“Adverse- selecting” Informed Customers: Evidence from the corporate bond market

By

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Abstract

Our empirical evidence suggests that dealers pre-classify their clients into informed and uninformed based on their identities. In doing so, dealers update accordingly their expectations regarding the price of a security, and in a sense, try to share in the informed traders profits. Essentially, our analysis identifies an extra parameter that dealers consider in their quote setting process, other than those already posited by market microstructure theory. We further substantiate this finding by complementing our empirical conclusions with a theoretical sequential trade model that explicitly incorporates the investor category as well as with a simulation exercise. The results of the simulation exercise suggest that the P&L generated for a dealer that uses the extended model is significantly higher relative to the respective P&L that he would have earned if he had employed the model of Easley O’Hara (1992). Considering that the excess returns enjoyed by each investor category have to be proportional to the level of the private information it possesses, we next find evidence that institutional investors do earn more often than not in the longer horizons, while retailers do lose more often than not in the longer horizons. Hence, we assert that dealers are right in a-priory classifying institutional investors as informed and retail investors as uninformed. The aforementioned pre-classification proves also to be much more profitable for the dealers themselves, relative to a “naive” strategy that would uniformly classify all investors as uninformed. To state it differently, our findings suggest that dealers “front-run” successfully informed traders. Finally, our results imply that dealers, being the market makers, are the fastest and most efficient news-traders. In particular, dealers are the ones benefiting in all the trades propelled by public information releases.

Keywords: dealer’s quote adjustment, sequential trade model, informed vs. uninformed investors, corporate bond excess returns, dealer’s P&L, public news trading.

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1. Introduction

Standard market microstructure theory posits that the price of OTC securities in "principal" ("dealer-to-customer") markets incorporates new information by means of a conceptually simple mechanism: As dealers adjust their quotes in response to the order flows they observe, they implicitly search for that price level at which no informed trader will have the incentive to transact. Given the expectation that uninformed/utility[3] traders will not act persistently on either of the offered quotes in the long term, it is through this mechanism that the market-maker "discovers" indirectly the price that informed traders agree upon. Earlier models describing this learning process (Kyle (1984), Glosten and Millgrom (1985), Easley and O' Hara (1992)) combine dealers' prior assumptions about the presence and intensity of possible new information with the intensity and directional persistence of the order flows they observe. Typically, in those models the customer's identity or other distinctive characteristics that may reveal his true incentives *do not* enter the dealer's decision process, and, arguably, for good reason: Identifying a client as informed, when he in fact is uniformed, will cause the dealer to overreact and thus lose at least part of her bid-ask spread. Quite the contrary, characterizing mistakenly a customer as uninformed, will inescapably compound her losses on any incidence of adverse-selection. Last but not least, any quote-setting strategy involving varying responses to sequences of cumulatively equal order flows would expose her to possible "bluffer" activity[4].

[3] Utility traders (Harris, 2002) constitute a special class of the uninformed market participants. It includes traders who transact ("utilize" liquidity services) for reasons that, although are exogenous to the price of the asset, they can still well be completely rational (e.g. hedging or asset-exchange). In a way, this kind of traders do not suffer from "ex-post regret" after having traded with the better-informed ones, simply because their own utility function is independent of the "true" asset's price.

[4] To illustrate this point with an example, a "bluffer" (according to the taxonomy of Harris, 2002) could be a reputedly sophisticated agent who will buy (or sell) from a market-maker in consecutive

Recent empirical evidence however, refutes this hypothesis and suggests in contrast, that certain features of the customer submitting the order can potentially help the dealer make a more efficient assessment of the level of information that each trade carries.

Probably because of its enhanced liquidity and transparency, most of this research concerns the foreign exchange market (Fan and Lyons (2003), Marsh and Rourke (2005), Frömmel et al (2008), Bjonnes et al (2011)) bringing forward a distinction between financial-sector and corporate customers. According to those studies, the former are the more likely to engage in informed trading as their activity, more often than not, incurs permanent impact on the exchange rate. At the same time, the correlation between their order flows and the probability of information-based trading (PIN - as proposed by Easley and O'Hara (2002)) is significantly positive. Finally, the trading style of this category is characterized by a markedly aggressive stance in terms of the immediacy required. Corporate/retail customers on the other hand appear to be relatively comfortable in the role of the short-term liquidity provider (King et al, 2013) who will on average pay a premium for using the market. Cerrato et al. (2011) and Bjonnes et al. (2005, 2005a) reach pretty much the same conclusion, by means of a similar categorization between profit-motivated (asset managers, hedge funds etc.) and private/utilitarian customers (non-financial companies, individuals).

Comparable studies conducted in the equity market, albeit fewer due to its exchange-based "agency" (or "customer-to-customer") structure, largely confirm the abovementioned client classification: On the one hand, Chakravarty (2001) shows that trades initiated from institutional clients constitute the main source of firm-specific

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trades to tempt her to overreact and then sell (or buy) the same position back to her concealed behind a broker. If the dealer is not size-consistent in her quote-setting strategy she will suffer a net loss from this roundtrip trade.

information. On the other hand, Underwood (2009) suggests that trades of this kind are by far the most informative, both at firm- and market-wide levels. Retail customer trades according to this paper's findings are not strictly utilitarian as they also appear to contribute information, which is, however, different from that conveyed by institutional client trades.

This paper fills an important gap in the relevant literature, by exploring the extent to which the Principal - i.e. the dealers themselves - have adopted in their quote-setting strategy an a-priori classification of this sort, thus violating the hypothesis underlying traditional sequential models (GM 1985, EOH 1992). Given that our sample classifies investors as institutional, block[5] or retail, we investigate whether dealers respond differently to each investor category in adjusting their quoted prices.

Our empirical evidence suggests that dealers pre-classify their clients into informed and uninformed based on their identities, giving rise to dealers' "prejudice" costs. Indeed, bond dealers regard institutional investors (IC – Institutional Clients) as informed traders, as dealers charge them higher bid-offer spreads so as to be compensated for bearing what is perceived as a higher adverse selection risk, and so indirectly participate in their profits. When IC are on the buying-side of a transaction, dealers respond by decreasing their quoted bond yields and so increasing transaction prices. Whereas, in case IC are on the selling-side of a trade, dealers increase their quoted bond yields, so that the traded prices fall. On the other hand, bond dealers adopt a different charging strategy when transacting with retail investors (RC – Retail

[5] Seeing that block investors are institutional investors who are in a hurry of trading big volumes, their treatment as a single investor category along with institutional investors is deemed appropriate. Hence, we would refer from this point onwards to both institutional and block investors as institutional.

