Dealer Inventory and the Cross-Section of Corporate Bond Returns

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Abstract

Inventory models of dealership markets following Ho and Stoll (1981) imply that intermediaries rely on pricing policies to reduce their exposure to inventory risk, i.e., the risk of unfavorable price movements in the assets on their inventories. Consequently, extreme inventory positions of intermediaries affect market prices, and thus, subsequent returns. We study dealer inventory positions in the US corporate bond market over the time period from 2003 to 2013 based on a complete set of transactions data. In particular, we examine asset pricing implications of inventory models by relating the cross-section of dealer inventories to bond returns. We find strong support for the implications of inventory models. A long-short quintile portfolio based on dealers' inventory positions yields significant positive risk-adjusted returns of 18 bp per week. The results are robust to different sample periods, i.e., full, pre-crisis, and crisis period.

JEL-Classification: G10, G12, G20
Keywords: otc market, dealer inventory, corporate bond returns, cross-sectional asset pricing

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1 Introduction

In financial markets, buy and sell orders from investors seeking liquidity do often not arrive at the same time. This creates temporary order imbalances in assets. In this respect, intermediaries play a central role by providing liquidity. Specifically, they act as counterparties and stand by to trade with investors, by temporarily holding these assets on their own inventories until new orders arrive which offset their positions. By providing liquidity, dealers might end up in unfavorable or extreme inventory positions in assets. However, they dislike these positions due to limited risk-bearing and inventory-carrying capacity. As a result, in order to be compensated for their liquidity service, dealers charge a bid-ask spread around the mid-price. The mid-price represents their marginal valuations of these assets given their inventory positions.

In order to diminish extreme inventory positions in assets, a dealer might reduce his liquidity provision by pursuing a specific pricing policy. This policy should ultimately generate order flow in the desired direction, and thus, allow the inventory to revert back to the desired level. In particular, if a dealer is net long in an asset, i.e., the inventory is above the desired target level, the dealer will push prices below the fundamental value of the asset to induce public buy orders. On the contrary, if the dealer is net short in an asset, i.e., the inventory is below the target level, the dealer pushes prices up to generate public sell orders. Once the dealers' inventory position is near the desired target, the price at which he is willing to transact an asset should be close to the fundamental value. As a result, this kind of pricing policy has two main implications, i.e., it will lead to mean reversion in dealer inventories and transaction prices.

Liquidity provisioning in over-the-counter (OTC) markets is naturally related to inventories of intermediaries, and will be of particular importance in markets which are per se more illiquid. In this context, those dimensions of illiquidity are especially harmful which induce inventory risk for dealers, e.g., markets which are characterized by slow moving capital in the sense that the representative investor is institutional in nature, e.g., insurance companies or pension funds which typically pursue static buy and hold strategies. Under these circumstances it is likely that dealers are stuck with temporary extreme positions in assets, implying long mean reversion rates in inventories driven by large order imbalances. In turn, this exposes dealers to inventory risk, i.e., the risk that prices of assets in extreme inventories move against them. The relation between inventory risk to transaction prices and the underlying (expected) returns is the focus of this study.

Following the discussion above, the market for US corporate bonds is an ideal laboratory to examine how dealer inventory is related to returns. First, US corporate bonds trade in an OTC market which is considered as being rather illiquid, and where a set of dealers intermediate between investors. Second, detailed transactions data on prices and volumes are entirely available from 2002 onwards in the Trade Reporting and Compliance Engine (TRACE) database, maintained by FINRA. Moreover, and most important, our version of TRACE contains individual dealer information, implying that we can assign each and every single transaction to a particular dealer, and thus, reconstruct dealers' inventory positions over time. This setup allows us to comprehensively study individual dealer positions in bonds, and consequently, permits us to address in detail the question of how dealer inventory is related to bond returns.

We make three contributions in this paper relative to the existing literature. First, we study, for the first time, dealer inventory positions in each bond in the US corporate bond market over the time period from 2003 to 2013. Such a study is important in the first place, as it allows identifying empirically whether inventory risk might be a concern in the US corporate bond market to begin with. This, in turn, relies on the quantification of the drivers of illiquidity which are particularly related to inventory risk, i.e., half-lives of inventories and order imbalances in each bond on the dealer level. Second, we study the asset pricing implications of inventory models. Specifically, we relate representative dealer inventories in individual corporate bonds to the underlying returns, for a large cross-section of bonds. In order to establish this link, we employ standard asset pricing tests which allow us to identify whether dealer inventory risk is related to the cross-section of bond returns. The economic rationale underlying our empirical tests is guided by the idea of inventory models that dealers reduce exposure to inventory risk by corresponding pricing policies. Thus, in our empirical tests, we simply attempt to exploit the desire of a dealer to unwind a risky inventory position by being willing to transact at prices different from fundamental values, which after inventory rebalancing should lead to subsequent transaction price rebounds. Third, given the large cross-section of bonds employed in our study, we examine the cross-sectional relation between dealer inventories and bond returns for several important sub-segments of the US corporate bond market, e.g., related to characteristics of the underlying bonds and firms, respectively.

Our study yields several distinct sets of findings. First, when analyzing inventory dynamics, we uncover that the average speed of mean reversion, i.e. half-life of individual bond inventories on the dealer level, is around 10 weeks. This is huge compared to other markets such as the equity market, where half-lives of stock inventories are on average way below a trading day (for recent evidence, see e.g., Hendershott and Menkveld (2014)). Second, the average order imbalance in a single bond exceeds $1 million every 10th day. Given that dealers typically trade on average in around 134 bonds per day, substantial order imbalances can arise. Moreover, the average bond turnover is around 9% per day traded, which is a considerable amount when relating to the average issue size of $220 million. All these figures highlight the importance of a deep analysis between the cross-sectional link of dealer inventory to bond prices and, thus, the underlying returns.

When turning to the core of our analysis we do find that bonds that generate inventory risk trade at prices different from fundamentals, conditioning on common risk factors. In particular, our findings demonstrate a clear cross-sectional relation between dealer inventory risk and corporate bond returns, i.e., bonds held in extreme inventories exhibit abnormal returns. We establish this result by a long-short portfolio based on dealer inventory holdings. Consistent with the underlying economic mechanism of inventory models, an equally weighted long-short quintile portfolio earns a significant positive risk-adjusted return of 18 bp per week. Moreover, also consistent with inventory models, the abnormal returns of the long-short portfolios are increasing in inventory holdings, i.e., the return differential based on decile portfolios is 27 bp per week. The results are robust to different sub-periods of the sample, i.e., the full, the pre-crisis, and the crisis period. Again, consistent with the theoretical foundations, we find that risk-adjusted returns of the portfolios are particularly high during the crisis, that is, in a period in which fundamental risk, as one of the key determinants of the inventory risk concern, is especially pronounced.

By continuing, our analysis of the various sub-segments provides additional economic insights. For example, in accordance with the notion of inventory risk-sharing, we do find that risk-adjusted returns of the long-short portfolios are smaller for bonds in which a relatively high fraction of dealers supply liquidity to the market, compared to bonds in which only a relatively low fraction of dealers provide liquidity. Therefore, large bonds are less prone to generate inventory risk as they are typically traded by a relatively high fraction of dealers in the market. As far as other sub-segments are concerned, e.g., non-financial vs. financial bonds or investment vs. speculative-grade bonds, respectively, our main insights regarding the cross-sectional relation between dealer inventory and returns are confirmed. In summary, we provide a comprehensive analysis going beyond the results that have been presented in the prior literature, by studying in detail the cross-sectional relation between dealer inventory risk and bond returns.

This paper is organized as follows: Section 2 reviews the literature. Section 3 provides the intuition on inventory models and gives guidance for the subsequent empirical tests. Section 4 explains in detail the construction of dealers' inventory positions. Section 5 presents the empirical study, including a description of the data and filtering procedures, and establishes our main results in cross-sectional tests. Section 6 concludes.

2 A guide through the related literature

Our paper is motivated by theoretical contributions modeling the role of inventories for the supply of liquidity services and their relation to transaction prices. Stoll (1978) introduces a discrete time model of a risk adverse monopolistic dealer who is exposed to return uncertainty on his inventory. Building on this framework, Ho and Stoll (1981) augment the setup by introducing transactions uncertainty in a dynamic optimization problem. A key implication of their model is that a dealer manages his inventory via a certain pricing policy in order to generate an order flow in the desired direction. A crucial ingredient in this framework is that the dealer is exposed to transactions uncertainty by absorbing order imbalances. In turn, this might result in suboptimal inventory positions. As a consequence, the dealer commands a compensation in the form of a bid-ask spread. Ho and Stoll (1983) elaborate on the inventory dynamics under competition. They show that the dealer with the most extreme inventory will quote best bid- or offer prices, allowing him to reduce the inventory position. Furthermore, another important theoretical contribution is given by Amihud and Mendelson (1980) who study the optimal inventory and pricing policy of a risk neutral dealer subject to exogenous inventory limits and transactions uncertainty. Again, they show that under these alternative assumptions a dealer has a preferred inventory position and any deviation from this target is attempted to be offset by a corresponding pricing policy. Grossman and Miller (1988) model liquidity as being determined by supply and demand of immediacy, the desire of an investor to sell earlier instead of at some time in the future.

From an empirical perspective, our paper is related to two broader streams of the literature. First, our paper is related to a number of contributions which study various aspects of the above mentioned theories related to inventories of intermediaries, but mainly in the context of stock markets. For example, Hansch et al. (1998) study the inventory dynamics of specialists on the London Stock Exchange (LSE) and test the implications of Ho and Stoll (1983). They show that inventories of specialists exhibit mean reversion, with reversion rates being nonlinear and increasing in inventory levels. Chordia et al. (2002) and Chordia and Subrahmanyam (2004) analyze the relation between aggregate order imbalances, market liquidity and stock returns, respectively, on the New York Stock Exchange (NYSE). Their analysis reveals that order imbalances increase following overall market declines, and thus, reduce market liquidity. Hendershott and Seasholes (2007) study the joint dynamics of inventories and prices of individual market makers, for a small sample of specialists on the NYSE. They document that specialists are compensated for providing the liquidity service by return reversals, that is, they tend to buy at low and sell at high prices. Moreover, Comerton-Forde et al. (2010) study the role of financing constraints for market liquidity in the spirit of Brunnermeier and Pedersen (2009) by examining trading revenues of specialists' inventory positions on the NYSE. They show that specialists that lose money on their inventories provide less liquidity going forward, with the results being more pronounced for high volatility stocks. A recent contribution is given by Hendershott and Menkveld (2014) who also study the joint dynamics of inventories and prices of NYSE specialists with a focus on the price pressure channel induced by extreme inventories. They estimate inventory reversion rates and quantify the price pressure of specialists induced by extreme inventories within a structural model.

Second, our paper is also related to empirical studies which examine liquidity effects in the US corporate bond market. Important contributions in this field include, e.g., Schultz (2001), Chen et al. (2007), Edwards et al. (2007), Lin et al. (2011), Acharya et al. (2013), Bao et al. (2011), Feldhütter (2012), Friewald et al. (2012) and Dick-Nielsen et al. (2012). These studies explore the cross-sectional properties of liquidity or liquidity risk, respectively, in bond prices. The results reveal that the obtained economic effects are non-negligible in this market, by either employing various methodologies for measuring liquidity or by focusing on cross-sectional differences in liquidity. For example, Bao et al. (2011) and Friewald et al. (2012) show that liquidity measured by common metrics such as, e.g. the Roll (1984) or the Amihud (2002) measure, is deteriorating in credit risk. Dick-Nielsen et al. (2012) further show that bonds get illiquid if a lead underwriter experiences funding issues, as suggested by Brunnermeier and Pedersen (2009). Moreover, Lin et al. (2011) show that liquidity risk on the aggregate market level in the spirit of Pastor and Stambaugh (2003) is a priced risk factor in the bond market, and that bonds with large exposures to this factor trade at lower prices. Recent contributions by Choi and Shachar (2013) study aggregate dealer inventories (the counterpart to aggregate order imbalances) and its implications for the credit default swap (CDS)-bond basis, while Dick-Nielsen (2013) studies the relation of aggregate dealer inventory to liquidity, again measured by common metrics. Both papers document a reduction in aggregate bond inventory during the recent financial crisis by as much as 80% compared to the level of the pre-crisis period.

