High-frequency Trading and Treasury Bond Returns*

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Abstract

This study provides a comprehensive analysis of the effects of High-frequency Trading (HFT) on expected returns of Treasury bonds. We document a strong and positive relationship between bond expected returns and a factor capturing the intensity at which HFT takes place in the market. We find that investing in bonds with the largest exposure to the HFT intensity factor and shorting those with the smallest generates large and significant returns. These returns are uncorrelated with conventional risk factors, are not affected by transaction costs and they are higher during periods when macroeconomic news shocks are larger than normal.

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1 Introduction

High-frequency Trading (HFT henceforth) refers to the set of activities that employ automated programs for generating, routing, executing and canceling orders in electronic markets (Cvitanic and Kirilenko, 2010).[1] One of the major features of these activities is that they are carried out at a very high speed using powerful computers and sophisticated algorithms (Clark, 2011; Moallemi and Saglam, 201; Hasbrouck, 2012; Scholtus and Van Djik, 2012; Scholtus et al., 2012 and the references therein). HFT has been defined as one of the most significant market structure developments in recent years (SEC, 2010) and it has become object of increased scrutiny especially in the aftermath of the 'flash crash' that affected the US equity market on May 6th, 2010 (Kirilenko et al. 2011; Easley et al. 2011; 2012) and similar events that occurred thereafter in various security markets around the world (e.g, the collapse of Knight Capital Partners[2] and the large losses faced by Everbright Securities in China[3]). Those events have shown that the obvious advantages of HFT, in terms of quick reactions to new information and reduction of monitoring and execution costs, can be compromised by non-negligible negative effects on market liquidity and, to a larger extent, price volatility.

The growing theoretical and empirical literature on HFT widely recognizes that trading at a very high speed can entail both benefits and, most importantly, risks.[4] More specifically these risks are related to the fact that automated traders may employ strategies that can

[1] HFT is generally regarded as a subset of a larger class of activities. This latter set, defined as algorithmic trading, mostly focuses on the intelligent working of orders to minimize market impact relative to a pre-defined benchmark (Chlistalla, 2011; Gomber et al., 2012). Since the main aim of this study is to investigate the impact of trading activity that is carried out at a very high speed on asset prices, we will only refer to the HFT group of activites throughout the text.

[2] See "Knight $440 Million Loss Sealed by Rules on Canceling Trades", *Bloomberg*, August 15th, 2012.

[3] See, "China Watchdog Embraces Risk After Everbright Fat Finger," *Bloomberg*, September 30th, 2013.

[4] An non-exhaustive list of recent studies that have investigated the impact of HFT on the overall quality of equity, FX and fixed income markets includes Hendershott et al. (2010), Hasbrouck and Saar (2011), Brogaard (2011a; 2011b; 2012), Hendershott and Riordan (2011), Egginton et al. (2012), Bohmer et al. (2012), Chaboud et al. (2009) and Jiang et al.(2013) and the references therein..

potentially overload exchanges with trade-messaging activity (Egginton et al., 2012), use their technological advantage to position themselves in front of incoming order flow, hence making more difficult to transact at posted prices; and withdraw their participation from the markets during periods of turbulence or when market making is difficult (Bohemer et al., 2012).[5] Combined together, these aspects suggest that higher-than-expected HFT is likely to generate systematic market disruptions and, as a consequence, increase systematic risk (Barker and Pomeranets, 2011; Biais and Wooley, 2012). Recent attempts to incorporate HFT into theoretical models of trading in financial markets have generated important insights into the interaction among different types of market participants (e.g. slow and fast traders) and its impact on asset prices. Kirilenko et al. (2011) and Biais et al. (2013) emphasize that HFT enables fast traders to process information before other traders and this competitive advantage is likely to impose adverse selection on slow traders[6] and generate profits at their expenses. These findings are corroborated by the empirical evidence in Baron et al. (2012) who suggest that most of the profits from HFT are generated from the interaction with fundamental traders, small and other traders who are unlikely to access (or use) strategies that are carried out at a very high speed.[7] A similar conclusion on the potentially dysfunctional role of HFT in financial markets is highlighted by Jarrow and Protter (2011). They show that fast players, contrary to conventional arbitrageurs, can create with their trades increased volatility and mispricing (deviations from fundamental values) that they exploit to their advantage.[8]

[5]Various studies commissioned by the UK Treasury under the Foresight Project emphasize increased concerns by institutional investors that HFT exacerbates market manipulation. See UK Government Office for Science (2012).

[6]See also Focault et al. (2012) for a theoretical analysis of news trading and speed.

[7]The fact that some market participants may systematically lose out against high frequency traders is also corroborated by the evidence of strong opposition to HFT direct trading allowance into financial markets. One example reported in the financial press is represented by the threat of leaving the market staged by Credit Suisse when MTS, Europe's premier facilitator for the electronic fixed income trading market, considered direct market access for hedge funds (See,"Credit Suisse Quits MTS In Protest of Open Trades", *Wall Street Journal* November 26th 2007).

[8]This theoretical finding is supported by the anecdotal evidence suggesting that some banks in various

A natural cross-sectional pricing implication arises from these findings: Investors holding assets that are largely exposed to common HFT strategies are likely to face a higher risk during high HFT activity in comparison with others holding assets which are not (or less) exposed to HFT. As a consequence, those investors may require a compensation in term of higher expected returns. The current price of the assets with greater exposure (or beta) to HFT risk should be lower (and its expected returns higher) if they experience a low payoff during periods of unexpectedly high HFT activity (denoting a negative beta to HFT risk).

In this paper we bring this conjecture to the data and provide the first comprehensive empirical analysis of the effect of HFT on the cross-section of expected returns of US Treasury bonds. The goal of our paper is to determine whether the intensity at which HFT occurs in the market is a priced risk factor and, if so, estimate the price of aggregate HFT risk. We focus on the US Treasury market since it is one of the largest in the world, with a daily trading volume nearly 5 times that of the US equity market, and because HFT has been increasing substantially since early 2000s.[9]

With the help of a large transaction dataset from BrokerTec, which contains tick-by-tick transactions and order book information for the 2-, 5- and 10-year on-the-run Treasury securities over the period of January 2003 – December 2011, we compute a HFT intensity factor. More specifically, as commercially available datasets do not provide information to identify automatic trading and quoting activities, we follow Jiang et al. (2013) and use the submission timing of orders and their subsequent alterations to classify high frequency trades and orders on the basis of the reaction time of order placements to changes in market

markets have actively engaged in questionable trading practices focused on generating mispricing over short periods of time. For example, the UK Financial Services Authority (FSA) fined Citigroup GBP 13.9 million in 2005 for "executing a trading strategy on the European government bond markets on 2 August 2004 which involved the firm building up and then rapidly exiting from very substantial long positions in European government bonds over a period of an hour" (FSA, 2005).

[9] Some recent anecdotal evidence suggests that BrokerTec, a major electronic communication networks (ECNs) intermediating bond transactions, experiences more than 50 percent of its bid and offer prices that are "black-box-oriented" and 45 percent of its overall trading in US Treasuries that is generated by computers (Kite, 2010).

conditions deemed to be beyond manual ability. The HFT intensity factor is then calculated as the average ratio between the number of high frequency trades and orders and the overall number of trades and orders in a given month across the three benchmark maturities.

We then adopt a portfolio approach to examine the cross-sectional relationship between Treasury bond expected returns and the exposure to the HFT intensity factor. Consistent with large literature aiming at explaining the cross-section of equity returns (see, among others, Fama and French, 2012 and the references therein) and in the spirit of the studies of the determinants of Treasury bond returns (see, inter alia, Li et al., 2009 and the references therein), we construct five portfolios of bonds according to their beta to the HFT intensity factor.[10]

Using a sample of 416 Treasury bonds and notes over the period January 2003 and December 2011, we find that investing in Treasury securities with the largest exposure to the HFT intensity factor and shorting the ones with the lowest provides a US investor significant excess returns of about 10 percent per annum. In support of our conjecture, we also find empirically that the securities with the largest exposure to the HFT intensity factor deliver low returns in times of high HFT activity (i.e. negative beta) while securities with the lowest exposure exhibit positive returns during the same times. We also find that the returns from the strategy are not a mere compensation for conventional risks in bond and equity markets and they are not affected by transaction costs. The performance of the portfolio strategy is higher during periods when macroeconomic announcement shocks are larger than normal.

A set of robustness checks confirms that the results from the baseline estimates are not affected by, among others, different portfolio formation and holding periods, the inclusion of bond specific characteristics in the asset pricing regressions and the use of alternative estimation procedures to carry out asset pricing tests. Furthermore, in the spirit of Adrian et al. (2013), we also show that a random noise HFT intensity factor does not spuriously

[10] In the baseline set of results, we estimate HFT intensity beta using the past 12 month of data and we rebalance the various portfolio every six months.

replicate the cross-sectional results reported in this study.

Our study is closely related to Skjeltorp et al. (2013) who investigate the impact of algorithmic trading on the cross-section of equity returns. The two studies share various similarities: First, both studies propose a methodology that infer the intensity of computer trading activity from publicly available information. Second, conditioning on the level of computer trading activity generates a large and economically significant return spread. Third, this return spread is not due to compensation to conventional sources of risk. However, the two studies differ in a number of significant ways. First, the two studies focus on two very different markets characterized by different institutional structures. Second, we compute our measure of HFT intensity on the basis of the reaction time of order placements to changes in market conditions deemed to be beyond manual ability. This allow us to capture the essence of the very quick pace of HFT activity. Skjeltorp et al. (2013), using a different rationale, look at the ratio between the number of orders submitted and trades for the same security to proxy for algorithmic trading activity. Third, we form portfolios on the basis of the exposure to the HFT intensity factor while Skjeltorp et al. (2013) rank directly stocks into portfolios on the basis of their estimated measure of algorithmic trading activity. These important distinctions are likely to be the main drivers of the diverging results reported in the two papers. In fact, unlike our study, Skjeltorp et al. (2013) record that stocks with higher computer trading activity have lower expected returns and this result is rationalized on the basis of an information diffusion hypothesis.

The rest of the paper is set out as follows. Section 2 discusses the construction of the HFT intensity factor, introduces the bond portfolio strategy and describes the empirical framework used to carry out asset pricing tests. Section 3 describes the datasets used in the empirical investigation and presents some key summary statistics. Sections 4 and 5 report the main empirical results and discuss a number of robustness checks. A final section concludes.

2 The Empirical Framework

In this section we discuss the empirical framework adopted in this study. More specifically, we first discuss the procedure for constructing the HFT intensity factor using bond trades and orders high-frequency data. Then we describe the bond portfolio strategy used to evaluate the effect of HFT on the cross-section of Treasury bond returns and the asset pricing tests used to understand the determinants of the returns from the bond strategy.