Clients). Specifically, when RC buy a bond, dealers do not increase the price of the security to be sold. While, when RC sell a bond, dealers' response is much less intense relative to the one for IC. Essentially, our findings reflect the lower adverse selection risk that dealers face when transacting with retail investors, who are the noise traders in the market.

As sequential trade models do not consider the type of the investor for the setting the Bid-Ask quotes, we propose an extension of the Easley O'Hara (1992) model so as to explicitly incorporate this determinant. Specifically, we first extend the event tree of Easley O'Hara (1992) by assigning a higher probability of institutional investors ($\mu 1$) being informed relative to retail investors ($\mu 2$) being informed ($\mu 1 > \mu 2$), and then we use the event tree so as to derive the respective equations for the determination of Bid-Ask quotes. Essentially, we do not only complement our empirical findings with a theoretical model that provides further insights on how dealers could determine their quotes, but also perform a simulation exercise that benchmarks our model relative to Easley O'Hara (1992). Our simulation exercise denotes that the P&L of a dealer that uses our extended model is significantly higher relative to the P&L that he would have enjoyed if he had used the model of Easley O'Hara (1992).

Furthermore, we ask whether dealers are right in pre-classifying their clients. That is, are institutional traders more likely to be informed rather than not? In case dealers are right, we expect that each investor category earns realized excess returns of different sign and magnitude. Typically we expect institutional investors, being the informed ones, to earn more often than not in the longer horizons. At the same time we also expect retail investors to suffer losses more often than not in the longer horizons. We test this hypothesis by segregating the buying-side from the selling-side traded flows, so as to distinguish between the fixed premiums earned by investors buying and by investors shorting a bond. Considering that the corporate bond excess returns might require some days before appearing in the market, particularly when limited market liquidity results in a slower price adjustment to new information, we examine the cumulative excess return for each bond after the trade day (t) up to t+1, t+2, t+3, t+4, t+5 & t+30 horizons.

Institutional investors appear to be on the "correct" side of the market more often than not, thus, verifying dealers' preconception that they are indeed informed. Regarding retail investors, they consistently lose across all the time horizons examined. This can be primarily attributed to the fact that RC are primarily utilitarian traders that are driven by private value considerations. That is, their investment decisions are also driven by the "value" they attribute to holding particular securities, which might result in neither selecting underpriced assets nor formulating efficient portfolios. As dealers' strategy predicted, RC find themselves consistently on the "wrong" side of the market. Our results also show that the price of a bond increases during the last days just before institutional investors sell it, indicating that this type of traders tend to close their positions with profit. All in all, the ex-post excess returns realized by each investor category fully support the dealers' adjusted quoting strategy we discovered on the first hypothesis.

However, what matters the most for the dealers is neither the profits nor the losses of their clients, but rather the potential impact of the strategy they pursue on their own daily P&L. Theory says that dealers cover their losses to the informed traders from the uninformed. It may be that by distinguishing their clients into informed and uniformed in a correct way more often than not, they obtain part of the information premium the informed traders enjoy. In that case, dealers decide to “front-run” successfully value traders. So, we next proceed by testing under the third hypothesis whether the pre-classification strategy followed by the dealers improves their daily P&L or not. The dealers’ all-sample average realized P&L margin amounts to 4.7 b.p. (i.e. P&L over traded volume). Whereas, had the dealers responded to all investors as being uninformed, they would have incurred a much lower gain of 0.9 b.p.. Indeed, the a-priory classification of investors as value and noise traders, proves to be much more profitable for the dealers relative to a “naïve” strategy that would uniformly classify all investors as uninformed.

Dealers appear to profit by correctly pre-classifying their clients. Nevertheless, their daily P&L volatility is found to be rather high, suggesting that certain trades are more profitable than others. It might be the case that dealers’ profits are rather concentrated around trades executed under certain conditions. That is, we expect that dealers earn more than their average P&L margin, when trading under conditions they have a competitive advantage over investors. Publicly announced information is continuously flowing into the market, spurring market participants in continuously updating the prices they are willing to transact. Therefore, being the market makers, we expect that dealers are the fastest and most efficient news-traders, essentially, benefiting the most from all the trades propelled by public information releases. For this purpose, we investigate under the forth hypothesis whether or not trading on the direction of public news constitutes a core driver in the formation of dealers’ realized P&L.

We define as public information events all single-day buy trades and single-day sell trades followed by the opposite direction on the next day, whose traded volume is above the average trading volume for that particular security. We also define as public information events all those sequences of unidirectional trades for which the magnitude of the yield change registered on the first day is larger than the magnitude of the cumulative yield change registered over the following days of the sequence. The idea is that whenever public information is released, day (t) is news trading, i.e. trading on the direction of the news, while during the following days a fine-tuning on the exact level of the updated price takes place. Our findings suggest that dealers dominate public information profits, as they do earn more than their average P&L margin on these public news days. As anticipated, dealers lose after the first day of a unidirectional sequence, since they do not participate in the fine tuning process pertaining to the determination of the exact level of the updated bond price by the value traders.

In short, the empirical findings under the four hypothesis examined in this study suggest the presence of an endogenous cost component in a firm's credit spread, as traders are being overcharged by the liquidity provider (dealer). On top of that, our analysis implies that value traders are the main type of speculators in the market, while news traders are the dealers.

The contribution of this empirical work is manifold. Firstly, our evidence regarding dealers' a-priory classification of their clients as informed and uninformed according to their identities, denotes a new parameter considered in the dealers' quote setting processes, other than those already posited by market microstructure theory. We further substantiate this finding by complementing our empirical conclusions with a theoretical model that explicitly incorporates the investor category in the quote setting process adopted by the dealers as well as with a simulation exercise. The results of the simulation exercise suggest that the P&L generated for a dealer that uses our extended sequential trade model is significantly higher relative to the respective P&L that he would have earned if he had employed the model of Easley O'Hara

(1992). Secondly, we extend the existing literature, which has identified that transaction flows are positively related to excess bond returns, by directly linking the investor category who trades with the excess return it subsequently enjoys. That is, we verify that value traders benefit while noise traders lose more often than not in the longer horizons. To the best of our knowledge, we are not aware of any other study that examines the abovementioned relation as such. Thirdly, we quantify the impact on the dealers' P&L margin for being the most efficient news traders. That is, we identify an average fixed component that augments dealers' P&L in public news trading days. Finally, our methodology pertaining to the calculation of excess returns over a matched by credit rating and maturity value-weighted portfolio, and not just over the risk free rate, is rather novel in the corporate bonds' literature. Actually, by controlling for the systematic component of excess bond returns, we can identify the part attributed to the investors' bond picking abilities. Thus, clearly distinguishing between value and noise traders.

