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Computer-based Trading, Institutional Investors and Treasury Bond Returns*

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Abstract

This study provides a comprehensive analysis of the effects of Computer-based Trad-ing (CBT) on Treasury bond expected returns. We document a strong relationship between bond expected returns and the overall intensity at which CBT takes place in the Treasury market. Investing in bonds with the largest beta to the aggregate CBT intensity and shorting those with the smallest generates large and significant returns. Those returns are not due to compensation for facing conventional sources of risk or to transaction costs. Our results are consistent with capital-flow based explanations implied by asset pricing models with institutional investors.

Keywords: Computer-based Trading, Asset Pricing, Institutional Investors, Asset Allocation.
JEL Classification: F31, G10.

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1 Introduction

Computer-based trading (CBT henceforth) refers to the set of activities that employ automated programs for generating, routing, executing and canceling orders in electronic markets (Chlistalla, 2011; Foresight Project Report, 2012).[1] CBT is widely used by investment banks, pension funds, mutual funds, and other buy-side (investor-driven) institutional traders, to manage market impact and risk. Sell-side traders, such as market makers and hedge funds, also use CBT to provide liquidity to the market, generating and executing orders automatically. The growing theoretical and empirical literature on CBT widely recognizes that trading carried out by machines without human supervision can entail both benefits and risks.[2] Some studies have pointed out that CBT has beneficial effects on security markets by improving liquidity, reducing transaction costs and making market prices become more efficient (Hendershott et al., 2010; Boehmer et al., 2012; Chaboud et al. 2014 and the references therein). However, others have emphasized that CBT increases risk as automated traders may employ strategies that can 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 transacting at posted prices more difficult; and withdraw their participation from the markets during periods of turbulence or when market making is difficult (Boehmer et al., 2012). The overall effect of CBT on asset prices is still uncertain, as the literature has yet to reach a consensus regarding the impact of CBT on

[1]In this study we do not distinguish between the subclasses of CBT activities (such as algorithmic trading and high-frequency trading) but we focus on the main effects of their common features on asset prices (see Foresight Project Report, 2012; Eurex, 2013 and the references therein).

[2]An non-exhaustive list of recent studies that have investigated the impact of CBT on the overall quality of equity, FX and fixed income markets includes Hendershott et al. (2010), Egginton et al. (2012), Bohmer et al. (2012), Hasbrouck and Saar (2013), Hendershott and Riordan (2013), Baron et al. (2014), Chaboud et al. (2014) and Jiang et al.(2014) and the references therein. See also the theoretical contributions by Biais et al. (2013) and Focault et al. (2012).

asset excess returns.[3]

In this paper we contribute to this debate by providing a comprehensive empirical analysis of the effect of CBT on the cross-section of expected returns of US Treasury bonds. 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 CBT has been increasing substantially since early 2000s.[4]

With the help of a large transaction dataset from BrokerTec, which includes tick-by-tick information on market and limit orders for the 2-, 5- and 10-year on-the-run Treasury securities, we compute a measure that captures the aggregate intensity at which CBT takes place in the US Treasury market. More specifically, as commercially available datasets do not provide information to identify computer trading and quoting activities, we use the procedure proposed by Jiang et al. (2014) and classify market and limit orders on the basis of the reaction time of order placements deemed to be beyond manual ability. The aggregate CBT intensity measure is then calculated as the average ratio between the total number of computer-based market and limit orders and the overall number of market and limit 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 (beta) to the aggregate CBT intensity

[3]Skjeltorp et al. (2013) in a concurrent study investigate the impact of algorithmic trading on the cross-section of equity returns. Our study shares various similarities with their as both studies propose a methodology that infers the intensity of CBT activity from publicly available information and investigate the impact of CBT on asset prices. However, there are also obvious differences as the two studies focus on two very different markets characterized by different institutional structures. Furthemore, our results are rationalized on the basis of the institutional investors' fund flows and they are consistent with the predictions of the theoretical model proposed by Vayanos and Wooley (2013), while Skjeltorp et al. (2013) explain their results on the basis of an information diffusion hypothesis.

[4]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).

measure. Consistent with the large literature 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 aggregate CBT intensity measure.[5] Using a sample of 416 Treasury bonds and notes over the period January 2003 and December 2011, we find that investing in Treasury bonds with the largest beta to the CBT intensity measure and shorting the ones with the lowest provides a US investor significant excess returns of about 10 percent per annum. We also find empirically that the bonds with the largest beta to the CBT intensity measure experience low returns in times of high CBT activity (i.e. negative beta), while securities with the lowest beta exhibit positive returns during the same times. The returns from the strategy are not a mere compensation for conventional sources of risk in bond and equity markets and they are not affected by transaction costs. We explain our findings by linking CBT in the Treasury market to institutional investors' fund flows originating from the management their Treasury holdings. Following the theoretical model proposed by Vayanos and Woolley (2013), we explain why bonds with largest beta to CBT intensity exhibit the largest excess returns and negative CBT intensity beta.[6] Furthermore, we test and validate the hypothesis that excess returns from the bond investment strategy are due to the risk premium accruing to bonds whose returns positively correlate with the ones of the portfolio of institutional investors.

A set of robustness checks confirms that the baseline findings are not affected by, among others, different portfolio formation and holding periods, the inclusion of portfolio-specific

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

[6] Our results are also consistent with the flight-from-maturity hypothesis recently proposed in Gorton et al. (2012).

characteristics in the asset pricing regressions (namely term to maturity and on/off the run characteristics) and the use of alternative estimation procedures to carry out asset pricing tests. Furthermore, in the spirit of Adrian et al. (2014), we also show that a purely random CBT intensity measure does not spuriously replicate the cross-sectional results reported in this study.

The rest of the paper is set out as follows. Section 2 discusses the construction of the CBT intensity measure, 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 propose an interpretation of the main findings. Section 6 discusses a number of robustness checks and 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 aggregate CBT intensity measure using market and limit orders high-frequency data. Then, we describe the bond portfolio strategy used to evaluate the effects of CBT intensity 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 Aggregate CBT Intensity Measure

Comprehensive data on CBT across various financial markets are scarce. In fact, commercially available dataset usually do not contain information about whether market or limit 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 CBT on asset prices difficult. In our study we overcome this problem by exploiting the procedure recently proposed by Jiang et al. (2014), which infers computer-based market and limit orders in the US Treasury secondary market on the basis of the reaction time of order placements deemed to be beyond manual ability.[7]

Once computer-based market and limit orders are identified, we construct the aggregate CBT intensity measure as the daily equally-weighted average of the ratios between the total number of computer-based market and limit orders and the total number of all market and limit orders as follows:

$$CBTI_t = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{CBO_t^i}{ALLO_t^i}\right) \tag{1}$$

where CBO_t^i denote the day t number of computer-based market and limit orders for the benchmark bond i and $ALLO_t^i$ denote the day t of total number of overall orders for the same benchmark bond.

The construction of the CBT intensity measure proposed in this study is similar in spirit to alternative procedures proposed in recent works. For example, Hendershott et al. (2010) use a normalized measure of electronic message traffic on NYSE as a proxy for algorithmic trading while Hasbrouck and Saar (2013) 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 infer computer trading and quoting activity from existing publicly-available high-frequency data.

In the empirical analysis, we focus on the innovations in the CBT intensity measure (denoted as $\widehat{CBTI}_t$) that are computed by taking the residuals from an autoregressive (AR)

[7] The full description of the Jiang et al. (2014) is reported in the Appendix to this paper.

model applied to the daily time-series data.[8]

2.2 Investment Strategy and Portfolio Formation

In this paper we investigate whether innovations of the CBT intensity measure are able to generate a cross-sectional variation in Treasury bond returns. We achieve this goal by implementing a bond portfolio strategy as follows: we form five portfolios based on the beta to the innovations of the CBT intensity measure estimated using daily data during the past 12 months. We allocate one fifth of the bonds 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 the last portfolio, P5. We keep the composition of the portfolios constant for six months and then we rebalance them on the basis of the betas 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 the exposure to the CBT intensity measure is able to generate a sufficient cross-sectional variation in bond returns, we should be able to obtain a significant average excess return from P5−P1.

2.3 Asset Pricing Tests

If the bond portfolio strategy highlighted in the previous section is able to uncover large and significant excess returns, the logical question to ask is whether such excess returns could be due to the mere compensation for facing well-known sources of risk. Hence, we assess the risk/return characteristics of our strategy using conventional cross-sectional asset pricing methods. Assume that excess returns on bond portfolio i, denoted by rx^i_{t+1}, satisfy the

[8]We find that an AR(5) model is able to generate innovations that exhibit zero mean and are serially uncorrelated. The detailed description of the resulting measure and its innovations is reported in Section 3.