2.1 The HFT Intensity factor

Comprehensive data on HFT across various financial markets are scarce. In fact, commercially available dataset do not contain information about whether trades or orders are placed through computers or manually and the few exceptions are limited to some markets and over very short periods of time. This limitation makes the investigation of the effect of HFT on asset prices difficult. In our study we overcome this problem by exploiting a procedure recently proposed in Jiang et al. (2013), which infers high frequency trades and orders in the US Treasury secondary market on the basis of the of the reaction time of order placements to changes in market conditions deemed to be beyond manual ability. In fact, for each of the Treasury benchmarks, it is possible to access the reference numbers that provide information on the submission timing of an order and its subsequent alteration, cancellation or execution. Hence, we are able to identify high frequency trades and orders by focusing on their reaction time after changes in market conditions.[11]

Once high frequency trades and orders are identified, we construct the HFT intensity

[11] More specifically, as in Jiang et al. (2013), we classify high frequency trades as the market buy (sell) orders that are placed to hit the best ask (bid) quote within a second of the changes of the best quotes. Similarly, we classify high frequency orders if 1) a limit order is cancelled or modified within one second of its placement regardless of market condition changes or 2) a limit order at the best quote is modified within one second of changes in best quotes on either side of the market or 3) a limit buy (sell) order placed at the second best quote is modified on either side of the market within one second of a change in the best quote on either side of the market (higher bid or lowest ask). For further details on the identification procedure, see Jiang et al. (2013) and the references therein.

factor as the equally weighted-average of the ratios between the total number of high frequency trades and orders and the total number of overall trades and orders (i.e. including both high-frequency and non-high frequency trades and orders, respectively) as follows:

$$HFTI_t = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{HFTO_t^i}{ALLTO_t^i}\right). \tag{1}$$

where $HFTO_t^i$ denote the day t number of high frequency trades and orders for the benchmark bond i and $ALLTO_t^i$ denote the day t of total number of overall trades and orders for the same benchmark bond.

The construction of the HFT intensity factor, $HFTI_t$, follows similar HFT measures proposed in recent studies. For example, Hendershott et al. (2010) use a normalized measure of electronic message traffic on NYSE as a proxy for algorithmic-high frequency trading while Hasbrouck and Saar (2011) construct a measure of low-latency activity based upon "strategic runs" which are linked to submissions, cancellations and executions of orders. In a similar fashion, Skjeltorp et al. (2013), compute a proxy for algorithmic trading as the order-to-trade ratio for each stock reported in the Trade and Quotes database (TAQ). All of these studies, in line with our approach, infer computer trading and quoting activity from existing publicly-available high-frequency data, and apply various filters that aim at capturing the quick reaction of traders to market changes.

In the empirical analysis, we focus on the innovations in the HFT intensity factor (denoted as $\widehat{HFTI}_t$) that are computed, as in various studies, by taking the residuals from an autoregressive (AR) model applied to the daily time-series data. We find that an AR(5) model is able to generate innovations that have zero mean and are serially uncorrelated.[12]

2.2 Bond Strategy and Portfolio Formation

In this paper we argue that holding assets that are largely exposed to common HFT strategies generate a higher risk during periods of high HFT activity in comparison with holding assets

[12]The detailed description of the resulting factor and its innovations are reported in Section 3.

which are not (or less) exposed to HFT. As a consequence, assets largely exposed to HFT are likely to command larger expected returns than the one accruing to assets with smaller exposure to HFT.

We test this conjecture by implementing a bond portfolio strategy as follows: we form five portfolios based on the exposure (beta) to the HFT intensity factor innovations estimated using daily data during the past 12 months. We allocate the one fifth of the bond exhibiting the smallest beta the to the first portfolio, P1, the next fifth to the second portfolio, and so on until the top fifth of bonds that exhibit the largest beta which we allocate to last portfolio, P5. We keep the composition of the portfolios constant for six months and then we rebalance them on the basis of the exposures computed, using again 12 month worth of daily data, at the end of the sixth month. Once the returns on the various portfolios are computed, the return difference between P5 and P1 can be understood as the excess return from a long-short strategy resulting from investing in the portfolio P5 and short-selling the portfolio P1. If our conjecture finds support in the data, we should be able to obtain a positive average excess return from P5−P1 which is due to compensation for facing HFT risk.

2.3 Asset Pricing Tests

In the previous subsection we have suggested that the returns originating from the bond portfolio strategy should be mostly due exposure to HFT risk. However, it may well be that the same returns could be due to the mere compensation for facing conventional sources of risk. Hence, it is natural to assess the risk/return characteristics of our strategy using cross-sectional asset pricing methods. Assume that excess returns on portfolio i, denoted by rx^i_{t+1}, satisfy the Euler equation:

$$E_t\left(rx^i_{t+1}m^h_{t+1}\right) = 0. \tag{2}$$

If we assume a linear SDF, $m^h_{t+1} = 1 - b'(f_{t+1} - \mu_h)$, where f_{t+1} denotes a vector of risk factors and μ_h is a vector of factor means, the combination of the linear SDF and the Euler equation (2) leads to the conventional beta representation for excess returns on each portfolio i:

$$E(rx^i) = \lambda' \beta_i.$$

We estimate the parameters of equation (2) using the traditional two-pass Fama-MacBeth (FMB) approach (Fama and MacBeth, 1973). We also use the Generalized Methods of Moments (GMM) of Hansen (1982). More specifically, we use a two-step approach, starting with the identity matrix as the GMM weighting matrix before re-optimizing. Our standard errors are based on Shanken (1992). We also compute the J-statistic relevant to the null hypothesis that the pricing errors are zero.

With regards to the risk factors f_{t+1}, we select those that have been found to be most relevant for understanding the cross-section of Treasury bond returns in addition to others that have been proven to price the cross-section of other financial asset returns or explain the time-series variation of Treasury risk premia. With regards to the former group of risk factors, the first logical candidate is represented by the bond market portfolio excess return computed as the weighted average of all Treasury issues returns in excess of the 1-month general collateral (GC) repo rate, BMR_t henceforth. This factor represents a zero-net strategy that invests in all bonds in our sample financing the purchases at the risk-free rate. The other candidate factors in the same group are (i) bond market illiquidity (Li et al., 2009), $ILLIQ_t$ (ii) an aggregate bond market probability of informed trading measure (Li et al., 2009), PIN_t and (iii) the term spread, computed as the difference between the yields on the 10 year T-note and the 3-month T-bill (Fama, 1984; Fama and Bliss, 1987), $TERM_t$.

The other risk factors used in our empirical investigation include (i) bond market volatility (Ang et al., 2006; 2009; and Menkhoff et al., 2012), VOL_t, (ii) bond market skewness (Dittmar, 2002; Conrad et al., 2009; Chang et al., 2010 and Rafferty, 2011), $SKEW_t$ (iii) a funding illiquidity measure (Garleanu and Pedersen, 2011), $FILL_t$ (iv) the Fama-French size and value factors, SMB_t, HML_t respectively (v) the equity momentum factor (Carhart, 1997), UMD_t and (vi) the digital put option on excess equity market returns (Krishnamurthy, 2002), $DUMMYDP_t$.

We compute the measure of bond market volatility and skewness as weighted-average of standard deviations and skewness for each bond in our sample using daily data during any given month. Similarly, the bond market illiquidity factor is computed as weighted-average of daily quoted bid-ask spreads for each bond in our sample during the month. The bond market PIN measure is computed as a weighted-average of individual PIN measures computed for the 2-, 5- and 10-year benchmark notes using intraday data over any given month (Easley et al., 2002; Li et al. 2009). For all of these measures the weights are computed using both equal- and value-weighting schemes. In the latter case, the weights are computed using the bond outstanding value at the end of each month.

We follow Garleanu and Pedersen (2011) and compute the funding illiquidity factor as the difference between the 1-month LIBOR (uncollateralized rate) and the 1-month GC repo rate (collateralized rate). We obtain data on the size and value factors and the US momentum factor from Ken French's website. Finally, we compute the digital put on excess equity market return as in Krishamurthy (2002). More specifically, we construct a dummy variable that is equal to 1 if, in any given month, the value of the equity market excess return is lower than the negative of the equity market volatility and zero otherwise. The equity market excess return data used in this computation is obtained from Ken French's website.

3 Data and Summary Statistics

The data on US Treasury securities used in this article are obtained from two sources: BrokerTec for the computation of the HFT intensity factor, and CRSP US Treasury database for all other information pertaining to the cross-section of individual Treasury bonds in our sample.

BrokerTec is a major interdealer ECNs operating in the US Treasury secondary market that emerged after 1999.[13] Since then the trading of on-the-run Treasuries has substantially (if not fully) migrated to electronic venues (Mizrach and Neely, 2009; Fleming and Mizrach, 2009).[14] We compute the HFT intensity factor by applying the procedure detailed in Section 2.1 on data relative to the on-the-run 2-, 5- and 10- year T-notes from the BrokerTec limit order book. The dataset contains the tick-by-tick observations of transactions, order submissions and order cancellations. It also includes the time stamp of transactions and quotes, the quantity entered and/or deleted, the side of the market and, in the case of a transaction, an aggressor indicator.

CRSP U.S. Treasury Database is the second dataset we use in our empirical investigation. It reports detailed information on every Treasury security that was outstanding since 1925. For each security, CRSP reports a number of characteristics, including, among others, the issue date, the final maturity, daily yields to maturity and end-of-the-day bid and ask prices. CRSP also provides monthly readings of the dollar face value of each instrument.[15] In our empirical investigation, we focus on the cross-section of all Treasury notes and bonds with remaining time to maturity longer than 1 year.[16]

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[13] Previously most of the transactions in US Treasury securities were vioce-broking intermediated. The data were disseminated by GovPX (see Fleming, 1997 and the references therein).

[14] According to Barclay et al. (2006), the electronic market shares for the 2-, 5- and 10-year bond are, respectively, 75.2%, 83.5% and 84.5% during the period of January 2001 to November 2002. By the end of 2004, the majority of secondary interdealer trading occurred through ECNs with over 95% of the trading of active issues. BrokerTec is more active in the trading of 2-, 3-, 5- and 10-year Treasuries, while eSpeed has more active trading for the 30-year maturity.

[15] Since 1996, CRSP gathered this information from GovPX first and then directly from ICAP after the latter acquired GovPX in 2008. Further details on the CSPR US Treasury database can be found online at http://www.crsp.com/documentation/product/treasury/b.ackground.html

[16] We adopt this filter for various reasons. First, a minimum of 12 month of data is required to compute the HFT intensity beta parameters. Second, the majority of the empirical asset pricing studies on the term structure of interest rates in the US focuses on maturities longer than 1 year (see, among others, Cochrane and Piazzesi, 2005; Thornton and Valente, 2012 and the references therein). Third, Treasury securities with maturity shorter than 1 year may exhibit significant idiosycrasies that are not shared by similar securities with longer-maturities (Duffee, 1996).

The sample period investigated in this study spans between January 2nd, 2003 and December 30th, 2011. The choice of this sample period is due to data availability and, more importantly, to the fact that HFT was not widely adopted in the US Treasury market before that period.[17] Overall, during this sample period, the two datasets provide us with more than 1 trillion observations relative to trades and limit orders for the three on-the-run benchmarks (BrokerTec) and 300,574 bond-days (CRSP).

Figure 1 plots the daily level series $HFTI_t$ and its innovations, $\widehat{HFTI}_t$. The level series, which can be interpreted as the average share of trading and quoting activity due to HFT for any given day, exhibits a marked upward trend. This pattern confirms the anecdotal evidence that the adoption of HFT strategies in the US Treasury secondary market increased substantially over the sample period. Furthermore, it is also worthwhile noting that the value of $HFTI_t$ at the end of the sample is in close to 40 percent. This value is not very different from the 45 percent estimated share of HFT in the US Treasury market reported in recent financial press (Kite, 2010). The innovations of this level series are very volatile and heteroskedastic with some spikes occurring at the beginning of the sample period. However, they do not exhibit any peculiar trend or evident serial correlation.