The core implication of our findings has to do with market microstructure models. Essentially, market microstructure models have to take into account some prior perception about the information the client has. Our analysis suggests that this can be achieved by segregating clients according to the investor category they belong. Indeed, the theoretical model we propose along with the simulation exercise that we conduct imply that dealers are better off by explicitly incorporating the customer type in their quote setting processes.

The rest of this study is organized as follows. In section 2 we introduce the data set and some summary statistics, while in section 3 we develop the hypotheses and present all the empirical results. Next, in section 4 we describe the robustness checks we have performed and finally in section 5 we conclude.

2. Sample, summary statistics and variable selection

2.1. Sample

Our dataset consists of corporate bonds participating in the formation of the JULI[6] index. JULI is a broad measure of the performance of the most liquid securities in the investment grade corporate bond market that provides performance comparisons and valuation metrics across a carefully defined universe of bonds. The data was kindly provided to us by one of the biggest bond dealers, namely J.P. Morgan. Our sample ranges from January 2012 up to June 2013 and includes daily bond level market data coupled with a wide range of bond specific attributes. J.P. Morgan constitutes one of the dominant banks[7] in providing clearing services for repos and security purchases/sales to other dealers (Duffie 2010). On top of that, J.P. Morgan is also a dominant dealer in providing custody services for tri-party repos (Duffie 2010), which amounted to $2.5 trillion per day in 2007 (Geithner 2008). Our sample represents rather adequately the activity in the corporate bond market, as it includes the trades performed by one of the dominant bond dealers.

The market-related variables that are available in our dataset include bond prices, credit spreads over various benchmarks, excess returns, aggregate buying-side and selling-side daily volumes per issue, and total traded volumes per investor group among others. While, static bond characteristics encompass issuer, coupon, maturity, outstanding amount, seniority, sector, credit ratings as well as other bond covenants. There are around 75 fields available for each bond in the sample. On top of that, we

[6] JPMorgan US Liquid Index.

[7] Along with Bank of New York Mellon.

further augment the dataset by downloading from Bloomberg equity volatility, equity returns as well as market based accounting ratios for each bond issuer.

There are around 900.000 observations in the initial sample, of which around 300.000 are not taken into account in the analysis as they pertain to days with no trading activity (zero traded volumes). Furthermore, missing fields for some observations further reduce the sample size, so leaving around 300.000 observations for hypotheses testing. All in all, our sample combines both a very large number of observations and a large number of available fields for each bond, making it ideal for the aims of this study.

2.2. Summary statistics

Our sample contains 2.779 unique bonds (ISINS), issued by 601 firms spanning 26 different countries and covering a period of one and a half years. Table 5-1 presents the Country, Sector and Credit rating profile of the sample, incorporating both the number of Issuers/ISINS and the percentage contribution of each classification characteristic to the total number of observations. About 85% of the observations pertain to firms from the USA while about 8% comes from Europe, representing the 79% (474/601) and the 10% (60/601) of the total number of issuers respectively.

Regarding the sector classification of the companies included in the sample, around 21.5% ((86+44)/601) of them belong to the financial sector while 11.6% (70/601) of them are related to the consumer sector, representing the 26% and 10.4% of the total observations. Interestingly, about 75% of the bonds have a credit rating of “A” at the last date available on the dataset, while 54.6% of the total observations come from BBB bonds, reflecting the gradual improvement in the credit quality of the corporate bonds throughout the sample period.

2.3. Variable selection

We consider a wide range of variables as potential determinants of yield changes (H.1) or of excess bond returns (H.2). In particular, the cross sectional determinants of excess returns are captured by introducing a series of static bond characteristics that are commonly used in the existing literature (Gebhardt 2005, Lin et al. 2011). Brandt (2004) points that the price discovery process is possibly not taking place unvaryingly in all the parts of the market. Hence, we control for any static bond characteristics that may give rise to fixed premiums in the excess bond returns. By doing so, any incremental explanatory power of investor-specific regressors on the dependent variable, over and above the components attributed to static bond features, is captured. In particular, we introduce the following control variables into the regression analysis:

i. Coupon (C). It has been widely used as an indicator of tax effects (Elton et al. 2001, Longstaff 2005) that might affect the required return of a bond. So, we control for the possibility that excess returns incorporate a tax-related part.

ii. Outstanding Amount (AMT). Bond issues with high outstanding amounts are considered more liquid (Fisher 1959), so that we use this variable to proxy for bond liquidity. Specifically, we use the logarithm of outstanding amount to mitigate the impact of outliers.

iii. Financial (FN). A dummy that indicates whether a bond is issued by a financial firm or not is also included. Fiancial bonds are considered riskier as they have lower recovery rates, so that investors require higher excess returns.

iv. Age (AGE). Newly issued bonds enjoy higher liquidity, so we include the years since a bond's issuance to capture any "on-the-run" effects (Longstaff 2005, Brandt 2004, Houweiling 2005).

v. Coc (COC). These bonds lack seniority, thus, they should compensate investors with higher returns.

vi. Domestic (DOM). Takes the value of 1 for firms issuing bonds into their domestic market and zero otherwise.

vii. Euro area (EUR). Flags firms in the Euro-area, whose returns might be somehow affected by the Euro area crisis.

viii. Market (MK). We distinguish between publicly traded (dummy value = 1) and private firms so as to capture the impact that lower disclosure requirements might have on the excess returns of private firms. Han and Zhou (2013) find that bonds issued by private firms have stronger information effects.

ix. Secured (SEC). We differentiate between bonds that are collateralized (dummy value = 1) and those that are not, since investors require higher returns unsecured bonds (Nashikkar 2011).

x. Seniority (SN). Segregates senior (dummy value = 1) from subordinated debt issues to accommodate for the higher priority of the former in case of liquidation, which justifies lower excess returns.

xi. Remaining Maturity (MAT). The longer the maturity of a bond, the higher the sensitivity of its price to interest rate movements and, in most cases, the lower its liquidity, so affecting its excess bond return.

xii. Rating (RAT1, RAT2, RAT3). The credit rating of a bond reflects the credit risk undertaken by the bond holders, being, in essence, a core determinant of its excess returns. To capture non-linearities in the impact of credit rating we employee three dummies, that is, RAT1 for AAA bonds, RAT2 for AA bonds, and RAT3 for A bonds.