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:

$$E(rx^i_{t+1}) = \lambda'\beta_i.$$

We estimate the parameters of equation (2) using the Generalized Methods of Moments (GMM) of Hansen (1982). We use a one-step approach, with the identity matrix as the GMM weighting matrix. With regards to the selection of risk factors f_{t+1}, we choose 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. The first set of candidates is represented by the Fama-French three equity factors, which have been used by Li et al. (2009) to explain the cross-section of Treasury bond returns. Other candidate factors are (i) equity and bond market illiquidity (Pastor and Stambaugh, 2003; Li et al., 2009), (ii) a funding illiquidity measure (Garleanu and Pedersen, 2011) and (iii) the term spread (Fama and French, 1993; Campbell and Ammer, 1993; Li et al., 2009).

We compute the bond market illiquidity factor as the weighted-average of daily quoted bid-ask spreads for each bond in our sample during the month. As equity market aggregate liquidity factor we use, in line with Li et al. (2009), the liquidity measure proposed by Pastor and Stambaugh (2003). 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 as well the equity market excess return data Ken French's website. We obtain the level and innovations of the Pastor and Stambaugh's (2003) liquidity factor from CRSP dataset.[9]

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 aggregate CBT intensity measure, 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.[10] 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).[11] We compute the CBT intensity measure by applying the procedure detailed in the Appendix 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.

[9]The descriptive statistics of the risk factors are reported in Table A1 of the Internet Appendix.

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

[11]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.

CRSP also provides monthly readings of the dollar face value of each instrument.[12] 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.[13]

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 CBT was not widely adopted in the US Treasury market before that period.[14] Overall, during this sample period, the two datasets provide us with more than 1 trillion observations relative to market and limit orders for the three on-the-run benchmarks (BrokerTec) and 300,574 bond-days (CRSP).

Figure 1 plots the daily level series $CBTI_t$ and its innovations, $\widehat{CBTI}_t$. The level series, which can be interpreted as the average share of trading and quoting activity due to CBT for any given day, exhibits a marked upward trend. This pattern confirms the anecdotal evidence that the adoption of CBT strategies in the US Treasury secondary market increased substantially over the sample period. Furthermore, it is also worthwhile noting that the value of $CBTI_t$ at the end of the sample is close to 40 percent. This value is not very different from the 45 percent estimated share of CBT 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

[12]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

[13]We adopt this filter for various reasons. First, a minimum of 12 month of data is required to compute the CBT 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).

[14]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.

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).[15] The baseline estimates are based on portfolio returns that are computed, in line with much empirical literature (see, among others, Menkhoff et al., 2012 and the references therein) using an equal-weighting scheme.[16]

Sorting bonds on the basis of their beta to the aggregate CBT intensity generates a large cross-sectional spread. In fact, the evidence reported in Table 1 suggests that bonds with the largest beta to CBT intensity experience higher expected returns. The strategy of investing in the portfolio comprising bonds with the largest CBT 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 CBT intensity measure 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 negative CBT intensity beta, i.e. that experience lower realized returns when CBT activity is 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.[17] Over the full sample period, the cumulative excess returns from the bond strategy are

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

[16] In Section 6, we show that our results are confirmed qualitatively and quantitatively if portfolio returns are computed using a value-weighting scheme.

[17] We compute the returns on the bond market benchmark as the equally-weighted average of the individual bond returns available in our sample during each month.

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.[18] 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).

Figure 3 plots the underlying characteristics of the two extreme portfolios introduced in Table 1. The portfolio with the largest beta to the CBT intensity measure (P5) contains Treasury securities which exhibit a long time to maturity, high volatility and a high bid-ask spread. Vice versa, the portfolio with the smallest beta to the CBT intensity measure (P1) records a comparatively shorter time to maturity, lower volatility and a bid-ask spread close to, albeit slightly smaller than, the one recorded for the portfolio P5. Some of these characteristics recorded in Figure 3 are broadly in line with the evidence reported in recent studies, but in different contexts (see, for example, Hendershott et al., 2010 and Brogaard, 2010).[19]

[18]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., 2014 and the references therein).

[19]For completeness, in Table A1 of the Internet Appendix we also report 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 illiquidity factor and the term spread 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. In Table A1 panel B), we show the remaining risk factors which are not constructed using data from the cross-section of Treasury bond returns.

4 Empirical Results

4.1 Asset Pricing Tests

The previous section shows that sorting bonds on the basis of their beta to the aggregate CBT intensity generates a large cross-sectional spread. Furthermore, investing in bonds with the largest CBT intensity beta and shorting the ones with the lowest yields about 10 per cent per annum. In this section we investigate whether any conventional risk factors can explain the returns of the cross-section of portfolios constructed as in Section 2.2 and the time series of returns from the bond strategy.

Table 2 reports the parameter estimates obtained by a one-step GMM procedure. In particular, because of the small size of the cross-section of portfolios in our exercise, in all specifications (1)-(7) we assess the explanatory power of each risk factor one at a time. The results of this estimation suggest that only the equity market return factor is able to deliver parameter estimates that are significant at least at the 10 percent statistical level and exhibits a p-value of the J-test that does not reject the null hypothesis of zero pricing errors. All of the other factors exhibit mixed results where at least one of the parameters of interest is statistically insignificant at conventional level.[20] It is worth noting that while some factors

[20]It is worthwhile noting that our GMM estimates record that the null hypothesis of zero pricing errors is not rejected at conventional level even in cases when the parameter estimates are statistically insignificant. This apparently counter-intuitive result can be rationalized in light of the simulation evidence reported in Cenedese et al. (2014). They show that when the time-series of portfolio return and the cross-section of assets are small, the J-statistics do not reject the null hypothesis even when portfolio returns are truly uncorrelated with risk factors. 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. The evidence reported in Table 2 of this study is computed using a similar cross-section of portfolios as the one reported in Cenedese et al. (2014). However, the time series of returns is considerably shorter. Hence, it is likely that the biases recorded in Cenedese et al. (2014) may be even more severe in our context. In light of that evidence, our results shows that none of the risk factors is able to deliver parameter estimates exhibiting t-statistics that are larger than 2 *and* consistently price the cross-section of portfolios.

are found significant in explaining the cross-section of bond portfolio returns, the price errors they generate are large. This suggests that while the pricing errors associated with some factors are overall statistically not different from zero, their economic significance might not be small.

We complement the cross-sectional results from Table 2 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. 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 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., 2012 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.[21] In our case, we use the CRSP Fama bond maturity portfolios as the set of 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 estimated conditional mean of the traded portfolio $\sum_{j=1}^{K} \widehat{b}_{BA} \cdot rx_t^{BA,j}$. [22]

[21]The non-tradable factors to which we apply the procedure are the funding illiquidity factor $FILL_t$ and the term spread $TERM_t$, as we directly use the factor-mimicking portfolio of the innovations of Pastor-Stambaugh (2002) liquidity measure obtained from CRSP dataset.

[22]This procedure yields factor-mimicking portfolios whose returns exhibit a correlation coefficient with

The results of the time-series estimations are reported in Table 3. Overall, the evidence broadly confirms the finding reported in the previous Table 2 that the equity market return factor exhibits explanatory power for the time-series of bond portfolio returns and most of the other factors are statistically insignificant at conventional level. However, and most importantly, Table 3 shows that 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 and close to 9 percent per annum across the two specifications. This tells us that the returns from the bond 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.[23]

4.2 Bond Portfolio Characteristics and Asset Pricing Tests

In Section 4.1 we show that the returns from the bond investment strategy are uncorrelated with sources of systematic risk in bond and equity markets. However, it may be possible that bond- or portfolio-specific characteristics (as opposed to exposures to systematic sources of risk) could generate the returns from strategy in Table 1. In particular, Figure 3 highlights that time to maturity is already one differentiating aspect between extreme portfolios, with portfolio P5 comprising mostly long-term bonds. In addition, the age of the individual Treasury bonds may be another important factor, as several bonds in our sample during any given month can be classified as off-the-run. The associated term and on-the-run premia

the non-tradable factors of 0.66 and 0.25 for $FILL$and $TERM$, respectively. These numbers are in line with ones recorded in recent studies (see, for example, Adrian et al., 2014 and Cenedese et al., 2014). We also test the pricing ability of the factor-mimicking portfolio as in 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., 2012 p. 699).

[23]The full set of alpha returns for each portfolio, across various specifications, is plotted in Figure A1 of the Internet Appendix.

may affect the results reported in the previous sections.

We assess the results reported in Section 4.1 against this issue in the spirit of the framework proposed by Brennan et al. (1998). More specifically, we expand the cross-sectional regression with two sets of characteristics that are specific to each portfolio. Put differently, we test whether bonds' time to maturity and age are priced characteristics in the cross-section of our portfolio returns. We measure bond portfolios' time to maturity as the equally-weighted average of the remaining time-to-maturity of each bond comprised in a given portfolio. In a similar vein, we measure portfolios' age as the equally-weighted average of the ratios of remaining time to maturity to the time to maturity at issuance for each bond comprised in a given portfolio.[24] The results of this exercise are reported in Table 4. We estimate three different specifications in which the characteristics are included one at a time (columns 1 and 2 in Table 4) or jointly (last column in Table 4). In all cases, the empirical evidence suggests that none of the portfolio-specific characteristics is statistically significant at conventional level. Hence time to maturity and bond's age are not the driving source of the returns variation in the cross-section of our bond portfolios.