None of these above mentioned papers, however, studies the role of dealer inventories on the individual bond level for the corresponding prices, and thus, the underlying returns. This lack of analysis is mainly dictated by data limitations. We thus void this gap by adding to the existing literature by explicitly studying inventories of dealers on the individual bond level. This allows us to examine and test several implications of inventory models related to the linkage between bond prices, their underlying returns and inventories. In particular, we elaborate on the liquidity dimensions that are directly related to inventory risk – an aspect which has been missing so far in the current literature. Specifically, our focus is on the cross-sectional properties of dealer inventory risk and its relation to corporate bond returns. Studying these cross-sectional properties of inventory risk is important, as it sheds light onto a much broader question related to the role of limited inventory-carrying capacity of intermediaries, and its effect on transaction prices.

3 A stylized dealer inventory model and its implications

In this section, we use a stylized one-period inventory risk model of a representative dealer to develop our hypotheses and to provide guidance for the subsequent empirical tests. Our simple framework provides the main insights obtained from models following Ho and Stoll (1981) with respect to the relation between dealer inventory risk and market prices. Thus, the presented framework should be understood as a stylized summary of the class of inventory models.[1]

We study a short sighted representative dealer trading in a single bond with mean-variance preferences over final wealth and risk aversion γ. Hence, at time t when considering whether to fill an incoming order, the dealer acts as if his inventory will be liquidated at time $t+1$ at the fundamental value $\mu_{t+1} = \mu_t + \epsilon_{t+1}$ with per period variance given by σ_ϵ^2. Thus, in pricing an order at time t the dealer must take into account the fundamental risk from t to $t+1$, i.e., the dealer faces the risk that public information ϵ_{t+1} about the fundamental value of the bond arrives

[1] The main insights given in our framework regarding the link between inventory risk and market prices are invariant to alternative model specifications, e.g., to pricing policies of dealers under various model setups related to the preferences towards inventory risk, to the time horizon of trading (e.g., one-period, multi-period) as well as to the structure of the dealer market (e.g., representative dealer, competition). We refer to, e.g., Hansch et al. (1998) or Foucault et al. (2013) for further discussions.

during the holding period. At time t, the dealer has cash c_t and a starting inventory of i_t, with $i_t > 0$ indicating a long and $i_t < 0$ indicating a short position in the bond, respectively. The wealth w_t of the dealer is valued at the current market price p_t and is, thus, given by

$$w_t = p_t i_t + c_t. \tag{1}$$

At time t, the dealer must decide the terms at which he is willing to engage in trading as it will directly affect his terminal wealth w_{t+1}. Specifically, in this framework the dealer passively sets the price in a way such that he is indifferent whether to fill an incoming order or not in terms of utility over terminal wealth. To distinguish, we denote the terminal wealth conditional on not trading by

$$w^*_{t+1} = \mu_{t+1} i_t + c_t. \tag{2}$$

However, if the dealer decides to trade one unit $|n_t|$ of the bond, with $n_t = 1$ indicating a public buy and $n_t = -1$ a public sell order, then his inventory and cash positions change accordingly, i.e.

$$i_{t+1} = i_t - n_t \quad \text{and} \quad c_{t+1} = c_t + p_t n_t, \tag{3}$$

respectively, resulting in an end-of-period wealth of

$$w_{t+1} = \mu_{t+1}(i_t - n_t) + c_t + p_t n_t. \tag{4}$$

The dealer's utility of terminal wealth conditional on not trading is given by

$$\begin{aligned} U(w^*_{t+1}) &= \mathbb{E}_t[w_{t+1}] - \frac{\gamma}{2}\mathbb{V}\mathrm{ar}_t[w_{t+1}] \\ &= \mu_t i_t + c_t - \frac{\gamma}{2}\sigma^2_\epsilon i^2_t, \end{aligned} \tag{5}$$

while conditional on trading it is given by

$$U(w_{t+1}) = \mu_t(i_t - n_t) + c_t + p_t n_t - \frac{\gamma}{2}(i_t - n_t)^2\sigma^2_\epsilon. \tag{6}$$

In equating utility of terminal wealth conditional on not trading to conditional on trading, i.e. $U(w^*_{t+1}) = U(w_{t+1})$, and making sure that in equilibrium the dealer supplies the amount n_t

necessary to clear the market, i.e. $n_t = d_t$, with d_t denoting the aggregate investors' demand in the bond, the equilibrium price is given by the expression

$$p_t = \mu_t - \gamma\sigma_\epsilon^2 i_t + \frac{\gamma}{2}\sigma_\epsilon^2 d_t. \tag{7}$$

This equilibrium relation already captures the economic insight that transaction prices will be low when inventories are high and vice versa. The corresponding bid b_t and ask a_t prices are given by

$$b_t = \mu_t - \gamma\sigma_\epsilon^2 i_t - \frac{\gamma}{2}\sigma_\epsilon^2 \qquad \text{and} \qquad a_t = \mu_t - \gamma\sigma_\epsilon^2 i_t + \frac{\gamma}{2}\sigma_\epsilon^2. \tag{8}$$

As a result, the equilibrium midprice m_t reflects the fundamental value of the bond as well as an inventory risk adjustment, in the form of a risk premium $RP \equiv \gamma\sigma_\epsilon^2$, and is given by

$$m(i_t) = \mu_t - \gamma\sigma_\epsilon^2 i_t. \tag{9}$$

This implies that the midprice is inversely related to the current inventory of the dealer in the bond. The slope of the midprice with respect to the inventory is given by the risk premium.

Now, one can easily consider a transformation of this pricing policy into a multi-period setup, in which we need to specify the order flow. Hence, for the ease of interpretation, let us assume that the public order flow is price sensitive. Thus, orders respond to the possibilities of profit and loss given by the dealers' pricing policy. In such an environment, this pricing policy has an intuitive interpretation to reduce the exposure to inventory risk: If the dealer is short in the bond he raises the price above the fundamental value in order to generate public sell orders. On the contrary, if the dealer is long in the bond, he will push the price below the fundamental value in order to generate public buy orders. Therefore, this type of pricing policy implies that the inventory of the dealer will revert back to its long-run mean. In addition, the inventory rebalancing is accompanied by mean reversion in the transaction price of the bond as well.

Cross-sectional implications for bond returns

The transaction price rebound induced by inventory rebalancing affects the underlying returns. Therefore, let us now focus on the cross-sectional relation between dealer inventory risk and returns. Consider two identical bonds L and H at time t with different inventory positions, i.e.

$i_t^L < i_t^H$. Then the derived pricing policy implies

$$m(i_t^H) < m(i_t^L). \tag{10}$$

Thus, the dealer pushes the price of bond H below the one of L. Let us now study the long-run effect on prices implied by the policy. Therefore, consider some point in time $T > t$, long enough in the future such that the inventories of the bonds are expected to mean revert, meaning that $\mathbb{E}_t[i_T^L] = \mathbb{E}_t[i_T^H] = 0$, then

$$\mathbb{E}_t[m(i_T^L)] = \mathbb{E}_t[m(i_T^H)] = \mu_t. \tag{11}$$

As a consequence, if dealer inventory risk is priced in the above sense, any cross-sectional variation in inventories at time t should be related to variation in expected returns. Hence, going long in bond H and short in L should yield a positive expected return $\mathbb{E}_t[r_T]$ proportional to

$$\mathbb{E}_t[r_T] \sim RP \cdot (i_t^H - i_t^L) \; > \; 0. \tag{12}$$

This expected return $\mathbb{E}_t[r_T]$ has intuitive features, i.e., it is increasing in the inventory gap $(i_t^H - i_t^L)$ and the risk premium RP, thus, it is increasing in risk aversion γ and fundamental risk σ_ϵ^2.

4 Inventory construction

Given that our data allows assigning each single transaction to a particular dealer, we can reconstruct bond inventory positions of dealers over time. Therefore, we start with the construction of the inventory series on the individual dealer-bond level. In order to do so, we follow the procedure by Hansch et al. (1998). In particular, let $Q_{i,t}^j$ denote the nominal level of dollar inventory of dealer i in bond j at time t. Further, let $q_{i,s}^j$ denote the corresponding signed transaction volume which is positive when the dealer buys and negative if he sells the bond. In each bond, we consider all transactions, i.e. public as well as interdealer trades. Denote by $K_{i,t}^j$ the number of transactions of dealer i in bond j up to time t indexed by s, then the nominal dollar inventory $Q_{i,t}^j$ is defined by

$$Q_{i,t}^j = Q_{i,0}^j + \sum_{s=1}^{K_{i,t}^j} q_{i,s}^j. \tag{13}$$

Hence, by applying this procedure we construct a time-series of dealer $i's$ inventory in each bond j, in which the dealer supplies liquidity, from the beginning ($t = 0$) to the end of our sample period ($t = T$). We then standardize the inventory by subtracting the sample mean $\bar{Q}_i^j$ and dividing by the sample standard deviation σ_i^j. Therefore, we obtain a standardized inventory $I_{i,t}^j$ of dealer i in bond j at time t defined as

$$I_{i,t}^j = \frac{Q_{i,t}^j - \bar{Q}_i^j}{\sigma_i^j}. \tag{14}$$

This standardization procedure is important for two reasons, one is technical in nature, while the other is economically motivated and a direct implication of the framework presented in Section 3. First, we do not have any information on the initial nominal inventory $Q_{i,0}^j$ of a dealer at the start of the sample period. Hence, from this perspective, demeaning is important since $I_{i,t}^j$ is independent of the initial nominal inventory $Q_{i,0}^j$ by construction (see Hansch et al. (1998) for a detailed derivation). Second, when studying cross-sectional properties of inventories, standardization is important from an economic perspective as well. The pricing policy, and thus, the underlying inventory dynamics depend crucially on the dealers' attitude towards risk, i.e. risk aversion. In this respect, standardization guarantees that inventories are comparable across dealers as it controls for differences in risk appetite. Hence, from an economic perspective, standardization is of first-order importance when relating dealer inventory risk to bond returns, as it captures the notion that several dealers perceive inventory risk in a similar way. This will be crucial in the employed empirical tests, when we study the cross-section of dealer inventory risk and bond returns. In order to see this, note that there is quite some variation across bonds in the number of dealers supplying liquidity to the market, as will become clearer in the subsequent analysis.

Consequently, when studying the cross-section of dealer inventory risk and bond returns, we need a unified measure of inventory risk in a bond j across dealers, who supply liquidity in this particular bond to the market. Thus, let N_t^j denote the number of dealers supplying liquidity in bond j at time t. We then calculate our inventory measure I_t^j for bond j at time t as follows

$$I_t^j = \frac{1}{N_t^j} \sum_i^{N_t^j} I_{i,t}^j. \tag{15}$$

This measure represents the inventory position of a representative dealer in a given bond and, thus, allows us to examine the cross-sectional relation between bond inventories and bond returns.

