}$	0.08**	0.33**	0.04	0.27**
	(2.41)	(2.44)	(1.41)	(2.14)
$\mathrm{TNA_{t-1}}$	-0.00***	-0.00**	-0.00***	-0.00**
	(-2.69)	(-2.43)	(-2.62)	(-2.01)
Fund FE	Y	Y	Y	Y
No. Obs.	130,928	63,888	138,463	56,384
Adj. R^2	0.287	0.320	0.302	0.311

Table 4 **Latent Fund Staleness and Corporate Bond Momentum: Portfolio Analysis.** This table reports the performance of corporate bond portfolios two-way sorted by past returns and latent fund staleness. At the end of month t, I sort corporate bonds into quintiles by their cumulative returns from month $t-7$ to month $t-1$, and I independently sort corporate bonds into terciles by latent fund staleness (see the definition in section 4.3) measured as of month t end. The two-way sorted portfolios are held from month $t+1$ to month $t+6$. Equal-weighted average portfolio returns are computed. To deal with overlapping portfolios in each holding month, I follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different months. Average monthly holding period returns or alphas during July 2002 to December 2019 are reported. Panel A reports average monthly excess returns. Panel B reports the average monthly alphas adjusted for exposures on default and term factors. Panel C reports the average monthly alphas adjusted for exposures on Fama and French (1993) stock-market three factors together with default and term factors. t-statistics are in parentheses.

	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5−1
Panel A: Excess returns						
Staleness 1 (Low)	0.52	0.39	0.35	0.35	0.43	−0.10
	(3.36)	(3.61)	(3.81)	(3.91)	(3.78)	(−0.79)
Staleness 2	0.44	0.32	0.32	0.35	0.42	−0.01
	(2.58)	(3.29)	(4.19)	(4.58)	(4.10)	(−0.10)
Staleness 3	0.01	0.22	0.29	0.37	0.45	0.44
	(0.02)	(1.98)	(3.46)	(4.43)	(3.73)	(2.73)
Staleness 3−1	−0.52	−0.30	−0.06	0.01	0.02	0.54
	(−3.06)	(−2.86)	(−0.95)	(0.17)	(0.21)	(4.13)
Panel B: Two-factor alphas						
Staleness 1 (Low)	0.22	0.13	0.12	0.13	0.15	−0.06
	(2.44)	(2.53)	(2.67)	(2.92)	(2.62)	(−0.60)
Staleness 2	0.17	0.11	0.14	0.17	0.20	0.03
	(1.56)	(1.99)	(3.59)	(3.97)	(3.31)	(0.23)
Staleness 3	−0.22	0.06	0.14	0.22	0.28	0.50
	(−1.25)	(0.69)	(2.47)	(4.11)	(3.12)	(3.28)
Staleness 3−1	−0.44	−0.15	0.02	0.09	0.13	0.56
	(−2.52)	(−1.36)	(0.40)	(1.64)	(1.46)	(4.31)
Panel C: Five-factor alphas						
Staleness 1 (Low)	0.19	0.12	0.12	0.13	0.13	−0.06
	(1.97)	(2.24)	(2.47)	(2.70)	(2.14)	(−0.51)
Staleness 2	0.11	0.10	0.12	0.16	0.16	0.05
	(0.94)	(1.62)	(2.98)	(3.51)	(2.52)	(0.38)
Staleness 3	−0.39	0.00	0.10	0.17	0.18	0.57
	(−2.28)	(−0.02)	(1.41)	(2.90)	(1.87)	(3.63)
Staleness 3−1	−0.59	−0.20	−0.02	0.04	0.04	0.63
	(−3.34)	(−1.43)	(−0.35)	(0.74)	(0.49)	(4.53)

Table 5 **Latent Fund Staleness and Corporate Bond Momentum: Fama-MacBeth Regressions.** This table reports Fama-MacBeth forecasting regressions of corporate bond returns. For a cross-sectional regression in month t, the dependent variable is the six-month cumulative return from month $t+1$ to $t+6$, PRET is the cumulative return from month $t-7$ to month $t-1$, and Staleness is the latent fund staleness measured as of month t end. In each month, I sort all corporate bonds into terciles by their latent fund staleness. I generate a dummy variable, Dummy_Stale, which equals one if a corporate bond is among the most stale tercile and equals zero elsewhere. Control variables include the bond maturity in months (Maturity), credit rating (Rating), natural logarithm of offering amount (Ln(Size)), fraction of zero-return day in the most recent quarter (ZRD_Ratio), natural logarithm of amihud illiquidity measure in the most recent quarter (Ln(Amihud)), and bond age in months (Age). Columns (1)-(4) report the results in full sample. Columns (5)-(6) (Columns (7)-(8)) report the results in the subsample of bonds in the top (non-top) staleness tercile in each month. t-statistics in parenthese are with Newey-West correction of five lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample				Stale Group		Non-Stale Group	
PRET	0.080*	0.087*	−0.026	−0.002	0.142**	0.121**	−0.028	−0.000
	(1.72)	(1.87)	(−0.70)	(−0.05)	(2.32)	(2.21)	(−0.59)	(−0.01)
PRET×Stalness			0.378**					
			(2.20)					
PRET×Dummy_Stale				0.135***				
				(3.25)				
Staleness			−0.009					
			(−1.09)					
Dummy_Stale				−0.001				
				(−0.82)				
Maturity		0.000**	0.000**	0.000**		0.000***		0.000**
		(2.45)	(2.40)	(2.47)		(3.25)		(2.19)
Rating		0.001	0.001	0.001		0.001		0.001*
		(0.99)	(1.21)	(1.05)		(0.67)		(1.83)
Ln(Size)		0.003***	0.002***	0.003***		0.002		0.003***
		(2.75)	(3.00)	(3.02)		(1.55)		(2.92)
ZRD_Ratio		0.005	0.005	0.005		0.009		0.003
		(1.24)	(1.38)	(1.30)		(1.58)		(1.11)
Ln(Amihud)		0.002**	0.002**	0.002**		0.001		0.003***
		(2.09)	(2.24)	(2.28)		(1.01)		(2.78)
Age		−0.000	−0.000	−0.000		−0.000		−0.000
		(−0.43)	(−0.61)	(−0.63)		(−1.33)		(−0.37)
No. Obs.	688,101	680,119	680,119	680,119	227,402	224,470	460,699	455,649
Adj. R^2	0.071	0.240	0.254	0.250	0.095	0.222	0.076	0.269

Table 6 **Latent Fund Staleness and Corporate Bond Momentum: Up- vs. Down-Market.** This table shows the staleness effect on corporate bond momentum in the market upturn and downturn separately. I analyze the following momentum strategy. In each month t, corporate bonds are sorted into quintiles based on cumulative returns from month $t-7$ to month $t-1$ (PRET). I long the top PRET quintile and short the bottom PRET quintile and hold the portfolios from month $t+1$ to month $t+6$. To deal with overlapping portfolios in each holding month, I follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different months. To split sample period into market downturn and upturn groups, I sort all holding period months from July 2002 to December 2019 into two groups based on the median value of past six-month market return. Specifically, for a given month t, I compute average monthly market return during month $t-7$ to $t-1$. Panel A reports the corporate bond momentum strategy returns or alphas in the market downturn and upturn separately. In Panel B, I follow Table 4 to sort corporate bonds into quintiles by PRET and terciles by Staleness. I define stale group as portfolios in the top staleness tercile and define non-stale group as portfolios in the bottom and medium staleness tercile. I follow Panel A to classify holding period months into market downturn and market upturn and report average monthly portfolio returns or alphas in the two sub-periods separately. 5-factor alpha is adjusted for the exposures on the Fama and French (1993) stock market three-factor, default factor, and term premium factor. t-statistics are in parentheses.

Panel A: Corporate bond momentum: market upturn vs. downturn					
		Market Downturn		Market Upturn	
		ExRet	5-Factor Alpha	Excess Ret	5-Factor Alpha
	PRET1	−0.01	−0.08	0.58	0.24
	PRET5	0.32	0.19	0.65	0.25
	PRET5−1	0.32	0.27	0.07	0.01
		(1.77)	(1.86)	(0.58)	(0.07)
Panel B: Staleness effect: market upturn vs. downturn					
		Market Downturn		Market Upturn	
		Excess Ret	5-Factor Alpha	Excess Ret	5-Factor Alpha
Non-Stale	PRET1	0.28	0.16	0.77	0.42
	PRET5	0.29	0.11	0.57	0.10
	PRET5−1	0.01	−0.05	−0.20	-0.32
		(0.03)	(−0.32)	(−1.57)	(−2.32)
Stale	PRET1	−0.62	−0.63	0.63	0.25
	PRET5	0.10	0.01	0.80	0.34
	PRET5−1	0.72	0.64	0.17	0.09
		(2.46)	(3.03)	(1.23)	(0.65)
Diff	PRET5−1	0.71	0.69	0.37	0.41
		(3.02)	(3.23)	(3.31)	(3.47)

Table 7 **Latent Fund Staleness and Flow-Induced Trading on Corporate Bonds.** This table analyzes the effect of staleness on generating persistent fundflows and flow-induced trading on corporate bonds. Panel A reports the regressions of monthly fund flows on the one-month lagged fund flows. Control variables include fund TNA and past six-month fund returns, and time fixed effects are included. t-statistics in parentheses are computed based on standard errors two-way clustered by fund and time. Columns (1)-(2) report the full-sample regression results. In columns (3)-(6), I sort corporate bond funds into stale and non-stale groups based on the median value of fund-level staleness in each month, and I report the regression results in the two groups separately. Panel B reports the regressions of monthly flow-induced trading (FIT) on the one-month lagged FIT. Flow-induced trading is defined as the aggregate mutual fund trading on a bond in a month that are driven by fund flows. Control variables include bond rating, months to maturity, bond age, natural logarithm of amihud illiquidity, fraction of zero-retun day, natural logarithm of offering amount, and cumulative returns in past six months. Time fixed effects are included. t-statistisc are computed based on standard errors two-way clustered by bond and time. Columns (1)-(2) report the full-sample regression results. In columns (3)-(6), I sort corporate bonds into terciles by latent fund staleness in each month, and I report the regression results in the stale group (top tercile) and non-stale group (bottom and medium terciles) separately. Panel C shows the price pressure of FIT on corporate bonds. In each month, I sort all corporate bonds into deciles by FIT in the month and compute equal-weighted average portfoio returns. Average monthly excess returns, two-factor alphas, and five-factor alphas are reported.