4.3 Portfolio Strategy Returns and Transaction Costs

Another potential concern associated with the results reported in Section 3 relates to the impact of transaction and financing costs on the returns of the bond portfolio strategy. In fact, as the strategy requires that several bonds are bought and short-sold at the end of each 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

[24] As discussed in Goyal (2012, section 2.5.2 and the references therein), we reduce the estimation problem associated with this type of regressions by moving the systematic factor betas to the left-hand side of the pricing equation. In our context, and in light of the results reported in Table 2, we use as the only systematic factor the equity market returns.

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.[25] 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:

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

[25]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. In line with Krishnamurthy (2002), we assume that haircuts are 0%.

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.[26]

The results of this exercise are reported in Table 5. When the repo spread is set to zero, 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 still positive, but statistically insignificant, over the full sample period. This result suggests that only very large transaction costs, in the form of large carry costs, are able to reduce the economic value of the bond investment 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, Duffie (1996) and Krishnamurthy (2002) show that the time variation in repo specialness can be very spiky and does not persist over time and repo spreads in the US Treasury market vary over time. Nonetheless, it is worthwhile noting that even under these restrictive circumstances, the

[26] 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. However, we do not explore this aspect in this robustness check.

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.

As a final check we also assess the impact of infrequent trading in determining the returns from the bond strategy. More specifically, as several bonds in our sample are classified as off-the-run, trading in such securities may be infrequent in comparison with bonds that are on-the-run or just off-the-run. We take into account this issue and remove from the five portfolios the bonds that have exhibited zero returns over at least a half of each trading month. The results of this exercise are reported in the last column of Table 5. As the average monthly return from the strategy, and the resulting annualized Sharpe ratio, are only marginally lower than the ones exhibited when all bonds are included in the calculations, we can conclude that the explicit consideration of infrequent trading does not affect substantially the results reported in Section 4.1.

5 Interpreting the Results: The Role of Institutional Investors

5.1 Simple Statistics

The findings reported in the previous section suggest that sorting bonds on the basis of their beta to aggregate CBT intensity generates a large cross-sectional spread. Bonds with the largest sensitivity to CBT intensity experience higher expected returns and are also the ones with negative CBT intensity beta, i.e. experience lower realized returns when CBT activity is high. The strategy of investing in the portfolio comprising bonds with the largest CBT intensity beta and shorting the portfolio comprising bonds with the smallest beta yields sizable returns which are not due to bonds' individual characteristics, compensation for exposures to conventional sources of risk and they are not due to transaction or financing costs.

This still leaves many questions unanswered: for example, why are the bonds with the largest exposure to CBT intensity the ones that exhibit higher expected returns? Why is the CBT intensity beta of such bonds negative? And most importantly, if the returns of the investment strategy introduced in Section 2.2 are not due to systematic sources of risk or transaction costs, what are their main drivers? In this section, we attempt to provide an answer to those important questions by bringing into the picture institutional investors and the management of their US Treasury holdings.

There is ample evidence suggesting that CBT is widely used by institutional traders to manage market impact and risk (Chlistalla, 2011; Gomber et al., 2011; Foresight Project Report, 2012). In addition, various studies document that institutional investors play an active role in determining prices in Treasury markets because of their maturity preferences and the management of their bond holdings (Vayanos and Greenwood, 2010 and the references therein). Furthermore, institutional flow-induced trading can have a significant impact on individual securities and drive their prices away from the information-efficient level (Coval and Stafford, 2007; Lou, 2012; Vayanos and Woolley, 2013; 2014 and the references therein).

Hence, it is natural to hypothesize that the evidence reported in the previous sections may be related to the behavior of institutional investors in the US Treasury market. We initially explore this line of reasoning by computing simple descriptive statistics which link together changes in Treasury holdings from institutional investors, changes in the measure of aggregate CBT intensity and measures capturing price/yield misalignments in the US Treasury market.[27] It is worthwhile noting that this initial exercise serves as preliminary

[27]The detailed description of the data sources and construction of the time series used in Section 5 are reported in the Appendix to this paper.

discussion leading to a more formal assessment that is proposed in Section 5.2. Nonetheless, the results of these computations, plotted in Figure 4, uncover a host of interesting patterns.

First, the graph in the upper-left corner shows that changes in holdings of Treasury securities from institutional investors are negatively correlated with changes in the measure of aggregate CBT intensity. Put differently, CBT intensity in the US Treasury market increases, or experiences positive shocks, when institutional investors reduce their holdings of Treasury securities. From a quantitative point of view, during our sample period, instances of negative changes in Treasury holdings from institutional investors are associated with an average monthly increment of the aggregate CBT intensity of slightly more than 3 percent.

The second pattern of interest is reported in the upper-right corner graph. The evidence therein suggests that, over the full sample period, short-term bonds and long-term bonds[28] experience a different degree and sign of mispricing. More specifically, short-term bonds are found to be overpriced while long-term bonds are slightly underpriced. Although the average level of mispricing seems small, this does not necessarily imply that mispricing has not occurred over the sample period. In fact, it is more likely that positive and negative yield deviations might have offset each other. Therefore we compute squared mispricings for both long and short-term bonds and their average values conditional upon positive and negative changes in the aggregate CBT intensity measure. The results of these final computations lead us to the third patterns of interest which are reported in the bottom row of Figure 4. When we compute squared yield deviations conditional upon the sign of the changes in the CBT intensity measure, we see that mispricings increase in size, for both long- and short-term bonds, when CBT intensity in the US Treasury market increases. However, the mispricings seem to be more pronounced for long-term bonds than short-term ones. A similar

[28]We define short-term bonds the ones with maturity ≤ 3 years while long-term bonds are defined as the ones with maturity longer than 3 years.

pattern, but with opposite sign, is recorded during instances in which CBT intensity in the US Treasury market decreases.

We can interpret the visual evidence in Figure 4 in light of the implications of theoretical model of Vayanos and Wooley (2013) which explicitly considers the role of institutional investors, and their investment flows, in affecting the price of financial securities. In fact, in that model, institutional investors exploit potential mispricings in given markets by buying underpriced securities. However, when institutional investors are forced to liquidate part of their portfolio, the assets that will experience the larger negative price impact will be the ones they overweight (i.e. the underpriced assets). Therefore, the underpriced assets will both experience high expected returns and will be more sensitive to institutional investor flows.

In Section 3 we documented that the portfolio P5 is the one comprising bonds with longer time-to-maturity, the largest and negative exposure to CBT intensity, and it is also the one exhibiting the highest expected returns. In light of the predictions of Vayanos and Woolley (2013) this evidence can be rationalized by the fact that long-term bonds are, over the sample period, the underpriced assets and therefore they have been subject to a higher sensitivity to institutional investors' outflows. As we found that changes in CBT intensity are negatively correlated with the changes in holdings of Treasury securities from institutional investors, it logically follows that this portfolio should be the one that exhibits a negative beta against CBT intensity and also exhibits the highest expected returns. This story also resonates with the evidence reported in the recent study by Gorton et al. (2012) where it is documented that, during the recent financial crises in 2008-2009, market participants tried to preserve the moneyness of their investments by shortening the maturity of their holdings, generating a flight from maturity. In our context the long-term bonds, the ones contained in portfolio P5, are also the ones sold the most when institutional investors reduce their holdings of

Treasury securities.

5.2 A Formal Test

The predictions of the theoretical model by Vayanos and Woolley (2013) are not only able to explain why bonds with the largest exposure to CBT intensity are the ones that exhibit higher expected returns and a negative CBT intensity beta, but they also point towards a potential rationalization of the main drivers generating the returns of the investment strategy proposed in Section 2.2. In fact, one of the main corollaries of the theoretical model states that asset expected returns, in the presence of institutional investors, should follow a two-factor representation where the factors are the market returns and the returns of the portfolio held by institutional investors, respectively. In addition, although the factor risk premium on the market return factor is constant over time, the factor risk premium on the returns of the institutional investors' portfolio is time varying and depends on the portfolio's fund flows (Vayanos and Wooley, 2013 p. 1102).

We put this conjecture to a formal test by considering the following conditional asset pricing model:

$$E_t(\widetilde{rx}^i_{t+1}) = \lambda_{F,t}\beta^F_{i,t}, \tag{6}$$

where $E_t(\widetilde{rx}^i_{t+1}) = E_t(rx^i_{t+1}) - \lambda_M\beta^M_{i,t}$, $E_t(rx^i_{t+1})$ denotes the conditional expectation of the excess returns from bond portfolio i, rx^M_{t+1} and rx^F_{t+1} denote excess returns on the market portfolio and the portfolio of institutional investors, respectively. $\beta^M_{i,t} = \frac{cov\left(rx^i_{t+1}, rx^M_{t+1}\right)}{var\left(rx^M_{t+1}\right)}$, $\beta^F_{i,t} = \frac{cov\left(rx^i_{t+1}, rx^F_{t+1}\right)}{var\left(rx^F_{t+1}\right)}$ are the time-varying market and institutional investors' portfolio beta, λ_M is the constant market factor risk premium and $\lambda_{F,t}$ denotes the time-varying institutional investors' portfolio factor risk premium, respectively. Equation (6) is consistent with the framework proposed in Vayanos and Woolley (2013) but, via a simple reparametrization, it shifts the emphasis only on the impact of the institutional investors' portfolio factor on expected returns.