Additionally, we incorporate in the analysis a series of bond-specific liquidity and information asymmetry measures to capture any microstructure effects across the cross-section of bond issues. These include:

i. Abnormal Volume [ABV = (Daily Volume – Average Volume)/Average Volume]. Abnormal volume assesses the trading volume of a bond on a given day relative to its average trading volume during the last 90 days (Li et al. 2009). Higher than “usual/average” volume is indicatory of unusually higher activity, possibly related to the presence of private information in the market (Easley et al. 2002).

ii. Net Trade Flow Imbalance [NTI = (Buy Traded Volume – Sell Traded Volume) / (Buy Traded Volume + Sell Traded Volume)]. Net trade flow imbalance is used by Li et al. (2009) as a metric related to potential asymmetric information as well as concerns arising in inventory management. Brandt (2004) provides further evidence for the potential information content of this variable by showing that traded flow imbalances can explain a material component of yield spread changes.

iii. Equity Volatility (VOL). The higher the equity volatility, the higher the uncertainty regarding a firm’s true valuation. Van Ness et al. (2001) find that equity volatility is positively correlated with information asymmetry. In a similar vein, Easley et al. (2002) examine whether the PIN[8] measure remains statistical significant for determining excess returns, even after controlling for the standard deviation of daily returns. Lastly, considering the unilateral volatility spill-over from the stock to the bond market (Fang 2006), we include in the analysis the 1 month equity returns historical volatility for each firm.

iv. Equity Returns (RET). Equity returns may capture information in the equity market that has not been yet incorporate in the corporate bond prices. As Forte and Pena (2009) show, bonds are the slowest in the price discovery.

v. Liquidity Score (LIQ). Liquidity Score is a metric that is available in our sample and summarizes the whole trading activity of each bond during the last month (average turnover, average price variability, percentage of trading days etc). Thus, it can be considered as a rather precise market proxy of bond-specific liquidity. The higher the bond illiquidity, the more persistent is its price, so that low liquidity give rise to high transaction costs that hinder value traders from discovering a bond's intrinsic value. On top of that, Chen et al. (2007) denote that the lower the bond liquidity, the higher its yield spread. Thus, suggesting that liquidity variables have also to be used in explaining observed yield spreads. We introduce two dummies (LIQ Buy, LIQ Sell) to capture the different impact of liquidity subject to the direction of the trade. In a sense, reflecting any liquidity premia present in yield changes. In Appendix C a model that identifies the determinants of liquidity score is presented. In doing so, a series of static bond characteristics along with volume related liquidity metrics are combined.

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[8] PIN stands for probability of information-based trading.

vi. Finally, we introduce dummy variables to characterize each day according to the investor category who dominated the trades for each bond. The variables are constructed by identifying the investor category with the highest traded volume, while simultaneously considering the position it undertakes, i.e. buying vs. selling side. Our sample contains volume information for three distinct investor groups, that is, institutional, retail and block. Institutional investors include banks and funds, while retail customers incorporate corporations, small banks and retailers. Block traders are institutional investors who ask bond dealers for ad-hoc quotes as they want to transact huge amounts. We would refer from this point onwards to both institutional and block investors as institutional, since, in essence, block investors are impatient institutional investors of trading large volumes. We employ two dummies (i.e. Buy, Sell) for each investor category (i.e. INST, RETAIL) to capture the distinct impact on the response variable. More information regarding the detailed estimation of the investor specific dummies is provided under the respective sections, since the way these dummies (slope or fixed terms) are structured is subject to the dependent variable in each hypothesis.

In table 2 we present some summary statistics for the variables included in the analysis. The excess returns distribution has high kurtosis and is positively skewed. It has a negative median value (-0.0111%) that is more than twice, in absolute terms, its mean (-0.0041%), reflecting that the majority of the traded flows do not compensate investors with positive excess returns. Both the mean and the median bond yield change amount to -0.0025%, with the yield changes distribution having negative skewness and high kurtosis. The bonds included in our sample have an average coupon rate of 4.89%, a mean outstanding balance of 966 mio, a mean liquidity score of 14.16 and are on average 3.38 years old. While, bond issuers exhibit a median leverage ratio of 38%. Lastly, the distribution of net traded flows is slightly negatively skewed with a mean of 0.74% and a high standard deviation, in essense, reflecting the persistence of big one-sided aggregate net trade flow imbalances.

3. Hypothesis testing

3.1. Hypothesis 1: Dealers pre-classify their clients into informed and uniformed trying this way to share in the value traders profits

The process of trading reflects the transition from a precisely defined informational state to an updated one, so that informational efficiency is attained in the market through the assimilation of new information into the prices. The continuous adjustment of asset prices to new information is interlinked with the returns' generation process as noted by Easley, Hvidkjaer and O'Hara (2002). The observed returns are therefore the combined effect of the dealers' quote setting strategies, reflecting their response to information uncertainty, and of the incoming orders they fill. Although trading orders are submitted by either informed or uniformed traders, market microstructure theory (Sequential models (Glosten-Millgrom 1985), Strategic trading models (Kyle 1985)) posits that dealers respond to the demanded flows they observe without making any prior classification of their clients' status as informed or uninformed.

Market microstructure theory assumes the stylized fact of clients with uniform characteristics. However, it might be that dealers may actually use the non-uniformity of their clients in seeking an equilibrium price for a security. Dealers might actually utilize additional characteristics for pre-classifying their clients into informed and uniformed. Motivated by current literature in the FX (King et al. 2013, Cerrato et al. 2011) and the in equity markets (Underwood 2009), it seems that the very first available criterion that dealers can employ so as to distinguish between informed and uniformed clients is their identities.

On the way to an equilibrium price, dealers not only try to avoid any potential losses that might arise from selling a security at a low price, which subsequently rises, or by buying a security at an expensive price, which afterwards falls, but also they may attempt to share part of the value traders profits. In a sense, dealers try to predict any security price adjustments that would follow during the next days. Hence, we anticipate that dealers place disproportional weight on the orders submitted by informed investors, resulting in larger adjustments to their quoted prices. For this purpose, we frame the first hypothesis so as to explore for any premiums in the contemporaneous yield changes that can be attributed to each investor group. In particular, we investigate whether the investor category that the dealers' counterparties belong, that is, whether they are retail or institutional investors, constitutes an additional driver that dealers consider under their quote adjustment processes. To do so, we use the daily yield changes (Δy) of each bond as dependent variable and we utilize panel data analysis to identify the potential determinants.

We include[9] in the model specification both bond-specific and issuer-specific variables. Bond characteristics can be directly considered by bond dealers in their price setting processes, or they may help dealers "guess" the private information of their client regarding particular issues. Issuer related data reflects the information transmitted in the corporate bond market via the equity market. The equity market

[9] A detailed description of the variables used under this hypothesis is provided in section 5.2.3.

variables that we incorporate in the regressions are equity returns and equity return volatility changes. Specifically, we use lags of these variables in the t-1, t-2 and t-3 intervals to avoid any endogeneity problems.