Panel A: Fund-level staleness and auto-correlation in fundflows						
DepVar: Flow_t	(1)	(2)	(3)	(4)	(5)	(6)
	All Funds		Stale Funds		Non-Stale Funds	
Flow_{t-1}	0.04***	0.04***	0.06***	0.06***	0.03	0.03
	(3.48)	(3.47)	(4.61)	(4.60)	(1.53)	(1.52)
Controls	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y
No. Obs.	172,777	172,777	82,700	82,700	89,299	89,299
Adj. R^2	0.005	0.005	0.008	0.008	0.004	0.004
Panel B: Bond-level staleness and auto-correlation in flow-induced trading						
DepVar: FIT_t	(1)	(2)	(3)	(4)	(5)	(6)
	All Bonds		Stale Group		Non-Stale Group	
FIT_{t-1}	0.21	0.15	0.29**	0.25*	0.05	0.04
	(1.55)	(1.28)	(2.00)	(1.89)	(0.29)	(0.24)
Controls	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y
No. Obs.	1,682,201	1,126,667	560,435	304,562	1,104,901	815,040
Adj. R^2	0.116	0.115	0.203	0.201	0.146	0.169

Table 7 Continued

Panel C: Flow-induced price pressure on corporate bonds						
	Excess Ret		2-Factor Alpha		5-Factor Alpha	
FIT Deciles	Estimates	t-stat	Estimates	t-stat	Estimates	t-stat
1 (low)	0.14	(0.96)	−0.05	(−0.49)	−0.16	(−1.53)
2	0.13	(1.03)	−0.08	(−0.89)	−0.16	(−1.78)
3	0.25	(2.34)	0.04	(0.68)	−0.01	(−0.14)
4	0.32	(3.16)	0.12	(2.44)	0.08	(1.57)
5	0.33	(3.47)	0.13	(3.12)	0.11	(2.45)
6	0.34	(3.42)	0.13	(3.24)	0.12	(2.57)
7	0.34	(3.51)	0.13	(3.27)	0.11	(2.41)
8	0.38	(3.91)	0.19	(3.83)	0.17	(2.70)
9	0.45	(4.29)	0.28	(4.98)	0.24	(3.66)
10 (high)	0.54	(4.73)	0.39	(6.35)	0.32	(4.98)
10−1	0.40	(5.00)	0.44	(4.85)	0.48	(4.88)

Table 8 **Connected Bond Momentum.** This table shows the performance of corporate bond portfolios sorted by connected bond returns and the performance of stock portfolios sorted by connected stock returns. I connect bonds or stocks through their common mutual fund owners. For a pair of corporate bond i and j at a given quarter t end, I define common mutual fund ownership as: $COWN_{i,j,t} = \sum_{f=1}^{F}(S_{i,t}^{f}P_i + S_{j,t}^{f}P_j)/(S_iP_i + S_jP_j)$, where $S_{i,t}^{f}$ is the shares of bond i held by fund f with a par value P_i, and $S_{i,t}P_i$ is the par value offering amount of bond i. At the end of quarter t, for each bond I compute connected bond returns as the COWN-weighted average of its connected bonds' returns in quarter t, and I sort corporate bonds into quintiles based on the connected bond returns. Corporate bonds with more than 20 mutual fund owners are excluded at the portfolio formation. The quintile portfolios are held over the next quarter and equal-weighted average portfolio returns are computed. Panel A reports the average monthly excess returns, two-factor alphas, and five-factor alphas of the quintile portfolios during the holding period. In Panel B, I follow Anton and Polk (2014) to compute connected stock returns for each common stock. The sample consists of NYSE, AMEX, or NASDAQ traded stocks with market capitalization above NYSE median value. At each quarter end, I sort sample stocks into quintiles based on connected stock returns and track equal-weighted portfolio returns over the next quarter. Panel B reports the average monthly portfolio excess returns and the alphas adjusted for risk exposures on Fama and French (2015) five-factor augmented with momentum factor. t-statistics are in parentheses.

Panel A: Connected-Bond Return Quintiles						
	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q5−Q1
Excess Return	0.11	0.31	0.37	0.46	0.66	0.55
	(0.86)	(3.25)	(3.69)	(4.46)	(5.29)	(4.16)
Two-Factor Alpha	-0.09	0.10	0.11	0.20	0.43	0.52
	(-0.90)	(1.64)	(2.41)	(4.10)	(5.12)	(3.65)
Five-Factor Alpha	-0.16	0.07	0.11	0.20	0.41	0.58
	(-1.45)	(1.00)	(1.89)	(3.70)	(4.78)	(3.66)
Panel B: Connected-Stock Return Quintiles						
	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q5−Q1
Excess Return	0.74	0.79	0.93	0.86	0.90	0.16
	(2.05)	(2.36)	(2.83)	(2.59)	(2.60)	(0.76)
FF5+UMD Alpha	−0.03	0.03	0.14	0.08	0.07	0.10
	(−0.28)	(0.42)	(1.85)	(0.94)	(0.65)	(0.58)

Table 9 **Connected Bond Staleness and Connected Bond Momentum.** This table analyzes the effect of connected bond staleness on connected bond momentum. Connected bonds, common mutual fund ownership (COWN) and connected bond returns (CB Ret) are defined following Table 8. For a bond i and a connected bond j at quarter t end, I define common owner staleness as the average fund-level staleness across mutual funds that commonly hold bond i and j. Then, for a bond i at quarter t end, I define connected bond staleness (CB Staleness) as the COWN-weighted average common owner staleness across the connected bonds of bond i. In this table, at each quarter-end, I sort corporate bonds into quintiles based on connected bond returns in the quarter. I further independently sort corporate bonds into two groups based on the median connected bond staleness. Corporate bonds that are held by more than 20 corporate bond funds are excluded at portfolio formation. The portfolios are held over the next 12 quarters and equal-weighted average portfolio returns are computed. This table reports the average monthly returns or alphas of the two-way sorted portfolios during the holding period, where column "Qtr k" reports average monthly returns or alphas in the k-th quarter after portfolio formation. Panel A, B, and C report the average monthly excess returns, two-factor alphas, and five-factor alphas, respectively. t-statistics for the "CB Ret high-minus-low" portfolios are reported in parentheses.

Panel A: Excess Returns

		Holding period quarters:			
CB Staleness	CB Ret	Qtr 1	Qtr 2-5	Qtr 6-8	Qtr 9-12
Non-Stale	1	0.27	0.40	0.31	0.30
	5	0.55	0.43	0.35	0.30
	5−1	0.29	0.03	0.04	−0.01
		(2.37)	(0.50)	(0.44)	(−0.08)
Stale	1	0.03	0.37	0.43	0.32
	5	0.65	0.41	0.27	0.39
	5−1	0.62	0.04	−0.15	0.07
		(4.45)	(0.48)	(−1.68)	(1.21)
Diff	5−1	0.34	0.00	−0.19	0.07
		(2.73)	(0.05)	(−2.01)	(1.05)

Table 9 Continued

Panel B: Two-Factor Alpha					
		Holding period quarters:			
CB Staleness	CB Ret	Qtr 1	Qtr 2-5	Qtr 6-8	Qtr 9-12
Non-Stale	1	0.06	0.20	0.11	0.10
	5	0.30	0.20	0.18	0.11
	5−1	0.24	0.00	0.07	0.01
		(2.01)	(-0.04)	(0.77)	(0.12)
Stale	1	−0.16	0.16	0.24	0.15
	5	0.44	0.21	0.10	0.22
	5−1	0.60	0.06	−0.14	0.07
		(3.81)	(0.64)	(−1.58)	(1.33)
Diff	5-1	0.36	0.06	−0.21	0.07
		(2.60)	(0.47)	(−1.84)	(0.91)
Panel C: Five-Factor Alpha					
		Holding period quarters:			
CB Staleness	CB Ret	Qtr 1	Qtr 2-5	Qtr 6-8	Qtr 9-12
Non-Stale	1	0.06	0.21	0.08	0.08
	5	0.30	0.17	0.15	0.05
	5−1	0.24	−0.04	0.07	−0.03
		(1.84)	(−0.41)	(0.70)	(−0.36)
Stale	1	−0.26	0.10	0.20	0.10
	5	0.41	0.15	0.01	0.16
	5−1	0.66	0.05	−0.19	0.06
		(3.76)	(0.46)	(−2.09)	(1.11)
Diff	5−1	0.43	0.09	−0.26	0.09
		(2.74)	(0.55)	(−2.12)	(1.16)

Table 10 **Flow-Performance Model Horse Race: Stale vs. Non-Stale Model.** This table analyzes whether investors consider fund staleness when evaluating fund performance, and the methodology is based on Berk and van Binsbergen (2016) (BvB). For this test, I compute fund monthly alphas in two models, with and without considering staleness in fund NAVs. For the model without considering fund NAV staleness (Non-Stale Model), in each month I regress monthly fund excess returns on contemporaneous corporate bond market excess returns using past 36-month observations to estimate the fund exposure on contemporaneous market factor. Then, I compute fund alpha in the month by subtracting the product of exposure on market factor and the realized market factor return from fund excess returns in the month. For the model that considers fund NAV staleness, I estimate fund exposures on both contemporaneous and one-month lagged market factor, and I compute fund alpha in the month by subtracting the product of exposures on market factor and the realized market factor return in both current and the previous month from fund excess returns in the month. In columns (1) and (2), I estimate the following regression model:

$$\Phi(Flow_{f,t}) = a + b \times \Phi(\alpha_{f,t-1}) + \epsilon_{f,t},$$

where $\Phi(Flow_{f,t})$ is the sign of the fund flow in monbth t and $\Phi(\alpha_{f,t-1})$ is the sign of fund alpha in month $t-1$. Standard errors are two-way clustered by fund and time. The regression is estimated using the fund alpha under either stale or non-stale model. I report coefficient estimates and t-statistics associated with b in columns (1) and (2), respectively. I follow Berk and van Binsbergen (2016) to compare the flow-performance relationship between stale and non-stale models. Specifically, I estimate the following regression model:

$$\Phi(Flow_{f,t}) = c + d \times \left(\frac{(\Phi(\alpha^{NS}_{f,t-1})}{Var(\Phi(\alpha^{NS}_{f,t-1}))} - \frac{(\Phi(\alpha^{S}_{f,t-1})}{Var(\Phi(\alpha^{S}_{f,t-1}))}\right) + \epsilon_{f,t},$$

where $\alpha^{S}_{f,t-1}$ and $\alpha^{NS}_{f,t-1}$ are the fund alphas in month $t-1$ computed based on stale model and non-stale model respectively, and $Var(\Phi(\alpha^{S}_{f,t-1}))$ is the variance of the sign of the fund alpha computed based on stale model. Standard errors are two-way clustered by fund and time. In column (3), I report the t-statistics associated with d from the above regression.