Table 1 reports the descriptive statistics of the bond portfolios constructed as discussed in Section 2.2. For all bonds in our sample, monthly returns are computed on the basis of the mid-quote price, coupon payments and accrued interest during the month (Lin et al., 2011).[18] The baseline estimates are based on portfolio returns that are computed, in line with much empirical literature (see, among others, Menkhoff et al., 2012) using an equal-weighting scheme.[19] [20]

[17] See Boni and Leach (2001); Mizrach and Neely (2009) and Fleming and Mizrach (2009) on the introduction and development of electronic trading in the US Treasury market.

[18] We investigate the impact of transaction costs on portfolio returns in Section 5.1.

[19] However, in the robustness Section 5 we show that our results are confirmed qualitatively and quantitatively if we portfolio returns are computed using value-weighting scheme.

[20] In the empirical estimations, for consistency, we use bond risk factors which are computed using the same weighting scheme adopted for bond portfolio returns. Hence, the baseline results are carried out using

Sorting bonds on the basis of the exposure to the HFT intensity factor generates a large cross-sectional spread. The evidence reported in Table 1 is supportive of our conjecture that bonds with the largest exposure to HFT intensity will also experience larger expected returns. In fact, the strategy of investing in the portfolio comprising bonds with the largest HFT intensity beta (P5) and shorting the portfolio comprising bonds with the lowest beta (P1) yields about 10 percent per annum with an annualized Sharpe ratio that comfortably exceeds 1. The fact that the exposure to the HFT intensity factor generates a large return spread in the cross-section of Treasury securities is further corroborated by the monotonicity test statistic (Patton and Timmermann, 2010) that rejects the null hypothesis of no-monotonicity with a p-value very close to zero. In addition we also find clear evidence that the bonds that exhibit higher expected returns are also the ones with more negative HFT intensity beta, i.e. that experience lower realized returns when HFT activity is unexpectedly high.

Figure 2, left panel, plots the cumulative excess returns from the bond strategy benchmarked against the ones exhibited a simple buy-and-hold strategy for the overall bond market. The satisfactory performance exhibited by our bond strategy is visually corroborated when it is compared against the market benchmark. In fact, over the full sample period, the cumulative excess returns from the bond strategy are always higher than those exhibited by the benchmark. At the end of the sample, our bond strategy delivers a cumulative excess return about 100 percentage points greater than that of a buy-and-hold strategy for the overall bond market.[21] This striking difference is also reflected in the annualized Sharpe ratios of the two strategies, reported in Figure 2, right panel. In fact, our bond strategy delivers a Sharpe ratio that is about twice larger than the one exhibited by the overall bond market (that is about 0.6).

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bond risk factors that are computed using a equal-weighting scheme. The same results carried out by using returns and risk factors computed with a value-weighting scheme are reported in the robustness Section 5.

[21] The performance of our bond strategy compares favorably against any of the ones exhibited by conventional US and international strategies over the same period of time. In fact, its Sharpe ratio is generally larger than the ones exhibited by those strategies (see, Cenedese et al., 2013 and the references therein).

Figure 3 plots the underlying characteristics of the extreme two portfolios introduced in Table 1. The portfolio with the largest exposure to the HFT intensity factor (P5) contains Treasury securities which exhibit a long time to maturity, high volatility and a relatively high bid-ask spread. Vice versa, the portfolio with the smallest exposure against the HFT intensity factor (P1) records a comparatively shorter time to maturity, lower volatility and a bid-ask spread close, albeit slightly smaller, to the one recorded for the portfolio P5. Some of these characteristics are broadly in line with the evidence reported in recent studies, but in different contexts, suggesting that assets that are highly volatile and sufficiently liquid are the likely targets of conventional HFT strategies and, hence, being more exposed to HFT activity (see, for example, Hendershott et al., 2010 and Brogaard, 2010).

For completeness, in Table 2 we also report a summary descriptive statistics of the factors that are used in the subsequent sections. In panel A) we show the relevant statistics relative to the factors computed bond market data. More specifically, we report the bond market excess returns, the term spread and the innovations of the bond market volatility, skewness, illiquidity and PIN factors as described in Section 2.3. The factor innovations are computed as the residuals from an AR(1) model estimated using the monthly time series and they are denoted with a hat.[22] In Table 2 panel B), we show the remaining risk factors which are not necessarily related to the cross-section of Treasury bond returns but they have been proven to successful in pricing the cross-section of other asset returns.

4 Empirical Results

This section reports the asset pricing tests carried out to understand the properties of the returns generated from the bond portfolio strategy. Put differently, we investigate whether any conventional risk factors that are found to explain the cross-section of Treasury bond

[22] We also computed the innovations as the residuals from an AR(2) model. The results, not reported to save space, are qualitatively and quantitatevely similar to the ones discussed in this and the subsequent sections.

returns or any other risk factors that are successful in explaining the cross-section of other financial asset returns also explains the returns of the cross-section of portfolios constructed as in Section 2.2.

Table 3 reports the parameter estimates obtained by employing a conventional two-pass FMB procedure. In particular, in all specifications (1)-(10) we consider the bond market portfolio excess returns together with any of the remaining selected risk factors. The results of this estimation suggest that none of the conventional bond and equity risk factors is constistently able to price the cross-section of bond portfolio formed on the basis of the exposure to the HFT intensity factor. This result is also confirmed when market prices of risk are estimated using a two-step GMM methodology (Table 4). In fact, in the vast majority of the cases the risk factors are statistically insignificant at the conventional statistical level and in the few cases where they are significant, they are not consistent across the two different methodologies. This suggests that the cross-section of portfolio returns reported in Table 1 cannot be easily explained as compensation for conventional sources of risk, including, among others, illiquidity and volatility.[23]

It is worthwhile noting that our GMM estimates (as well as the FMB estimates in Table 3) record relatively high cross-sectional R^2 and the null hypothesis of zero pricing errors is not rejected at conventional level even in cases when parameter estimates are statistically insignificant. This apparently counter-intuitive result can be rationalized in light of the simulation evidence reported in Cenedese et al. (2013). They show that when the time-series of portfolio return and the cross-section of assets are small, cross-sectional R^2 tend to be large and the J-statistics do not reject the null hypothesis even when portfolio returns

[23] We have also assessed the robustness of this conclusion to a different approach. More specifically, we have computed the summary statistics of the P5-P1 returns when the portfolio are formed using the innovations of the HFT intensity factor that are orthogonalized against the innovations of relevant risk factors, namely volatility, liquidiy, skewness and PIN. The results, reported in Table A8 of the Internet Appendix, show that even after orthogonalizing against the innovations of risk factors which may be strongly associated with HFT, the returns from the bond strategy remains large, positive and statistically signficant at conventional level.

are truly uncorrelated with risk factors. However, they also show that the Shanken (1992) corrected t-statistics are more reliable.[24]

The evidence reported in Tables 3 and 4 of this study is computed using a similar cross-section of portfolios as the one reported in Cenedese et al. (2013). However, the time series of returns is considerably shorter. Hence, it is likely that the biases recorded in Cenedese et al. (2013) may be even more severe in our context. Nonetheless, even by taking that evidence at face value, our results shows that none of the risk factors is able to exhibit corrected t-statistics that are larger than 2 *and* consistently price the cross-section of portfolios across the two different methodologies.

We complement the cross-sectional results from Tables 3 and 4 with a regression that relates the P5-P1 return time-series to the time-series variation of all our risk factors simultaneously. We believe that this may be a rather powerful test since, unlike the cross-sectional approach adopted in the previous tables, it allows for the joint consideration of all of the risk factors over the full sample period.[25] We run two regressions: one that includes the time-series of the original risk factors, and another one which includes factor-mimicking portfolio returns that replace the time series of the non-tradable risk factors. This dual analysis is motivated by the fact that by converting non-tradable factors into portfolio returns allows us to scrutinize the factor price of risk in a more natural way (see, Breeden et al., 1989; Ang et al., 2006; Menkhoff et al., 2010 and the references therein). We construct factor mimicking portfolios by projecting the innovations of the non-tradable factors onto the space of traded returns of a set of base assets.[26] In our case, we consider the CRSP Fama bond maturity

[24] In fact, in their experiment, the boundaries of the 5% rejection region implied by the bootstrap distribution of t-statistics do not exceed the interval [-2, 2]. Thus, they suggest that when t-statistics of estimated factor prices are larger than 2, in absolute value, one can be relatively confident about the statistical significance of the candidate factors.

[25] The joint inclusion of all risk factors is not feasible in the cross-sectional asset pricing context because of the small cross-section of portfolios (i.e. 5) considered in our empirical investigation.

[26] The non-tradable factors in our context are represented by VOL_t, $ILLQ_t$, $FILL_t$, $SKEW_t$ and PIN_t.

portfolios as base assets and we estimate the following regression:

$$\widehat{X}_t = a + \sum_{j=1}^{K} b_{BA} \cdot rx_t^{BA,j} + e_t, \tag{3}$$

where $\widehat{X}_t$ denotes the non-tradable factor and $rx_t^{BA,j}$ denote the excess returns from the portfolio $j = 1, ..., K$ comprised in the set of base assets. The returns from the factor-mimicking portfolios are given by the mean of the traded portfolio $\sum_{j=1}^{K} \widehat{b}_{BA} \cdot rx_t^{BA,j}$. This procedure yields factor-mimicking portfolios whose returns exhibit a correlation coefficient with the non-tradable factors ranging between 0.26 and 0.66. These numbers are in line with ones recorded in recent studies (see, for example, Adrian et al., 2013 and Cenedese et al., 2013).[27]

The results of the time-series estimations are reported in Table 5. Overall, the evidence broadly confirm the finding reported in the previous Tables 3 and 4 that most of the factors have no explanatory power for the time-series of bond portfolio returns. The only exception is represented by the Fama-French size factor that is found to be significant at 5 percent level. However, and most importantly, Table 5 shows that in all of the cases the intercept, or alpha, of the time-series regression of the returns on the P5-P1 portfolio on all of the risk factors is positive and statistically significant, ranging between about 5.5 and 6 percent per annum across the two specifications. This tell us that returns from our investment strategy are not simply due to compensation for conventional sources of risk. In fact, even after having accounted for various plausible sources of risk, a sizeable and unexplained average return remains.[28]

[27] We also test the pricing ability of the factor-mimicking portfolios (Lewellen et al., 2010). For both factor-mimicking portfolios the average excess returns are very close to, and statistically insignificantly different from, the factor price of risk obtained for the cross-section of the same base assets. These results are comforting since they imply that factors price themselves and the do not allow for arbitrage opportunities (see also Menkhoff et al., 2010 p. 699).

[28] This evidence also suggests that there may be other drivers of such returns. We leave the analysis of alternative potential explanations for future work.

5 Robustness

This section checks the robustness of the baseline results reported in Section 4. More specifically, we test whether our results are sensitive to 1) the inclusion of transaction and financing costs when computing the returns of the bond portfolio strategy, 2) the choice of different formation and holding periods, 3) the inclusion of portfolio-specific factors when carrying out the asset pricing tests, 4) the use of value-weighted returns and 5) a different methodology used to account for potential biases in the asset pricing tests when liquidity factors are used. Finally, in the spirit of Adrian et al. (2013), we also test whether a random noise HFT intensity factor is able to spuriously replicate the cross-sectional results reported in this study. We show that our baseline results are robust to all these issues. In addition, in light of the evidence regarding HFT and macroeconomics announcements in the US Treasury market (Jiang et al., 2013), we provide a refinement of our baseline results and investigate the relationship between the returns from our bond portfolio and macroeconomic announcement shocks.