5 Empirical analysis

5.1 Data description

To study the relation between inventory and bond returns we rely on several data sources. We obtain detailed transaction data of the US corporate bond market between January 2003 and December 2013 from TRACE which is maintained by FINRA. The data comprise transaction prices and volumes, trade direction and the exact date and time of the trade. An important difference between our proprietary dataset and the publicly available TRACE data is that our sample allows us to link each transaction to a particular dealer. However, the exact dealer identity is coded, and hence concealed. We also have information on whether a transaction is a customer or an interdealer trade. Therefore, using the dealer identities and the transaction volumes, we can reconstruct dealers' inventory positions over our sample period (see Section 4).

The reporting of all transactions to TRACE is obligatory for all broker-dealers trading in the US corporate bond market and must be conducted within a time frame of 15 minutes following a trade execution. The detailed rules for reporting are set by the Securities and Exchange Commission (SEC). However, a cross comparison with other OTC markets suggests that TRACE is rather unique with respect to its reporting standards and comprehensiveness. For example, in the CDS market, detailed transaction information must usually be obtained either from an individual dealers' trading book, with the potential disadvantage of having only a very limited view on the market, or even worse, by relying on quoted prices.

We account for reporting errors using standard filtering procedures commonly used for the TRACE transaction data (see, e.g., Friewald et al. (2012) and Dick-Nielsen et al. (2012)).[2] Furthermore, we also account for give-up and locked-in trades to correctly assign each transaction to the actual dealers behind the trade.[3] We merge our transaction data with bond specific information such as maturity, coupon, amount issued and credit ratings (Fitch, Moody's and Standard and Poor's) which we obtain from the Mergent Fixed Income Securities Database (FISD). As a further bond characteristic, we compute the round-trip cost measure as a proxy for a bonds' liquidity. We follow Goldstein et al. (2007) and define the round-trip cost as the price difference,

[2] These include (i) same-day trade corrections and cancellations and (ii) trade reversals which refer to corrections and cancellations conducted not on the trading day but thereafter.

[3] In a *give-up trade* one party reports on behalf of another party who has reporting responsibility. In a *locked-in trade* one party is responsible to report for both sides of a trade in a single report, thus satisfying both sides' reporting requirements. This locked-in trade can either refer to a transaction between the reporting party and its correspondent (single locked-in) or a transaction occurring between two correspondents (two-sided locked-in).

for a given dealer, between buying (selling) a certain amount of a bond and selling (buying) the same amount of this bond, within a particular time period, e.g., one day. Note that a round-trip may consist of a series of buy followed by a series of sell transactions, as long as both the total buy and sell volumes match. Finally, following the common literature related to corporate bonds we exclude bonds that are convertible, putable, privately placed and have variable coupons.

For the empirical asset pricing tests we use the standard risk factors, i.e. the market (MKTF), size (SMB), book-to-market (HML), and momentum factor (UMD) which we retrieve from Kenneth French's website.[4] Furthermore, we use the Pastor and Stambaugh (2003) illiquidity factor (PS) obtained from WRDS, two corporate bond indices (investment and speculative-grade) from FINRA and a long-term government bond index from Bloomberg. We then calculate the default premium (DEF) as the difference between the return on the investment-grade and the 10-year government bond index and the term premium (TERM) as the difference between 10-year government bond index and the one-month Treasury bill rate, respectively.

To begin with, we focus on the 30 most active dealers with respect to trading activity to make our empirical analysis manageable. This leaves us with a dataset covering 38 million trades in $43,000$ bonds. These 30 dealers account for approximately 60% of the overall transactions and more than 90% of all bonds traded in the corporate bond market. Furthermore, we restrain ourselves on a weekly sampling frequency, i.e. we use end-of-week observations of inventories and compute weekly market prices of each bond by averaging all transaction prices that have occurred during a week. Given the trade volumes and dealer identities we then compute a weekly time-series of nominal inventories for each dealer in a given bond. We then standardize these inventories in accordance with the procedure described in Section 4, which results in inventories $I_{i,t}^{j}$ on the dealer-bond level. Our inventory measure I_t^j for bond j that we use throughout the empirical analysis is obtained by averaging the inventories over all dealer i at time t.

Table 1 provides detailed cross-sectional summary statistics on the underlying bonds used in our study. All variables exhibit considerable cross-sectional variation. For example, the average amount issued is around \$218 million with a standard deviation of \$420 million. The cost for a round-trip transaction is on average 74 bp, with a standard deviation of around 59 bp. Particularly interesting, as additional information available to our dataset, is the average number of dealers supplying liquidity in a given bond to the market, which is around 10. However, there is substantial

[4] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french.

cross-sectional variation as indicated by the standard deviation of 8. Moreover, our inventory measure I_t^j exhibits strong dispersion of 0.67 around the mean of 0.19. The average estimate of I_t^j indicates that, cross-sectional over our sample period, dealers are slightly long in the bonds.

5.2 Inventory changes and contemporaneous returns

The implied pricing policy of our stylized inventory model presented in Section 3 suggets that changes in inventories and contemporaneous bond returns exhibit a negative relation and that inventories and transaction prices revert back to their long-run mean. Therefore, we test the first implication concerning inventory rebalancing by the following regression model that we run for each dealer i in bond j:

$$\Delta I_{i,t}^j = \alpha_i^j + \beta_i^j I_{i,t-1}^j + \epsilon_{i,t}^j \tag{16}$$

We find that the median inventory *half-life* given by $h_i^j = \log(2)/\log|1-\beta_i^j|$ is about 10 weeks. Hence, it follows that, on average, it takes the dealer roughly 2.5 months to reduce a bonds' deviation from its desired long-run target inventory by half. The estimated half-life is in huge contrast to estimates usually obtained for equity markets where inventories revert much faster to their mean, see e.g. Hendershott and Menkveld (2014). Moreover, we also find that for the US corporate bond market the mean inventory half-life exhibits considerable variation across dealers and bonds with the 25% (75%) quantile being 5 (22) weeks. These figures highlight that dealers are stuck for quite some time with bonds in their inventories which suggests that inventory concerns are of fundamental relevance in the corporate bond market.

Furthermore, to test whether dealers rely on corresponding pricing policies to bring inventories back to their long-run target, we regress inventory changes on contemporaneous returns, again for each dealer and bond. In this analysis, the results reveal a significant and negative average coefficient of -0.03. Thus, from an economic perspective, a one standard deviation decrease in the inventory position of a dealer in a particular bond, is associated with a statistically significant positive realized return of 3 bp per week. These results highlight that inventory changes and contemporaneous returns are in fact negatively related in our data.

In summary, these figures confirm that due to the overall illiquidity in the corporate bond market dealer inventories, and the potential risk inherent in these positions, play a central role for prices and suggest the relevance of a cross-sectional study that links bond inventories to returns.

5.3 Portfolio sorts

In this section we focus on the cross-sectional relation between dealer inventory risk and expected bond returns. More specifically, we employ standard asset pricing tests which allow us to identify whether inventory risk is related to subsequent realized returns. Again, the economic rationale underlying our empirical tests is guided by the idea of inventory models that dealers reduce their exposure to inventory risk by relying on certain pricing policies, leading to subsequent price rebounds going forward (see Section 3). Consequently, if inventory risk is priced, any cross-sectional variation in bond inventories should be related to returns. Therefore, we proceed in the following manner: At the end of each week t we sort bonds into quintile (decile) portfolios based on our inventory measure I_t^j given in Equation 15. P1 represents the portfolio of bonds with the lowest quintile (decile) value of I_t^j, while P5 (P10) represents bonds with the highest. We construct long-short portfolios by buying P5 (P10) and selling P1. For each portfolio we calculate equally weighted returns. In our empirical analysis, we consider three sample periods, i.e. the full period (January 2003 to December 2013), the pre-crisis period (January 2003 to June 2007), and, the crisis period (July 2007 to June 2010). The investigation of sub-samples allows us to verify whether our results are solely driven by the crisis period.

5.3.1 Portfolio returns

Before turning to the asset pricing tests, we first study the patterns of raw returns of the portfolios in order to grasp whether sorting bonds based on I_t^j is associated with variation in returns per se. Figure 1 shows the average returns of the quintile portfolios P1 to P5. Panel A provides the returns for the full period. Consistent with the notion of inventory risk, the increase in I_t^j from -0.40 in P1 to 0.57 in P5 is associated with a monotone increase in returns from 0 bp to 18 bp per week. Panel B gives the corresponding returns for the pre-crisis period. Again, bond returns increase between P1 to P5 from around -3 bp to 17 bp per week while the corresponding inventory measure I_t^j ranges between -0.47 in P1 and 0.59 in P5. Thus, in the pre-crisis period our results of raw returns already indicate that returns tend to be negative when inventory is negative, and vice versa, which is consistent with the idea of inventory models. We also find, in relative terms, that dealers are more net short in bonds implying that inventories are below the long-run target, compared to the full period. Finally, Panel C provides the raw returns for the crisis period. The results reveal that by moving from P1 to P5 returns increase monotonically from 3 bp to 24 bp per week. Thus, during the crisis period the return differential between P5 and P1 widens, although the variation in I_t^j across the portfolios shrinks from -0.37 in P1 to 0.52 in P5. This result indicates that the higher return differential is likely to be driven by an increase in fundamental risk.

Figure 2 gives the corresponding unconditional returns for the decile portfolios for the full (Panel A), the pre-crisis (Panel B), and the crisis period (Panel C). Generally, in line with theoretical frameworks, we find that the return differentials between the lower and upper decile portfolios are larger, on average, compared to the results of the quintile portfolios. Moreover, the overall finding obtained in the case of the quintile portfolios is confirmed. Raw returns increase by moving from P1 to P10, e.g., for the full period from 0 bp to 26 bp per week. Again, we find that especially in the case of the pre-crisis period, returns of the lower portfolios are negative while for the upper portfolios they are positive, i.e. returns range from -2 bp in P1 to 26 bp in P10.

5.3.2 Portfolio characteristics

The above discussion reveals that inventories and returns share some common cross-sectional variation. In order to study whether the performance of the portfolios is attributable to bond specific characteristics, we examine in detail the structure of the underlying bonds in the portfolios. Table 2 gives the summary statistics on the characteristics of the quintile portfolios for the full (Panel A), the pre-crisis (Panel B) as well as the crisis period (Panel C). The characteristics comprise our inventory measure I_t^j, amount issued, coupon, time-to-maturity, bond age, credit rating, round-trip cost, the number of dealers supplying liquidity in a bond to the market as well as the raw portfolio returns. For the discussion below we focus on the full period, since the results are qualitatively very similar to the two sub-periods. Note that each of our quintile portfolios comprises on average $1,660$ bonds (not reported in the Table). Focusing on Panel A, and following the discussion above, we see that I_t^j increases from -0.40 to 0.57 as we move from P1 to P5, which is accompanied by an increase in raw returns. A t-test indicates that raw returns are significantly positive in the portfolios P4 and P5.