Single-factor conditional asset pricing models of the kind reported in equation (6) have been largely investigated in the literature. We follow Jagannathan and Wang (1996) and take the unconditional expectation of both sides of equation (6) as follows:

$$E(\widetilde{rx}^{i}_{t+1}) = \overline{\lambda_F}\overline{\beta^F_i} + cov\left(\lambda_{F,t}, \beta^F_{i,t}\right) = \overline{\lambda_F}\overline{\beta^F_i} + \psi_i var\left(\lambda_{F,t}\right), \tag{7}$$

where $\overline{\lambda_F} = E\left(\lambda_{F,t}\right), \overline{\beta^F_i} = E\left(\beta^F_{i,t}\right)$ and the beta-premium sensitivity $\psi_i = \frac{cov\left(\lambda_{F,t}, \beta^F_{i,t}\right)}{var\left(\lambda_{F,t}\right)}$. Equation (7) suggests that the cross-sectional variation of average bond portfolio excess returns, corrected for market risk, depend on the dispersion of the average sensitivity against the returns of the portfolio of institutional investors, $\overline{\beta^F_i}$ and the dispersion in the beta-premium sensitivity ψ_i. Put differently, average excess returns on bond portfolios are higher if their returns positively correlate, on average, with the ones exhibited by the portfolio of institutional investors and when, in case of a positive beta-premium sensitivity, the price of institutional investor portfolio risk is high. The time-varying effect on average returns is captured in the context of equation (7) by the beta-premium sensitivity.

In light of the evidence reported in Figure 4, we expect that the returns from the extreme portfolios P5 and P1 will behave very differently when assessed using the framework reported in equation (7). More specifically, we expect portfolio P5 to exhibit a higher and positive average $\overline{\beta^F_i}$ (in comparison with portfolio P1) and/or a large and positive ψ_i. If the first scenario applies, the higher excess returns characterizing P5 are due to a constant effect related to the correlation of the returns from this portfolio with the returns of the portfolio of institutional investors. If the second scenario applies, then the higher excess returns associated with P5 are mostly due to a time-varying effect for which bonds exhibit high risk when the price of institutional investors' portfolio risk is high, which occurs when there are large outflows from the institutional investor portfolios. If both scenarios apply at the same time, then the excess returns accruing to P5 are due to both a constant and a time-varying effect and the relative magnitude is a function of the size of the estimated parameters, $\overline{\beta_i^F}$ and ψ_i.

We estimate the parameters in equation (7) in the spirit of the methodology proposed in Pektova and Zhang (2005). In particular, as both $\lambda_{F,t}$ and $\beta_{i,t}^F$ are time-varying and unobservable, we estimate conditional betas using a rolling-windows of 6, 12 and 24 months and we regress, in light of the predictions of theoretical model of Vayanos and Woolley (2013), the realized institutional investors' portfolio excess returns from time t to $t+1$ on the change in holdings of US Treasury securities from institutional investors known at time t:

$$rx_{t+1}^F = \delta_0 + \delta_1 FLOW_t + e_{t+1}, \tag{8}$$

and we define the institutional investor's portfolio factor risk premium as the fitted value from equation (8), $\widehat{\lambda}_{F,t} = \widehat{\delta}_0 + \widehat{\delta}_1 FLOW_t$. The factor beta-premium sensitivity, ψ_i is then estimated using the following equation:

$$\widehat{\beta}_{i,t}^F = c + \psi_i \widehat{\lambda}_{F,t} + \epsilon_t. \tag{9}$$

The results of the estimations are reported in Table 6. Panel A) reports the estimates of the average $\widehat{\lambda}_{F,t}$ and the parameter δ_1 for different specifications of equation (8). In particular, as the theoretical model of Vayanos and Woolley (2013) is mute about the lag effect of fund flows on the factor risk premium $\lambda_{F,t}$, we assess the robustness of the modelling choice reported in equation (8) against two alternatives: the first in which the FLOW variable is included with one- and two-month lags (specification 2) and a second one in which the FLOW variable is computed as the average over the past three months (specification 3). The estimation of all model specifications suggests that the correlation between the FLOW variable and the factor risk premium is negative and statistically significant, consistent with the predictions of Vayanos and Woolley (2013). Put differently, the negative sign of the parameter δ_1 confirms that outflows from the portfolio of institutional investors increase the factor risk premium. In turn, in the context of equation (6), this increases the excess returns of the securities whose returns covary positively with the returns of this portfolio. The average magnitude of the factor risk premium over the sample period is slightly more than 30 basis points on a monthly basis and it is statistically significant, at conventional levels, across model specifications.

Panel B) of Table 6 helps us understand better the determinants of the average returns from the strategy proposed in Section 2.2. In fact, regardless of the length of the moving windows used to estimate rolling-windows beta $\beta_{i,t}^{F}$, a common finding emerges: bonds included in portfolio P5 exhibit higher excess returns because they are the ones that positively covary with the portfolio of institutional investors (a large, positive and significant $\overline{\beta_i^F}$) *and* they are also the ones that exhibit a large, positive and significant factor-beta sensitivity ψ_i. Hence, the high excess returns associated with P5 are explained by a combination of both a constant and time-varying effect. The bonds included in portfolio P5 are more risky on average, and exhibit a higher risk when risk, or the price of risk, increases. Vice versa, bonds included in portfolio P1 only exhibit a significant factor-beta sensitivity, but its magnitude is roughly a half of the one exhibited by portfolio P5. Interestingly, bonds included in portfolio P1 exhibit a negative, albeit statistically insignificant, correlation with the portfolio of institutional investors.

Given the evidence reported in Table 6, we ask a final question and assess whether a conditional asset pricing model consistent with the predictions of Vayanos and Woolley's (2013) model is able to fully explain the excess returns of our bond investment strategy. We do this in the spirit of Shanken (1990), Ferson and Harvey (1999), Pektova and Zhang (2005) by estimating the magnitude, and the statistical significance, of the Jensen's alpha from the conditional regression:

$$rx_{t+1}^{P5-P1} = \alpha + \beta_{P5-P1,t}^{F} rx_{t+1}^{F} + u_{t+1}, \quad (10)$$

where rx_{t+1}^{P5-P1} denotes the excess return from the bond investment strategy proposed in Section 2.2 and $\beta_{P5-P1,t}^{F}$ is the 12-month rolling-window factor beta of the strategy returns. The p-value of the null hypothesis that $\alpha = 0$ is reported in the last row of Table 6, Panel B) for all model specifications. As the null hypothesis cannot be rejected, with p-values that are higher than 0.7 in all cases, the evidence suggests that the conditional asset pricing model in equation (6) is able to fully explain the excess returns from the bond investment strategy.

6 Robustness

This section checks the robustness of the baseline results reported in Section 4. More specifically, we test whether our results are sensitive to the choice of different formation and holding periods, the use of value-weighted returns and 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. (2014), we also test whether a random CBT intensity measure 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.

6.1 Different Portfolio Formation and Holding Periods

In Section 3 we implement our portfolio strategy by estimating the beta to the CBT intensity measure 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.[29] The results of this robustness check are reported in Table 7. 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 7 shows that sorting bonds on the basis of their exposure to the CBT intensity measure still generates a large and significant cross-sectional spread. In fact, the average returns from the bond portfolio strategy P5-P1 are positive and statistically significant and their annualized Sharpe ratios are still sizable.

6.2 Uninformative CBT Intensity Measure

The second 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. (2014), we test whether a random CBT intensity measure is able to spuriously replicate the cross-sectional results reported in this study. Specifically we simulate a CBT intensity measure by randomly drawing from the distribution of the computed CBT intensity measure with replacement. For each of the 10,000 replications we construct a time series of the CBT intensity measure that has the same length of the original series. 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 CBT intensity measure exhibit roughly the same returns

[29]We do not consider shortening either the formation or the holding periods since these would result in more imprecise estimations of the CBT intensity beta and higher transaction costs due to a more frequent portfolio rebalancing.

and, therefore a zero cross-sectional spread.

The results in Table 8 show that sorting bonds into portfolios on the basis of a random CBT intensity measure 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 1 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 random measure does not carry any pricing information. Taken together, the results reported in this sub-section suggest that finding we discover and discuss in Section 3 of the main text are unlikely to be due to mere chance.