	(1)	(2)	(3)
Model	b	t-stat of b	BvB test t-stat
Non-Stale	0.041	5.77	2.49
Stale	0.034	4.93	

Table 11 **Flow Mis-Allocation and Beta Anomaly.** This table examines the time-series relationship between flow mis-allocation to stale funds and the profitability from beta anomaly arbitrage. To form beta arbitrage portfolio in corporate bond market, I follow Frazzini and Pedersen (2014) to use Bloomberg Barclays corporate bond credit indices. In each month, I long the Bloomberg Barclays US Corporate Aaa index and short the Bloomberg Barclays US Corporate Ca-D index and compute the long-short return as the beta arbitrage return. I also follow Frazzini and Pedersen (2014) to compute hedged beta arbitrage returns by hedging out the interest rate risk exposures of the credit indices (see section 6.2 for details). I estimate the market-level flows that are mis-allocated due to fund NAV staleness as follows. First, for each fund-month, I compute the difference between fund alpha under stale model and fund alpha under non-stale model. Second, I take the product of difference in fund alpha and flow-to-performance sensitive as the estimate for the mis-allocated flow at fund-level. Third, I take the TNA-weighted average mis-allocated flows across mutual funds as the market-level mis-allocated flow. Finally, in each month, I generate a variable Mis_Flow which is the average of market-level mis-allocated flow in the past 12 months. This table reports results from the time-series regression of beta arbitrage return in month $t+1$ on market-level mis-allocated flow computed in month t. For contorl variables, I include the realization of corporate bond market factor and Fama and French (2015) stock-market five factors in month $t+1$, and I also include Baker and Wurgler (2006) sentiment index, Ted Spread, Inflation, and Investment-to-capital ratio in month t. The sample period is from July 2000 to December 2018. t-statistics in parentheses are computed based on standard errors with Newey-West correction of one lag.

Table 11 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
DepVar:	Beta Arbitrage Ret_{t+1}			Hedged Beta Arbitrage Ret_{t+1}		
$Mis\_Flow_{t-11,t}$	4.78**	2.89*	6.85**	4.47*	2.39*	5.32*
	(2.18)	(1.79)	(2.26)	(1.87)	(1.76)	(1.69)
Corp Bond $MktRf_{t+1}$		−0.85			−2.23**	
		(−1.19)			(−2.46)	
Stk $MktRf_{t+1}$		−0.61***			−0.26	
		(−4.02)			(−1.62)	
Stk SMB_{t+1}		−0.77***			−0.85***	
		(−3.23)			(−3.06)	
Stk HML_{t+1}		−0.82**			−0.60*	
		(−2.37)			(−1.91)	
Stk RMW_{t+1}		0.23			0.25	
		(1.04)			(1.07)	
Stk CMA_{t+1}		0.67			0.63	
		(1.37)			(1.33)	
BW $Sentiment_t$			−0.00			0.00
			(−0.14)			(0.14)
Ted $Spread_t$			1.30			−0.90
			(0.31)			(−0.23)
$Inflation_t$			2.86			4.83
			(0.83)			(1.16)
Investment-to-$capital_t$			4.77			4.10
			(0.68)			(0.53)
Intercept	−0.01	0.00	−0.19	−0.01**	−0.00	−0.17
	(−1.08)	(0.35)	(−0.81)	(−2.00)	(−0.42)	(−0.64)
No. Obs.	234	234	223	234	234	223
Adj. R^2	0.016	0.312	0.037	0.011	0.285	0.059

Appendix

Table A.1 **Staleness of Corporate Bond Funds: Lagged Betas on Default and Term Factors.** This table reports mutual funds' exposures on contemporaneous and lagged default factor (DEF) and term factor (TERM). I estimate funds' exposures (betas) on default/term factors through regressing monthly fund excess returns on the contemporaneous default/term factor returns and three lags of monthly default/term factor returns. TERM is difference in the monthly long-term government bond return and one month T-bill returns. DEF is the difference in the monthly long-term investment grade corporate bond returns and long-term government bond return. I use returns on Bloomberg Barclays US Corp 10+ Years Index to proxy for monthly long-term investment grade corporate bond returns. Column (1) reports the regression results in the full sample. In columns (2)-(4), in each month I sort the corporate bond funds into terciles by fund TNA, and I report the regression results for each tercile of corporate bond funds separately. In column (5), I report the regression results for US domestic equity funds for comparison. The market excess return for equity funds is the CRSP value-weighted market excess returns. For all regressions, I control for the one-month lagged fund TNA. Fund fixed effects are included and standard errors are two-way clustered by fund and time. The sample period is from January 1998 to December 2019. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	All	Small-Size	Medium-Size	Large-Size
$\mathrm{DEF_t}$	0.41***	0.39***	0.39***	0.43***
	(14.76)	(14.15)	(14.29)	(13.13)
$\mathrm{DEF_{t-1}}$	0.08***	0.08***	0.08***	0.09***
	(2.82)	(2.86)	(2.83)	(2.75)
$\mathrm{TERM_t}$	0.28***	0.26***	0.27***	0.30***
	(13.60)	(13.24)	(14.12)	(12.75)
$\mathrm{TERM_{t-1}}$	0.04**	0.05**	0.05***	0.04**
	(2.49)	(2.69)	(2.63)	(2.12)
$\mathrm{TNA_{t-1}}$	−0.00**	−0.00	−0.00**	−0.00**
	(−2.47)	(−1.60)	(−3.06)	(−2.55)
Fund FE	Y	Y	Y	Y
No. Obs.	195,006	64,844	65,077	64,997
Adj. R^2	0.290	0.310	0.239	0.349

Table A.2 **Staleness of Corporate Bond Funds: Zero-return Day Ratio and Duration.** This table reports summary statistics on the ratio of zero-return days (ZRD Ratio) and the duration of zero-return days based on the fund-by-month level observations. ZRD Ratio is defined as the ratio of number of trading days with zero or missing fund returns (based on NAV change) in a month. I report the summary statistics of ZRD ratio on corporate bond funds and US domestic equity funds separately. Duration of zero-return days is the number of consecutive trading days with zero or missing fund returns when a fund enters a zero-return day episode.

	Mean	SD	P10	P25	P50	P75	P90
ZRD Ratio							
Corporate Bond Funds	0.206	0.205	0.000	0.050	0.143	0.286	0.478
Equity Funds	0.039	0.111	0.000	0.000	0.000	0.048	0.095
Duration of ZRD							
Corp Bond Funds	1.536	5.357	1.000	1.000	1.143	1.455	2.000

Table A.3 **Staleness of Corporate Bond Funds: Auto-correlation in Fund Returns.** This table reports the panel regressions of weekly fund returns on the lagged fund returns in the past four weeks. The dependent variable is fund returns in week w. The independent variables are four lags of weekly fund returns from week $w-4$ to $w-1$. Fund TNA at the end of week $w-1$ is included as control. Fund fixed effects and week fixed effects are also included. Column (1)-(3) report regression results for corporate bond funds. Columns (4)-(6) report regression results for US domestic equity funds. t-statistics in parentheses are computed based on standard errors two-way clustered by fund and time. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Corporate Bond Funds			Equity Funds		
Ret_{w-1}	0.07**	0.06*	0.06*	−0.03**	−0.00	−0.02***
	(2.10)	(1.87)	(1.71)	(−2.29)	(−0.58)	(−5.96)
Ret_{w-2}	0.07***	0.07***	0.06***	−0.01	0.00	−0.02***
	(2.81)	(3.06)	(2.84)	(−0.82)	(0.50)	(−3.39)
Ret_{w-3}	0.02	−0.01	−0.02	−0.05	−0.02	−0.03
	(0.80)	(−0.56)	(−0.81)	(−1.47)	(−1.32)	(−1.64)
Ret_{w-4}	0.03	0.04**	0.03*	−0.02	−0.01	−0.01
	(1.15)	(2.05)	(1.76)	(−0.58)	(−0.41)	(−0.74)
TNA_{w-1}	−0.00	−0.00	−0.00	−0.00	0.00*	−0.00
	(−1.29)	(−0.23)	(−1.20)	(−0.76)	(1.79)	(−1.20)
Time FE	N	Y	Y	N	Y	Y
Fund FE	Y	N	Y	Y	N	Y
No. Obs.	833,257	833,264	833,257	4,533,999	4,534,046	4,533,999
Adj. R^2	0.0166	0.345	0.347	0.0141	0.143	0.156

Table A.4 **Staleness of Corporate Bond Funds: Additional Analysis on Asymmetric Beta.** This table reports panel regressions of fund returns on contemporaneous and lagged market factors in the subsamples classified by fund characteristics. The dependent variable is fund excess returns in month t and the key independent variables are market excess returns in month t and month $t-1$. In columns (1)-(2), I split corporate bond funds into two groups based on the size of their management companies. Specifically, for each month during 1998-2018, I compute the total corporate bond fund TNA manged by each management company, and then I take the time-series average of total TNA across management companies. Top 5 management companies with largest average TNA are defined as large companies and the rest of management companies are defined as small companies. In columns (3)-(4), corporate bond funds are classified into institutional-oriented and retail-oriented funds following Goldstein et al. (2017). Specifically, I first use information in CRSP database to define each share class as institutional or retail share class. Then, I define a fund as institutional-oriented fund if more than 80% of its TNA is from institutional share classes, and I define a fund as retial-oriented fund if less than 20% of its TNA is from institutional share classes. In all regressions, fund TNA at the end of month $t-1$ is controlled, and fund fixed effects are included. t-statistics are computed based on standard errors two-way clustered by fund and time. The sample period is from January 1998 to December 2019. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Subsample by:	Mgmt Company Size		Inst vs. Retail	
	Large	Small	Institutional	Retail
$\mathrm{MktRf_t}$	0.64***	0.56***	0.56***	0.57***
	(12.60)	(13.85)	(18.63)	(12.65)
$\mathrm{MktRf_{t-1}}$	0.06	0.13**	0.08**	0.14**
	(1.34)	(2.36)	(2.27)	(2.30)
$\mathrm{TNA_{t-1}}$	-0.00***	-0.00***	-0.00***	-0.00***
	(-3.41)	(-2.93)	(-2.80)	(-4.03)
Fund FE	Y	Y	Y	Y
No. Obs.	12,984	182,053	70,005	94,364
Adj. R^2	0.324	0.290	0.362	0.301

Table A.5 **Evidence of Return Smoothing from Reported Price of Holding.** This table reports the regressions of holding-level price discrepancy on the market return or fund return. The analysis is conducted based on holding-by-quarter level observations. The dependent variable, price discrepancy, is defined as $100\times(\mathrm{P}^{\mathrm{Report}}_{\mathrm{i,f,t}}\text{-}\mathrm{P}^{\mathrm{Trade}}_{\mathrm{i,t}})/\mathrm{P}^{\mathrm{Trade}}_{\mathrm{i,t}}$, where $\mathrm{P}^{\mathrm{Report}}_{\mathrm{i,f,t}}$ is the reported price of bond i by fund f at a reporting quarter t end, and $\mathrm{P}^{\mathrm{Trade}}_{\mathrm{i,t}}$ is the volume-weighted average daily traded price of bond i at quarter t end from TRACE database. If there is no traded price at a quarter-end date, I use the latest traded price on a trading day that is within 5-day before the quarter-end date. The key independent variable are dummy variables indicating whether the corporate bond market return or the fund return are negative in quarter t. Control variables include bond rating, months to maturity, natural logarithm of Amihud illiquidity, zero-return day ratio, and Fund TNA. Bond fixed effects are included. Standard errors are two-way clustered by bond and time.