Generally, there is no clear evidence that the various bond characteristics associated with different risk aspects could economically explain the return patterns across our portfolios. Specifically, the average amount issued exhibits an inverse U-shaped pattern with the lowest value of $282 million in P5 and the highest value of $392 million in P4. Credit risk indicators such as the coupon and the ratings are nearly constant across the portfolios, i.e., the average coupon is around 6% of face value, while the average credit rating is around 8 which is considered as investment-grade and corresponds to a BBB+ rating in the notion of Standard and Poor's. Thus, the variation in returns across the portfolios is not driven by credit risk. The time-to-maturity of the bonds decreases slightly monotone from 9.4 years in P1 to 7.6 years in P5, while the average age of the bonds exhibits an inverse U-shaped pattern across the portfolios. Here, the lowest value of 4.0 years is given in P1, and, the highest value of 5.2 years is given in P4. By examining the round-trip costs, the results reveal a monotone decrease from 86 bp in P1 to 60 bp in P5. In this respect, the decreasing pattern in the round-trip costs is important from an economic perspective, as it clearly demonstrates that the relatively high raw returns in P5 are not attributable to illiquid bonds, and hence, cannot be explained by high transaction costs per se. If this was the case, the large returns could potentially be the result of an effect as discussed by Amihud and Mendelson (1986), in which assets which are characterized by high transaction costs need to offer higher returns to compensate investors for holding these assets. Finally, when studying the number of dealers supplying liquidity in a bond, we see that this characteristic exhibits an inverse U-shaped pattern across the portfolios. The smallest number of around 14 to 15 dealers is given in P1 and P5, while the highest number of around 18 to 19 is given in P3 and P4. The economic role underlying the characteristic of dealer coverage is risk-sharing, hence, inventory risk could differ depending on the fraction of dealers supplying liquidity in a given bond. In turn, this could affect the premium associated with inventory risk, and thus, the underlying bond returns (see Section 5.4.1 for further discussions). Hence, the inverse U-shaped pattern indicates that the high raw returns in P5 are not driven by this characteristic.

Given the discussion above, the results reveal that there is no economic relation between the characteristics of the underlying bonds and the obtained portfolio returns. As far as the long-short portfolio is concerned, where we buy P5 and sell P1, we find that bonds in P1 tend to be smaller, have relatively longer time-to-maturities, and have somewhat higher round-trip costs compared to the overall cross-section. Bonds in P5 also tend to be smaller, have relatively shorter time-to-maturities but are characterized by smaller round-trip costs. Thus, an economic justification of the return patterns described in the previous section cannot be based on differences in characteristics attributable to credit and liquidity concerns. Given the rather low overall dispersion of bond characteristics across portfolios, our inventory measure I_t^j obviously conveys information for bond returns different than the above described characteristics.

For completeness, Table 3 presents the characteristics of the decile portfolios, again for the sub-periods given by the full (Panel A), the pre-crisis (Panel B) and the crisis period (Panel C). In general, the results are very similar to the obtained patterns for quintile portfolios. Apparently, the deciles allow for a more refined view on the variation in bond characteristics across portfolios. Due to the similarities, we focus on the most interesting additional insights, and concentrate the discussion on the full sample period given in Panel A. On average, the decile portfolios comprise a cross-section of 830 bonds (not reported in the Table). By construction, the gap in I_t^j between the lower and upper portfolios widens from -0.54 in P1 to 0.88 in P10. We find that raw returns are significantly positive in portfolios P7 to P10. Again, the amount issued exhibits an inverse U-shaped pattern, with the lowest values of \$198 million in P10 and \$264 million in P1, respectively. This result provides some indication that variation in bond size could provide additional insights for portfolio returns, thus, we will particularly elaborate on the role of this characteristic in the subsequent tests. Portfolios share almost identical characteristics in terms of the coupon and credit rating. The time-to-maturity and the round-trip costs are again slightly decreasing from P1 to P10. Furthermore, similar to the quintile results, the number of dealers supplying liquidity in a bond exhibits an inverse U-shaped pattern across the portfolios, with the smallest number of around 12 in P1 and P10, and the highest number of around 19 in P6 and P7. In Section 5.4.1 we will examine the economic role of inventory risk-sharing for the underlying bond returns.

In summary, we conclude that the bond characteristics are very similar across the quintile and decile portfolios. Most importantly, from an economic perspective, the discussion shows that sorting bonds into portfolios based on our inventory measure I_t^j conveys additional information for corporate bond returns compared to the above described characteristics.

5.3.3 Asset pricing tests

In this section we employ asset pricing tests in order to investigate whether the cross-section of inventory risk is related to corporate bond returns. We rely on a linear factor model that includes standard risk factors commonly used in the corporate bond literature, see e.g., Lin et al. (2011). We regress the returns r_t of our quintile and decile long-short portfolios against contemporaneous returns of factor mimicking portfolios. Specifically, we adopt the following factor model

$$\begin{aligned} r_t = \boldsymbol{\alpha} + &\boldsymbol{\beta_1} \cdot (\text{MKTF})_t + \boldsymbol{\beta_2} \cdot (\text{SMB})_t + \boldsymbol{\beta_3} \cdot (\text{HML})_t + \boldsymbol{\beta_4} \cdot (\text{UMD})_t \\ &+ \boldsymbol{\beta_5} \cdot (\text{TERM})_t + \boldsymbol{\beta_6} \cdot (\text{DEF})_t + \boldsymbol{\beta_7} \cdot (\text{PS})_t + e_t \end{aligned} \tag{17}$$

where MKTF is the market, SMB the size, HML the book-to-market and UMD the momentum factor. TERM refers to the term, DEF to the default and PS to the Pastor and Stambaugh (2003) illiquidity factor. There are important economic reasons to include equity market factors (MKTF, SMB, HML, and UMD) in the bond pricing model. First, bonds and stocks are claims on the value of the same underlying assets, thus, equity market factors should share common variation in equity and bond returns. Second, expected default losses of corporate bonds change with equity value, i.e., as the value of equity appreciates the underlying default risk of the firm decreases which induces a structural component affecting corporate bond returns. In addition, following the literature, we include bond market factors (TERM, DEF, and PS) in the pricing model. Fama and French (1993) study common factors in corporate bonds. Their results reveal that term and default factors capture most of the variation in corporate bond returns. Moreover, in line with studies which examine liquidity risk of corporate bonds, e.g., Lin et al. (2011) or Acharya et al. (2013), we include a liquidity factor to capture cross-sectional variation in exposure to liquidity.

Table 4 presents the results for the long-short quintile portfolios. We estimate the model for different sample periods separately, i.e., the full (Models 1 to 4), the pre-crisis (Models 5 to 8), and the crisis period (Models 9 to 12). For each sub-period we use four different model specifications. First, we regress returns of our long-short portfolio on a constant. Second, we regress returns on a constant and common equity market factors. Third, the model specification comprises a constant and bond market factors, and fourth, we regress the returns on all our factors. We find that the regression alphas of the different specifications within each sample period are very stable. Thus, for the interpretation of our results we focus on the full specification as given in Equation 17. Consistent with the implications of inventory models for bond returns as described in Section 3, we obtain a positive risk-adjusted return of 18 bp per week (Model 4). Hence, cross-sectional variation in inventory risk, as perceived by the measure I_t^j, captures variation in bond returns. The result is robust to the different sample periods. However, a detailed examination of the sub-periods reveals interesting economic insights. In particular, in the pre-crisis period the abnormal return is 20 bp per week (Model 8) while the alpha increases to 22 bp per week when we focus on the crisis period (Model 12). Thus, this result indicates that risk-adjusted returns of the long-short portfolio are higher during the crisis period, i.e., a period in which fundamental risk is likely to be high. This is in accordance with the insights given by inventory models which imply that fundamental risk, i.e., the risk that asset values unexpectedly move, is a key determinant of the inventory risk concern. Furthermore, note that, the higher alpha in the crisis period is not a result of larger cross-sectional variation in our inventory measure I_t^j, as discussed in Section 5.3.

We now focus on the results of the return differential based on decile portfolios. Table 5 provides the results for the different model specifications. Following the above procedure, we gradually augment the models by the various factors within the three different sample periods given by the full (Models 1 to 4), the pre-crisis (Models 5 to 8) and the crisis period (Models 9 to 12). To begin with, an important economic insight is that risk-adjusted returns are higher for decile compared to the quintile portfolios. As a result, consistent with the economic intuition on the relation between inventory risk and returns, more dispersed cross-sectional variation in I_t^j is associated with an increase in risk-adjusted returns. Moreover, within each sub-period the obtained alphas are basically invariant to conditioning on different factors. Thus, for the interpretation, we again restrict ourselves to the results of the complete factor model. In particular, over the full period we obtain a risk-adjusted return of 27 bp per week. We find that the difference between the alphas of the pre-crisis period (29 bp) and the crisis period (34 bp) is particularly pronounced. Again, this finding is supported by the underlying economic rationale presented earlier (see Equation 12), and, is attributable to an increase in fundamental risk. Since, by construction, I_t^j is more dispersed across the decile compared to the quintile portfolios, any given increase in fundamental risk induces a more pronounced return pattern for the decile portfolios.

In summary, our cross-sectional findings provide strong support for the implications of inventory models in which dealers reduce the exposure to inventory risk by corresponding pricing policies, leading to subsequent price rebounds. Thus, these results highlight the importance of the effect of limited risk-bearing capacity of intermediaries on transaction prices. In order to put the obtained economic effects into relation to other common return patterns in the US corporate bond market, we compute cumulative returns following our long-short inventory strategy and compare these patterns to the cumulative excess returns (over Treasury bill) of investment and speculative-grade bond indices. Thus, we can benchmark the economic forces induced by inventory risk.

The corresponding return dynamics are shown in Figure 3. The cumulative excess return of the investment-grade index over the period from 2003 to 2013 is around 45%, while the corresponding return for the speculative-grade index is approximately 75%. However, the cumulative return of the inventory portfolio over the same period amounts to around 100% (145%) based on the quintile (decile) portfolios. In addition, the return dynamics of the inventory strategy is very stable over the sample period with an annualized volatility of around 1%. On the contrary, the annualized volatilities of the investment-grade (speculative-grade) indices are around 5% (13%). This provides further evidence that the results of the long-short portfolios are not driven by systematic differences in the bonds underlying P5 (P10) and P1. Overall, the results highlight the economic effects induced by inventory risk concerns, and clearly demonstrate that the uncovered forces are non-negligible compared to other common return dynamics in the corporate bond market.

5.4 Sub-segments

In this section we focus on important sub-segments of the US corporate bond market to obtain additional economic insights into the cross-sectional relation between dealer inventory and bond returns. In particular, we examine differences in (i) bonds in which a low number of dealers (low dealer coverage) vs. bonds in which a high number of dealers (high dealer coverage) supply liquidity to the market, (ii) small vs. large bonds, (iii) non-financial vs. financial bonds and (iv) investment vs. speculative-grade bonds. In the following study of the sub-segments, we present results for the return differential based on the quintile portfolios.

5.4.1 Low vs. high dealer coverage

In the US corporate bond market there is some dispersion in the number of dealers supplying liquidity in a particular bond to the market. Dealer coverage of a bond in the market might have implications on the pricing policy described in Section 3, and thus, affects the cross-sectional relation of inventory risk and bond returns. In order to provide some intuition, consider the following economic rationale: Suppose that instead of one dealer, several dealers supply liquidity in a particular bond to the market and, by doing so, share inventory risk. For example, from an institutional point of view, inventory risk-sharing could be the result of an active interdealer market in a given bond.[5] The theoretical implication would be that the risk premium RP associated with

[5] We refer to, e.g., Hansch et al. (1998) or Foucault et al. (2013) for further discussions on the role of an active interdealer market and its implications for inventory risk.

inventory risk (given in Equation 9) would be diminished, as it would decrease the collective risk aversion of the dealers, and would even disappear in the limit, i.e., when a large number of dealers share the inventory risk in a particular bond. Therefore, the cross-sectional relation between dealer inventory risk and corporate bond returns should be more pronounced for bonds in which a low number of dealers (low dealer coverage) compared to bonds in which a high number of dealers (high dealer coverage) supply liquidity to outside investors. Thus, we should obtain higher risk-adjusted returns for a long-short portfolio of bonds with low compared to high dealer coverage.