Volume slope dummies that capture the combined effect of the signal as well as of the information probability are also incorporated in the model. The signal is reflected both in the direction (buying-side vs. selling-side) and in the logarithm of the traded volume. Thus, directly associating the impact of high volume buying-side or selling-side trades to yield adjustments. This approach is deemed appropriate as high buying-side volumes are expected to drive prices upwards and bond yields downwards, while high selling-side volumes are expected to drive prices downwards and bond yields upwards. On the other hand, the information probability is transmitted by the investor category that initiated the trade. In a sense, reflecting the dealers' distinct price reactions to each investor category.

We also include in the model changes in the net trade flow imbalances[10], which constitute a core indicator of the information transmitted via the trading process in the bond market (Li et al. 2009, Brandt 2004). Additionally, we augment the model with two liquidity specific dummies, one for the buying and another one for the selling side trades. This way, we capture the smaller impact of traded flows on the yield changes for highly liquid bonds. Indeed, when an investor buys a liquid bond, its price rises less compared to an illiquid bond. Thus, leading to a lower bond yield decrease and so justifying a positive coefficient. On the other hand, when an investor sells a liquid bond, its price falls less compared to an illiquid bond, so that the lower yield increase justifies a negative dummy coefficient. We allocate the bonds in the

[10] More details on the definition and the use of this variable are provided in section 5.2.3.

sample into five quantiles according to their liquidity score, and then take the two upper quantiles as the ones comprising of the most liquid bonds. That is, bonds with a liquidity score above the 60% quantile are considered as being highly liquid.

In identifying the determinants of yield changes we employing random-effects[11] GLS panel data analysis with robust clustered standard errors. The respective equation is presented below.

$$\begin{aligned}\Delta y_{i,t} = b_0 + b_1 C_{i,t} + b_2 AMT_{i,t} + b_3 FN_{i,t} + b_4 AGE_{i,t} + b_5 COC_{i,t} + b_6 DOM_{i,t} \\ + b_7 EUR_{i,t} + b_8 MK_{i,t} + b_9 SEC_{i,t} + b_{10} SN_{i,t} + b_{11} MAT_{i,t} \\ + b_{12} RAT1_{i,t} + b_{13} RAT2_{i,t} + b_{14} RAT3_{i,t} + b_{15} LIQ\_B_{i,t} \\ + b_{16} LIQ\_S_{i,t} + b_{17} \Delta VOL1_{i,t} + b_{18} \Delta VOL2_{i,t} + b_{19} \Delta VOL3_{i,t} \\ + b_{20} RET1_{i,t} + b_{21} RET2_{i,t} + b_{22} RET3_{i,t} + b_{23} \Delta NTI_{i,t} \\ + b_{24} InstBlock\_Buy\_Vol_{i,t} + b_{25} InstBlock\_Sell\_Vol_{i,t} \\ + b_{26} Retail\_Buy\_Vol_{i,t} + b_{27} Retail\_Sell\_Vol_{i,t}\end{aligned}$$

(Equation 1)

Our findings, presented in table 3, suggest that dealers tend to pre-classify their clients as informed and uninformed, and use this a-priori classification to adjust their response towards the observed traded flow. In case institutional investors are on the buying-side, dealers decrease the required bond yields (negative coefficient). Whereas, in case institutional investors are on the selling-side, dealers raise bond

[11] Breusch and Pagan Lagrangian multiplier test indicated that random effects are preferable to a pooled regression (Reject H_0: variances of groups are zero). Furthermore, Hausman specification test indicated that random effects are preferable to fixed effects (Accept H_0), since the difference between the fixed effects and the random effects coefficients is not systematic at the 1% confidence level.

yields (positive coefficient). A plausible interpretation of the abovementioned reactions can be that bond dealers consider institutional investors as informed, so that they contemporaneously adjust their quoted prices to be compensated for bearing a higher adverse selection risk. In a sense, it seems that dealers try to participate directly in the profits of informed traders.

On the other hand, bond dealers respond differently when transacting with retail investors. In particular, in case retail investors ask to buy a bond, dealers adjust upwards their quoted yields (positive coefficient) and so selling at lower prices. While, in case retail investors sell a bond, dealers increase quoted bond yields (positive coefficient) and so buying at lower bond prices. To state it differently, when retail investors buy a bond, bond dealers do not overprice the securities to be sold. Whereas, when retail investors sell a bond, bond dealers react to a potential deviation from their desired level of inventory, thus, charging retail investors an additional premium in their quoted prices. Not surprisingly, though, the coefficient reflecting the dealers' response to securities sold by institutional investors is about four times higher than the respective coefficient for the retail investors. Essentially, highlighting the higher adverse selection risk incorporated in the dealers' quoting strategies when transacting with institutional investors.

As far as the other independent variables are concerned, they have the expected signs. In detail, we can note the following:

- A decrease in equity returns drives yields upwards, plausibly hinting at changes in the financial health of the bond issuer.
- Surprisingly, equity volatility changes are not significant in determining bond yield changes in any conventional confidence level.

- The response of dealers in trading liquid bonds is milder relative to the illiquid ones, as reflected in the respective dummy coefficients.
- The higher the maturity, the lower the credit rating, and the lower the coupon of a bond, the higher the yield changes, so reflecting the more intense dealers' response for bonds bearing higher interest rate and credit risk.
- Finally, the coefficient of changes in Net Trade Flow imbalances is negative, signaling that increased buying pressure drives yields down (prices up), while increased selling pressure drives yields up (prices down).

3.1.1 Extend a sequential trade model to consider the customer type

We have identified under Hypothesis 1 that dealers consider under their quote adjustment strategies the investor category that their counterparties belong. So, they could also assign different probabilities to informed relative to uniformed traders subject to their investor category. That is, the parameter regarding the percentage of informed traders that dealers incorporate under their pricing processes might not be the same across institutional and retail investors, but rather depends on each investor's type. Hence, we include different probabilities of institutional and of retail traders to be informed in the sequential trade model proposed by Easley O'Hara (1992) (EO) so as to develop an extended model (CV).