	(1)	(2)	(3)	(4)	(5)	(6)
Negative Mkt Ret	0.08***	0.08***	0.07***			
	(9.60)	(9.51)	(8.66)			
Negative Fund Ret				0.03***	0.04***	0.04***
				(4.53)	(5.58)	(5.16)
Rating			0.03***			0.03***
			(2.73)			(2.72)
Maturity			-0.00***			-0.00***
			(-11.21)			(-11.19)
Ln(Amihud)			-0.02			-0.02
			(-1.08)			(-1.13)
ZRD_Ratio			0.37***			0.37***
			(6.18)			(6.26)
Fund TNA			-0.00**			-0.00**
			(-2.08)			(-2.05)
Bond FE	Y	Y	Y	Y	Y	Y
No. Obs.	3,836,461	3,836,458	3,600,785	3,836,461	3,836,458	3,600,785
Adj. R^2	0.084	0.107	0.081	0.084	0.105	0.081

Table A.6 **Staleness of Corporate Bond Funds: Holding Characteristics.** This table examines the relationship between holding characteristics and corporate bond fund staleness through panel regressions. The dependent variale is fund-level staleness esitmated in month t. The independent variables are portfolio-weighted average characteristics of bond holdings in the most recent quarter. ZRD_Ratio is the fraction of trading days with zero-return day in a quarter. Dummy_IG is a dummy variable that equals one for investment grade bond and zero for non-investment grade bond. Dummy_Short_Maturity is a dummy variable that equals one if maturity is less than or equal to 12 months and equals zero elsewhere. Lipper objective code-by-time level fixed effects are included. t-statistics in parentheses are computed based on standard errors two-way clustered by fund and by time. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
ZRD_Ratio	-0.07***			-0.05**
	(-3.03)			(-2.50)
Dummy_IG		0.18***		0.18***
		(9.01)		(8.83)
Dummy_Short_Maturity			0.02	0.02
			(1.03)	(0.91)
Lipper_Obj×Time FE	Y	Y	Y	Y
No. Obs.	100,216	101,825	101,833	100,208
Adj. R^2	0.565	0.578	0.565	0.578

Table A.7 **Corporate Bond Momentum.** This table shows the profitability of a corporate bond momentum strategy. In each month t, I sort corporate bonds into deciles based on their cumulative returns from month $t-6$ to month $t-1$. The portfolios are held from month $t+1$ to month $t+6$, and equal-weighted average portfolio returns are computed. To deal with overlapping portfolios in each holding month, I follow Jegadeesh and Titman (1993) to take the equal-weighted average return across portfolios formed in different months. This table reports average monthhly excess returns, two-factor alpha, five-factor alpha of the decile portfolios during the holding period of 2002.07-2019.12.

	Excess Ret		2-Factor Alpha		5-Factor Alpha	
PRET Deciles	Estimates	t-stat	Estimates	t-stat	Estimates	t-stat
1 (low)	0.22	(1.17)	-0.04	(-0.32)	-0.14	(-1.17)
2	0.36	(3.40)	0.14	(2.33)	0.11	(1.71)
3	0.33	(3.93)	0.14	(2.86)	0.12	(2.24)
4	0.31	(4.39)	0.14	(3.70)	0.13	(3.05)
5	0.32	(4.75)	0.16	(4.44)	0.15	(3.87)
6	0.31	(4.87)	0.16	(4.72)	0.15	(4.12)
7	0.32	(4.93)	0.17	(4.74)	0.16	(4.20)
8	0.35	(4.82)	0.18	(4.63)	0.17	(3.95)
9	0.38	(4.65)	0.19	(4.25)	0.17	(3.37)
10 (high)	0.58	(5.35)	0.38	(5.30)	0.31	(4.02)
10-1	0.36	(2.35)	0.42	(3.08)	0.45	(3.09)

Table A.8 **Correlation between Latent Fund Staleness and Other Bond Characteristics.** This table reports Pearson correlation coefficients between latent fund staleness and other bond characteristics. The correlation coefficients are estimated based on bond-by-month level observations. Staleness is the latent fund staleness estimated at the end of a month. Other characteristics include natural logarithm of months to maturity, numerical rating, natural logarithm of bond age (in months), natural logarithm of bond amihud illiquidity estimated in the most recent quarter, natural logarithm of bond offering amount, and past six-month cumulative returns.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Staleness	1.000						
(2) Ln(Maturity)	-0.123	1.000					
(3) Rating	0.479	-0.002	1.000				
(4) Ln(Age)	-0.007	-0.148	-0.020	1.000			
(5) Ln(Amihud)	0.066	0.126	0.089	0.303	1.000		
(6) Ln(Size)	-0.105	0.027	-0.201	-0.202	-0.120	1.000	
(7) PRET	-0.002	0.001	0.005	0.003	0.004	-0.012	1.000

Table A.9 **Residual Staleness and Corporate Bond Momentum.** This analyzes the effect of residual staleness on corporate bond momentum. I estimate the residual staleness through cross-sectional regressions of latent fund staleness on bond rating, natural logarithm of bond age, natural logarithm of bond amihud illiquidity, natural logarithm of bond offering amount, and past six-month cumulative returns. I take the residuals from the cross-sectional regressions as the residual staleness. Then, I follow Table 4 to for corporate bond portfolios two-way sorted by past six-month returns (skip the most recent month) and residual staleness and examine the portfolio performance in the six-month holding period. Panel A reports average monthly excess returns. Panel B reports the average monthly alphas adjusted for exposures on default and term factors. Panel C reports the average monthly alphas adjusted for exposures on Fama and French (1993) stock-market three factors together with default and term factors. t-statistics are in parentheses.

	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Panel A: Excess Returns						
Res_Staleness 1 (Low)	0.48	0.39	0.35	0.34	0.42	-0.06
	(2.83)	(3.71)	(4.01)	(3.81)	(3.58)	(-0.49)
Res_Staleness 2	0.42	0.31	0.31	0.32	0.39	-0.03
	(2.49)	(3.14)	(3.80)	(4.04)	(3.45)	(-0.24)
Res_Staleness 3	0.18	0.28	0.30	0.36	0.47	0.28
	(0.97)	(2.82)	(4.01)	(4.97)	(4.33)	(2.00)
Res_Staleness 3-1	-0.29	-0.20	-0.05	0.02	0.05	0.34
	(-3.70)	(-2.12)	(-1.44)	(0.60)	(0.93)	(4.27)
Panel B: Two-factor Alphas						
Res_Staleness 1 (Low)	0.16	0.15	0.14	0.12	0.16	0.00
	(1.71)	(2.92)	(3.37)	(3.03)	(2.48)	(-0.04)
Res_Staleness 2	0.14	0.11	0.12	0.14	0.17	0.03
	(1.27)	(1.62)	(2.62)	(3.28)	(2.40)	(0.21)
Res_Staleness 3	-0.06	0.09	0.14	0.21	0.27	0.34
	(-0.45)	(1.40)	(3.38)	(5.20)	(3.83)	(2.53)
Res_Staleness 3-1	-0.23	-0.07	0.00	0.09	0.11	0.34
	(-2.80)	(-0.93)	(0.09)	(2.97)	(2.53)	(4.17)
Panel C: Five-Factor Alphas						
Res_Staleness 1 (Low)	0.10	0.13	0.12	0.12	0.12	0.02
	(0.98)	(2.19)	(2.50)	(2.52)	(1.64)	(0.19)
Res_Staleness 2	0.06	0.09	0.11	0.12	0.10	0.04
	(0.50)	(1.28)	(2.20)	(2.60)	(1.33)	(0.29)
Res_Staleness 3	-0.20	0.05	0.11	0.17	0.19	0.39
	(-1.34)	(0.67)	(2.42)	(3.97)	(2.46)	(2.69)
Res_Staleness 3-1	-0.30	-0.05	-0.02	0.06	0.07	0.37
	(-3.36)	(-0.60)	(-0.49)	(1.92)	(1.67)	(4.09)

Table A.10 **Latent Fund Staleness and Corporate Bond Momentum: TRACE Return Only.** This reports robustness check for the staleness effect on corporate bond momentum. In this test, I only use corporate bond returns computed based on TRACE data to implement the corporate bond momentum strategy and examine the effect of latent fund staleness. Specifically, I follow Table 4 to for corporate bond portfolios two-way sorted by past six-month returns (skip the most recent month) and latent fund staleness and examine the portfolio performance in the six-month holding period. Panel A reports average monthly excess returns. Panel B reports the average monthly alphas adjusted for exposures on default and term factors. Panel C reports the average monthly alphas adjusted for exposures on Fama and French (1993) stock-market three factors together with default and term factors. t-statistics are in parentheses.

	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Panel A: Excess Returns						
Staleness 1 (Low)	0.47	0.37	0.34	0.34	0.44	-0.03
	(2.77)	(3.09)	(3.53)	(3.64)	(3.69)	(-0.25)
Staleness 2	0.35	0.29	0.29	0.32	0.41	0.06
	(2.09)	(2.86)	(3.72)	(4.03)	(3.79)	(0.43)
Staleness 3	-0.03	0.23	0.29	0.34	0.43	0.45
	(-0.13)	(1.87)	(3.18)	(3.79)	(3.22)	(2.93)
Staleness 3-1	-0.50	-0.24	-0.05	-0.01	-0.02	0.49
	(-2.91)	(-2.10)	(-0.79)	(-0.08)	(-0.14)	(3.78)
Panel B: Two-factor Alphas						
Staleness 1 (Low)	0.16	0.11	0.12	0.12	0.17	0.01
	(1.56)	(1.71)	(2.39)	(2.71)	(2.81)	(0.09)
Staleness 2	0.09	0.09	0.12	0.14	0.19	0.10
	(0.78)	(1.41)	(2.90)	(3.38)	(3.06)	(0.73)
Staleness 3	-0.24	0.06	0.14	0.19	0.25	0.48
	(-1.30)	(0.61)	(2.21)	(3.18)	(2.54)	(3.18)
Staleness 3-1	-0.39	-0.10	0.02	0.06	0.08	0.47
	(-2.12)	(-0.75)	(0.23)	(1.00)	(0.78)	(3.56)
Panel C: Five-factor Alphas						
Staleness 1 (Low)	0.13	0.10	0.11	0.11	0.14	0.01
	(1.14)	(1.40)	(2.06)	(2.26)	(2.14)	(0.10)
Staleness 2	0.03	0.08	0.10	0.13	0.14	0.11
	(0.23)	(1.11)	(2.37)	(2.70)	(2.07)	(0.75)
Staleness 3	-0.46	-0.01	0.08	0.12	0.12	0.58
	(-2.53)	(-0.11)	(1.10)	(1.84)	(1.15)	(3.60)
Staleness 3-1	-0.59	-0.14	-0.03	0.01	-0.02	0.56
	(-2.95)	(-0.86)	(-0.37)	(0.12)	(-0.22)	(3.92)

Table A.11 **Latent Fund Staleness and Corporate Bond Momentum: Value-weighted Portfolio Returns.** This reports robustness check for the staleness effect on corporate bond momentum. I follow Table 4 to for corporate bond portfolios two-way sorted by past six-month returns (skip the most recent month) and latent fund staleness and examine the portfolio performance in the six-month holding period. In this table, portfolio performance are evaluated based on offering amount-weighted portfolio returns, where the offering amount is the par value of the bond issue when it's initially offered. Panel A reports average monthly excess returns. Panel B reports the average monthly alphas adjusted for exposures on default and term factors. Panel C reports the average monthly alphas adjusted for exposures on Fama and French (1993) stock-market three factors together with default and term factors. t-statistics are in parentheses.