As a result, in order to obtain further insights into the cross-sectional return implications of inventory risk induced by dealer coverage, we split the full sample of bonds into two sub-samples depending on the number of dealers providing liquidity to the bond. The sample with low dealer coverage is characterized by bonds where less than eight dealers supply liquidity, while the sample with high dealer coverage includes bonds with eight or more dealers supplying liquidity in these bonds. This cutoff-level for the assignment into low vs. high dealer coverage is based on the cross-sectional median given in Table 1. The results for the risk-adjusted return differential based on quintile portfolios for the full model specification given in Equation 17 are presented in Table 6. We estimate the model for the low and high dealer coverage segment and for the three sample periods, i.e., the full, the pre-crisis, and the crisis period. In accordance with the above described economic forces, we find that, throughout all sub-periods, risk-adjusted returns of the segment of bonds with low dealer coverage are higher compared to the segment with high dealer coverage. In quantitative terms, the return differential is 23 bp per week for the low compared to 17 bp per week for the segment of high dealer coverage when considering the full sample period. The corresponding figures for the pre-crisis are 26 bp (19 bp) for the segment of low (high) dealer coverage and 27 bp (21 bp) for the crisis period, respectively.

In summary, the results clearly demonstrate that inventory concerns are less pronounced for those bonds in which a relatively high fraction of dealers supply liquidity to the market. This finding is consistent with the idea of risk-sharing, which ultimately leads to a reduction in the premium associated with inventory risk, and consequently in the obtained returns. In general, this has interesting empirical implications as well. Specifically, we would expect similar cross-sectional return implications for individual bonds which exhibit characteristics that are likely to be associated with dealer coverage of these bonds in the market. Therefore, in what follows, we will further elaborate on this issue in the context of bond size.

5.4.2 Small vs. large bonds

The discussion above suggests examining the economic link between the fraction of dealers supplying liquidity in a bond (dealer coverage) and the corresponding bond characteristics. The analysis of the portfolio characteristics in Section 5.3 reveals that both, the amount issued and the number of dealers supplying liquidity exhibit inverse U-shaped patterns across the portfolios. Therefore, this might suggest that these two variables are likely to share some common variation. Indeed, we find that the overall cross-sectional correlation between the number of dealers supplying liquidity in a bond and the amount issued is 0.53, which manifests the interdependence between these two characteristics. Hence, smaller bonds tend to be traded by a lower fraction of dealers in the market, implying low dealer coverage, and vice versa. Thus, the size of the bond is likely to be a specific characteristic exhibiting variation in inventory risk.

As a consequence, this finding suggests that it is worthwhile to elaborate on the role of the bond size for portfolio returns. Hence, in order to do so, we split the sample into small and large bonds. Small (large) bonds have an amount issued of less (equal or more) than $25 million. Again, the cutoff-level for the splitting is based on the cross-sectional median (see Table 1). In the cross-sectional tests, we proceed in the same manner as for the analysis of the sub-segments defined by dealer coverage (see Section 5.4.1). Thus, we employ the full model specification and, again, consider the three different sample periods (full, pre-crisis, crisis period). Table 7 presents the results for the sub-segment related to bond size. Overall, we obtain significant and positive risk-adjusted returns for both, small and large bonds throughout all three sample periods. Consequently, this implies, as suggested by the discussion related to the portfolio characteristics, that the return differential between P5 and P1 is not driven by bond size per se. Specifically, over the full period, we find an alpha of 38 bp for small bonds, while the corresponding alpha for large bonds is 7 bp per week. Furthermore, when focusing on the pre-crisis period the alpha is 44 bp for small and 8 bp per week for large bonds, respectively. In the crisis period, the return differential of small (large) bonds is 40 bp (10 bp) per week.

To sum up, these results suggest that risk-adjusted returns of the long-short portfolio are higher for small compared to large bonds. This was to be expected given the underlying findings concerning the evident economic association between the number of dealers supplying liquidity in a bond and the corresponding size of the bond.

5.4.3 Non-financial vs. financial bonds

The previous findings highlight the necessity of studying additional sub-segments of the US corporate bond market which are likely to exhibit variation in inventory risk due to, e.g., differences in the organizational structure. Typically, institutional differences would also manifest themselves in the characteristics of the corresponding bond indentures. In this respect, an important sub-segment of the corporate bond market is given by the overall industry affiliation of the firms underlying the bonds, i.e., non-financial and financial bonds. Characteristics of non-financial bonds are typically quite diverse from those of financial bonds. In turn, this could naturally feed back into inventory concerns of dealers, i.e. the perceived inventory risk inherent in these bonds is different, which will affect the cross-sectional relation between inventories and returns.

Therefore, in order to provide some insights into common differences between non-financial and financial bonds, we elaborate on their characteristics in more detail. For example, non-financial bonds tend to be substantially larger in size than financial bonds, i.e., the average size of a non-financial bond in our sample is \$350 million (median of \$250 million), while it is \$131 million (median of \$7 million) of financial bonds. Given this large difference in bond size, one would expect similar variation in the fraction of dealers supplying liquidity in a bond, as a result of the strong economic tie between these two characteristics, as discussed in Section 5.4.2. Indeed, a novel insight which we obtain from our dataset is that liquidity for non-financial bonds seems to be supplied by a higher fraction of dealers compared to financial bonds. Specifically, on average 12 dealers (median of 11) trade in a non-financial bond per week compared to 8 dealers (median of 6) for a financial bond. Moreover, on average, a non-financial bond tends to have a longer time-to-maturity of around 7.5 years (median of 4.9 years) compared to a financial bond with 5.8 years (median of 3.0 years). Similar differences are evident for the coupon and the credit rating. For example, the average coupon of a non-financial bond (7.5% of face value) is higher compared to that of a financial bond (4.3% of face value). In addition, the average creditworthiness of a non-financial bond as assessed by the credit rating is about 10, which corresponds to, e.g., BBB− in the rating framework of Standard and Poor's. Thus, the average non-financial bond is right at the edge between being categorized into either investment or speculative-grade. In contrast, the average credit rating of a financial bond is much better with around 6.2, which corresponds to a A rating in the framework of Standard and Poor's.

Clearly, these general differences in bond characteristics inevitably suggest studying the cross-section of dealer inventory risk and bond returns separately for non-financial and financial bonds. Therefore, in order to examine whether the previously obtained findings regarding the risk-adjusted returns of the long-short portfolio are consistently observable across non-financial and financial bonds, we split the sample into these two segments. We then estimate the full model specification given in Equation 17 separately for non-financial and financial bonds, and for the three different sample periods (full, pre-crisis, crisis period). Table 8 presents the results. In accordance with the previous findings, we consistently obtain positive risk-adjusted returns for non-financial and financial bonds throughout all sample periods. Thus, the overall cross-sectional linkage between inventory risk and returns is not driven by one of these two sub-segments per se. Interestingly, risk-adjusted returns of non-financial bonds are smaller compared to financial bonds, i.e., over the full period the alpha is 7 bp per week for the former while it is 27 bp for the latter sub-segment. This difference of around 20 bp per week between the alphas of non-financial and financial bonds is also evident in the pre-crisis and the crisis period.

In general, when recapitulating these findings they are consistent with the insights obtained from the previous analysis of the sub-segments defined by dealer coverage and size. Specifically, the inventory effect is not just prevalent in the sub-segment of bonds with high dealer coverage and large bonds but also in the sub-segment of non-financial bonds. The reason is that non-financial bonds are tilted towards high dealer coverage and large bonds. Moreover, the relevance of these sub-segments seems to outweigh other characteristics which might also affect inventory risk such as, e.g., credit risk as captured by credit ratings. In summary, the cross-sectional relation between inventory risk and bond returns is robust to the sub-segment of non-financial and financial bonds, and exhibits interesting variation across these two groups attributable to the characteristics of the underlying bonds.

5.4.4 Investment vs. speculative-grade bonds

In this section, we further elaborate on another important sub-segment of the corporate bond market, i.e. creditworthiness of the underlying bonds. In particular, from an institutional perspective, bonds are typically classified into either being investment or speculative-grade, depending on their credit ratings. The cutoff for classification is given by a rating of around 10, which corresponds to a BBB− (in the notion of Standard and Poor's). In order to examine the variation in inventory risk across these two groups, we split the sample accordingly. We start with a discussion of the differences in bond characteristics between the sub-segments of investment and speculative-grade bonds. This gives some guidance for comparing these two groups with respect to the cross-sectional link between inventory risk and returns, and provides intuition for the interpretation of the results. To begin with, on average, investment-grade bonds are smaller in size with a value of $218 million (median of $19 million) compared to speculative-grade bonds with a value of $260 million (median of $160 million). This size differential also manifests itself in the fraction of dealers supplying liquidity in a bond, which is slightly lower for investment-grade bonds. The corresponding figures show that, on average, 11 dealers (median of 9) compared to 12 dealers (median of 11) trade in investment and speculative-grade bonds, respectively. Furthermore, when focusing on the average time-to-maturity, we find only a marginal difference between investment-grade bonds with a time-to-maturity of 7.2 years (median of 4.2 years) compared to speculative-grade bonds with 5.6 years (median of 4.3 years). Obviously, there are differences in the average coupon and credit rating, both of which are lower for investment compared to speculative-grade bonds. For example, the average credit rating of investment-grade bonds is 6 (corresponding to A) compared to 14 (corresponding to B+) for speculative-grade bonds.

In general, this comparison of the characteristics between investment and speculative-grade bonds demonstrates strong similarities to the discussion on the differences between non-financial and financial bonds. Indeed, our analysis reveals that the segment of investment-grade bonds is slightly tilted towards financial bonds, while in contrast, speculative-grade bonds are more tilted towards non-financial bonds. As a consequence, we expect similar cross-sectional effects regarding the linkage between inventory risk and returns within the sub-segment of investment and speculative-grade bonds compared to the sub-segment of non-financial and financial bonds.

We now focus on the cross-sectional analysis and estimate the full model specification given by Equation 17 separately for investment and speculative-grade bonds and for the three sample periods (full, pre-crisis, crisis period). The results are summarized in Table 9. Overall, we obtain positive and significant risk-adjusted returns for both sub-segments and for all our sample periods. Therefore, we find that the results are not driven by the degree of creditworthiness of the bonds. Moreover, as indicated by the discussion on the portfolio characteristics, the return differential is higher for investment compared to speculative-grade bonds, confirming the above conjecture. For example, over the full period we obtain an alpha of 19 bp (12 bp) per week in the case of investment-grade (speculative-grade) bonds. The corresponding figures in the pre-crisis period are 23 bp and 11 bp per week for investment and speculative-grade bonds, respectively. Interestingly, in the crisis period the alpha of investment-grade bonds slightly decreases to 21 bp, while in contrast, the alpha of speculative-grade bonds increases to 22 bp. This result might be triggered by three effects. First, one possible explanation might be a so-called flight-to-quality phenomenon, whereby investors rebalance their portfolios towards high creditworthy instruments, thus, the increased demand of investors diminishes dealers long positions. In turn, this narrows the variation in I_t^j within the sub-segment of investment-grade bonds, leading to a lower risk-adjusted return. Second, especially during the crisis period, several financial bonds were downgraded to speculative-grade, which in combination with the previous findings related to financial bonds, leads to a larger alpha. Third, changes in the risk perception of speculative-grade bonds by dealers might increase the risk aversion, leading to an increased inventory risk premium RP.

In summary, the results clearly demonstrate that inventory concerns are also present across investment and speculative-grade bonds, and confirm the overall obtained findings regarding the cross-sectional relation between inventory risk and corporate bond returns.