6.3 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, in line with existing studies, 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 A2-A4 of the Internet Appendix. When portfolios returns are computed using a value-weighting scheme, the evidence discussed in Sections 3 and 4 is quantitatively and qualitatively confirmed.

6.4 Liquidity Biases and Asset Pricing Tests

We also 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 adopting the methodology proposed 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 A5 of the Internet Appendix. They largely confirm the results of the asset pricing test reported in Tables 2 and 3 as only the equity market factor and the funding illiquidity factor prices of risk are found to be statistically significant at 10 percent level.

6.5 Additional Robustness Checks

As a final check we also re-estimated parameters of the equations reported in Table 6, Panel B) by computing $\widetilde{rx}^i_{t+1}$ as portfolio i's excess returns corrected for market and funding illiquidity risk. We do this as the asset pricing tests reported in Section 4.1 suggests that in addition to the equity market factor, the funding illiquidity factor exhibit some significance across various specifications. The results of this exercise reported in Table A6 of the Internet Appendix confirm that the baseline results reported in Table 6 are robust to the correction for funding illiquidity risk when computing $\widetilde{rx}^i_{t+1}$.

7 Conclusions

This study investigates the effect of CBT on the cross-section of Treasury bond returns. We construct a novel measure of aggregate CBT intensity using tick-by-tick data and sort bonds into portfolios according to their beta to the CBT intensity measure. Then we assess the profitability of a strategy that goes long in the portfolio of bonds with the largest beta to CBT intensity and short the one with the smallest.

Using data over the period January 2003 and December 2011, we find that sorting bonds on the basis of their beta to aggregate CBT intensity generates a large cross-sectional spread. Bonds with the largest beta to CBT intensity experience higher expected returns and are also the ones that experience lower realized returns when CBT activity is high. The strategy of investing in the portfolio comprising bonds with the largest CBT intensity beta and shorting the portfolio comprising bonds with the smallest beta yields sizable returns which are not due to bonds' individual characteristics, compensation for exposures to conventional sources of risk and they are not due to transaction or financing costs. 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 with noisy liquidity factors. We also provide simulation evidence that the our main results are not due to mere chance.

We explain our findings by linking CBT in the Treasury market to institutional investors' fund flows originating from the management of their Treasury holdings. Following the theoretical model proposed by Vayanos and Woolley (2013), we explain why bonds with largest exposure to CBT intensity exhibit the largest excess returns and negative CBT intensity beta. Furthermore, we test and validate the hypothesis that excess returns from the bond investment strategy are due to the risk premium accruing to bonds whose returns positively correlate with the ones of the portfolio of institutional investors.

8 Appendix

8.1 Computer-based Market and Limit Orders Classification

In this section we summarize the procedure proposed in Jiang et al. (2014) to identify computer-based market and limit orders from publicly-available limit-order-book data. The BrokerTec dataset employed in this study includes reference numbers that provide information on the timing of an order submission and its subsequent execution, alteration or cancellation. Using this information, we classify computer-based market and limit orders if they are placed at a speed deemed beyond manual ability. Specifically, the following filtering rules are used:

- Computer-based market orders (CBMO) – Market orders (buy or sell) that are placed within a second of a change in the best quote on either side of the market (highest bid or lowest ask).

- Computer-based limit orders (CBLO1) – Limit orders (buy or sell) that are cancelled or modified within one second of their placements, regardless of changes in market conditions;

- Computer-based limit orders (CBLO2) – Limit orders (buy or sell) at the best quotes that are modified within one second of a change of the best quotes on either side of the market (highest bid or lowest ask);

- Computer-based limit orders (CBLO3) – Limit orders (buy or sell) at the second-best quote that are modified within one second of a change of the best quote on either side of the market (highest bid or lowest ask).

The above procedure is specifically designed to identify computer-based market and limit orders on the basis of the speed at which they are submitted, executed or altered. We exclude those orders deleted by the central system, orders deleted by the proxy, stop orders, and passive orders that are automatically converted by the system to aggressive orders due to a locked market.[30]

Although the above filtering rules are likely to capture the salient features of orders originating from computers, some caveats are in order. For example, manual orders can be mistakenly identified as computer-based orders if manual orders are placed earlier but arrive

[30]On the BrokerTec platform, the percentages of these types of orders account for 1.5%, 1% and 0.8% of the total number of orders for the 2-, 5- and 10-year notes, respectively.

within one second of market condition changes. Similarly, some computer-based orders may be classified as manual orders if they arrive at the system beyond one second of market condition changes. As a result, some manual market and limit orders may be labelled incorrectly.

Once we identify market and limit orders originating from computers, we calculate the numerator of the ratio in equation (1) of the main text as follows:

$$CBO_t^i = n^i_{CBMO,t} + n^i_{CBLO1,t} + n^i_{CBLO2,t} + n^i_{CBLO3,t},$$

where $n^i_{X,t}$ denotes the number of X-type computer-based orders recorded during the day t for the benchmark bond i.

8.2 Institutional Investors Data Construction

This section describes the sources and methodology used to compile the dataset used in Section 5 of the main text. The statistics discussed in Section 5.2 and reported in Figure 4, refer to two sets of measures (in addition to the time series of the CBT intensity measure): 1) changes in US Treasury holdings by institutional investors; and 2) measures capturing price/yield misalignments. We compute the first measure by using data from the US Flow of Funds, Federal Reserve Statistical Release Z.1. More specifically, we choose the sum of the aggregates Money Market Funds (Table L.120), Mutual Funds (Table L.121) and Close-End and Exchange Traded Funds (Table L.122) as a suitable proxy for institutional investors, in light of the findings reported in Lou (2012). We measure changes in holdings of Treasury securities, as the changes in outstanding holdings of Treasury securities, not seasonally adjusted and expressed in US dollar billions, recorded at the end of each quarter. As the time-series of the CBT intensity factor is available on a high-frequency but the holding data are available on a quarterly basis, we construct monthly changes in Treasury holdings by interpolation assuming that every month records one third of the change accruing during the whole quarter.[31] [32] We compute measures of price/yield misalignments in the spirit of the framework proposed in Hu et al. (2013). More specifically, over the sample period we compute differences between market-observed yields for bonds available at the time for curve fittings recorded in the CRSP Treasury dataset and the interpolated yields computed using a spline-based method as in Svensson (1994). Differently from Hu et al. (2013) we compute the measures of misalignment for two maturity segments of the yield curve: the short-end (including maturities up to 3 years) and the long-end (with maturities ranging between 3 and 10 years). Furthermore, for both maturity segments, we compute average signed (AD) and squared differences (AS) as follows:

$$AD = \frac{1}{N}\sum_{i=1}^{N}\left(y_t^i - \widetilde{y}_t^i\right) \text{ and } AS = \frac{1}{N}\sum_{i=1}^{N}\left(y_t^i - \widetilde{y}_t^i\right)^2,$$

where $i = 1, ...N$ denotes the number of bonds available on day t, y_t^i and $\widetilde{y}_t^i$ denote the market-observed yield to maturity and the model-implied yield, respectively.

The empirical analysis reported in Section 5.2 requires an additional data series. In particular, equations (6), (7) and (8) use a proxy for institutional investors' portfolio excess returns, rx_{t+1}^F. Consistent with the rationale adopted above, we compute the portfolio returns of institutional investors using the aggregates Money Market Funds (Table L.120), Mutual Funds (Table L.121) and Close-End and Exchange Traded Funds (Table L.122) recorded in the US Flow of Funds, Federal Reserve Statistical Release Z.1. More specifically, we focus on five main asset classes which are available and comparable across aggregates: 1) Cash, 2) Treasury securities 3) Corporate bonds 4) Equities and 5) Other assets. For each asset class and for every quarter during the sample period, we compute the ratio of the amount

[31] We have also computed an alternative interpolation scheme whereby values in the intermediate months between two end of quarters are computed using a linear interpolation. The results, not reported to save space, are qualitatively similar to the ones reported in Section 5.

[32] This monthly series is also the time-series $FLOW_t$ used in the estimation of equation (8) of the main text.

outstanding, in US dollar billion, as a fraction of the sum of the outstanding amount of the five asset classes.[33] The items included in each asset class for each aggregate are reported in the following tables:[34]

	Money market funds (L.120)
1. Cash	Checkable deposits and currency (3) Security Repurchase Agreements (5)
2. Treasury securities	Treasury securities (8)
3. Corporate bonds	Corporate and foreign bonds (11)
4. Equities	
5. Other assets	Agency- and GSE-backed securities (9)

	Mutual funds (L.121)
1. Cash	Security Repurchase Agreements (2)
2. Treasury securities	Treasury securities (5)
3. Corporate bonds	Corporate and foreign bonds (8)
4. Equities	Corporate equities (10)
5. Other assets	Agency- and GSE-backed securities (6)

	Close-end and Exchange Traded Funds (L.122)
1. Cash	
2. Treasury securities	Treasury securities (3,10)
3. Corporate bonds	Corporate and foreign bonds (5,12)
4. Equities	Corporate equities (6,13)
5. Other assets	

[33]We did not use compute ratios against total amount of assets for the various aggregates as the sum of the outstanding amounts of five asset classes is not equal to the total asset, because of other items not included in our calculations. However, the sum of the amounts of the five asset classes is able to span a large proportion of the total assets for all aggregates with a share that exceeds 75 percent over the full sample.