	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Panel A: Excess Returns						
Staleness 1 (Low)	0.55	0.40	0.35	0.35	0.44	-0.12
	(3.25)	(3.38)	(3.58)	(3.64)	(3.61)	(-0.90)
Staleness 2	0.40	0.32	0.31	0.33	0.41	0.01
	(2.15)	(3.07)	(3.92)	(4.06)	(3.74)	(0.04)
Staleness 3	0.21	0.28	0.30	0.36	0.43	0.22
	(1.02)	(2.63)	(3.62)	(4.30)	(3.44)	(1.71)
Staleness 3-1	-0.35	-0.27	-0.05	0.01	-0.01	0.34
	(-2.37)	(-2.46)	(-0.81)	(0.09)	(-0.07)	(3.18)
Panel B: Two-factor Alphas						
Staleness 1 (Low)	0.21	0.12	0.11	0.11	0.13	-0.07
	(1.87)	(1.92)	(2.18)	(2.32)	(2.31)	(-0.59)
Staleness 2	0.10	0.09	0.12	0.14	0.17	0.07
	(0.78)	(1.40)	(2.84)	(2.93)	(2.63)	(0.42)
Staleness 3	-0.03	0.11	0.14	0.20	0.24	0.27
	(-0.22)	(1.46)	(2.99)	(4.17)	(2.82)	(1.94)
Staleness 3-1	-0.24	-0.10	0.04	0.09	0.10	0.34
	(-1.71)	(-0.87)	(0.68)	(1.73)	(1.14)	(3.46)
Panel C: Five-factor Alphas						
Staleness 1 (Low)	0.19	0.11	0.10	0.11	0.12	-0.07
	(1.49)	(1.66)	(1.94)	(2.12)	(1.81)	(-0.51)
Staleness 2	0.04	0.08	0.11	0.14	0.14	0.10
	(0.26)	(1.10)	(2.46)	(2.60)	(1.92)	(0.55)
Staleness 3	-0.18	0.06	0.10	0.16	0.13	0.31
	(-1.28)	(0.67)	(1.89)	(3.07)	(1.54)	(2.07)
Staleness 3-1	-0.36	-0.13	-0.01	0.05	0.01	0.37
	(-2.56)	(-0.94)	(-0.09)	(0.85)	(0.13)	(3.64)

Table A.12 **Latent Fund Staleness and Corporate Bond Momentum: Sort by Past 12-month Returns.** This reports robustness check for the staleness effect on corporate bond momentum. In this analysis, I use past 12-month return for the sorting on momentum effect, and I follow Table 4 to form corporate bond portfolios two-way sorted by past 12-month returns (skip the most recent month) and latent fund staleness and examine the portfolio performance in the six-month holding period. In this table, portfolio performance are evaluated based on offering amount-weighted portfolio returns, where the offering amount is the par value of the bond issue when it's initially offered. Panel A reports average monthly excess returns. Panel B reports the average monthly alphas adjusted for exposures on default and term factors. Panel C reports the average monthly alphas adjusted for exposures on Fama and French (1993) stock-market three factors together with default and term factors. t-statistics are in parentheses.

			Panel A: Excess Returns			
	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Staleness 1 (Low)	0.56	0.44	0.39	0.38	0.40	-0.16
	(3.56)	(3.86)	(3.91)	(4.04)	(3.57)	(-1.29)
Staleness 2	0.48	0.35	0.33	0.35	0.40	-0.08
	(2.72)	(3.29)	(4.02)	(4.47)	(4.06)	(-0.56)
Staleness 3	0.11	0.26	0.30	0.34	0.46	0.35
	(0.43)	(2.03)	(3.24)	(3.93)	(4.16)	(1.85)
Staleness 3-1	-0.46	-0.30	-0.09	-0.04	0.05	0.51
	(-2.59)	(-2.86)	(-1.21)	(-0.51)	(0.57)	(3.66)
			Panel B: Two-factor Alphas			
Staleness 1 (Low)	0.26	0.16	0.14	0.14	0.12	-0.14
	(2.85)	(3.02)	(2.96)	(3.29)	(2.11)	(-1.28)
Staleness 2	0.23	0.13	0.14	0.16	0.17	-0.06
	(1.97)	(2.17)	(3.24)	(3.99)	(2.96)	(-0.43)
Staleness 3	-0.13	0.09	0.15	0.20	0.29	0.42
	(-0.66)	(0.86)	(2.07)	(3.28)	(3.92)	(2.32)
Staleness 3-1	-0.38	-0.17	0.01	0.06	0.17	0.56
	(-2.13)	(-1.42)	(0.18)	(0.94)	(2.27)	(3.80)
			Panel C: Five-factor Alphas			
Staleness 1 (Low)	0.22	0.15	0.14	0.14	0.11	-0.12
	(2.31)	(2.62)	(2.77)	(3.04)	(1.75)	(-1.02)
Staleness 2	0.15	0.11	0.13	0.15	0.14	-0.02
	(1.26)	(1.69)	(2.83)	(3.41)	(2.17)	(-0.12)
Staleness 3	-0.31	0.01	0.10	0.14	0.21	0.52
	(-1.66)	(0.10)	(1.12)	(2.05)	(2.69)	(2.84)
Staleness 3-1	-0.53	-0.21	-0.04	0.00	0.10	0.63
	(-3.03)	(-1.51)	(-0.53)	(0.07)	(1.36)	(4.27)

Table A.13 **Latent Fund Staleness and Corporate Bond Momentum: Sub-Sample Periods.** This table reports robustness check for the staleness effect on corporate bond momentum. Specifically, I follow Table 4 to for corporate bond portfolios two-way sorted by past six-month returns (skip the most recent month) and latent fund staleness and examine the portfolio performance in the six-month holding period. In this table, I report the average monthly holding period returns or alphas in the first half (2002.07-2011.03) and second half (2011.04-2019.12) of the sample period in Panel A and Panel B, respectively.

Panel A: First-half sample period						
	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Panel A.1: Excess Returns						
Staleness 1 (Low)	0.50	0.40	0.38	0.39	0.47	-0.02
	(1.79)	(2.00)	(2.32)	(2.64)	(2.84)	(-0.12)
Staleness 2	0.39	0.31	0.37	0.41	0.47	0.09
	(1.27)	(1.76)	(2.84)	(3.55)	(3.29)	(0.36)
Staleness 3	-0.07	0.17	0.31	0.41	0.48	0.55
	(-0.17)	(0.80)	(1.99)	(2.90)	(2.37)	(1.98)
Staleness 3-1	-0.56	-0.33	-0.07	0.02	0.01	0.57
	(-1.90)	(-1.77)	(-0.67)	(0.22)	(0.05)	(2.55)
Panel A.2: Two-factor alphas						
Staleness 1 (Low)	0.22	0.14	0.16	0.19	0.25	0.04
	(1.60)	(1.91)	(2.27)	(2.85)	(3.03)	(0.23)
Staleness 2	0.16	0.12	0.21	0.26	0.32	0.16
	(0.93)	(1.41)	(3.43)	(4.11)	(3.52)	(0.83)
Staleness 3	-0.26	0.02	0.17	0.29	0.35	0.61
	(-0.93)	(0.17)	(1.88)	(3.37)	(2.39)	(2.62)
Staleness 3-1	-0.48	-0.20	0.01	0.10	0.10	0.58
	(-1.66)	(-1.02)	(0.14)	(1.17)	(0.76)	(2.69)
Panel A.3: Five-factor alphas						
Staleness 1 (Low)	0.25	0.14	0.17	0.20	0.24	0.00
	(1.78)	(2.01)	(2.40)	(2.95)	(2.67)	(-0.02)
Staleness 2	0.13	0.13	0.21	0.27	0.30	0.17
	(0.69)	(1.51)	(3.27)	(3.96)	(3.06)	(0.80)
Staleness 3	-0.37	-0.01	0.14	0.26	0.28	0.65
	(-1.54)	(-0.07)	(1.48)	(2.90)	(1.98)	(2.90)
Staleness 3-1	-0.62	-0.26	-0.02	0.06	0.04	0.66
	(-2.33)	(-1.21)	(-0.22)	(0.72)	(0.31)	(3.07)

Table A.13 Continued

	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Panel B: Second-half sample period						
Panel B.1: Excess Returns						
Staleness 1 (Low)	0.55	0.38	0.32	0.32	0.38	-0.17
	(3.81)	(4.60)	(3.84)	(3.04)	(2.50)	(-1.22)
Staleness 2	0.49	0.32	0.26	0.29	0.38	-0.11
	(3.22)	(4.33)	(3.50)	(2.91)	(2.53)	(-0.81)
Staleness 3	0.08	0.28	0.28	0.32	0.42	0.34
	(0.36)	(3.36)	(4.06)	(3.79)	(3.19)	(1.99)
Staleness 3-1	-0.48	-0.27	-0.04	0.00	0.03	0.51
	(-2.89)	(-2.77)	(-0.77)	(-0.03)	(0.30)	(3.74)
Panel B.2: Two-factor alphas						
Staleness 1 (Low)	0.26	0.18	0.12	0.07	0.01	-0.25
	(2.89)	(4.67)	(2.83)	(1.18)	(0.08)	(-1.89)
Staleness 2	0.21	0.16	0.09	0.05	0.01	-0.20
	(2.25)	(4.09)	(2.07)	(1.04)	(0.17)	(-1.58)
Staleness 3	-0.14	0.14	0.15	0.15	0.18	0.32
	(-0.81)	(2.52)	(3.31)	(2.88)	(2.33)	(2.04)
Staleness 3-1	-0.40	-0.12	0.02	0.09	0.17	0.57
	(-2.61)	(-1.47)	(0.51)	(1.41)	(1.83)	(3.86)
Panel B.3: Five-factor alphas						
Staleness 1 (Low)	0.19	0.14	0.09	0.03	-0.04	-0.23
	(2.06)	(3.50)	(2.07)	(0.53)	(-0.42)	(-1.53)
Staleness 2	0.14	0.12	0.05	0.02	-0.05	-0.19
	(1.31)	(2.79)	(1.27)	(0.34)	(-0.66)	(-1.25)
Staleness 3	-0.33	0.05	0.07	0.07	0.04	0.37
	(-1.71)	(0.91)	(1.65)	(1.39)	(0.55)	(2.04)
Staleness 3-1	-0.52	-0.14	-0.02	0.04	0.08	0.60
	(-3.04)	(-1.70)	(-0.44)	(0.66)	(0.82)	(3.62)

Table A.14 **Latent Fund Staleness and Corporate Bond Momentum: IG versus HY Bonds.** This table reports subsample analysis for the staleness effect on corporate bond momentum. In this table, I split the corporate bonds into investment-grade bonds and high-yield bonds, and I follow Table 4 to conduct the portfolio analysis in each group of bonds separately. Specifically, I form corporate bond portfolios two-way sorted by past six-month returns (skip the most recent month) and latent fund staleness and examine the portfolio performance in the six-month holding period. Panel A and Panel B reports the results for high-yield bonds and investment-grade bonds, respectively.