We first construct an event tree that considers different probabilities between informed retail and informed institutional investors. Then, we use the structure of the tree so as to derive the formulas that dealers employ to determine their Bid and Ask quotes. The event tree, presented in Figure 1, goes as follows:

i. There is probability (θ) that there is an information event and ($1-\theta$) that there is no information event in the market.

ii. In case of an information event (θ), there is probability (δ) of bad news that would drive the price of the security down (Vd) and probability ($1-\delta$) of good news that would drive the price of the security up (Vu).

iii. There is probability (μ) that an informed trader will arrive and ($1- \mu$) that an uninformed investor will arrive.

iv. However, there is a different probability of an institutional investor being informed ($\mu 1$) relative to the probability of a retail investor being informed ($\mu 2$), where $\mu 1>\mu 2$.

v. If the investor that arrives is informed, he will decide to trade or not based on the information he possesses. In case the investor decides to trade, there is 50% probability that he will trade with the dealer (TR: Trade) and 50% that he will trade with another dealer (LT: Lose Trade). That is, we consider in our modeling process two competing dealers that set their quotes in the market.

vi. Whereas, if the investor is uninformed, there is a 50% probability of being a buyer and 50% of being a seller. Furthermore, there is possibility of (ε) that the uninformed trader (buyer or seller) will ultimately decide to trade (TR) and probability of ($1-\varepsilon$) of not trade (NT: Not Trade). In case the investor decides to trade, we assign to each dealer the same probability of being selected by the trader ($\varepsilon/2$).

vii. Finally, when there is no information event ($1-\theta$), only an uninformed investor can potentially trade, with 50% of being a buyer and 50% of being a seller and with a probability of (ε) that the uninformed trader (buyer or seller) will eventually decide to trade and probability of ($1-\varepsilon$) of not trade (NT). Similarly, we consider that each dealer has the same probability of being selected by the trader (ε/2).

However, whether the extended model (CV – Chalamandaris, Vlachogiannakis) outperforms, in terms of the P&L that it generates for the dealers, relative to a model that doesn't consider the type of the counterparty (Easley O'Hara 1992 (EO)) is something that remains open[12]. To this end, we perform a simulation exercise for three different market states. In the first population there is no information in the market (State: No Info), in the second there is negative news in the market resulting in the value of the security to reach Vd at the end of the day (State: Vd), while in the third state there is positive news in the market leading in the value of the security to reach Vu at the end of the day (State: Vu). Each day we have 200 different transactions, for which we perform 2000 permutations so as to calculate the dealer's P&L distribution both with the model developed by Easley O'Hara (EO) and by the extended model (CV).

We utilize the empirical cumulative P&L distribution so as to assess the superiority[13] of the one model relative to the other. In particular, in Figure 2 we can notice that the Realized P&L generated by the CV model is much higher relative to

[12] The detailed equations used under the CV model are presented in Appendix B.

[13] The superiority of the one model relative to the other can be statistically assessed by testing for stochastic dominance in their P&L distributions. There are two main types of stochastic dominance. In the first order stochastic dominance, event A first order stochastically dominates event B if $P(A>x) \geq P(B>x)$ for all x, or $F_A(x) \leq F_B(x)$ where F_A and F_B represent the cumulative density functions of A and B respectively. Whereas, we say that event A second order stochastically dominates event B if they are singly crossing (i.e. intersect only in one point) with $F_A(x) \geq F_B(x)$ for low x and $F_A(x) \leq F_B(x)$ for high x, so that $E(A) \geq E(B)$. For a comprehensive analysis of the topic see Cowell (2009).

the one generated by EO. The realized P&L pertain to the matched trades during the day (i.e. min(number of buys, number of sells)). At the same time, in Figure 3, we observe that the unrealized P&L of CV is higher than the one by EO. The unrealized P&L regards the excess volume that remains in the dealer's inventory at the end of the day. Finally, in Figure 4 we present the histogram based on the empirical cumulative distribution function for the total P&L generated by the CV model over the model of EO. Our findings indicate that the model of CV over-performs relative to EO in terms of the P&L that it generates for the dealer.

All in all, our analysis points that the a-priory information held by traders is not neutral across different investor types, but is rather dependent on each investor category. Thus, should a dealer consider a counterparty prejudice cost in his quote adjustment process, he will attain a higher P&L relative to the case of not considering this type of information at all.

3.2. Hypothesis 2: Dealers are right in pre-classifying their clients as informed and uninformed

A question that arises naturally from the previous findings pertains to whether dealers are ex-post justified in pre-classifying their clients. That is, to what extent the mapping of retail investors as uninformed and of institutional investors as informed is indeed linked more often than not with subsequent losses for the former and with subsequent gains for the latter. In a sense, the second hypothesis provides evidence for the faultlessness of the dissimilar dealers' quoting responses to each investor category.

The diffusion of private information to the corporate bond market occurs via the trading process. So, we can reasonably expect that investors utilizing private information earn statistically significant excess returns around the day they transact. We analyze separately the two distinct time periods determined by the trade day as cutoff point. The first period focuses on the excess returns following a trade while the second concentrates on the excess returns before the trade day. We consider that these two periods are complementary in unveiling the excess returns earned by each investor category. Further intuition behind the reasoning for examining both the period after and the period before a trade takes place is provided in the next two paragraphs via some illustrative examples.

Consider an informed investor who purchases a bond based on some good news for the prospects of a firm. We anticipate the bond to earn a positive return the next days, as the private information will be gradually reflected in its price, so increasing the gains for the buyer. Similarly, negative news for the outlook of a firm is expected to decrease the price of the bond over the next days, as the private information will be made public progressively. Thus, an informed investor could either avoid this potential negative return by selling any outstanding bond balances in his portfolio, or even manage to earn a positive return by shorting that particular bond. To this end, we initially structure the analysis in such a way so as to investigate whether trades that are initiated by institutional or retail investors on day (t), are followed by different cumulative excess returns for the (t+1) up to (t+5) and for the (t+30) horizons.

Recognizing that many investors actively manage their bond portfolios by regularly buying or/and selling securities, it is highly likely that when informed investors sell a bond at (t) they do not open a short position, but rather they close a long position they hold from the past. By doing so, they are either locking their profits (take-profit) in case bond prices have increased over the last days, or they are just averting any loses (stop-loss) from a subsequent drop in bond prices. Similarly, informed investors can buy bonds whose prices have dropped significantly over the last days, as they might think that their current yields more than offset the underlying risks. An analysis of the period before the trade day sheds therefore additional light on the realized excess returns earned by investors taking a particular position on the trade day. For this purpose, we subsequently complement our analysis by investigating whether trades that are initiated by institutional or retail investors on day (t), are preceded by different cumulative excess returns for the (t-1) up to (t-5) & (t-30) horizons.