5.1 Bond Strategy Returns and Transaction Costs

Our first robustness check aim at exploring the impact of transaction and financing costs on the returns of the bond portfolio strategy. In fact, since the strategy requires that several bonds are bought and short-sold at the end of the annual holding period, the explicit consideration of transaction and financing costs may reduce or completely offset the returns of the strategy. We assess the impact of such costs by including in the computation of returns bid and ask prices and the repo costs of financing the long and short positions. Although bid-ask spreads are relatively small in electronic markets during our sample period (Mizrach and Neely, 2009; Fleming and Mizrach, 2009), the bond portfolio strategy discussed in Section 2.2 require financing at the repo rates. In fact, long positions are to be financed entering in a repo transaction and to create a short position in a bond traders must execute a sale jointly with a reverse repo transaction (Krishnamurthy, 2002). In the latter case, traders will deposit cash equal to the value of the bond with the counterpart and receiving bonds in return. At maturity, when the short position is reversed the trader will buy back the bonds and deliver them against the reverse-repo receiving back the cash plus the accrued repo.[29] Hence, in the context of our strategy, traders will pay the repo rate for financing the long positions but they will receive the reverse-repo rate for entering the reverse-repo transactions. In line with Krishnamurthy (2002), we compute the profits (per unit of notional value) from each bond considered in the long positions of our strategy as follows:

$$\left[P^b_{t+k} - P^a_t - P^a_t\left(f_{t,t+k}\frac{d}{360}\right)\right], \tag{4}$$

where P^b_{t+k} denotes the bond's bid full price (i.e. including accrued interest and coupon payments) recorded at the end of month $t+k$, P^a_t bond's ask full price recorded at the end of month t, $f_{t,t+k}$ denotes the annualized repo rate accruing between t and $t+k$ and d are the number of actual trading days occurring between t and $t+k$. Similarly the profits (per unit of notional value) from each bond considered in the short positions of our strategy as computed as follows:

$$-\left[P^b_{t+k} - P^a_t - P^a_t\left(\widehat{f}_{t,t+k}\frac{d}{360}\right)\right], \tag{5}$$

where $\widehat{f}_{t,t+k}$ denotes the annualized reverse-repo rate. In our baseline computations k, in line with the investment holding period, is equal 6 month. We define the difference between the two repo rates, $f_{t,t+k} - \widehat{f}_{t,t+k}$, as the repo spread. In the robustness exercise we assume that $\widehat{f}_{t,t+k} = f_{t,t+k}$ (zero repo spread) or $f_{t,t+k} - \widehat{f}_{t,t+k} = 25bps$ per annum.[30]

The results of this exercise are reported in Table 6. When the repo spread is set to zero,

[29] Krishnamurthy (2002, p. 469) points out that it is common that repo transactions require haircuts to be left with the repo dealer as credit margin. For simplicity, and in line with Krishnamurthy (2002) we assume that haircuts are 0%.

[30] In our calculations we also assume that the notional value invested in both long and short positions is identical. It is worthwhile noting that it is also common that the notional values invested in the long and short positions are chosen so that profits are invariant to an equal level change in the yield of each bond. For the sake of simplicity, we do not explore this aspect in this robustness check.

i.e. both repo and reverse-repo transaction are financed at the same 1-month GC repo rate, the bond portfolio strategy is able to deliver a performance that is very similar to the one reported in Table 1 over the same sample period. The inclusion of transaction costs does not hinge on the annual return of the strategy which, at 10 percent per annum, is virtually identical to the one reported in Table 1. However, the standard deviation of the strategy returns is also higher, which leads to a smaller Sharpe ratio than the one reported in Table 1.

If we assume a non-zero repo spread by setting the reverse-repo rate equal to the repo rate plus 25bps per annum, the returns from the strategy, reported in Table 5, are obviously reduced but still positive, but statistically insignificant, over the full sample period. This result shows that only very large transaction costs, in the form of large carry costs, are able to reduce the economic value of the bond strategy. However, it is important to emphasize that average carry costs of the order of 25bps per annum are unlikely to occur consistently for all bonds in the short portfolios over the full sample period. In fact, Krishnamurthy (2002, p. 474) show that repo spreads in the US Treasury market vary over time and they usually tend to be smaller than the value of 25 bps per annum used in this exercise.[31] Nonetheless, it is worthwhile noting that even under these restrictive circumstances, the annualized Sharpe ratio generated by the strategy is at par with, or slightly better than, the Sharpe ratios exhibited by the overall bond market without the inclusion of transaction and financing costs.[32]

As a further check, we also investigated whether the net-of-transaction-costs returns from the strategy correlate with the menu of risk factors reported in Table 5. The results of this

[31] Also Duffie (1996) show that the time variation in repo specialness can be very spiky and does not persist over time.

[32] It is important to emphasize that once financing costs are included in the computation of the strategy returns, the variable $DUMMYDP_t$ becomes significant at 5 percent level. This is not surprising, since Krishnamurthy (2002) shows that i) the time-series dynamics of profits from convergence trade between on-the-run and just-off-the-run bonds are associated with the dynamics of repo spreads and ii) the profits from the strategy involve systematic risk that resembles an out-of-the-money put option.

additional robustness check, reported in Table 7, confirm that even by taking into account various sources of risk, the bond strategy is able to deliver positive alpha that now range between 4.8 and 5.6 percent per annum. However, to echo the results reported in Table 6, the alpha estimates are only statistically significant at 10 percent level when a zero repo spread is assumed.

5.2 Different portfolio formation and holding periods

In Section 3 we implement our portfolio strategy by estimating the exposure (beta) to the HFT intensity factor using daily data over the past 12 months (formation period) and computing the portfolio returns assuming that the portfolio is rebalanced every 6 months (holding period). Although our choice is made to provide reasonably accurate beta estimates over a relatively limited sample period, it is natural to check whether any other plausible combination of formation and holding periods may affect our baseline results. In this robustness check we compute portfolio returns, and the relative P5-P1 strategy returns, when either the formation period or the holding period are increased. More specifically, in the first exercise, we leave the formation period unchanged but we lengthen the holding period to 12 months. Differently, in the second exercise, we leave the holding period constant and extend the formation period to 18 months. We do not consider shortening either the formation or the holding periods since these would result in more imprecise estimations of the factor exposures and higher transaction costs due to a more frequent portfolio rebalancing. The results of this robustness check are reported in Table 8. In both cases, we are able to confirm that lengthening either the formation or the holding periods does not affect our main baseline results. In fact, Table 8 shows that sorting bonds on the basis of their exposure to the HFT intensity factor still generate a large and significant cross-sectional spread. In fact, in both panels, the average returns from the bond portfolio strategy P5-P1 are positive and statistically significant and their annualized Sharpe ratios are still sizable.

5.3 Portfolio-specific Factors

In Section 4 we showed that the return from the bond strategy are uncorrelated with a large menu of sources of systematic risk in bond and equity markets. However, it may be possible that bond- or portfolio-specific sources of risk (as opposed to systematic risk) may be responsible for the performance of the strategy. We assess the results reported in Section 4 against this issue in the spirit of the framework adopted by Christophe et al. (2012). More specifically, we augment the FMB second pass estimation with a set of factors that are specific to each portfolio. We follow Ang et al. (2009) and Akbas et al. (2011), and focus our attention to the role of portfolio-specific volatility and illiquidity. We also explore the role of idiosyncratic skewness (Boyer et al., 2010). In particular, we extend the asset pricing framework outlined in Section 2.3 by including in turn the volatility, illiquidity and skewness of the individual five portfolios. We compute the portfolio-specific factors as weighted–average of the variables of interest of the individual bonds included in each portfolio. If portfolio-specific volatility, illiquidity or skewness factors are important in explaining the cross-section of bond portfolio returns, they will exhibit statistical significance in our asset pricing tests.

In order to meet the necessary identification conditions, we carry out the asset pricing tests by adding to the bond market excess return both the systematic bond risk factors ($\widehat{VOL}_t$, $\widehat{ILLIQ}_t$ and $\widehat{SKEW}_t$) and the portfolio-specific factors (denoted as $\widehat{PVOL^i}_t$, $\widehat{PILLIQ^i}_t$ and $\widehat{PSKEW^i}_t$, respectively). The results of this robustness check, reported in Table 9, confirm the baseline results discussed in Section 4, as none of the systematic or portfolio-specific risk factors is statistically significant at conventional level.

5.4 Value-weighted Returns

As a further check we investigate the robustness of the baseline results to a different way of computing portfolio returns. In Section 4, line with existing studies (see Menkhoff et al., 2012 and the references therein), we computed portfolio returns using an equal-weighting scheme. In this subsection, we assess the baseline results by computing portfolio returns using a value-weighting scheme where each bond return is weighted by the bond's dollar outstanding value of at the end of each month.

The results of this exercise are reported in Tables A1-A6 of the Internet Appendix. When portfolios returns and aggregate factors are computed using a value-weighting scheme, the evidence discussed in Sections 3 and 4 is quantitatively and qualitatively confirmed.

5.5 Liquidity Biases and Asset Pricing Tests

In this subsection, we assess the robustness of the results reported in Section 4 to potential biases affecting the asset pricing tests when noisy liquidity measures are used as risk factors. We do this by correcting the standard errors of the FMB estimated parameters as in Asparouhova et al. (2010, Section 4.4). The results of this robustness exercise computed for both equal-weighted and value-weighted returns, are reported in Table A7 of the Internet Appendix. They largely confirm and strengthen the asset pricing test results reported Tables 3 and 4 since none of the conventional risk factors is consistently able to explain the cross-section of bond portfolio returns.

5.6 Uninformative HFT Intensity Factor

The last robustness check we carry out aims to assessing whether the results reported in Section 3 are simply due to chance. More specifically, in the spirit of Adrian et al. (2013), we test whether a random noise HFT intensity factor is able to spuriously replicate the cross-sectional results reported in this study. Specifically we simulate a HFT intensity factor by randomly drawing from the distribution of the computed HFT intensity factor with replacement. For each of the 10,000 replications we construct a time series of the HFT intensity factor that has the same length of the one of the original factor. We then use those series to carry out the portfolio sorting exercise as described in Section 2.2. Since the factor is randomly drawn, it should not be able to generate portfolios that exhibit a substantial cross-sectional spread. Put differently, we should find that, portfolios constructed on the basis of the exposures against the a random noise factor exhibit roughly the same returns and, therefore a zero cross-sectional spread.

The results in Table A9 confirm our argument and show that sorting bonds into portfolios on the basis of a noise HFT factor generates returns that are homogenous across portfolios (around 0.4 percent per month). As a consequence the returns from the strategy P5-P1 are very close to zero and statistically insignificant. Moreover, the probability of randomly achieving the P5-P1 average return as high as we report in Table 3 is only a mere 0.03 percent. The null hypothesis of the test proposed by Patton and Timmermann (2010) is never rejected with a p-value close to 50 percent, further validating the fact that the simulated noise factor does not carry any pricing information. Taken together, the results reported in this subsection suggest that finding we discover and discuss in Sections 3 and 4 of the main text are unlikely to be due to mere chance.