Panel A: High-Yield Bond						
	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Panel A.1: Excess Returns						
Staleness 1 (Low)	0.26	0.41	0.45	0.49	0.52	0.26
	(0.96)	(2.42)	(3.68)	(4.48)	(3.49)	(1.24)
Staleness 2	-0.08	0.44	0.46	0.49	0.38	0.46
	(-0.27)	(2.53)	(3.51)	(4.08)	(2.45)	(2.16)
Staleness 3	-0.15	0.35	0.39	0.43	0.48	0.63
	(-0.45)	(1.87)	(2.87)	(3.39)	(2.94)	(2.58)
Staleness 3-1	-0.41	0.08	-0.06	-0.06	-0.04	0.37
	(-2.92)	(0.48)	(-1.40)	(-1.36)	(-0.58)	(2.57)
Panel A.2: Two-factor Alphas						
Staleness 1 (Low)	0.06	0.23	0.32	0.36	0.39	0.33
	(0.27)	(1.81)	(3.58)	(4.45)	(2.98)	(1.68)
Staleness 2	-0.29	0.24	0.30	0.34	0.25	0.54
	(-1.18)	(1.90)	(2.95)	(3.80)	(2.12)	(2.62)
Staleness 3	-0.34	0.16	0.25	0.30	0.36	0.71
	(-1.25)	(1.09)	(2.24)	(2.87)	(2.77)	(3.07)
Staleness 3-1	-0.40	0.10	-0.07	-0.06	-0.03	0.37
	(-2.84)	(0.56)	(-1.32)	(-1.38)	(-0.48)	(2.48)
Panel A.3: Five-factor Alphas						
Staleness 1 (Low)	-0.17	0.11	0.24	0.28	0.25	0.42
	(-0.83)	(0.82)	(2.39)	(3.18)	(1.82)	(1.95)
Staleness 2	-0.56	0.10	0.21	0.24	0.11	0.67
	(-2.50)	(0.80)	(1.76)	(2.44)	(0.88)	(3.17)
Staleness 3	-0.64	0.04	0.16	0.20	0.20	0.84
	(-2.45)	(0.22)	(1.20)	(1.66)	(1.46)	(3.47)
Staleness 3-1	-0.47	0.20	-0.08	-0.09	-0.04	0.43
	(-3.00)	(0.98)	(-1.34)	(-1.71)	(-0.65)	(2.53)

Table A.14 Continued

Panel B: Investment-grade Bonds						
	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Panel B.1: Excess Returns						
Staleness 1 (Low)	0.47	0.35	0.33	0.33	0.40	-0.07
	(3.23)	(3.26)	(3.43)	(3.39)	(3.36)	(-0.64)
Staleness 2	0.42	0.31	0.29	0.31	0.37	-0.05
	(2.96)	(3.35)	(3.77)	(3.84)	(3.56)	(-0.45)
Staleness 3	0.25	0.27	0.27	0.31	0.41	0.15
	(1.47)	(3.24)	(4.08)	(4.47)	(4.68)	(1.02)
Staleness 3-1	-0.22	-0.21	-0.06	-0.02	0.01	0.22
	(-2.16)	(-2.54)	(-1.47)	(-0.53)	(0.13)	(2.62)
Panel B.2: Two-factor Alphas						
Staleness 1 (Low)	0.13	0.08	0.08	0.08	0.10	-0.03
	(1.86)	(1.63)	(1.80)	(1.79)	(1.80)	(-0.34)
Staleness 2	0.14	0.10	0.10	0.11	0.12	-0.02
	(1.61)	(1.83)	(2.62)	(2.61)	(2.11)	(-0.17)
Staleness 3	-0.02	0.09	0.11	0.14	0.20	0.22
	(-0.13)	(1.65)	(2.99)	(3.84)	(4.23)	(1.51)
Staleness 3-1	-0.15	-0.04	0.03	0.06	0.11	0.25
	(-1.49)	(-0.72)	(1.26)	(2.71)	(3.17)	(2.81)
Panel B.3: Five-factor Alphas						
Staleness 1 (Low)	0.12	0.08	0.10	0.09	0.11	-0.01
	(1.65)	(1.47)	(1.87)	(1.92)	(1.95)	(-0.07)
Staleness 2	0.11	0.09	0.10	0.12	0.12	0.01
	(1.21)	(1.59)	(2.46)	(2.63)	(2.01)	(0.09)
Staleness 3	-0.07	0.08	0.11	0.14	0.19	0.26
	(-0.46)	(1.34)	(2.78)	(3.50)	(3.67)	(1.61)
Staleness 3-1	-0.19	-0.05	0.02	0.05	0.08	0.27
	(-1.66)	(-0.77)	(0.60)	(2.01)	(2.26)	(2.58)

Table A.15 **Staleness and Corporate Bond Short-Term Reversal.** This table analyzes the effect of latent fund staleness on corporate bond short-term reversal. At the end of month t, I sort corporate bonds into quintiles by their returns in month t (STREV), and I independently sort corporate bonds into terciles by latent fund staleness measured as of month t end. The two-way sorted portfolios are held over month $t+1$, and equal-weighted average portfolio returns are computed. Average monthly holding period returns or alphas during July 2002 to December 2019 are reported. Panel A reports average monthly excess returns. Panel B reports the average monthly alphas adjusted for exposures on default and term factors. Panel C reports the average monthly alphas adjusted for exposures on Fama and French (1993) stock-market three factors together with default and term factors. t-statistics are in parentheses

	STREV 1 (Low)	STREV 2	STREV 3	STREV 4	STREV 5	STREV 5-1
Panel A: Excess Returns						
Staleness 1 (Low)	0.84	0.44	0.38	0.37	0.19	-0.65
	(5.36)	(4.15)	(4.05)	(3.52)	(1.29)	(-5.16)
Staleness 2	0.64	0.31	0.28	0.32	0.25	-0.39
	(4.13)	(3.74)	(3.79)	(3.85)	(1.97)	(-3.33)
Staleness 3	0.39	0.30	0.27	0.33	0.36	-0.03
	(1.88)	(2.53)	(2.80)	(3.40)	(2.51)	(-0.20)
Staleness 3-1	-0.45	-0.54	-0.10	-0.04	0.17	0.62
	(-2.72)	(-4.44)	(-1.37)	(-0.50)	(1.40)	(4.16)
Panel B: Two-factor Alphas						
Staleness 1 (Low)	0.54	0.18	0.15	0.10	-0.17	-0.71
	(4.83)	(3.10)	(2.81)	(2.13)	(-2.58)	(-5.39)
Staleness 2	0.40	0.13	0.11	0.12	-0.04	-0.43
	(3.75)	(2.56)	(2.35)	(2.95)	(-0.53)	(-3.64)
Staleness 3	0.17	0.12	0.12	0.16	0.15	-0.03
	(1.09)	(1.11)	(1.40)	(2.39)	(1.63)	(-0.17)
Staleness 3-1	-0.37	-0.42	-0.03	0.06	0.32	0.69
	(-2.01)	(-2.67)	(-0.40)	(0.82)	(3.28)	(3.93)
Panel B: Five-factor Alphas						
Staleness 1 (Low)	0.51	0.17	0.14	0.10	-0.18	-0.70
	(4.04)	(2.44)	(2.26)	(1.78)	(-2.57)	(-4.69)
Staleness 2	0.35	0.11	0.09	0.11	-0.07	-0.42
	(2.94)	(1.88)	(1.70)	(2.47)	(-1.05)	(-3.23)
Staleness 3	0.00	0.06	0.07	0.11	0.07	0.07
	(0.03)	(0.44)	(0.70)	(1.48)	(0.82)	(0.41)
Staleness 3-1	-0.51	-0.46	-0.06	0.02	0.26	0.77
	(-2.71)	(-2.49)	(-0.81)	(0.23)	(2.56)	(3.98)

Table A.16 **Residual Staleness and Corporate Bond Momentum: Fama-MacBeth Regressions.** This table reports Fama-MacBeth forecasting regressions of corporate bond returns. For a cross-sectional regression in month t, the dependent variable is the six-month cumulative return from month $t+1$ to $t+6$, PRET is the cumulative return from month $t-7$ to month $t-1$, and Res_Staleness is the residual latent fund staleness estimated in month t end. I estimate the residual staleness through cross-sectional regressions of latent fund staleness on bond rating, natural logarithm of bond age, natural logarithm of bond amihud illiquidity, natural logarithm of bond offering amount, and past six-month cumulative returns. I take the residuals from the cross-sectional regressions as the residual staleness. Based on residual staleness, I generate a dummy variable, Dummy_Stale, which equals one if a corporate bond is among the most stale tercile and equals zero elsewhere. t-statistics in parenthese are with Newey-West correction of five lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample				Stale Group		Non-Stale Group	
PRET	0.080*	0.087*	0.078*	0.054	0.134**	0.113**	0.034	0.052
	(1.72)	(1.87)	(1.70)	(1.30)	(2.10)	(1.99)	(0.70)	(1.26)
PRET×Res_Stalness			0.199					
			(1.52)					
PRET×Dummy_Stale				0.069**				
				(2.10)				
Staleness			-0.007					
			(-0.83)					
Dummy_Stale				-0.002				
				(-1.46)				
Maturity		0.000**	0.000**	0.000**		0.000***		0.000**
		(2.45)	(2.40)	(2.42)		(3.25)		(2.21)
Rating		0.001	0.001	0.001		0.001		0.001
		(0.99)	(0.99)	(1.01)		(1.05)		(1.01)
Ln(Size)		0.003***	0.002***	0.002***		0.002*		0.003***
		(2.75)	(2.72)	(2.77)		(1.76)		(2.81)
ZRD_Ratio		0.005	0.004	0.004		0.006		0.004
		(1.24)	(1.15)	(1.17)		(1.18)		(1.19)
Ln(Amihud)		0.002**	0.002**	0.002**		0.002*		0.002**
		(2.09)	(2.15)	(2.16)		(1.68)		(2.22)
Age		-0.000	-0.000	-0.000		-0.000		-0.000
		(-0.43)	(-0.49)	(-0.45)		(-0.91)		(-0.20)
No. Obs.	688,101	680,080	680,080	680,080	226,388	226,348	453,767	453,732
Adj. R^2	0.071	0.240	0.250	0.249	0.090	0.239	0.025	0.255