3.2.1 Excess Returns Estimation

We use, in turn, three distinct approaches for defining corporate bond realized excess returns in testing the second hypothesis, each one focusing on a different dimension of corporate bond trading. Under the first one, daily excess bond returns are calculated over the return of a matched by rating and maturity value-weighted portfolio. The second one regards excess bond return over a benchmark risk free rate, while the third approach entails the use of aggregate excess returns of the matched by rating and maturity value-weighted sub-portfolios as an extra independent variable.

In particular, excess returns over a matched by rating and maturity value-weighted portfolio consider the part of an investor's return that can be attributed to his credit-picking ability. This methodology is similar to the one used to calculate abnormal returns around certain events, like in event studies. The trigger event in our study is how concrete trading positions undertaken by different investor categories impact on corporate bond excess returns. Our approach also seems appropriate in light of the findings by Bessembinder (2009), who performs a comparative analysis of the methods used to calculate abnormal returns. He posits that the use of daily data (compared to monthly) along with the measurement of abnormal returns over a value-weighted (relative to equally weighted) benchmark portfolio substantially improve the robustness of the statistical tests used for the identification of abnormal returns. Excess bond returns over a matched by rating and maturity value-weighted portfolio also capture the impact of any macroeconomic announcements, which are expected to affect analogously bonds that share similar maturity and credit risk features. Whereas, at the same time, the idiosyncratic component of excess returns that is probably related with the exploitation of private information remains intact.

By controlling bond returns for the term and for the default premiums (Fama and French 1993), the first approach is aligned with the asset pricing literature, in which the estimation of sensitivities (betas) for systematic factors is performed across all bonds allocated in the same maturity or/and rating sub-portfolio (Li et al. 2009). However, it doesn’t suffer from the calibration uncertainties of asset pricing models, which are related to the estimation of factor loadings (sensitivities). That is, the fact that factor loadings are time varying as well as contingent on the length of the rolling-window used for their calculation.

According to the second approach, which is the most commonly used in the literature, we estimate the excess return for each bond over a benchmark risk free rate. This approach considers an all-in type of excess return over the funding cost of investors. Hence, it captures both the returns attributed to investors’ bond picking abilities and systematic trading strategies.

Finally, the third approach entails the use of aggregate excess returns of the matched by rating and maturity value-weighted sub-portfolios as an extra regressor for determining excess bond returns over a benchmark risk free rate. Particularly, this variable is structured in such a way so as to link the sub-portfolio excess returns with the position (buying-side or selling-side) undertaken by each investor category. In a sense, we shed light on the significance of investors' bond picking abilities or/and systematic trading strategies in the formation of the excess returns they earn.

The three approached described above for the estimation of excess returns are complementary. Indeed, the return of a bond (R_B) over the risk free (R_F) rate can be decomposed into two parts. The first captures the return of the respective market sub-portfolio (R_M) over the risk free rate (R_F), reflecting the systematic trading premium in bond excess returns. Whereas, the second denotes the return of a bond (R_B) over the return of the matched by rating and maturity market sub-portfolio (R_M), denoting the excess returns attributed to investors' bond picking skills. Specifically, the excess bond return over the risk free rate, as calculated under the second approach, equals the excess return of the respective market segment over the risk-free rate, as estimated according to the third approach, plus the excess bond return over the respective market sub-portfolio, as computed in the first method. That is, $(R_B - R_F) = (R_M - R_F) + (R_B – R_M)$.

3.2.1. Identifying the corporate bond excess returns, over a matched by rating and maturity value-weighted portfolio, earned by institutional and retail investors

The returns earned by each investor category can be considered as being proportional to the level of the private information it possesses. Provided that dealers are right, we expect the realized excess returns earned by each investor group to vary. In discriminating between dealers' clients, we use separate dummies for capturing the returns generated by the buying-side relative to the selling-side traded flows. This way, any fixed premiums are directly linked to the positions undertaken by each investor group. Considering that the corporate bond excess returns might require some days before appearing in the market, we examine the cumulative excess return for each bond after the trade day (t) up to t+1, t+2, t+3, t+4, t+5 & t+30 horizons. This approach reveals whether certain investors select bonds that consistently over-perform during the next days, while at the same time captures cases where limited market liquidity results in a slower price adjustment to new information, which decelerates the excess returns generation process.

In testing H2 we perform a total of 12 regressions. Specifically, we examine separately the excess returns earned by each investor category[14] (x 2 models) over the t+1 up to t+5 & t+30 horizons (x 6 models). We present below the regression equations for each investor category and for the case in which the dependent variable is the excess bond returns over the matched by rating and maturity sub-portfolio in the (t+1) horizon. The remaining equations include the same regressors, while the dependent variable is changed to reflect each horizon examined.

Institutional Investors

[14] This approach is required so as to avoid multicollinearity

$$ExRet_{i,t+1} = b_0 + b_1C_{i,t} + b_2AMT_{i,t} + b_3FN_{i,t} + b_4AGE_{i,t} + b_5COC_{i,t} + b_6DOM_{i,t} + b_7EUR_{i,t} + b_8MK_{i,t} + b_9SEC_{i,t} + b_{10}SN_{i,t} + b_{11}LIQ_{i,t} + b_{12}ABV_{i\,,t} + b_{13}VOL_{i,t} + b_{14}RET_{i,t} + b_{15}RET1_{i,t} + b_{16}RET2_{i,t} + b_{17}RET3_{i,t} + b_{18}NTI_{i,t} + b_{19}INST\_BUY_{i,t} + b_{20}INST\_SELL_{i,t}$$

<u>Retail Investors</u>

$$ExRet_{i,t+1} = b_0 + b_1C_{i,t} + b_2AMT_{i,t} + b_3FN_{i,t} + b_4AGE_{i,t} + b_5COC_{i,t} + b_6DOM_{i,t} + b_7EUR_{i,t} + b_8MK_{i,t} + b_9SEC_{i,t} + b_{10}SN_{i,t} + b_{11}LIQ_{i,t} + b_{12}ABV_{i\,,t} + b_{13}VOL_{i,t} + b_{14}RET_{i,t} + b_{15}RET1_{i,t} + b_{16}RET2_{i,t} + b_{17}RET3_{i,t} + b_{18}NTI_{i,t} + b_{19}RETAIL\_BUY_{i,t} + b_{20}RETAIL\_SELL_{i,t}$$

(Equation 2)

Seeing that the number of ISINS is almost five times the number of issuers, it may be that some issuers dominate the sample. For this reason, we employ a panel data analysis with cluster robust standard errors so as to allow for any correlation among the bonds of the same issuer. Specifically, we adjust the standard errors for the case that observations are independent across issuers but not necessarily within each issuer. Last, we utilize a random effects GLS estimator[15] to produce a matrix-weighted average of the between and within estimates, so capturing any non-observable heterogeneity among the firms in our sample.