5.7 Bond Portfolio Returns and the Size of Macroeconomic News Shocks

Finally, as a refinement of our baseline results, we compute the returns from the bond portfolio strategy conditioning upon the size of macroeconomic news shocks. It is a stylized empirical fact that macroeconomic variables drive the price of Treasury securities (e.g. Fleming and Remolona 1997; 1999; Balduzzi et al., 2001; Andersen et al., 2003; 2007; Menkveld et al., 2012 and Hoerdahl et al., 2013 and the references therein)[33]. Computers, with their

[33] There has been a vast literature examining the effect of macroeconomic news announcements in the US Treasury markets. Fleming and Remolona (1997) and Andersen et al. (2003; 2007) find that the largest price changes are mostly associated with macroeconomic news announcements in the Treasury spot and futures markets. Balduzzi et al. (2001), Fleming and Remolona (1999), Green (2004) and Hoerdahl et al. (2012) point out that the price discovery process of bond prices mainly occurs around major macroeconomic news announcements and the same announcements are responsible for changes in risk premia across different

speed and capacity to handle a large amount of information, are well positioned to execute multiple actions in response to information shocks. Recent studies have documented that HFT increases significantly after macroeconomic announcement news in various financial markets (Scholtus et al., 2012; Jiang et al., 2013) and a larger HFT intensity is associated with larger macroeconomic announcement shocks (Jiang et al., 2013). The predictability of bond returns appear to accrue especially around news announcements. Therefore, a trading strategy that takes position in bonds only around news announcements is able to deliver extra returns to investors (Faust and Wright, 2012).

To check whether our baseline results are in line with the evidence reported in previous studies, we compute in the spirit of Pasquariello and Vega (2007) and Hoerdahl et al. (2013) an aggregate binary indicator that is equal to one if the monthly cross-sectional average of standardized announcement news shocks computed across 34 major macroeconomic announcements[34] is larger than its time-series average (or median), computed over the full sample period, and zero otherwise. We then compute the returns from the bond portfolio strategy over the two regimes, one characterized by contexts where macroeconomic announcement shocks are larger than normal and the other one characterized by normal, or less than normal, announcement shocks.

Figure 4 reports the annualized Sharpe ratios of the strategy in the two regimes. The results reported in the left (right) panel of Figure 4 are computed by conditioning upon the average (median) standardized announcement news shocks. A clear pattern arises. In fact, it is visually evident that the profitability from the bond portfolio strategy increases during the periods where announcement news shocks are larger than normal. During those times, annualized Sharpe ratios are higher than the ones reported in Table 3 and close to a value

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maturities. Menkveld et al. (2012) record similar findings for 30-year Treasury bond futures. Pasquariello and Vega (2007) find that private information manifests on announcement days with larger belief dispersion.

[34] The data on macroeconomic news announcements and the survey of market participants are obtained from Bloomberg. For further details on the construction of the data and the description of the various macroeconomic announcement see Jiang et al. (2013).

of 2. Vice versa, when returns are computed during the times when announcement news shocks are normal, or less than normal, the annualized Sharpe ratios of the bond strategy are substantially smaller. This suggests that the size of macroeconomic news shocks matters in generating higher returns from the bond strategy. This is broadly in line with the results reported in recent studies and complement nicely the evidence that HFT intensity is larger when shocks affecting major macroeconomic variables are sizable and strategies that exploit information around macroeconomic announcement times can be profitable. Our evidence is also consistent with the argument that common systematic shocks may affect the profitability of strategies based on the high-frequency seasonalities of asset returns (Keloharju et al., 2013) and the fact that the asset pricing effect of HFT may be partially linked to information (Skjeltorp et al., 2013).

6 Conclusions

This study investigates the effect of HFT on the cross-section of Treasury bond returns. We argue that investors holding assets that are largely exposed to common HFT strategies might face a higher risk in comparison with the ones holding assets which are less (or not) exposed to HFT. As a consequence, those investors will demand a higher risk premium than the one due to assets with smaller exposure to HFT. We construct a novel HFT intensity factor using tick-by-tick data and we adopt a portfolio approach to address our main research question. More specifically, we first sort bonds into portfolios according to exposure of bond returns to innovations in the HFT intensity factor. Then we assess the profitability of a strategy that goes long in the portfolio of bonds with the largest exposure to the HFT intensity factor and short the one with the smallest.

Using data over the period January 2003 and December 2011, we find that this long-short strategy is able to yield a US investor significant excess returns of about 10 percent per annum. The returns of the bonds exhibiting the largest exposure to HFT intensity negatively correlate with innovation in the HFT intensity factor. Hence, those bonds provide low returns when HFT activity is unexpectedly high and vice versa.

We also find that the returns from the strategy are not due to a mere compensation for facing conventional sources of risk, including, among others, illiquidity and volatility and they are not affected by transaction costs, comprising bid-ask spreads and the repo market financing rates. Finally, we also find that the bond portfolio strategy performs better during periods when macroeconomic announcement news shocks are larger than normal. Importantly, the qualitative conclusions are robust to various issues, including among others, the choice of different formation and holding periods, the inclusion of portfolio-specific factors when carrying out the asset pricing tests and the use of different methodologies to account for potential biases in the asset pricing tests when noisy liquidity factors. We also provide simulation evidence that the our main results are not due to mere chance.

Overall, our findings confirm that HFT exerts important first order effects on expected returns of Treasury bonds and these effects can generate a substantial economic value to investors who adopt a strategy based upon the exposure to HFT risk.

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Table 1. Descriptive Statistics of Bond Portfolios

This table reports descriptive statistics for the monthly excess returns of bond portfolios sorted according to their exposure (beta) to the innovations of the measure of HFT intensity, $\widehat{HFTI}_t$ computed using daily data over the past 12 months. The holding period is six months. Portfolio returns are computed using an equal-weighting (EW) scheme and they are expressed in monthly percentage points. Portfolio 1 (P1) contains bonds with the smallest HFT beta while Portfolio 5 (P5) contains bonds with the largest HFT beta. Mean, Stdev, Skew and Kurt denotes the average, standard deviation, skewness and excess kurtosis of the various portfolio returns, respectively. AC(1) denotes the first−order autocorrelation coefficient of portfolio returns. Pre-ranking beta are the average beta estimates computed across all individual bonds in each portfolios over the full sample period. SR denotes annualized Sharpe ratios and MR is the p-value of the null-hypothesis of no monotonicity as in Patton and Timmermann (2010). Values in parenthesis denote $t-$statistics of the average portfolio returns computed using HAC standard errors as in Newey and West (1987). Values in brackets denote the average $t-$statistics of the pre-ranking beta of each portfolio.

	P1	P2	P3	P4	P5	P5−P1	MR
Mean	−0.0809	0.0771	0.2334	0.4800	0.7899	0.8709	<0.01
	(−0.5619)	(0.5306)	(1.3612)	(2.4025)	(2.5827)	(3.2322)	
Stdev	1.7203	1.4520	1.6092	1.9088	2.7092	2.5413	
Skew	−2.0734	−0.4883	−0.4022	0.4481	1.3097	1.0580	
Kurt	12.3646	1.1194	0.3032	2.0702	3.7940	2.6981	
AC(1)	−0.0899	0.0254	0.0872	0.1227	0.2018	0.2035	
Pre-ranking beta	0.2721	−0.3931	-0.8722	−1.4547	−2.2353		
	[0.6175]	[−0.9823]	[−2.0225]	[−3.4299]	[−4.3470]		
SR	−0.1630	0.1839	0.5025	0.8712	1.0101	1.1871	

Table 2. Descriptive Statistics of Risk Factors

This table reports descriptive statistics for the risk factors constructed as discussed in Section 2.3. Panel A) comprises bond-specific risk factors: BMR_t is the monthly excess returns of the bond market portfolio, $\widehat{VOL}_t$, $\widehat{ILLIQ}_t$, $\widehat{PIN}_t, \widehat{SKEW}_t$ are the AR(1) innovations of monthly bond volatility, illiquidity, PIN and skewness factors, respectively. $TERM_t$ denotes the yield spread between the 10-year T-note and the 3-month T-bill. Panel B) reports other risk factors used in the empirical analysis: $\widehat{FILL}_t$ denotes the AR(1) innovations of the monthly series of the funding liquidity measure. SMB_t, HML_t and UMD_t are the Fama−French size and value factors, and the US equity momentum factors, respectively. The sample period is January 2003−December 2011. See also notes to Table 1.

Panel A) Bond Risk Factors

	BMR_t	$\widehat{VOL}_t$	$\widehat{ILLIQ}_t$	$\widehat{PIN}_t$	$\widehat{TERM}_t$	$\widehat{SKEW}_t$
Mean	0.2774	−0.0032	0.0006	0.0001	−0.0056	0.0218
Stdev	1.3054	0.0759	0.0974	0.0053	0.2051	0.5442
Skew	0.0269	1.2200	2.6373	0.5299	0.5924	0.1160
Kurt	0.9028	3.2063	14.1943	0.9530	1.7438	1.3310
AC(1)	0.0893	−0.2239	0.0953	0.0352	0.3484	−0.0968

Panel B) Other Risk Factors

	$\widehat{FILL}_t$	SMB_t	HML_t	UMD_t
Mean	0.0060	0.2356	0.1107	−0.0183
Stdev	0.3081	2.4522	3.5754	5.2325
Skew	4.3610	0.8920	1.5902	−3.2224
Kurt	26.3465	2.3233	9.2550	20.0748
AC(1)	−0.0882	-0.0697	0.2236	0.2669

Table 3. Cross−sectional Asset Pricing Regressions (FMB)

This table reports the Fama−MacBeth (1973) factor premium for linear factor models. The test assets are the five bond portfolios reported in Table 1. Values in parentheses are $t-$statistics computed as in Shanken (1992). Adj R^2 denotes the adjusted coefficient of determination. The sample period is January 2003−December 2011. Returns are computed using a EW scheme. See also notes to Tables 1 and 2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR_t	1.0524	0.3062	0.5688	0.4136	0.5688	2.9015	0.6424	0.4850	1.0604	0.5848
	(2.1043)	(0.1600)	(1.5533)	(0.2871)	(1.5533)	(0.1792)	(1.5075)	(0.8753)	(2.3765)	(1.0675)
$\widehat{VOL}_t$	−0.0596									
	(−0.7523)									
$\widehat{LIQ}_t$		−0.4483								
		(−0.3935)								
$\widehat{FLIQ}_t$			−0.1962							
			(−1.6332)							
$\widehat{SKEW}_t$				−1.3878						
				(−0.3721)						
$\widehat{PIN}_t$					−0.0677					
					(−0.1291)					
$\widehat{TERM}_t$						−0.2272				
						(−1.4077)				
$DUMMYDP_t$							0.2747			
							(1.8124)			
SMB_t								2.9749		
								(0.9636)		
HML_t									0.9709	
									(0.4315)	
UMD_t										−7.8441
										(−1.0647)
Adj R^2	0.9398	0.9819	0.9742	0.9435	0.9742	0.9443	0.9722	0.9749	0.9366	0.9865

Table 4. Cross-sectional Asset Pricing Regressions (GMM)