Table A.17 **Residual Staleness and Corporate Bond Momentum: Fama-MacBeth Regressions.** This table reports Fama-MacBeth forecasting regressions of corporate bond returns. For a cross-sectional regression in month t, the dependent variable is the six-month cumulative return from month t+1 to t+6, PRET is the cumulative return from month $t-7$ to month $t-1$, and Res_Staleness is the residual latent fund staleness estimated in month t end. I estimate the residual staleness through cross-sectional regressions of latent fund staleness on bond rating, natural logarithm of bond age, natural logarithm of bond amihud illiquidity, natural logarithm of bond offering amount, and past six-month cumulative returns. I take the residuals from the cross-sectional regressions as the residual staleness. Based on residual staleness, I generate a dummy variable, Dummy_Stale, which equals one if a corporate bond is among the most stale tercile and equals zero elsewhere. t-statistics in parenthese are with Newey-West correction of five lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
PRET	0.080*	0.087*	0.349**	-0.001
	(1.72)	(1.87)	(2.07)	(-0.02)
PRET×Stalness			0.377**	
			(2.16)	
PRET×Dummy_Stale				0.127***
				(3.08)
Staleness			-0.010	
			(-1.05)	
Dummy_Stale				-0.002
				(-0.84)
E[FIT]		5.581	12.783*	8.469
		(0.79)	(1.74)	(1.28)
Maturity		0.000**	0.000**	0.000**
		(2.50)	(2.41)	(2.48)
Rating		0.001	0.001	0.001
		(0.95)	(1.19)	(1.03)
Ln(Size)		0.003**	0.003***	0.003***
		(2.58)	(2.78)	(2.81)
ZRD_Ratio		0.005	0.005	0.005
		(1.28)	(1.36)	(1.27)
Ln(Amihud)		0.002**	0.002**	0.002**
		(2.30)	(2.42)	(2.44)
Age		-0.000	-0.000	-0.000
		(-0.37)	(-0.54)	(-0.56)
No. Obs.	688,101	669,298	669,298	669,298
Adj. R2.	0.071	0.243	0.259	0.252

Table A.18 **Latent Fund Staleness and Corporate Bond Momentum: Top 3 versus Non-Top 3 Asset Management Companies.** This table reports subsample analysis for the staleness effect on corporate bond momentum. In this table, I split corporate bond funds into two groups based on the size of their management companies. Specifically, for each month during 1998-2018, I compute the total corporate bond fund TNA manged by each management company, and then I take the time-series average of total TNA across management companies. The three management companies with largest average TNA are assigned into "top 3" group and the rest of management companies are assigned into "non-top 3" group. Also, corporate bond funds managed by each management company are assigned into the corresponding groups. After that, I compute bond-level staleness using fund-level staleness from funds in top 3 group and funds in non-top 3 group separately. Finally, following Table 4, I form corporate bond portfolios two-way sorted by past six-month returns (skip the most recent month) and latent fund staleness and examine the portfolio performance in the six-month holding period. Panel A (Panel B) reports results from the portfolio analysis where the bond-level staleness is computed based on funds managed by top 3 (non-top 3) asset management company.

Panel A: Top 3 asset management companies						
	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Panel A.1: Excess Returns						
Staleness 1 (Low)	0.52	0.39	0.36	0.41	0.47	-0.04
	(3.14)	(3.05)	(3.07)	(3.62)	(3.58)	(-0.32)
Staleness 2	0.39	0.32	0.28	0.30	0.35	-0.03
	(2.56)	(3.20)	(3.13)	(3.31)	(3.21)	(-0.29)
Staleness 3	0.12	0.30	0.28	0.30	0.40	0.22
	(0.53)	(3.10)	(3.74)	(4.06)	(4.12)	(1.51)
Staleness 3-1	-0.29	-0.25	-0.06	-0.06	-0.03	0.28
	(-2.74)	(-2.64)	(-1.14)	(-1.06)	(-0.41)	(2.74)
Panel A.2: Two-Factor Alphas						
Staleness 1 (Low)	0.14	0.07	0.07	0.10	0.13	0.01
	(1.77)	(1.37)	(1.59)	(2.18)	(2.47)	(0.07)
Staleness 2	0.10	0.10	0.06	0.08	0.10	0.00
	(1.13)	(1.88)	(1.34)	(1.61)	(1.87)	(-0.00)
Staleness 3	-0.17	0.12	0.12	0.14	0.22	0.28
	(-0.92)	(1.63)	(2.71)	(3.55)	(3.60)	(1.90)
Staleness 3-1	-0.20	-0.07	0.05	0.05	0.10	0.32
	(-2.01)	(-1.02)	(1.32)	(1.35)	(1.79)	(2.86)
Panel A.3: Five-Factor Alphas						
Staleness 1 (Low)	0.12	0.06	0.06	0.10	0.13	0.02
	(1.50)	(1.11)	(1.28)	(1.96)	(2.19)	(0.19)
Staleness 2	0.08	0.08	0.04	0.07	0.08	0.00
	(0.81)	(1.52)	(0.71)	(1.38)	(1.30)	(-0.00)
Staleness 3	-0.28	0.08	0.10	0.13	0.16	0.31
	(-1.33)	(1.18)	(2.16)	(2.71)	(2.41)	(1.99)
Staleness 3-1	-0.27	-0.08	0.04	0.04	0.05	0.34
	(-2.52)	(-1.05)	(1.01)	(0.96)	(0.94)	(2.90)

Table A.18 Continued

Panel B: Non-Top 3 asset management companies						
	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Panel B.1: Excess Returns						
Staleness 1 (Low)	0.52	0.37	0.36	0.36	0.43	-0.09
	(3.18)	(3.64)	(4.27)	(4.29)	(3.92)	(-0.71)
Staleness 2	0.36	0.29	0.33	0.35	0.42	0.05
	(1.92)	(2.81)	(4.23)	(4.50)	(3.81)	(0.38)
Staleness 3	0.02	0.27	0.29	0.37	0.45	0.43
	(0.10)	(2.32)	(3.17)	(4.15)	(3.58)	(2.52)
Staleness 3-1	-0.49	-0.25	-0.07	0.02	0.03	0.52
	(-2.85)	(-2.31)	(-1.02)	(0.28)	(0.28)	(3.98)
Panel B.2: Two-Factor Alphas						
Staleness 1 (Low)	0.21	0.14	0.16	0.15	0.17	-0.04
	(2.31)	(2.74)	(3.51)	(3.55)	(2.82)	(-0.36)
Staleness 2	0.09	0.08	0.15	0.17	0.19	0.10
	(0.71)	(1.33)	(3.80)	(4.08)	(2.92)	(0.71)
Staleness 3	-0.21	0.10	0.14	0.22	0.28	0.49
	(-1.14)	(1.12)	(2.07)	(3.60)	(2.93)	(3.10)
Staleness 3-1	-0.42	-0.11	-0.02	0.07	0.11	0.53
	(-2.37)	(-0.95)	(-0.26)	(1.04)	(1.11)	(4.04)
Panel B.3: Five-Factor Alphas						
Staleness 1 (Low)	0.18	0.13	0.15	0.15	0.14	-0.04
	(1.86)	(2.50)	(3.20)	(3.10)	(2.24)	(-0.31)
Staleness 2	0.00	0.06	0.13	0.15	0.13	0.13
	(0.00)	(0.87)	(3.09)	(3.50)	(1.93)	(0.88)
Staleness 3	-0.39	0.04	0.08	0.16	0.17	0.56
	(-2.21)	(0.36)	(1.06)	(2.38)	(1.70)	(3.53)
Staleness 3-1	-0.57	-0.14	-0.07	0.01	0.03	0.60
	(-3.26)	(-1.04)	(-0.83)	(0.21)	(0.26)	(4.51)

Table A.19 **Latent Fund Staleness and Corporate Bond Momentum: Institutional- versus Retail-Oriented Funds.** This table reports subsample analysis for the staleness effect on corporate bond momentum. In this table, I split corporate bond funds into institutional- versus retail-oriented groups. Specifically, I first use information in CRSP database to define each share class as institutional or retail share class. Then, I define a fund as institutional-oriented fund if more than 80% of its TNA is from institutional share classes, and I define a fund as retial-oriented fund if less than 20% of its TNA is from institutional share classes. After that, I compute bond-level staleness using fund-level staleness from institutional- and retail-oriented funds separately. Finally, following Table 4, I form corporate bond portfolios two-way sorted by past six-month returns (skip the most recent month) and latent fund staleness and examine the portfolio performance in the six-month holding period. Panel A (Panel B) reports results from the portfolio analysis where the bond-level staleness is computed based on instituional-oriented (retail-oriented) funds.