6 Conclusion

Guided by inventory models in the spirit of Ho and Stoll (1981), we examine the role of inventories and its effects on US corporate bond returns over the time period from 2003 to 2013, based on a complete set of transactions data obtained from FINRA. Specifically, these models suggest that dealers with extreme inventory positions rely on pricing policies in which they are willing to trade at prices different from fundamentals, in order to reduce their inventory risk exposures. Hence, extreme inventory positions of dealers affect transaction prices and, thus, the subsequent realized returns.

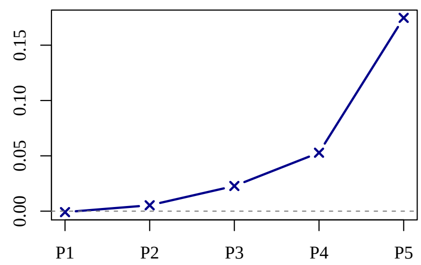
We study the cross-sectional asset pricing implications of inventory models. In particular, we examine, for the first time, individual inventories of a very large cross-section of corporate bonds of representative dealers by reconstructing inventory positions over time. This allows us to relate corporate bond inventories to prices and, thus, to study the role of inventory risk for subsequent realized returns by employing a large cross-section of bonds.

We provide three important contributions. First, in order to elaborate on the relevance of inventory risk in the bond market, we provide insights into the dynamics of bond inventories on the dealer level. For example, we find that the average speed of mean reversion, i.e., half-life of bond inventories is rather long at about 10 weeks. This is particularly harmful in the notion of inventory risk, as it exposes a dealer for a substantial amount of time to fundamental risk – a key determinant of the inventory risk concern. Second, having quantified the dynamic nature of bond inventories, we turn to the cross-sectional relation between extreme inventories – which expose dealers to inventory risk – and bond returns. We find that bonds held in risky inventories exhibit abnormal returns, conditioning on common risk factors. Guided by a simple model, we establish this result by a long-short portfolio based on inventory holdings in individual bonds of a representative dealer. Consistent with the underlying economic mechanism of inventory models, the long-short quintile (decile) portfolio earns a significant positive risk-adjusted return of 18 bp (27 bp) per week. The results are robust to different sample periods, i.e., the full, the pre-crisis, and the crisis period. Moreover, also in accordance with economic intuition, the uncovered effect is more pronounced during the crisis. As a third contribution, we elaborate on the relation between inventory risk and bond returns for different sub-segments of the corporate bond market defined by dealer coverage, bond size, industry classification, and credit quality. Overall, the results are robust to these sub-segments, and highlight the importance of inventory risk-sharing. For example, risk-adjusted returns of our portfolios are lower for bonds in which a relatively high fraction of dealers supply liquidity to the market.

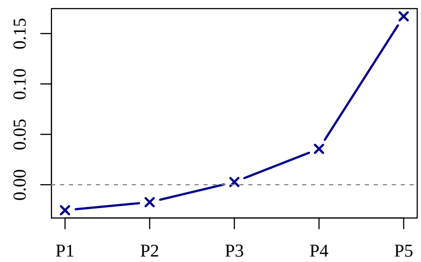
In summary, we provide a comprehensive analysis going beyond the results that have been presented in the prior literature, by studying in detail on the bond level the cross-sectional relation between inventory risk and returns, and shed light onto a much broader question related to the role of limited risk-bearing capacity of intermediaries and its effects on transaction prices.

Figures and Tables

(a) Full period



(b) Pre-crisis period



(c) Crisis period

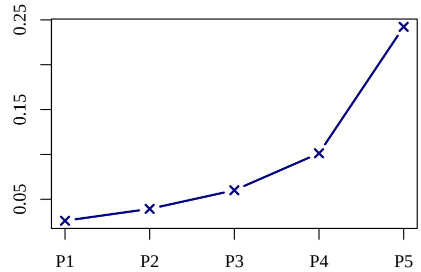
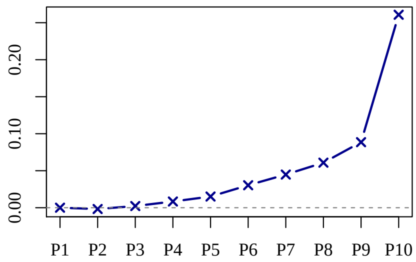
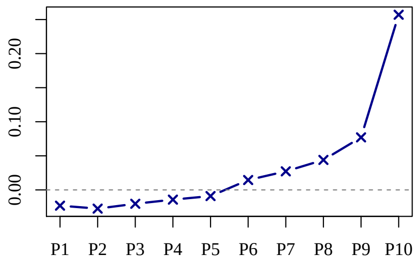


Figure 1: Corporate bond returns of quintile portfolios sorted by inventory positions. We weekly sort bonds based on their average end-of-week dealer inventories (I_t^j) into quintile portfolios and calculate equally weighted returns. P1 contains bonds with the lowest inventories, P5 the ones with the highest. We plot returns for the full period (January 2003 to December 2013) in Panel (a), the pre-crisis period (January 2003 to June 2007) in Panel (b) and the crisis period (July 2007 to June 2010) in Panel (c). Returns are based on a transaction dataset of US corporate bonds obtained from TRACE and maintained by FINRA.

(a) Full period



(b) Pre-crisis period



(c) Crisis period

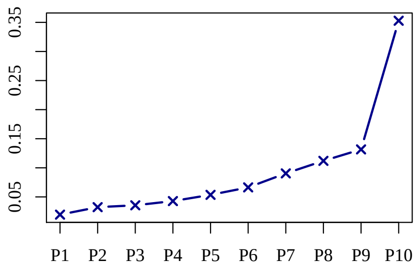


Figure 2: Corporate bond returns of decile portfolios sorted by inventory positions. We weekly sort bonds based on their average end-of-week dealer inventories (I_t^j) into decile portfolios and calculate equally weighted returns. P1 contains bonds with the lowest inventories, P10 the ones with the highest. We plot returns for the full period (January 2003 to December 2013) in Panel (a), the pre-crisis period (January 2003 to June 2007) in Panel (b) and the crisis period (July 2007 to June 2010) in Panel (c). Returns are based on a transaction dataset of US corporate bonds obtained from TRACE and maintained by FINRA.

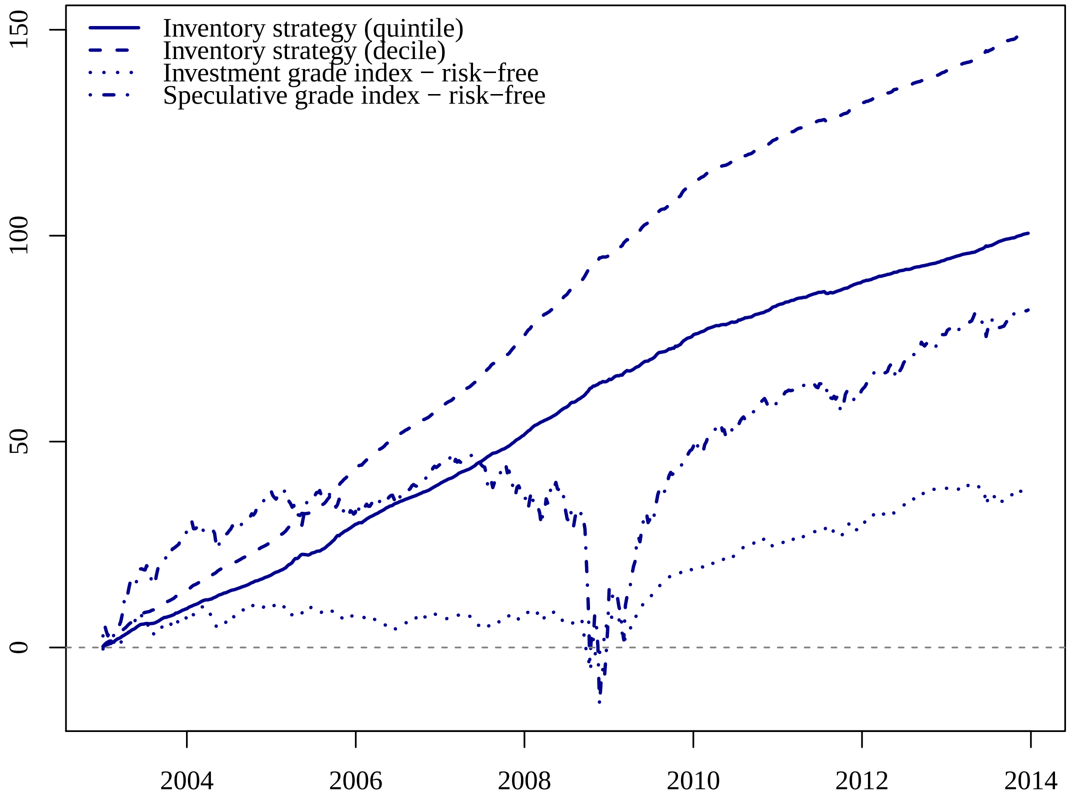


Figure 3: Cumulative excess returns. We plot cumulative returns of a long-short inventory strategy using weekly data for quintile and decile portfolios where we sort bonds based on their average end-of-week dealer inventories (I_t^j) into quintile and decile portfolios and calculate equally weighted excess returns. We also plot cumulative excess returns over Treasury bills of an investment and speculative-grade index obtained from FINRA. Returns are based on a transaction dataset of US corporate bonds obtained from TRACE and maintained by FINRA.

	Mean	SD	Q_{10}	Q_{25}	Q_{50}	Q_{75}	Q_{90}
Amount issued [mln]	217.96	419.44	1.32	3.86	25.00	260.00	600.00
Coupon [%]	5.23	2.72	0.00	4.00	5.50	6.88	8.25
Time-to-maturity [years]	6.48	7.55	0.69	1.63	3.87	8.27	17.71
Age [years]	3.69	3.28	0.94	1.54	2.71	4.73	8.08
Credit rating	7.77	4.25	3.06	4.98	7.00	9.75	14.10
Round-trip cost [bp]	74.00	58.63	17.53	32.60	58.70	100.06	155.70
Number of dealers	9.90	8.04	1.00	3.00	8.00	16.00	22.00
Inventory measure I_t^j	0.19	0.67	−0.17	−0.01	0.04	0.23	0.76

Table 1: Descriptive statistics. This table presents cross-sectional summary statistics of the underlying bonds in our analysis. Data are sampled at a weekly frequency. We summarize descriptive statistics for the amount issued, coupon, time-to-maturity, age, credit rating, round-trip costs, number of dealers and the inventory measure I_t^j. We assign integer numbers to the credit ratings (i.e. $AAA = 1, AA+ = 2, \ldots, D = 21$) and average credit ratings across the three major rating agencies (Fitch, Moody's, Standard and Poor's). We report over the full sample period (January 2003 to December 2013) across all bonds, the means, standard deviations, and the 10%, 25%, 50%, 75% and 90% quantiles.