This table reports the two-step GMM estimation of factor premium for linear factor models. The sample period is January 2003−December 2011. See notes to Tables 1, 2, and 3.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR_t	0.3254	0.3193	0.2211	0.2157	0.1111	0.1606	0.2460	0.2140	0.2783	0.2149
	(1.1114)	(0.9280)	(1.5239)	(1.2154)	(0.3951)	(0.6753)	(1.8166)	(1.2390)	(1.9018)	(0.6072)
$\widehat{VOL}_t$	0.2226									
	(0.7770)									
$\widehat{ILLIQ}_t$		−0.4413								
		(−0.5977)								
$\widehat{FILL}_t$			−0.3097							
			(−2.8133)							
$\widehat{SKEW}_t$				−1.8390						
				(−0.5650)						
$\widehat{PIN}_t$					0.0313					
					(0.5894)					
$\widehat{TERM}_t$						−0.2682				
						(−1.6163)				
$DUMMYDP_t$							0.4271			
							(1.4751)			
SMB_t								4.4892		
								(1.1889)		
HML_t									−10.7627	
									(−0.9193)	
UMD_t										−12.8960
										(−0.5799)
J_T	1.9315	0.3093	5.2746	0.9705	0.2510	2.0450	1.3577	1.1635	0.3189	1.0873
$p-value$	0.5868	0.9583	0.1528	0.8084	0.9690	0.5631	0.7155	0.7618	0.9564	0.7801

Table 5. Time Series Regressions

This table reports the time series regression coefficients of the excess return from the strategy P5−P1 as in Table 1 on the various risk factors. Values in parentheses are $t-$statistics computed using HAC standard errors as in Newey and West (1987). The sample period is January 2003−December 2011. See also notes to Tables 1, 2 and 3.

	non−tradable factors	mimicking portfolios
Const	0.4620	0.5018
	(2.1232)	(2.8251)
BMR_t	0.5349	0.5618
	(1.8360)	(1.5414)
$\widehat{VOL}_t$	-0.9019	-0.1517
	(-0.2667)	(-0.0145)
$\widehat{ILLIQ}_t$	−2.1095	−3.7272
	(−0.4927)	(−0.4420)
$\widehat{FILL}_t$	−1.4499	−1.9717
	(−1.3083)	(−1.1213)
$\widehat{SKEW}_t$	−0.4253	−1.5376
	(−0.8576)	(−0.8748)
$\widehat{PIN}_t$	18.7227	30.6878
	(0.6893)	(1.3963)
$\widehat{TERM}_t$	−1.7246	−2.1318
	(−1.2014)	(−1.6086)
$DUMMYDP_t$	1.7921	1.6120
	(1.5391)	(1.8394)
SMB_t	0.1865	0.1906
	(2.1472)	(2.1843)
HML_t	−0.2276	−0.1799
	(−1.4447)	(−1.8828)
UMD_t	−0.1619	−0.1147
	(−1.6911)	(−1.6778)
Adj R^2	0.3401	0.3540

Table 6. Trading Strategy Returns and Transaction Costs

This table reports descriptive statistics for the P5−P1 strategy as in Table 1. The returns net of transaction costs are computed using full bid and ask prices and they are adjusted for the repo financing costs (as discussed in Section 5.1). We report the results for a repo spread equal to zero and 25bp per annum. Portfolio returns are computed using an EW scheme. The sample period is January 2003−December 2011. See also notes to Table 1.

		repo spread =	
	no TC	0bp	25bp
Mean	0.8709	0.8420	0.6700
	(3.2322)	(1.9835)	(1.5790)
Stdev	2.5413	3.4897	3.4905
Skew	1.0580	0.6694	0.6624
Kurt	2.6981	1.3518	1.3481
AC(1)	0.2035	0.1999	0.1997
SR	1.1871	0.8358	0.6650

Table 7. Time Series Regressions: Transaction Costs and Factor−mimicking Portfolios

This table reports descriptive statistics for the P5−P1 strategy returns net of transaction and financing costs as reported in Table 6. See also notes to Tables 4 and 5.

		repo spread =	
	no TC	0 bps	25bps
Const	0.5018	0.4710	0.3999
	(2.8251)	(1.7382)	(1.2151)
BMR_t	0.5618	0.6975	0.6984
	(1.5414)	(1.6194)	(1.6244)
$\widehat{VOL}_t$	-0.1517	2.6092	2.7274
	(-0.0145)	(0.1870)	(0.1954)
$\widehat{ILLIQ}_t$	−3.7272	−0.2677	−0.3040
	(−0.4420)	(−0.0254)	(−0.0289)
$\widehat{FILL}_t$	−1.9717	−2.9932	−2.9846
	(−1.1213)	(−1.2245)	(−1.2213)
$\widehat{SKEW}_t$	−1.5376	−0.8674	−0.8730
	(−0.8748)	(−0.3691)	(−0.3719)
$\widehat{PIN}_t$	30.6878	26.3360	26.5758
	(1.3963)	(0.8025)	(0.8084)
$\widehat{TERM}_t$	−2.1318	−2.4685	−2.4793
	(−1.6086)	(−1.1833)	(−1.1920)
$DUMMYDP_t$	1.6120	2.4264	2.4148
	(1.8394)	(2.2423)	(2.2333)
SMB_t	0.1906	0.1832	0.1813
	(2.1843)	(1.4749)	(1.4598)
HML_t	−0.1799	−0.2309	−0.2304
	(−1.8828)	(−1.5418)	(−1.5394)
UMD_t	−0.1147	−0.1539	−0.1524
	(−1.6778)	(−1.4539)	(−1.4426)
Adj R^2	0.3540	0.3014	0.3007

Table 8. Portfolios Returns with Different Formation and Holding Periods

This table reports descriptive statistics for the monthly excess returns of bond portfolios sorted according to their beta to the innovations of HFT intensity measure, $\widehat{HFTI}_t$ with different formation and holding periods. See also notes to Table 1.

Panel A) 12 months of formation period, rebalanced every 12 months

	P1	P2	P3	P4	P5	P5−P1	MR
Mean	−0.0518	0.1611	0.3235	0.4728	0.7113	0.7631	<0.01
	(−0.3255)	(1.0362)	(1.7845)	(2.1550)	(2.4095)	(2.2682)	
Stdev	1.5581	1.5231	1.7765	2.1494	2.8924	2.8228	
Skew	−1.3948	−0.6963	−0.1593	0.4408	1.1601	1.4806	
Kurt	8.1298	1.4284	0.4342	1.5488	2.8603	3.8501	
AC(1)	−0.1107	0.0437	0.0674	0.1135	0.2123	0.2649	
SR	−0.1151	0.3663	0.6309	0.7619	0.8519	0.9364	

Panel B) 18 months of formation period, rebalanced every 6 months

	P1	P2	P3	P4	P5	P5-P1	MR
Mean	0.0443	0.2252	0.2634	0.5006	0.7012	0.6569	0.0330
	(0.2416)	(1.5166)	(1.6262)	(2.3208)	(2.4293)	(2.0466)	
Stdev	1.7379	1.4089	1.5369	2.0464	2.7382	2.7137	
Skew	−0.9310	−0.3226	−0.1142	0.8391	1.4635	1.2614	
Kurt	5.5702	0.5668	0.3575	1.7638	3.7246	3.2253	
AC(1)	−0.0847	−0.0415	0.0260	0.1994	0.2517	0.2046	
SR	0.0882	0.5538	0.5938	0.8474	0.8871	0.8368	

Table 9. Cross−sectional Regressions with Portfolio−specific Factors

This table reports the Fama−MacBeth (1973) factor premium for linear factor models. $\widehat{PVOL}^i{}_t$,$\widehat{PILLIQ}^i{}_t$, $\widehat{PSKEW}_t^i$ are portfolio-specific volatility, liquidity and skewness factors constructed as in Section 5.2. Values in parentheses are t−statistics computed as in Shanken (1992). The sample period is January 2003−December 2011. See also notes to Tables 1, 2 and 3.

	(1)	(2)	(3)
BMR_t	−1.1428	−0.1492	0.2308
	(−0.1144)	(−0.0790)	(0.0867)
$\widehat{VOL}_t$	−0.0813		
	(−0.1476)		
$\widehat{ILLIQ}_t$		−0.4719	
		(−0.3850)	
$\widehat{SKEW}_t$			−1.4913
			(−0.1181)
$\widehat{PVOL}_t^i$	9.4921		
	(0.2042)		
$\widehat{PILLIQ}_t^i$		0.3451	
		(0.3314)	
$\widehat{PSKEW}_t^i$			4.3498
			(0.4681)
adj R^2	0.3248	0.8414	0.6444