[34]The numbers reported in parentheses are the line numbers of each item within the Tables of the US Flow of Funds.

The ratios for each asset class can be interpreted as a proxy of the weights of the various asset class within the portfolio held by institutional investors. As the empirical investigation is carried out at the monthly frequency, we convert quarterly weights into monthly by assuming that each month experiences one third of the overall change occurring during the quarter. Once the portfolio weights are computed, we calculate the returns accrued to the portfolio of institutional investors as follows:

$$r_F^t = \sum_{k=1}^{5} \omega_t^k r_{t+1}^k$$

where w_t^k denotes the weight in asset class $k = 1, ..., 5$ prevailing at the end of month t and $r_{t+1}^k$is the actual return accrued on asset class k between the end of month t and $t+1$. We proxy for the actual returns of the five asset classes as follows: 1) **Cash** holdings are assumed to yield the risk-free rate which is proxied by the 1-month US Tbill rate and downloaded from Ken French's website, 2) the returns on **Treasury securities** are proxied by the equal-weighted average of returns accruing to the 12 Fama-Bliss bond-maturity portfolios recorded in the CRSP dataset, 3) the returns on **Corporate bonds** are proxied by the actual returns, expressed in US dollar, on the BoFA Merrill Lynch Global Corporate Index downloaded from Bloomberg, 4) the returns on **Equities** are proxied by the US equity market return downloaded from Ken French's website and 5) the returns on **Other assets** are proxied by the actual returns on BoFA Merrill Lynch US Composite Agency Index downloaded from Bloomberg.[35] We finally compute rx_{t+1}^F as the difference between r_{t+1}^F and 1-month US Tbill rate.

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[35] We have also used alternative proxies for broad indices returns for some asset classes and the results, not reported to save space, are qualitatively and quantitatively similar to the ones discussed in the main text.

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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 CBT intensity, $\widehat{CBTI}_t$ 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 CBT intensity beta while Portfolio 5 (P5) contains bonds with the largest CBT intensity 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. Cross-sectional Asset Pricing Regressions

The Table reports the coefficients from one-step GMM estimations of the various asset pricing models. The analysis uses the five portfolios reported in Table 1 and in each specification one single factor is used. The final two rows of the table report the the GMM J-test statistics and their relative p-values. The sample period is January 2004−December 2011. For a detailed description of the risk factors see Section 3 of the main text and the notes to Table A1. See also notes to Table 1.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$
MKT_t	−0.165	−4.167												
	(−2.07)	(−1.75)												
$\widehat{ILLIQ}_t^B$			−7.540	−0.070										
			(−1.73)	(−1.50)										
LIQ_t^E					−12.794	−0.069								
					(−1.37)	(−1.47)								
$\widehat{FILL}_t$							−4.641	−0.435						
							(−1.34)	(−2.79)						
$TERM_t$									3.693	5.637				
									(0.22)	(0.20)				
SMB_t											−0.279	−1.662		
											(−1.34)	(−1.49)		
HML_t													−0.710	−8.993
													(−0.85)	(−0.38)
J_T		4.05		5.48		7.32		5.18		0.86		7.34		1.13
p-value		0.39		0.24		0.12		0.26		0.92		0.11		0.88

Table 3. Time-series Regression

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 used simultaneously. Factor-mimicking portfolios of non-tradable assets ($\widehat{FILL}_t$ and $TERM_t$) are computed using the Fama-Bliss bond portfolios as base assets. The factor-mimicking portfolio return of the Pastor and Stambaugh's (2003) measure is obtained from CRSP. Values in parentheses are $t-$statistics computed using HAC standard errors as in Newey and West (1987). The last row reports the value of the adjusted R^2. The sample period is January 2004−December 2011. See also notes to Tables 1, 2.

	non−tradable factors	mimicking portfolios
Const	0.762	0.758
	(2.76)	(2.75)
MKT_t	−0.188	−0.200
	(−2.29)	(−2.68)
LIQ_t^E	−3.191	3.011
	(−0.90)	(0.333)
$\widehat{FILL}_t$	−2.516	−4.279
	(−2.14)	(−2.65)
$TERM_t$	0.028	1.859
	(0.231)	(1.79)
SMB_t	0.154	0.215
	(1.40)	(1.74)
HML_t	−0.001	0.002
	(−0.001)	(0.02)
Adj R^2	0.112	0.195

Table 4. Cross-sectional Regressions with Bond Portfolio Characteristics

This table reports the asset pricing regression with portfolio characteristics discussed in Section 4.2 of the main text. The coefficient estimates are time-series averages of cross-sectional OLS regressions (Brennan et al., 1998; Goyal, 2012). The dependent variable is the excess return risk-adjusted for the MKT factor. The portfolio characteristics are defined as follows: TTM is the portfolio's average remaining time to maturity of the individual constituent bonds and OFF denotes the portfolio's average ratio of remaining time to maturity to the original time to maturity at issuance of the individual constituent bonds. Values in parentheses are $t-$statistics computed as in Shanken (1992).

	(1)	(2)	(3)
TTM	0.017		0.019
	(1.05)		(1.14)
OFF		0.919	−0.171
		(1.14)	(−0.55)

Table 5. 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 4.3 of the main text. We report the results for a repo spread equal to zero and 25bp per annum. The last colum of the table reports the returns net of transaction and financing costs (with repo spread set equal to zero) where bonds in each portfolio are included only if they trade more than 50% of the trading days in each month of the holding period. Portfolio returns are computed using an EW scheme. The sample period is January 2004−December 2011. See also notes to Table 1.

		repo spread =		trading > 50% month
	no TC	0bp	25bp	0bp
Mean	0.870	0.842	0.670	0.748
	(3.23)	(1.98)	(1.57)	(1.76)
Stdev	2.541	3.489	3.490	3.491
Skew	1.058	0.669	0.662	0.655
Kurt	2.698	1.351	1.348	1.344
AC(1)	0.203	0.199	0.199	0.199
SR	1.187	0.835	0.665	0.742

Table 6. Institutional Investors and Bond Portfolio Returns

The Table reports the estimates of the parameters of interest relative to the conditional asset pricing model discussed in Section 5 of the main text. Panel A) reports the estimates of the average factor risk premium $\overline{\lambda_F}$ together with the estimate of the parameter δ_1 in equation (8) of the main text. Values in parentheses denote the p-value of the null hypothesis that $\widehat{\delta_1} = 0$. Values in brackets are the t-statistics of the estimates $\overline{\lambda_F}$. The three specifications reported in the panel refer to different lag lenghts of the $FLOW$ variable chosen when estimating equation (8) as discussed in Section 5. Panel B) reports the estimates of the average factor betas $\overline{\beta_i^F}$ of the two portfolios P5 and P1 computed using rolling windows of size k = 12, 6 and 18 months, respectively. It also reports the beta-premium sensitivities ψ_i as in equation (9) of the main text. Values in parentheses are asymptotic standard errors. The last row of Panel B denotes the p-value of the null hypothesis that Jensen's alpha from conditional regressions for the excess return P5-P1 are equal to zero. We compute $\widetilde{rx}^i_{t+1}$ as portfolio i's excess returns corrected for market risk. All statistics of interests are computed using heteroskedasticity and autocorrelation consistent (HAC) standard errors. The sample period is January 2004−December 2011. See also notes to Table 4.

Panel A) Factor risk premium $\lambda_{F,t}$ estimates

	(1)		(2)		(3)	
$\widehat{\delta_1}$	−0.049	(0.03)	−0.070	(< 0.01)	−0.064	(0.03)
$\overline{\lambda_F}$	0.359	[4.59]	0.334	[3.41]	0.323	[3.28]

Panel B) Rolling-windows betas and beta-premium sensitivities

	k =12 month		k = 6 month		k = 18 month	
	$\overline{\beta_i^F}$	ψ_i	$\overline{\beta_i^F}$	ψ_i	$\overline{\beta_i^F}$	ψ_i
P5	0.108	0.159	0.167	0.175	0.137	0.129
	(0.03)	(0.06)	(0.05)	(0.08)	(0.03)	(0.04)
P1	−0.031	0.079	−0.038	0.049	−0.024	0.073
	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)
p-value		[0.72]		[0.85]		[0.98]

Table 7. 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 CBT intensity measure, $\widehat{CBTI}_t$ 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 8. Strategy Returns with random CBT Intensity Measure

This table reports descriptive statistics for the monthly excess returns of bond portfolios sorted according to their beta to the simulated series $\widehat{CBTI}_t^S$ computed using daily data over the previous 12 months. $\widehat{CBTI}_t^S$ is obtained by randomly drawing from the distribution of the actual $\widehat{CBTI}_t$ 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	