Panel A: Institutional-Oriented Funds						
	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Panel A.1: Excess Returns						
Staleness 1 (Low)	0.43	0.39	0.31	0.34	0.36	-0.08
	(2.21)	(3.36)	(3.15)	(3.60)	(2.93)	(-0.51)
Staleness 2	0.34	0.36	0.31	0.32	0.37	-0.04
	(1.70)	(3.30)	(3.56)	(3.60)	(3.12)	(-0.27)
Staleness 3	0.19	0.31	0.33	0.38	0.43	0.24
	(0.81)	(2.40)	(3.24)	(3.68)	(3.17)	(1.41)
Staleness 3-1	-0.26	-0.12	0.01	0.04	0.07	0.35
	(-1.67)	(-0.92)	(0.09)	(0.49)	(0.73)	(2.60)
Panel A.2: Two-factor Alpha						
Staleness 1 (Low)	0.07	0.13	0.08	0.11	0.07	0.00
	(0.55)	(2.30)	(1.54)	(2.25)	(1.18)	(-0.03)
Staleness 2	0.03	0.12	0.11	0.12	0.11	0.01
	(0.26)	(2.02)	(2.61)	(2.60)	(1.79)	(0.06)
Staleness 3 (High)	-0.07	0.11	0.16	0.20	0.24	0.30
	(-0.42)	(1.13)	(2.15)	(2.49)	(2.30)	(1.92)
Staleness 3-1	-0.16	0.04	0.06	0.09	0.16	0.32
	(-0.98)	(0.27)	(0.70)	(1.03)	(1.76)	(2.42)
Panel A.3: Five-factor Alphas						
Staleness 1 (Low)	0.05	0.12	0.08	0.10	0.04	-0.02
	(0.35)	(2.01)	(1.35)	(2.04)	(0.61)	(-0.12)
Staleness 2	-0.06	0.10	0.09	0.10	0.06	0.03
	(-0.39)	(1.63)	(2.12)	(1.98)	(0.86)	(0.20)
Staleness 3	-0.27	0.02	0.09	0.12	0.13	0.39
	(-1.73)	(0.20)	(1.02)	(1.32)	(1.18)	(2.37)
Staleness 3-1	-0.35	-0.02	-0.01	0.02	0.08	0.43
	(-2.27)	(-0.14)	(-0.10)	(0.17)	(0.79)	(3.29)

Table A.19 Continued

	PRET 1 (Low)	PRET 2	PRET 3	PRET 4	PRET 5	PRET 5-1
Panel B: Retail-Oriented Funds						
Panel B.1: Excess Returns						
Staleness 1 (Low)	0.57	0.48	0.42	0.37	0.42	-0.15
	(2.96)	(4.07)	(4.46)	(4.09)	(3.52)	(-1.07)
Staleness 2	0.32	0.32	0.34	0.36	0.41	0.09
	(1.57)	(2.85)	(4.23)	(4.40)	(3.47)	(0.58)
Staleness 3	-0.05	0.26	0.32	0.36	0.39	0.44
	(-0.20)	(1.81)	(3.02)	(3.54)	(2.92)	(2.42)
Staleness 3-1	-0.62	-0.31	-0.10	-0.01	-0.03	0.59
	(-3.30)	(-2.29)	(-1.19)	(-0.11)	(-0.26)	(4.03)
Panel B.2: Two-factor Alphas						
Staleness 1 (Low)	0.23	0.22	0.20	0.16	0.16	-0.07
	(1.97)	(4.12)	(4.31)	(3.41)	(2.34)	(-0.56)
Staleness 2	0.06	0.13	0.18	0.20	0.21	0.14
	(0.47)	(1.82)	(3.95)	(4.05)	(2.67)	(1.00)
Staleness 3	-0.27	0.09	0.17	0.21	0.23	0.50
	(-1.33)	(0.75)	(2.09)	(2.71)	(2.30)	(2.99)
Staleness 3-1	-0.49	-0.14	-0.03	0.05	0.07	0.57
	(-2.49)	(-0.94)	(-0.34)	(0.63)	(0.73)	(3.81)
Panel B.3: Five-factor Alphas						
Staleness 1 (Low)	0.17	0.19	0.19	0.14	0.11	-0.06
	(1.37)	(3.47)	(3.83)	(2.85)	(1.55)	(-0.46)
Staleness 2	-0.06	0.09	0.15	0.16	0.12	0.18
	(-0.46)	(1.23)	(3.15)	(3.07)	(1.46)	(1.14)
Staleness 3	-0.50	0.00	0.09	0.13	0.11	0.61
	(-2.64)	(-0.03)	(1.00)	(1.54)	(1.07)	(3.60)
Staleness 3-1	-0.67	-0.18	-0.10	-0.01	0.00	0.67
	(-3.29)	(-0.96)	(-0.94)	(-0.13)	(0.02)	(4.35)

Table A.20 **Connected Bond Staleness and Connected Bond Momentum: Fama-MacBeth Regression.** This table analyzes the effect of connected bond staleness on connected bond momentum through Fama-MacBeth regressions. The dependent variable is corporate bond returns in month $t+1$. The key independent variable is connected bond returns (CB Ret) in the most recent quarter before month $t+1$. The definition of CB Ret follows Table 9, and I standardize the CB Ret within each cross-section. Control variables include past six-month bond returns (PRET), months to maturity (Maturity), a dummy variable indicating investment-grade bond (Dummy_IG), natural logarithm of offering amount (Ln(Size)), fraction of zero-return day in the most recent quarter (ZRD Ratio), natural logarithm of Amihud illiquidity (Ln(Amihud)), and bond age in months (Age). Corporate bonds which are held by more than 20 mutual funds are excluded from the regression sample. Corporate bonds Columns (1)-(2) report the regression results in full sample. In Columns (3)-(6), I split corporate bonds into "Low CB Staleness" group and "High CB Staleness" group based on the median connected bond staleness (CB Staleness) in the month, and I report regressions results in the two subsamples separately. The definition of connected bond staleness follows Table 9. t-statistics are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		*Low CB Staleness*		*High CB Staleness*	
CB Ret	0.186***	0.074***	0.058	0.044	0.244***	0.092***
	(4.06)	(3.49)	(1.13)	(1.55)	(4.19)	(3.40)
PRET		0.991**		-0.803		1.769***
		(2.52)		(-1.40)		(3.00)
Maturity		0.001**		0.001**		0.001**
		(2.05)		(2.18)		(2.50)
Dummy_IG		-0.115		-0.103		-0.099
		(-0.98)		(-0.67)		(-0.90)
Ln(Size)		-0.010		-0.026		0.012
		(-0.50)		(-1.25)		(0.40)
ZRD Ratio		-0.005		-0.036		0.021
		(-0.08)		(-0.54)		(0.27)
Ln(Amihud)		-0.012		0.011		-0.017
		(-0.58)		(0.59)		(-0.69)
Age		0.000		-0.000		0.000
		(0.33)		(-0.32)		(0.37)
No. Obs.	730,320	697,433	368,138	352,706	362,182	344,727
Adj. R^2	0.032	0.123	0.033	0.153	0.033	0.129

Table A.21 **Flow-Performance Model Horse Race: Two-Factor Model.** This table shows a robustness check for Table 10. For this test, I compute fund monthly alphas in two models, with and without considering staleness in fund NAVs. For the model without considering fund NAV staleness (Non-Stale Model), in each month I regress monthly fund excess returns on contemporaneous DEF/TERM factor returns using past 36-month observations to estimate the fund exposures on contemporaneous DEF and TERM. Then, I compute fund alpha in the month by subtracting the product of exposures on DEF/TERM and the realized DEF/TERM return from fund excess returns in the month. For the model that considers fund NAV staleness, I estimate fund exposures on both contemporaneous and one-month lagged DEF/TERM factor, and I compute fund alpha in the month by subtracting the product of exposures on DEF/TERM and the realized DEF/TERM in both current and the previous month from fund excess returns in the month. In columns (1) and (2), I estimate the following regression model:

$$\Phi(Flow_{f,t}) = a + b \times \Phi(\alpha_{f,t-1}) + \epsilon_{f,t},$$

where $\Phi(Flow_{f,t})$ is the sign of the fund flow in monbth t and $\Phi(\alpha_{f,t-1})$ is the sign of fund alpha in month $t-1$. Standard errors are two-way clustered by fund and time. The regression is estimated using the fund alpha under either stale or non-stale model. I report coefficient estimates and t-statistics associated with b in columns (1) and (2), respectively. I follow Berk and van Binsbergen (2016) to compare the flow-performance relationship between stale and non-stale models. Specifically, I estimate the following regression model:

$$\Phi(Flow_{f,t}) = c + d \times (\frac{(\Phi(\alpha^{NS}_{f,t-1})}{Var(\Phi(\alpha^{NS}_{f,t-1}))} - \frac{(\Phi(\alpha^{S}_{f,t-1})}{Var(\Phi(\alpha^{S}_{f,t-1}))}) + \epsilon_{f,t},$$

where $\alpha^{S}_{f,t-1}$ and $\alpha^{NS}_{f,t-1}$ are the fund alphas in month $t-1$ computed based on stale model and non-stale model respectively, and $Var(\Phi(\alpha^{S}_{f,t-1}))$ is the variance of the sign of the fund alpha computed based on stale model. Standard errors are two-way clustered by fund and time. In column (3), I report the t-statistics associated with d from the above regression.

	(1)	(2)	(3)
Model	b	t-stat of b	BvB test t-stat
Non-Stale	0.047	6.15	2.07
Stale	0.409	5.35	

Table A.22 **Flow Mis-Allocation and Beta Anomaly Short-Leg Return.** This table examines the time-series relationship between flow mis-allocation to stale funds and the short-leg return of beta anomaly. I define the beta anomaly short-leg return as the returns from short-selling Bloomberg Barclays US Corporate Ca-D index in each month. I also follow Frazzini and Pedersen (2014) to compute hedged beta arbitrage short-leg returns by hedging out the interest rate risk exposures of the credit index. The key dependent variable is the market-level mis-allocated flows defined following Table 11. This table reports results from the time-series regression of beta arbitrage short-leg return in month $t+1$ on market-level mis-allocated flow computed in month t. For contorl variables, I include the realization of corporate bond market factor and Fama and French (2015) stock-market five factors in month $t+1$, and I also include Baker and Wurgler (2006) sentiment index, Ted Spread, Inflation, and Investment-to-capital ratio in month t. The sample period is from July 2000 to December 2018. t-statistics in parentheses are computed based on standard errors with Newey-West correction of one lag.

	(1)	(2)	(3)	(4)	(5)	(6)
DepVar:	Short-Leg Ret_{t+1}			Hedged Short-Leg Ret_{t+1}		
$\mathrm{Mis\_Flow}_{t-11,t}$	4.57**	2.40*	6.07**	4.45*	2.31	5.25*
	(2.00)	(1.68)	(2.00)	(1.81)	(1.52)	(1.72)
Corp Bond MktRf_{t+1}		-1.77***			-2.58***	
		(-5.57)			(-7.44)	
Stk MktRf_{t+1}		-0.52***			-0.30*	
		(-3.59)			(-1.92)	
Stk SMB_{t+1}		-0.76***			-0.88***	
		(-3.67)			(-3.90)	
Stk HML_{t+1}		-0.78***			-0.57**	
		(-3.49)			(-2.31)	
Stk RMW_{t+1}		0.22			0.23	
		(0.84)			(0.81)	
Stk CMA_{t+1}		0.64**			0.60*	
		(2.02)			(1.74)	
BW $\mathrm{Sentiment}_t$			-0.00			0.01
			(-0.12)			(0.25)
Ted Spread_t			1.08			-0.93
			(0.62)			(-0.50)
$\mathrm{Inflation}_t$			3.36**			4.99***
			(2.10)			(2.92)
Investment-to-$\mathrm{capital}_t$			4.05			4.06
			(0.86)			(0.81)
Intercept	-0.01*	0.00	-0.17	-0.01**	-0.00	-0.17
	(-1.86)	(0.11)	(-1.02)	(-2.26)	(-0.19)	(-0.94)
No. Obs.	234	234	223	234	234	223
Adj. R^2	0.013	0.346	0.034	0.010	0.326	0.058