Figure 1. High Frequency Trading Intensity

20-days moving averages

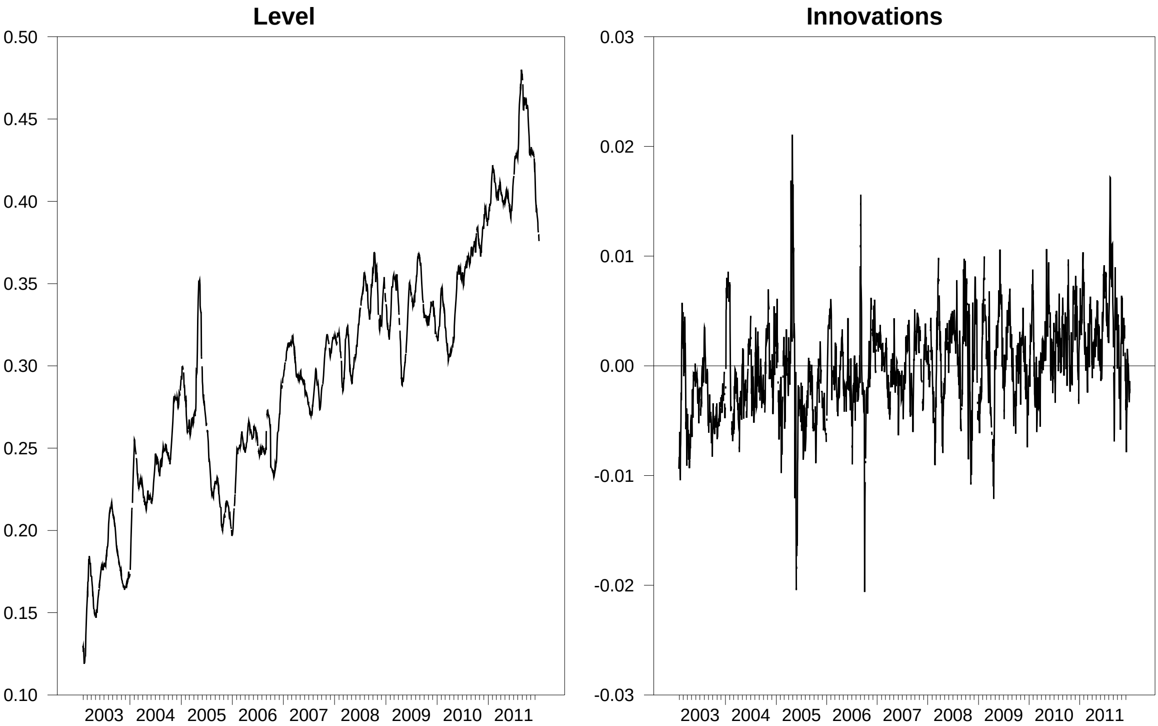


Figure 2. Bond Strategy and Bond Market Returns

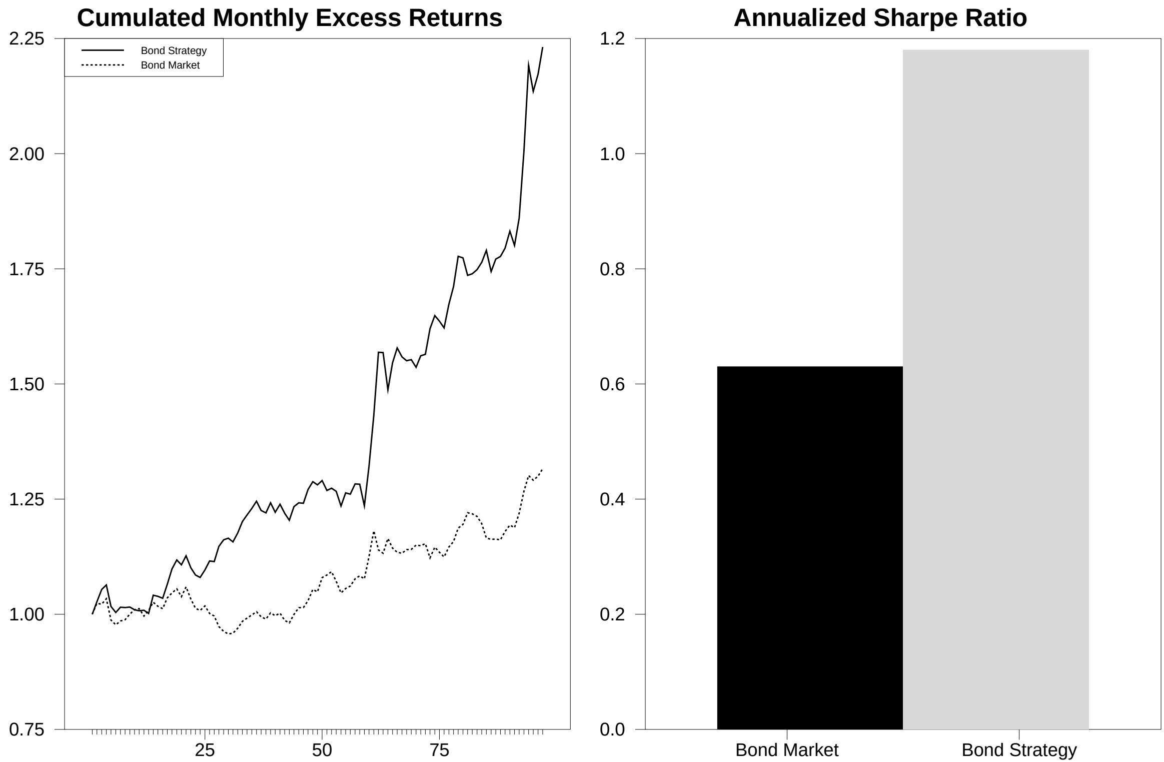


Figure 3. Bond Portfolio Characteristics

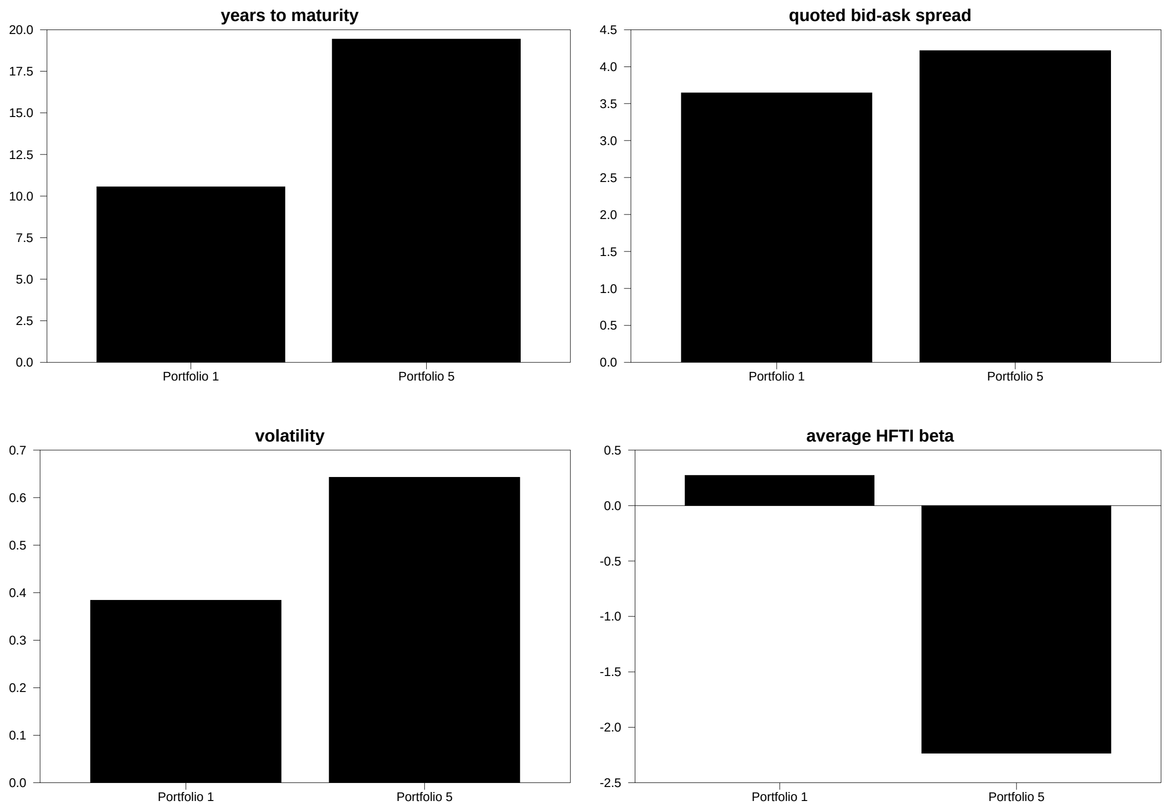
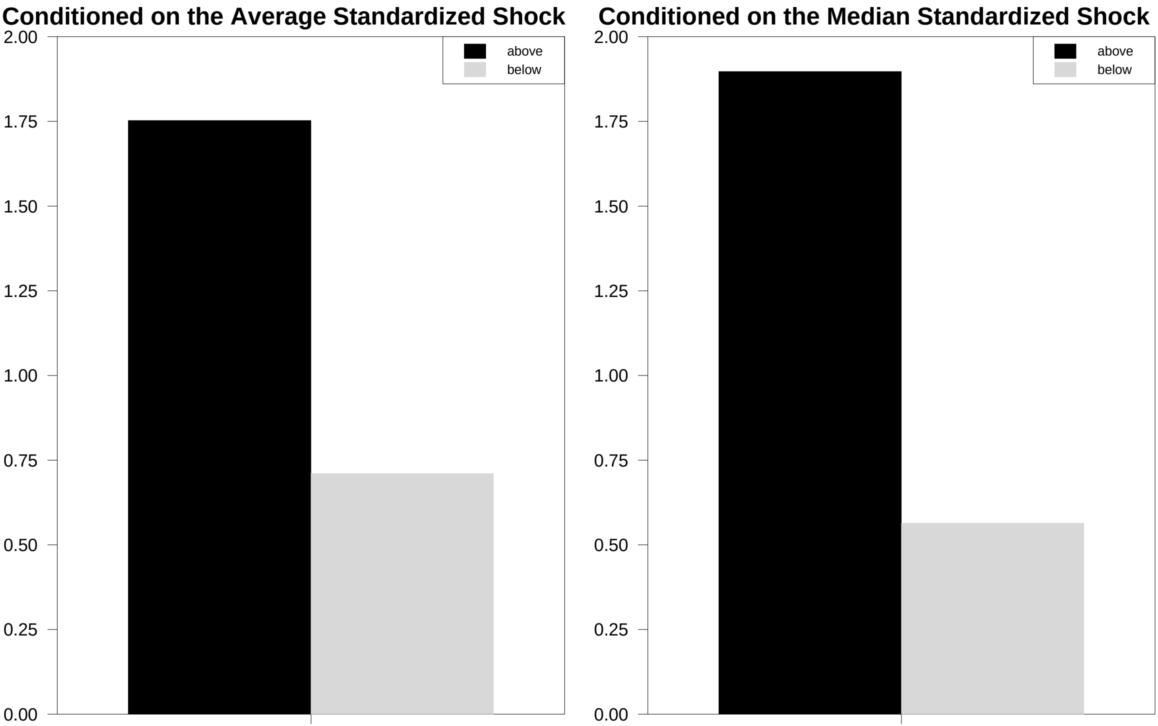


Figure 4. Bond Portfolio Strategy and News Shocks

Annualized Sharpe Ratios



High-frequency Trading and Treasury Bond Returns: Internet Appendix

This draft: January 6, 2014

Table A1. Descriptive Statistics of Bond Portfolios (VW scheme)

This table reports descriptive statistics for the monthly excess returns of bond portfolios sorted according to their exposure (beta) to the innovations of the measure of HFT intensity, $\widehat{HFTI}_t$ computed using daily data over the past 12 months. The holding period is six months. Portfolio returns are computed using a value-weighting (VW) scheme and they are expressed in monthly percentage points. The weights are computed using the outstanding value of any bond at the end of each month. Portfolio 1 (P1) contains bonds with the smallest HFT beta while Portfolio 5 (P5) contains bonds with the largest HFT beta. Mean, Stdev, Skew and Kurt denotes the average, standard deviation, skewness and excess kurtosis of the various portfolio returns, respectively. AC(1) denotes the first−order autocorrelation coefficient of portfolio returns. Pre-ranking beta are the average beta estimates computed across all individual bonds in each portfolios over the full sample period. SR denotes annualized Sharpe ratios and MR is the p-value of the null-hypothesis of no monotonicity as in Patton and Timmermann (2010). Values in parenthesis denote $t-$statistics of the average portfolio returns computed using HAC standard errors as in Newey and West (1987). Values in brackets denote the average $t-$statistics of the pre-ranking beta of each portfolio.

	P1	P2	P3	P4	P5	P5−P1	MR
Mean	−0.0723	0.0768	0.2443	0.4743	0.7756	0.8479	<0.01
	(−0.5010)	(0.5210)	(1.3547)	(2.3407)	(2.5888)	(3.2566)	
Stdev	1.6948	1.4795	1.6528	1.9017	2.6699	2.4781	
Skew	−1.9526	−0.5603	−0.4236	0.4638	1.2775	0.9639	
Kurt	10.6713	0.9910	0.3690	1.9502	3.8559	2.3683	
AC(1)	−0.0789	0.0271	0.1145	0.1419	0.2039	0.2012	
SR	−0.1477	0.1798	0.5121	0.8640	1.0063	1.1852	

Table A2. Descriptive Statistics of Risk Factors (VW scheme)

This table reports descriptive statistics for the risk factors constructed as discussed in Section 2.3 using a VW scheme. BMR_t is the monthly excess returns of the bond market portfolio, $\widehat{VOL}_t$, $\widehat{ILLIQ}_t$, and $\widehat{SKEW}_t$ are the AR(1) innovations of monthly aggregate bond volatility, liquidity, and skewness measures, respectively. The sample period is January 2003−December 2011. See also notes to Tables 2 and A1.