Figure 1. Computer-based Trading Intensity

20-days moving averages

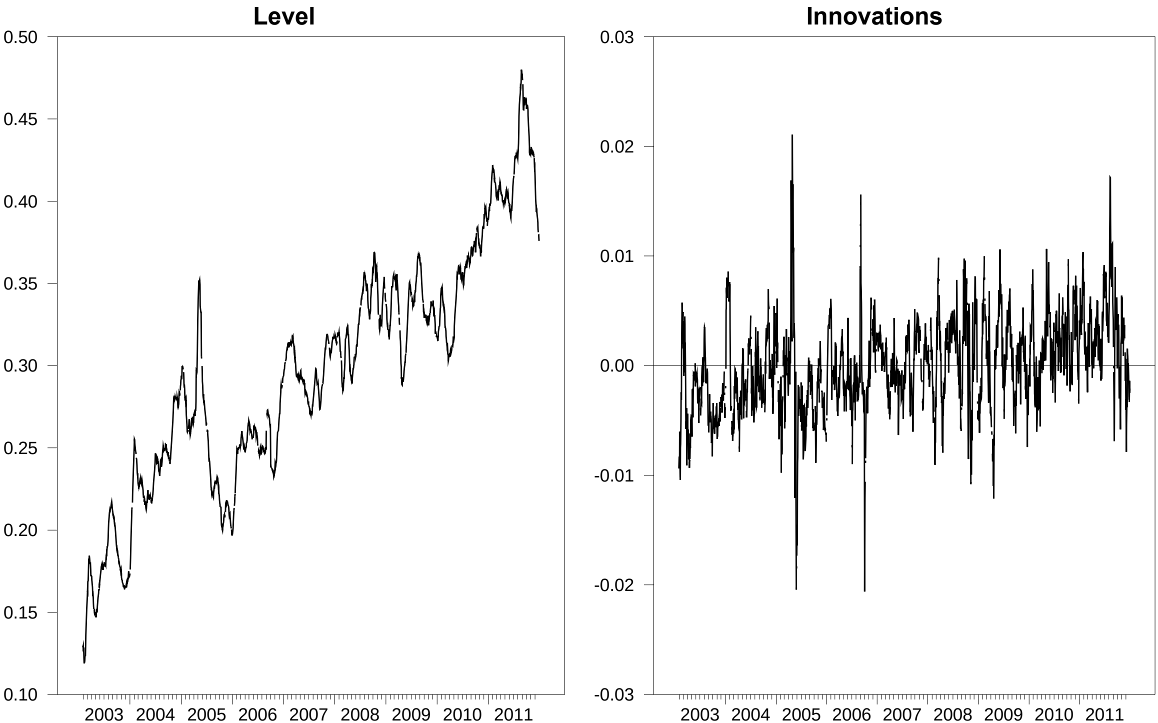


Figure 2. Bond Strategy and Bond Market Returns

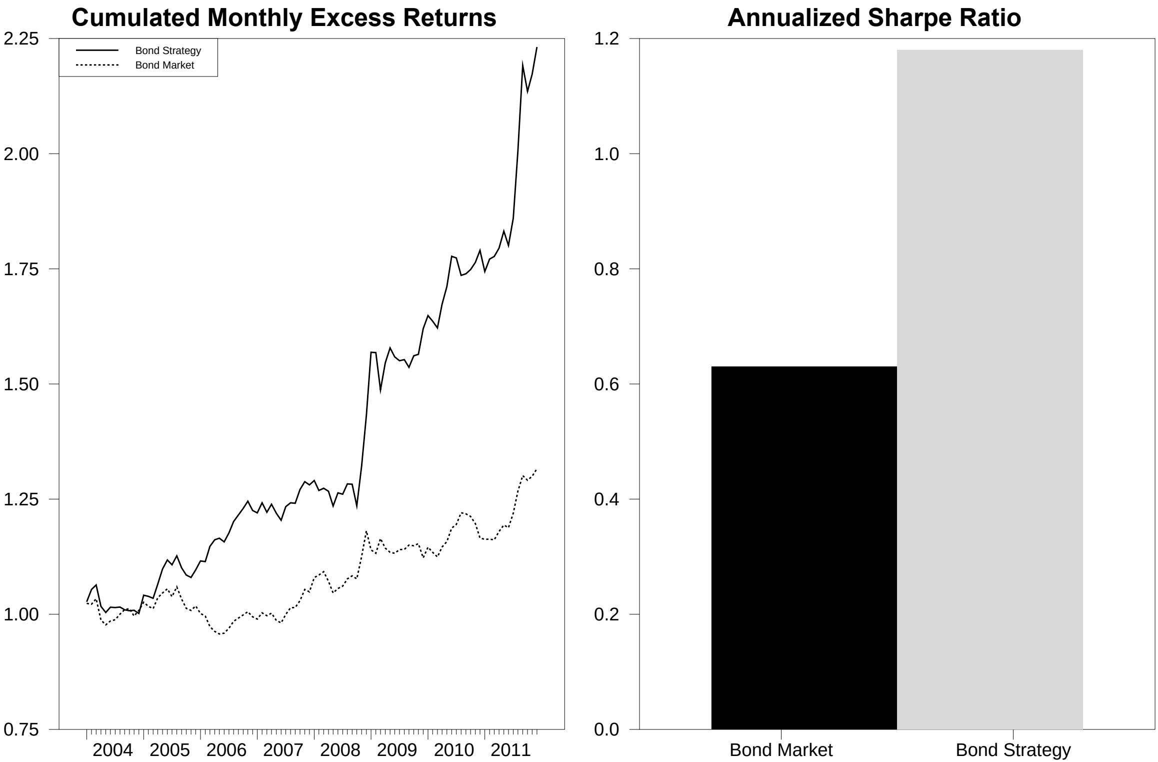


Figure 3. Bond Portfolio Characteristics

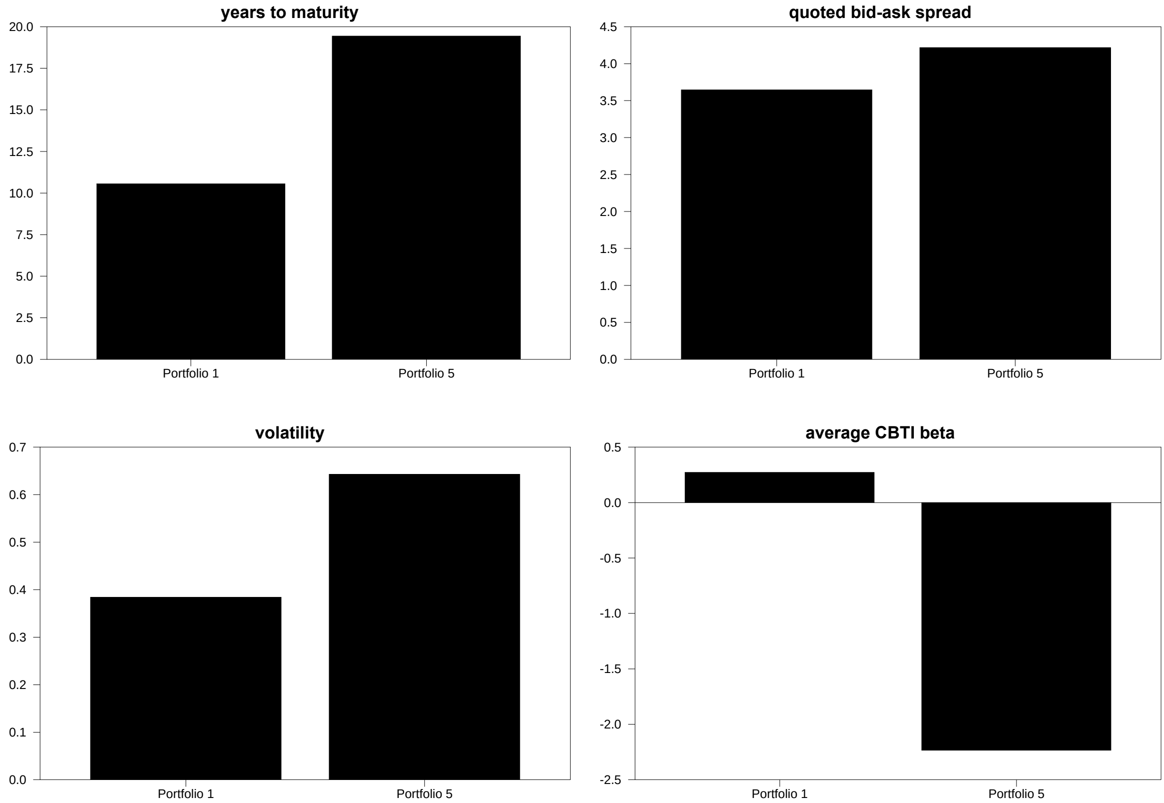
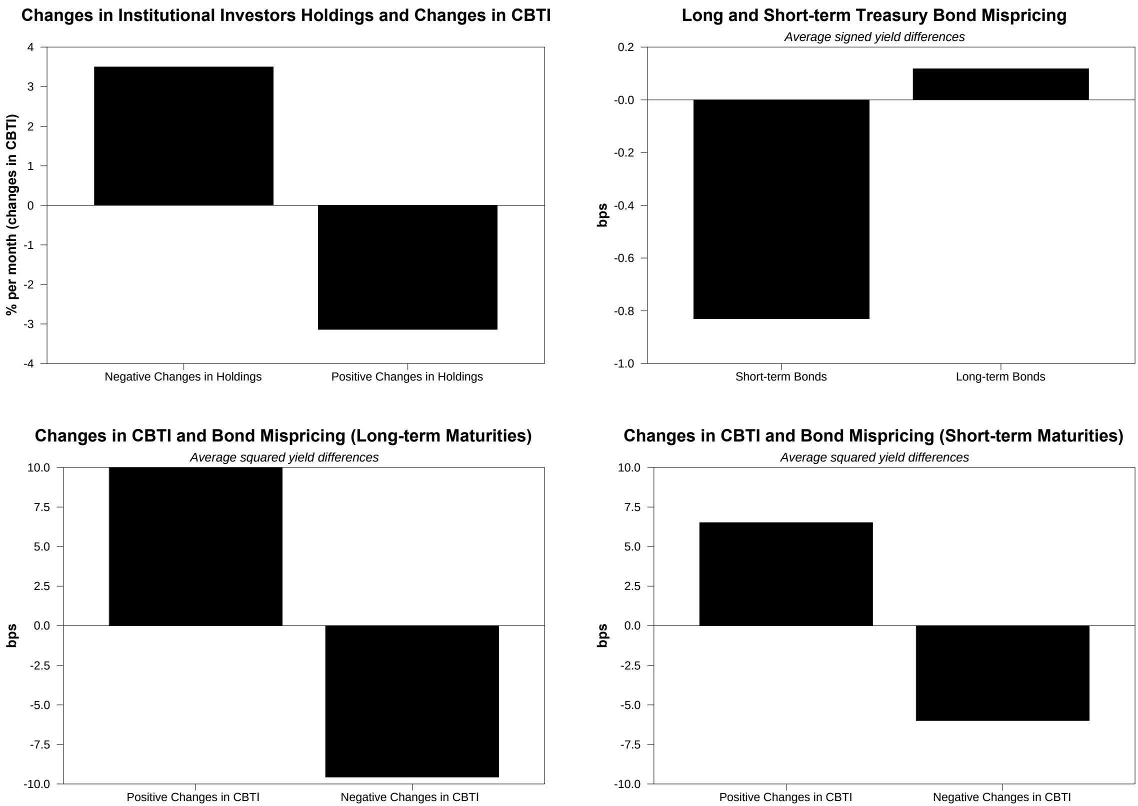