Panel A: Full period

	P1	P2	P3	P4	P5
I_t^j	−0.396	−0.134	−0.023	0.101	0.570
Amount issued [mln]	286.455	326.096	361.535	391.522	281.876
Coupon [%]	5.978	6.007	6.087	6.144	5.859
Time-to-maturity [years]	9.432	8.882	8.616	8.371	7.551
Age [years]	3.986	4.827	5.134	5.181	4.804
Credit rating	8.022	7.773	7.897	8.278	8.405
Round-trip cost [bp]	86.272	75.810	70.712	64.414	60.068
Number of dealers	14.394	17.461	18.431	18.598	14.515
r_t	−0.001	0.005	0.023	0.053^{**}	0.175^{***}
t-statistic	(−0.037)	(0.217)	(0.931)	(2.043)	(7.940)

Panel B: Pre-crisis period

	P1	P2	P3	P4	P5
I_t^j	−0.468	−0.163	−0.046	0.084	0.591
Amount issued [mln]	192.690	239.840	286.850	326.989	239.605
Coupon [%]	6.429	6.189	6.303	6.385	6.349
Time-to-maturity [years]	9.495	8.192	8.015	7.901	7.325
Age [years]	3.659	4.257	4.526	4.529	4.203
Credit rating	8.057	7.508	7.572	7.933	8.243
Round-trip cost [bp]	114.667	95.654	86.928	78.503	73.151
Number of dealers	13.542	16.235	17.412	17.516	13.577
r_t	−0.025	−0.017	0.003	0.036	0.167^{***}
t-statistic	(−0.941)	(−0.615)	(0.093)	(1.160)	(6.703)

Panel C: Crisis period

	P1	P2	P3	P4	P5
I_t^j	−0.370	−0.149	−0.057	0.049	0.515
Amount issued [mln]	285.370	311.250	338.288	375.215	267.267
Coupon [%]	5.775	5.991	6.048	6.104	5.652
Time-to-maturity [years]	9.326	9.498	9.066	8.708	7.402
Age [years]	3.845	5.016	5.358	5.397	4.843
Credit rating	7.583	7.648	7.920	8.500	8.314
Round-trip cost [bp]	85.602	81.248	77.187	69.212	62.383
Number of dealers	14.718	18.152	18.798	19.157	14.843
r_t	0.026	0.039	0.060	0.101	0.242^{***}
t-statistic	(0.360)	(0.527)	(0.815)	(1.290)	(3.827)

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2: Characteristics of quintile portfolios. This table summarizes the characteristics based on the underlying bonds in the portfolios. We sort bonds based on average end-of-week dealer inventories (I_t^j) into quintile portfolios, where P1 contains bonds with lowest inventories, P5 the ones with highest. Characteristics are given for the full period in Panel A (January 2003 to December 2013), the pre-crisis period in Panel B (January 2003 to June 2007), and the crisis period in Panel C (July 2007 to June 2010). We provide descriptive statistics for the amount issued, coupon, time-to-maturity, age, credit rating, round-trip cost, and the number of dealers. We assign integer numbers to the credit ratings (i.e. $AAA = 1, AA+ = 2, \ldots, D = 21$) and average credit ratings across the three major rating agencies (Fitch, Moody's, Standard and Poor's). We also report the raw portfolio returns r_t and the corresponding t-statistics.

Panel A: Full period

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
I_t^j	−0.540	−0.251	−0.165	−0.103	−0.050	0.003	0.063	0.138	0.258	0.883
Amount issued [mln]	264.429	308.494	319.059	333.133	350.202	372.872	388.297	394.746	365.081	198.720
Coupon [%]	5.936	6.020	5.990	6.024	6.061	6.112	6.139	6.150	6.126	5.591
Time-to-maturity [years]	9.512	9.352	9.001	8.764	8.663	8.569	8.473	8.268	7.981	7.120
Age [years]	3.565	4.408	4.725	4.929	5.073	5.194	5.192	5.170	5.098	4.511
Credit rating	8.145	7.902	7.780	7.766	7.826	7.968	8.176	8.381	8.576	8.231
Round-trip cost [bp]	89.533	83.105	78.288	73.210	72.148	69.194	66.656	62.268	58.928	61.473
Number of dealers	12.545	16.245	17.181	17.741	18.168	18.694	18.776	18.420	17.213	11.818
r_t	0.000	−0.002	0.002	0.008	0.015	0.030	0.045^{*}	0.061^{**}	0.089^{***}	0.261^{***}
t-statistic	(0.001)	(−0.072)	(0.090)	(0.349)	(0.625)	(1.239)	(1.711)	(2.388)	(3.634)	(13.001)

Panel B: Pre-crisis period

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
I_t^j	−0.642	−0.295	−0.196	−0.130	−0.074	−0.018	0.045	0.124	0.252	0.931
Amount issued [mln]	172.656	212.737	232.469	247.210	272.821	300.884	320.941	333.036	311.742	167.512
Coupon [%]	6.584	6.274	6.176	6.202	6.273	6.333	6.367	6.402	6.431	6.267
Time-to-maturity [years]	10.056	8.933	8.390	7.995	8.048	7.983	7.916	7.887	7.677	6.974
Age [years]	3.392	3.926	4.157	4.356	4.478	4.575	4.537	4.522	4.409	3.997
Credit rating	8.262	7.853	7.557	7.459	7.517	7.627	7.835	8.032	8.279	8.207
Round-trip cost [bp]	121.296	107.592	99.424	91.878	90.436	83.379	82.571	74.746	72.247	74.160
Number of dealers	12.013	15.071	16.007	16.464	17.134	17.690	17.680	17.352	16.116	11.040
r_t	−0.023	−0.027	−0.020	−0.014	−0.009	0.014	0.027	0.044	0.077^{***}	0.257^{***}
t-static	(−0.904)	(−0.979)	(−0.718)	(−0.504)	(−0.309)	(0.504)	(0.884)	(1.516)	(2.709)	(11.849)

Panel C: Crisis period

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
I_t^j	−0.494	−0.246	−0.175	−0.124	−0.079	−0.035	0.016	0.082	0.190	0.841
Amount issued [mln]	261.852	308.901	308.134	314.366	327.718	348.862	371.030	379.398	353.697	180.886
Coupon [%]	5.593	5.957	5.983	5.999	6.018	6.078	6.104	6.103	6.027	5.278
Time-to-maturity [years]	8.939	9.713	9.585	9.412	9.125	9.008	8.937	8.479	7.913	6.891
Age [years]	3.259	4.431	4.916	5.117	5.279	5.437	5.437	5.357	5.223	4.463
Credit rating	7.565	7.599	7.633	7.663	7.790	8.050	8.362	8.638	8.786	7.841
Round-trip cost [bp]	85.341	86.254	84.306	77.907	77.072	77.192	71.138	67.130	60.379	65.013
Number of dealers	12.475	16.963	17.937	18.368	18.486	19.109	19.398	18.916	17.610	12.077
r_t	0.020	0.032	0.036	0.043	0.054	0.066	0.090	0.112	0.132^{*}	0.353^{***}
t-statistic	(0.284)	(0.451)	(0.465)	(0.601)	(0.733)	(0.945)	(1.141)	(1.447)	(1.810)	(6.811)

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3: Characteristics of decile portfolios. This table summarizes the characteristics based on the underlying bonds in the portfolios. We sort bonds based on average end-of-week dealer inventories (I_t^j) into decile portfolios, where P1 contains bonds with lowest inventories, P10 the ones with highest. Characteristics are given for the full period in Panel A (January 2003 to December 2013), the pre-crisis period in Panel B (January 2003 to June 2007), and the crisis period in Panel C (July 2007 to June 2010). We provide descriptive statistics for the amount issued, coupon, time-to-maturity, age, credit rating, round-trip cost, and the number of dealers. We assign integer numbers to the credit ratings (i.e. $AAA = 1, AA+ = 2, \ldots, D = 21$) and average credit ratings across the three major rating agencies (Fitch, Moody's, Standard and Poor's). We also report the raw portfolio returns r_t and the corresponding t-statistics.

	Full period				Pre-crisis period				Crisis period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	0.176^{***}	0.176^{***}	0.178^{***}	0.179^{***}	0.192^{***}	0.198^{***}	0.201^{***}	0.204^{***}	0.216^{***}	0.217^{***}	0.220^{***}	0.221^{***}
	(23.744)	(21.701)	(24.203)	(26.678)	(18.155)	(18.356)	(19.123)	(19.508)	(15.178)	(16.791)	(16.389)	(17.275)
MKTF		−0.001		0.000		−0.007		−0.002	0.001		0.001	
		(−0.363)		(0.020)		(−1.485)		(−0.321)		(0.260)		(0.211)
SMB		−0.006		-0.008^{*}		-0.018^{**}		-0.016^{**}		−0.007		−0.009
		(−1.206)		(−1.708)		(−2.068)		(−2.029)		(−0.858)		(−1.239)
HML		0.001		0.003		−0.017		−0.015		0.004		0.006
		(0.174)		(0.492)		(−1.612)		(−1.638)		(0.412)		(0.700)
UMD		−0.003		−0.004		0.006		0.002		0.001		−0.002
		(−1.109)		(−1.176)		(0.767)		(0.316)		(0.126)		(−0.392)
TERM			-0.037^{***}	-0.041^{***}			−0.033	−0.023			-0.051^{***}	-0.058^{***}
			(−3.046)	(−3.538)			(−1.009)	(−0.703)			(−3.822)	(−4.205)
DEF			-0.035^{**}	-0.041^{***}			−0.075	−0.059			-0.042^{***}	-0.052^{***}
			(−2.575)	(−2.738)			(−1.593)	(−1.250)			(−3.145)	(−3.479)
PS			-0.002^{**}	-0.002^{**}			−0.003	−0.002			−0.001	−0.001
			(−2.470)	(−2.368)			(−1.440)	(−1.263)			(−0.968)	(−0.783)
Adj. R^2	0.000	0.002	0.049	0.056	0.000	0.041	0.064	0.084	0.000	−0.018	0.089	0.088
Obs.	573	573	573	573	235	235	235	235	156	156	156	156

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4: Corporate bond returns based on quintile portfolios. We sort bonds based on their average end-of-week dealer inventories (I_t^j) into quintile portfolios and calculate equally weighted excess returns. P1 contains bonds with lowest inventories, P5 the ones with highest. P5–P1 presents the results for going long in P5 and short in P1. We report weekly alpha estimates of regressing excess returns on a constant given in Models (1), (5) and (9), on equity factors (MKTF, SMB, HML, UMD) given in Models (2), (6) and (10), on bond factors (TERM, DEF, PS) given in Models (3), (7) and (11), as well as by employing all factors given in Models (4), (8) and (12), respectively. Values in paranthesis are t-statistics based on HAC standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). Results are based on a transaction data set comprising TRACE data for US corporate bonds for the full period (January 2003 to December 2013), the pre-crisis period (January 2003 to June 2007) and the crisis period (July 2007 to June 2010).

	Full period				Pre-crisis period				Crisis period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	0.261***	0.263***	0.266***	0.268***	0.280***	0.289***	0.291***	0.295***	0.333***	0.334***	0.342***	0.343***
	(24.750)	(23.990)	(23.692)	(26.507)	(21.436)	(22.555)	(22.522)	(24.356)	(15.490)	(16.900)	(16.882)	(17.246)
MKTF		−0.006		−0.003		−0.011**		−0.004		−0.003		−0.002
		(−1.262)		(−0.722)		(−2.000)		(−0.752)		(−0.504)		(−0.380)
SMB		−0.011		−0.013**		−0.030***		−0.028***		−0.014		−0.016
		(−1.561)		(−1.987)		(−3.277)		(−3.164)		(−1.316)		(−1.641)
HML		−0.004		0.000		−0.026*		−0.022*		−0.002		0.002
		(−0.623)		(−0.073)		(−1.945)		(−1.680)		(−0.147)		(0.249)
UMD		−0.004		−0.005		0.008		0.004		0.000		−0.004
		(−0.998)		(−1.375)		(0.981)		(0.456)		(−0.058)		(−0.858)
TERM			−0.068***	−0.069***			−0.051	−0.031			−0.080***	−0.084***
			(−4.061)	(−3.987)			(−1.302)	(−0.878)			(−4.092)	(−4.016)
DEF			−0.074***	−0.072***			−0.103*	−0.073			−0.081***	−0.084***
			(−3.827)	(−3.381)			(−1.842)	(−1.401)			(−4.014)	(−4.048)
PS			−0.003*	−0.003*			−0.003	−0.003			0.000	0.000
			(−1.898)	(−1.945)			(−1.419)	(−1.158)			(0.071)	(0.073)
Adj. R^2	0.000	0.018	0.080	0.093	0.000	0.081	0.059	0.110	0.000	−0.006	0.116	0.113
Obs.	573	573	573	573	235	235	235	235	156	156	156	156

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5: Corporate bond returns based on decile portfolios. We sort bonds based on their average end-of-week dealer inventories (I_t^j) into decile portfolios and calculate equally weighted excess returns. P1 contains bonds with lowest inventories, P10 the ones with highest. P10–P1 presents the results for going long in P10 and short in P1. We report weekly alpha estimates of regressing excess returns on a constant given in Models (1), (5) and (9), on equity factors (MKTF, SMB, HML, UMD) given in Models (2), (6) and (10), on bond factors (TERM, DEF, PS) given in Models (3), (7) and (11), as well as by employing all factors given in Models (4), (8) and (12), respectively. Values in paranthesis are t-statistics based on HAC standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). Results are based on a transaction data set comprising TRACE data for US corporate bonds for the full period (January 2003 to December 2013), the pre-crisis period (January 2003 to June 2007) and the crisis period (July 2007 to June 2010).