	BMR_t	$\widehat{VOL}_t$	$\widehat{ILLIQ}_t$	$\widehat{PIN}_t$	$\widehat{SKEW}_t$
Mean	0.2940	−0.0034	0.0003	0.0002	0.0240
Stdev	1.3311	0.0752	0.0947	0.0051	0.5827
Skew	0.0855	1.3066	2.4492	0.6582	0.4383
Kurt	0.5948	3.4999	13.3502	1.4000	1.0575
AC(1)	0.0834	−0.2135	0.1156	0.0186	−0.0831

Table A3. FMB Cross-sectional Asset Pricing Regressions (VW scheme)

This table reports the Fama-MacBeth (1973) factor premium for linear factor models. The test assets are the five bond portfolios reported in Table A1. Portfolio returns and risk factors are computed using a VW scheme. Values in parentheses aret-statistics computed as in Shanken (1992). Adj R^2 denotes the adjusted coefficient of determination. The sample period is January 2003−December 2011. See also notes to Tables 3, A1 and A2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR_t	1.0063	0.3919	0.5485	0.6389	0.7942	0.8486	0.6954	0.3478	1.0730	0.6290
	(1.8580)	(0.3179)	(1.5890)	(1.1571)	(0.4782)	(1.8927)	(1.6046)	(0.6202)	(1.9490)	(1.2683)
$\widehat{VOL}_t$	−0.0868									
	(−0.9447)									
$\widehat{ILLIQ}_t$		−0.3438								
		(−0.5444)								
$\widehat{FILL}_t$			−0.2108							
			(−1.7131)							
$\widehat{SKEW}_t$				−0.6903						
				(−0.8847)						
$\widehat{PIN}_t$					0.0125					
					(0.1554)					
$\widehat{TERM}_t$						−0.0973				
						(−0.7898)				
$DUMMYDP_t$							0.2770			
							(1.6354)			
SMB_t								3.4009		
								(1.0535)		
HML_t									3.3844	
									(0.8277)	
UMD_t										−7.2990
										(−1.1447)
Adj R^2	0.9537	0.9920	0.9823	0.9860	0.9465	0.9432	0.9793	0.9889	0.9500	0.9939

Table A4. GMM Cross-sectional Asset Pricing Regressions (VW scheme)

This table reports the GMM estimation of factor premium for linear factor models. The sample period is January 2003−December 2011. See also notes to Tables 3, A1, A2 and A3.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR_t	0.2966	0.1737	0.2674	0.0473	0.3425	0.1807	0.2884	0.2297	0.2767	0.3267
	(2.0986)	(0.6525)	(1.8952)	(0.1387)	(0.2144)	(1.1052)	(2.0267)	(1.2727)	(1.8344)	(0.6739)
$\widehat{VOL}_t$	0.0312									
	(0.8179)									
$\widehat{ILLIQ}_t$		−0.4406								
		(−0.5983)								
$\widehat{FILL}_t$			−0.3065							
			(−2.8293)							
$\widehat{SKEW}_t$				−1.5473						
				(−0.6820)						
$\widehat{PIN}_t$					0.0487					
					(0.3774)					
$\widehat{TERM}_t$						−0.2586				
						(−1.5422)				
$DUMMYDP_t$							0.4489			
							(1.3982)			
SMB_t								4.0214		
								(1.2929)		
HML_t									−10.3300	
									(−0.4043)	
UMD_t										−11.5400
										(−0.6674)
J_T	6.9815	0.2292	5.5063	0.7972	0.1140	2.5609	1.0333	0.8482	0.3944	0.9269
$p-value$	0.0725	0.9727	0.1383	0.8501	0.9901	0.4644	0.7932	0.8379	0.9414	0.8189

Table A5. Time Series Regressions (VW scheme)

This table reports the time series regression coefficients of the excess return of the strategy P5−P1 as in Table A1 on the various risk factors. Portfolio returns and risk factors are computed using a VW scheme. Values in parentheses are t-statistics computed using HAC standard errors as in Newey and West (1987). The sample period is January 2003−December 2011. See also notes to Table 4.

	non-tradable factors	mimicking portfolios
Const	0.4533	0.5364
	(2.0849)	(2.8528)
BMR_t	0.5562	0.6154
	(1.9144)	(1.3149)
$\widehat{VOL}_t$	−0.7972	4.0068
	(−0.2384)	(0.3598)
$\widehat{ILLIQ}_t$	−2.4725	−2.8332
	(−0.5429)	(−0.2694)
$\widehat{FILL}_t$	−1.3770	−2.3144
	(−1.3478)	(−1.5026)
$\widehat{SKEW}_t$	−0.5597	−1.5046
	(−1.2142)	(−0.8958)
$\widehat{PIN}_t$	15.5191	17.1146
	(0.5300)	(0.6349)
$\widehat{TERM}_t$	-1.7626	-2.0665
	(-1.3549)	(-1.7638)
$DUMMYDP_t$	1.5707	1.4829
	(1.4806)	(1.9168)
SMB_t	0.2037	0.1861
	(2.3039)	(2.1007)
HML_t	−0.2299	−0.1858
	(−1.4468)	(−1.8822)
UMD_t	−0.1621	−0.1229
	(−1.6713)	(−1.7338)
Adj R^2	0.3561	0.3582

Table A6. Cross-sectional Regressions with Portfolio−specific Factors (VW scheme)

This table reports the Fama-MacBeth(1973) factor premium for linear factor models. The test assets are the five bond portfolios reported in Table A1. $\widehat{PVOL^i}_t$,$\widehat{PILLIQ^i}_t$, $\widehat{PSKEW}_t^i$ are portfolio-specific volatility, liquidity and skewness factors constructed as in Section 5.2. Portfolio returns and risk factors are computed using a VW scheme. Values in parentheses are t-statistics computed as in Shanken (1992). The sample period is January 2003−December 2011. See also notes to Table 7.

	(1)	(2)	(3)
BMR_t	-1.0851	0.4604	-0.0134
	(-0.1065)	(0.4476)	(-0.0038)
$\widehat{VOL}_t$	-0.0794		
	(-0.1690)		
$\widehat{ILLIQ}_t$		-0.3435	
		(-0.5479)	
$\widehat{SKEW}_t$			0.0138
			0.0048
$\widehat{PVOL}_t^i$	9.0355		
	(0.1959)		
$\widehat{PILLIQ}_t^i$		-0.0588	
		(-0.0553)	
$\widehat{PSKEW}_t^i$			7.9809
			(0.2730)
adj R^2	0.2800	0.9881	0.0412

Table A7. Fama-MacBeth Regression: Asparouhova et al. (2010) correction

This table reports the Fama-MacBeth (1973) as in Tables 3 and A3 where t-statistics are computed using Weighted Least Square standard errors constructed as Asparouhova et al. (2010). See also notes to Table A7.

Panel A. EW Scheme

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR_t	1.0187	0.0256	0.5313	0.1891	2.7933	0.0542	0.6189	0.4615	1.0227	0.5280
	(2.3381)	(0.1807)	(1.4866)	(0.0910)	(0.2151)	(0.0874)	(1.5343)	(0.8627)	(2.4558)	(0.9664)
$\widehat{VOL}_t$	−0.0376									
	(−0.5366)									
$\widehat{ILLIQ}_t$		−0.4288								
		(−0.4473)								
$\widehat{FILL}_t$			−0.2063							
			(−1.7089)							
$\widehat{SKEW}_t$				−1.8465						
				(−0.3732)						
$\widehat{PIN}_t$					−0.0617					
					(−0.1590)					
$\widehat{TERM}_t$						−0.2828				
						(−1.3645)				
$DUMMYDP_t$							0.2728			
							(1.9146)			
SMB_t								3.0965		
								(1.0191)		
HML_t									0.0818	
									(0.0435)	
UMD_t										−8.1924
										(−1.1029)
Adj R^2	0.9255	0.9868	0.9748	0.9371	0.9793	0.9405	0.9723	0.9729	0.9240	0.9873

Panel B. VW Scheme

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BMR_t	0.9753	0.3813	0.5166	0.6103	1.0905	0.7125	0.6823	0.3248	1.0468	0.5862
	(1.9770)	(0.3337)	(1.5137)	(1.1179)	(1.2049)	(1.6824)	(1.6713)	(0.5926)	(2.1327)	(1.1969)
$\widehat{VOL}_t$	−0.0772									
	(−0.9015)									
$\widehat{ILLIQ}_t$		−0.3334								
		(−0.5881)								
$\widehat{FILL}_t$			−0.2187							
			(−1.7632)							
$\widehat{SKEW}_t$				−0.7392						
				(−0.9334)						
$\widehat{PIN}_t$					−0.0131					
					(−1.1437)					
$\widehat{TERM}_t$						−0.1253				
						(−1.0206)				
$DUMMYDP_t$							0.2782			
							(1.7577)			
SMB_t								3.4682		
								(1.0889)		
HML_t									2.4813	
									(0.7652)	
UMD_t										−7.4799
										(−1.1843)
Adj R^2	0.9413	0.9939	0.9831	0.9853	0.8194	0.9349	0.9793	0.9881	0.9370	0.9943

Table A8. Bond Portfolio Strategy and Orthogonalized $\widehat{HFTI}_t$

This table reports descriptive statistics for the P5−P1 strategy returns computed as in Table 1. non-orth denotes the returns from the strategy where $\widehat{HFTI}_t$ are not orthogonalized. orth($\widehat{X}_t$) are P5−P1 strategy returns computed by investing in the portfolio of bonds with the largest negative $\widehat{HFTI}_t$ beta orthogonalized against the innovation of the variable X_t, denoted as $\widehat{X}_t$, and shorting the portfolio of bonds with the largest positive/smallest negative $\widehat{HFTI}_t$ beta orthogonalized against $\widehat{X}_t$. See also notes to Table 1.

	non-orth	orth($\widehat{VOL_t}$)	orth($\widehat{LIQ_t}$)	orth($\widehat{SKEW}_t$)	orth($\widehat{PIN_t}$)
Mean	0.8709	0.7148	0.4708	0.9203	0.7096
	(3.2322)	(2.4830)	(1.7563)	(3.7640)	(2.9419)
Stdev	2.5413	2.5358	2.3334	2.5184	2.2707
Skew	1.0580	1.2360	1.5684	0.6557	1.1251
Kurt	2.6981	3.1352	4.4451	2.3651	3.6149
AC(1)	0.2035	0.2174	0.1616	0.1429	0.1701
SR	1.1871	0.9764	0.6990	1.2659	1.0825

Table A9. Strategy Returns with random HFT Intensity Factor

This table reports descriptive statistics for the monthly excess returns of bond portfolios sorted according to their beta to $\widehat{HFTI}_t^S$ computed using daily data over the 12 months. $\widehat{HFTI}_t^S$ is computed by randomly drawing from the distribution of the actual $\widehat{HFTI}_t$ with replacement. Each simulated series has the same length of the one of the original factor. The various statisics of interests are obtained from their empirical distributions calculated over 10,000 replications.

	P1	P2	P3	P4	P5	P5−P1	MR
Mean	0.4449	0.4416	0.4522	0.4453	0.4486	0.0037	0.5005
95% interval	[0.4419,0.4480]	[0.4403,0.4429]	[0.4514,0.4530]	[0.4439,0.4468]	[0.4456,0.4417]	[−0.0023,0.0097]	[0.4943,0.5068]
Stdev	0.1590	0.0657	0.0417	0.0754	0.1595	0.3123	
Skew	0.0971	0.0594	0.2289	−0.0267	0.0303	−0.0351	
Kurt	−0.2783	−0.2309	0.2518	−0.1906	−0.3359	−0.3061	
AC(1)	−0.0079	0.0022	−0.0055	−0.0031	−0.0087	−0.0083	