Figure 4. Computer-Based Trading and Institutional Investors



Computer-based Trading, Institutional Investors and Treasury Bond Returns: Internet Appendix

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This draft: July 30, 2018

Table A1. 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 market-specific risk factors: $\widehat{ILLIQ}_t^B$ are the AR(1) innovations of monthly bond while $TERM_t$ 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: MKT_t denotes the monthly excess returns of the equity market portfolio, $\widehat{FILL}_t$ denotes the innovations of the monthly series of funding liquidity measure. SMB_t, HML_t and LIQ_t^E are the Fama−French size and value factors, and the innovations in the Pastor and Stambaugh's (2002) equity market liquidity measure, respectively. The sample period is January 2003−December 2011. See also notes to Table 1.

Panel A) Bond Risk Factors

	$\widehat{ILLIQ}_t^B$	$TERM_t$
Mean	−	1.770
Stdev	0.095	1.226
Skew	2.541	−0.474
Kurt	16.420	−1.238
AC(1)	0.090	0.986

Panel B) Other Risk Factors

	MKT_t	LIQ_t^E	$\widehat{FILL}_t$	SMB_t	HML_t
Mean	0.525	−0.032	−	0.398	0.201
Stdev	4.513	0.071	0.292	2.457	3.483
Skew	−0.642	−1.120	4.560	0.741	1.517
Kurt	1.786	2.962	31.215	1.742	8.958
AC(1)	0.220	−0.049	−0.084	−0.015	0.224

Table A2. 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 CBT intensity, $\widehat{CBTI}_t$ 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 CBT intensity beta while Portfolio 5 (P5) contains bonds with the largest CBT intensity 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 A3. Cross-sectional Asset Pricing Regressions (VW Scheme)

The Table reports the coefficients from one-step GMM estimations of the various asset pricing models. The analysis uses the five portfolios reported in Table 1 and in each specification one single factor is used. The final two rows of the table report the the GMM J-test statistics and their relative p-values. Portfolio returns are computed using a value-weighting (VW) scheme and they are expressed in monthly percentage points. The sample period is January 2004−December 2011. See also notes to Tables 1 and A1.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$	$\widehat{b}$	$\widehat{\lambda}$
MKT_t	−0.191	−4.011												
	(−2.03)	(−1.74)												
$\widehat{ILLIQ}_t^B$			−7.796	−0.069										
			(−1.69)	(−1.49)										
LIQ_t^E					−12.649	−0.069								
					(−1.39)	(−1.48)								
$\widehat{FILL}_t$							−4.649	−0.436						
							(−1.38)	(−2.90)						
$TERM_t$									3.343	5.103				
									(0.24)	(0.22)				
SMB_t											−0.270	−1.612		
											(−1.32)	(−1.47)		
HML_t													−0.648	−8.209
													(−0.84)	(−0.29)
J_T		3.47		4.11		5.32		5.70		0.95		7.18		1.46
p-value		0.48		0.39		0.25		0.22		0.91		0.12		0.83

Table A4. 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 are computed using a value-weighting (VW) scheme and they are expressed in monthly percentage points. Values in parentheses are t-statistics computed using HAC standard errors as in Newey and West (1987). The sample period is January 2004−December 2011. See also notes to Table 4.

	non−tradable factors	mimicking portfolios
Const	0.738	0.715
	(2.80)	(2.79)
MKT_t	−0.179	−0.189
	(−2.28)	(−2.69)
LIQ_t^E	−3.528	1.641
	(−0.98)	(0.19)
$\widehat{FILL}_t$	−2.530	−4.222
	(−2.21)	(−2.73)
$TERM_t$	0.020	1.905
	(0.163)	(1.81)
SMB_t	0.160	0.222
	(1.45)	(1.79)
HML_t	0.001	0.002
	(0.01)	(0.02)
Adj R^2	0.116	0.202

Table A5. Fama-MacBeth Regression with Asparouhova et al. (2010) correction

This table reports the Fama-MacBeth (1973) as in Tables 2 and A3 where t-statistics are computed using Weighted Least Square standard errors constructed as Asparouhova et al. (2010). See notes to Tables 2 and A3.

Panel A) EW Scheme

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MKT_t	−6.698						
	(−1.89)						
$\widehat{ILLIQ}_t^B$		−0.175					
		(−1.57)					
LIQ_t^E			−0.210				
			(−1.10)				
$\widehat{FILL}_t$				−0.353			
				(−2.15)			
$TERM_t$					7.278		
					(0.54)		
SMB_t						7.476	
						(0.92)	
HML_t							−13.145
							(−0.86)

Panel B) VW Scheme

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MKT_t	−7.085						
	(−1.82)						
$\widehat{ILLIQ}_t^B$		−0.172					
		(−1.56)					
LIQ_t^E			−0.195				
			(−1.17)				
$\widehat{FILL}_t$				−0.352			
				(−2.14)			
$TERM_t$					8.232		
					(0.48)		
SMB_t						9.646	
						(0.78)	
HML_t							−15.468
							(−0.73)

Table A6. Institutional Investors and Bond Portfolio Returns

The Table reports the estimates of the average factor betas of the two portfolios P5 and P1 computed using rolling windows of size k = 12, 6 and 18 months, respectively. It also reports the beta-premium sensitivities ψ_i as in equation (9) of the main text. Values in parentheses are HAC standard errors. The last row denotes the p-value of the null hypothesis that Jensen's alpha from conditional regressions for the excess return P5-P1 are equal to zero. We compute $\widetilde{rx}^i_{t+1}$ as portfolio i's excess returns corrected for market and funding illiquidity risk. The sample period is January 2004−December 2011. See also notes to Table 6.

	k =12 month		k = 6 month		k = 18 month	
	$\overline{\beta}$	ψ_i	$\overline{\beta}$	ψ_i	$\overline{\beta}$	ψ_i
P5	0.102	0.155	0.159	0.168	0.133	0.127
	(0.03)	(0.06)	(0.05)	(0.08)	(0.03)	(0.04)
P1	−0.023	0.085	−0.027	0.059	−0.018	0.077
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)
p-value		[0.68]		[0.96]		[0.99]

Figure A1. Monthly Alpha Returns