	Full period		Pre-crisis period		Crisis period	
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
α	0.233***	0.168***	0.256***	0.193***	0.269***	0.212***
	(33.698)	(21.476)	(38.025)	(15.803)	(18.554)	(14.491)
MKTF	0.000	0.000	−0.006	−0.003	0.005	0.000
	(0.045)	(−0.074)	(−1.222)	(−0.468)	(0.696)	(0.044)
SMB	−0.003	−0.010*	−0.015**	−0.018**	−0.002	−0.013
	(−0.465)	(−1.916)	(−2.001)	(−2.005)	(−0.156)	(−1.484)
HML	−0.005	0.006	−0.008	−0.015	−0.014	0.012
	(−0.694)	(1.023)	(−1.064)	(−1.315)	(−1.185)	(1.400)
UMD	−0.002	−0.003	0.002	0.002	−0.004	0.000
	(−0.709)	(−0.872)	(0.363)	(0.231)	(−0.726)	(0.062)
TERM	−0.017	−0.035**	0.033*	−0.023	−0.035	−0.056***
	(−1.047)	(−2.533)	(1.867)	(−0.573)	(−1.554)	(−3.003)
DEF	−0.023	−0.031*	0.012	−0.062	−0.038	−0.044**
	(−1.082)	(−1.844)	(0.479)	(−1.077)	(−1.344)	(−2.463)
PS	−0.002	−0.002**	−0.002	−0.001	−0.001	−0.001
	(−1.518)	(−2.154)	(−1.512)	(−0.560)	(−0.416)	(−1.145)
Adj. R^2	0.008	0.039	0.127	0.063	0.008	0.070
Obs.	573	573	235	235	156	156

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 6: Corporate bond returns of bonds traded by a low and high number of dealers. We sort bonds based on their average end-of-week dealer inventories (I_t^j) into quintile portfolios and calculate equally weighted excess returns. P1 contains bonds with lowest inventories, P5 the ones with highest. P5–P1 presents the results for going long in P5 and short in P1. We report weekly alpha estimates of regressing excess returns on a constant, on equity factors (MKTF, SMB, HML, UMD), and on bond factors (TERM, DEF, PS). The sample is split into bonds traded by a low number of dealers (< 8) given in Models (1), (3) and (5) as well as into bonds traded by a high number of dealers (≥ 8) given in Models (2), (4) and (6), respectively. Values in paranthesis are t-statistics based on HAC standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). Results are based on a transaction data set comprising TRACE data for US corporate bonds for the full period (January 2003 to December 2013), the pre-crisis period (January 2003 to June 2007) and the crisis period (July 2007 to June 2010).

	Full period		Pre-crisis period		Crisis period	
	Small	Large	Small	Large	Small	Large
	(1)	(2)	(3)	(4)	(5)	(6)
α	0.383***	0.069***	0.443***	0.081***	0.397***	0.096***
	(43.651)	(10.054)	(37.932)	(7.351)	(20.690)	(7.196)
MKTF	0.005	−0.003	−0.004	−0.003	0.009	−0.006
	(1.273)	(−0.873)	(−0.908)	(−0.566)	(1.498)	(−0.741)
SMB	−0.008	−0.006	−0.018**	−0.009	−0.008	−0.005
	(−1.154)	(−1.203)	(−2.261)	(−1.004)	(−0.603)	(−0.646)
HML	−0.014*	0.011**	−0.024**	−0.008	−0.019*	0.020***
	(−1.809)	(2.229)	(−2.089)	(−0.815)	(−1.733)	(2.722)
UMD	−0.004	−0.002	0.008	−0.006	−0.003	0.000
	(−1.169)	(−0.813)	(1.098)	(−0.644)	(−0.457)	(−0.031)
TERM	−0.020*	−0.026*	−0.025	−0.023	−0.023	−0.043*
	(−1.662)	(−1.751)	(−1.216)	(−0.545)	(−1.352)	(−1.958)
DEF	−0.014	−0.017	−0.034	−0.059	−0.020	−0.025
	(−0.826)	(−0.988)	(−1.144)	(−0.965)	(−0.915)	(−1.158)
PS	−0.001	−0.002**	−0.001	−0.004*	−0.001	0.000
	(−1.017)	(−1.966)	(−0.540)	(−1.823)	(−0.764)	(−0.369)
Adj. R^2	0.015	0.041	0.032	0.061	−0.001	0.090
Obs.	573	573	235	235	156	156

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 7: Corporate bond returns of small and large bonds. We sort bonds based on their average end-of-week dealer inventories (I_t^j) into quintile portfolios and calculate equally weighted excess returns. P1 contains bonds with lowest inventories, P5 the ones with highest. P5–P1 presents the results for going long in P5 and short in P1. We report weekly alpha estimates of regressing excess returns on a constant, on equity factors (MKTF, SMB, HML, UMD), and on bond factors (TERM, DEF, PS). The sample is split into small bonds ($<$ \$25 million) given in Models (1), (3) and (5) as well as into large bonds ($\geq$ \$25 million) given in Models (2), (4) and (6), respectively. Values in paranthesis are t-statistics based on HAC standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). Results are based on a transaction data set comprising TRACE data for US corporate bonds for the full period (January 2003 to December 2013), the pre-crisis period (January 2003 to June 2007) and the crisis period (July 2007 to June 2010).

	Full period		Pre-crisis period		Crisis period	
	Non-financial	Financial	Non-financial	Financial	Non-financial	Financial
	(1)	(2)	(3)	(4)	(5)	(6)
α	0.072***	0.273***	0.084***	0.313***	0.090***	0.324***
	(10.055)	(27.955)	(12.044)	(21.335)	(6.062)	(17.029)
MKTF	−0.008**	0.004	−0.005	−0.007	−0.015**	0.011
	(−2.264)	(1.134)	(−1.173)	(−1.058)	(−2.484)	(1.639)
SMB	−0.005	−0.010	−0.004	−0.026**	−0.012	−0.007
	(−1.187)	(−1.506)	(−0.533)	(−2.417)	(−1.493)	(−0.673)
HML	0.007	0.000	−0.014	−0.024**	0.020***	−0.003
	(1.543)	(−0.057)	(−1.441)	(−1.985)	(3.240)	(−0.302)
UMD	0.003	−0.007**	−0.005	0.011	0.005	−0.004
	(1.243)	(−2.137)	(−0.754)	(1.217)	(1.424)	(−1.012)
TERM	−0.033*	−0.044***	0.043*	−0.083*	−0.060**	−0.057***
	(−1.815)	(−3.715)	(1.839)	(−1.809)	(−2.153)	(−5.167)
DEF	−0.026	−0.044**	0.047	−0.149**	−0.042*	−0.055***
	(−1.394)	(−2.563)	(1.416)	(−2.136)	(−1.708)	(−3.577)
PS	−0.003**	−0.002*	−0.002*	−0.002	−0.002**	0.000
	(−2.461)	(−1.682)	(−1.772)	(−0.882)	(−2.081)	(−0.054)
Adj. R^2	0.101	0.037	0.071	0.134	0.267	0.061
Obs.	573	573	235	235	156	156

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8: Corporate bond returns of non-financial and financial bonds. We sort bonds based on their average end-of-week dealer inventories (I_t^j) into quintile portfolios and calculate equally weighted excess returns. P1 contains bonds with lowest inventories, P5 the ones with highest. P5–P1 presents the results for going long in P5 and short in P1. We report weekly alpha estimates of regressing excess returns on a constant, on equity factors (MKTF, SMB, HML, UMD), and on bond factors (TERM, DEF, PS). The sample is split into non-financial bonds given in Models (1), (3) and (5) as well as into financial bonds given in Models (2), (4) and (6), respectively. Values in paranthesis are *t*-statistics based on HAC standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). Results are based on a transaction data set comprising TRACE data for US corporate bonds for the full period (January 2003 to December 2013), the pre-crisis period (January 2003 to June 2007) and the crisis period (July 2007 to June 2010).

	Full period		Pre-crisis period		Crisis period	
	Investment (1)	Speculative (2)	Investment (3)	Speculative (4)	Investment (5)	Speculative (6)
α	0.194***	0.124***	0.233***	0.110***	0.214***	0.223***
	(23.489)	(8.419)	(23.668)	(5.803)	(13.529)	(6.979)
MKTF	0.001	−0.015**	−0.003	−0.015*	0.002	−0.013
	(0.236)	(−1.987)	(−0.789)	(−1.861)	(0.540)	(−0.854)
SMB	−0.004	−0.021**	−0.014*	−0.014	−0.006	−0.038**
	(−0.858)	(−2.058)	(−1.860)	(−1.145)	(−0.864)	(−2.048)
HML	0.004	0.004	−0.013	−0.031*	0.005	0.018
	(0.971)	(0.310)	(−1.588)	(−1.672)	(0.728)	(0.989)
UMD	−0.001	−0.006	0.004	0.007	0.001	−0.002
	(−0.284)	(−1.081)	(0.602)	(0.567)	(0.345)	(−0.320)
TERM	−0.035***	−0.053*	−0.012	−0.032	−0.044***	−0.098**
	(−3.670)	(−1.674)	(−0.402)	(−0.622)	(−4.628)	(−2.217)
DEF	−0.042***	−0.060	−0.053	−0.046	−0.049***	−0.093*
	(−3.495)	(−1.389)	(−1.133)	(−0.614)	(−4.357)	(−1.726)
PS	−0.002**	0.000	0.000	−0.005	−0.002**	0.006
	(−2.241)	(0.060)	(−0.125)	(−1.332)	(−2.247)	(1.384)
Adj. R^2	0.043	0.054	0.111	0.032	0.103	0.060
Obs.	573	573	235	235	156	156

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 9: Corporate bond returns of investment and speculative-grade bonds. We sort bonds based on their average end-of-week dealer inventories (I_t^j) into quintile portfolios and calculate equally weighted excess returns. P1 contains bonds with lowest inventories, P5 the ones with highest. P5–P1 presents the results for going long in P5 and short in P1. We report weekly alpha estimates of regressing excess returns on a constant, on equity factors (MKTF, SMB, HML, UMD), and on bond factors (TERM, DEF, PS). The sample is split into investment-grade bonds given in Models (1), (3) and (5) as well as into speculative-grade bonds given in Models (2), (4) and (6), respectively. Values in paranthesis are t-statistics based on HAC standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). Results are based on a transaction data set comprising TRACE data for US corporate bonds for the full period (January 2003 to December 2013), the pre-crisis period (January 2003 to June 2007) and the crisis period (July 2007 to June 2010).

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