Our results for the t+1 horizon suggest that the models are overall highly statistically significant (Prob > X^2 equals 0) with an explanatory power around 6%, as indicated by the R-squared, which decreases as we consider cumulative excess returns over longer horizons. In table 4 we present the detailed output of the

[15] Breusch and Pagan Lagrangian multiplier test indicate that random effects are preferable.

regression analysis for the t+1 horizon. The signs[16] for the investor category dummy coefficients indicate that institutional investors do gain, while retail investors do lose for this horizon. Thus, providing some preliminary evidence that dealers correctly pre-classify their clients as informed and uninformed.

We can also note in table 4 that higher transaction flow imbalances are followed by higher positive excess bond returns for the buying side trades and by higher negative excess bond returns for the selling side trades. That is, excess buying and selling volumes drive upwards and downwards bond prices respectively. As posited by market microstructure theory, dealers adjust their quoted prices to reflect the direction of the trade, in line with the results of Li et al. (2009).

Regarding the positive coefficients for the lagged equity returns, they indicate that corporate bond excess returns accommodate for any news in the equity market. In particular, positive (negative) equity returns lead to increased (decreased) bond prices and so positive (negative) excess bond returns. The coefficient for equity returns volatility is negative and significant at the 10% confidence level. That is, increased volatility, reflecting heightened uncertainty, drives bond prices downwards so that negative bond returns are generated. All in all, our results imply a news transmission process from the equity to the bond market, as lagged equity market variables are significant in determining excess bond returns.

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[16] In interpreting the coefficients of the investor-specific dummy variables, the following have to be considered. A positive coefficient indicates a positive excess bond return (positive premium) that arises from an increase in the bond price, denoting a gain for the buyer and a loss for the seller of the bond. On the other hand, a negative coefficient shows a negative excess bond return (negative premium) that stems from a decrease in the bond price, signifying a gain for the seller and a loss for the buyer of the bond.

The negative relation between liquidity score and excess returns verifies the smaller premiums required by investors transacting on highly liquid bonds. To state it differently, investors demand an illiquidity premium in the form of an additional excess return so as to invest in less liquid bonds.

Certain static bond characteristics also affect corporate bond excess returns. On the one hand, the higher the coupon and the age the higher the excess bond returns. Higher coupon bonds provide a higher return for their holder, while more aged bonds usually carry a higher return so as to compensate investors for higher illiquidity. On the other hand, the negative coefficients of the variables related to the "Domestic" and to the "Market" dummies, confirm that the risk of debt issued in the domestic country or by public firms is more easily monitored by the bondholders. Seeing that the pricing of these bonds entails less asymmetric information, lower excess returns are anticipated. Finally, the positive coefficient for the dummy related to bonds issued by "Financial" firms suggests the presence of a fixed premium in the excess returns of financial firms. Seeing the closer interconnectedness of financial relative to non-financial firms with the global money and capital markets, investors have to be compensated for undertaking higher systematic risk.

In table 5 panel A1 we present only the coefficients of the dummy variables that capture the cumulative excess returns (fixed premiums) for each investor category along all the time horizons examined. For institutional investors our results suggest that they consistently benefit when they buy a bond in all the horizons examined as well as when they sell a bond for horizons t+1 up to t+3 & t+30. In particular, the positive coefficients in the former case and the negative coefficients in the latter one, denote a price increase (benefiting the buyer) and a price decrease (benefiting the seller) respectively. Institutional investors appear to be on the “correct” side of the market more often than not, reflecting the privileged information they have access to. Thus, verifying the dealers’ conception that they are indeed the value traders in the market.

Regarding retail investors, they consistently lose for almost all the horizons examined. Specifically, when retail investors buy a bond its price subsequently decreases, while when they sell a bond its price afterwards increases. Retail investors are mainly utilitarian traders that are driven by private value considerations, while at the same time they are the ultimate counterparties of informed investors via the dealers’ intermediation. As dealer’s strategy predicted, retail investors appear to be on the “wrong” side of the market more often than not. Thus, the dealer’s perception that they are noise traders is once again confirmed.

Our results provide evidence that the transaction flows placed by different categories of investors are directly linked to the ex-post excess returns that each group realizes. In a sense, the existence of different access levels to “privileged” information, among different investor groups in the corporate bond market, is justified on the grounds of the different excess returns earned by each investor group.

Investors that manage actively their bond portfolios by buying or/and selling securities may not open a short position when selling a bond, but rather they may close a long position they held from the past. To this end, we further test for the existence of any fixed premiums in the corporate bond excess returns before a trade takes place. That is, we explore for a bond’s preceding excess returns along the t-1 up to t-5 and the t-30 horizons before the trade day.

The specifications we employ so as to test for investor-type premius before a trade takes place are similar to the ones under equation (2), except that the dependent variable is now referring to the horizons before the trade day. Our results, presented in table 5 panel A2, indicate that retail clients appear to buy bonds the prices of which have increased over the previous day. Specifically, the statistically significant positive coefficient for the t-1 horizon implies that there is a positive premium in the prices of the bonds bought by retail investors at (t), possibly reflecting their expectation for a further bond price increase over the next days. Furthermore, retail investor appear to sell bonds the prices of which have decreased over the t-3 up to t-5 periods, possibly deciding to close their positions at a cost . In particular, the negative coefficients for the t-3[17], t-4[18] and t-5 horizons reflect the decrease in the price of bonds sold by retail investors at (t). Overall, the returns of the retail investors exhibit a negative correlation with realized bond returns before their trade, thus, justifying the characterization of "uninformed".

On the other hand, the returns of institutional investors are positively correlated with realized bond returns before their trade. That is, they benefit by buying bonds the prices of which have decreased during the t-1 up to t-2 horizons and by selling bonds the prices of which have increased over the t-3 up to t-5 horizons. Essentially, institutional investors buy bonds in decreased prices while locking their profits by selling the bonds they have in their portfolios at increased prices. To sum up, institutional investors profit from the preceding realized bond returns before their trade, confirming once again that they are the informed ones in the market.

[17] Marginally insignificant at the 10% confidence level.

[18] Significant at the 10% confidence level.

All in all, our findings both for the periods before and after the trade day suggest that institutional investors consistently benefit whereas retail investors consistently lose.

3.2.2. Identifying the corporate bond excess returns over the risk-free rate earned by institutional and retail investors

In this sub-section we repeat the analysis described above, but this time we calculate excess returns over the risk free rate and not over a matched by rating and maturity value weighted portfolio. Implicitly, this approach takes into account an all-in type of excess return over investors' funding cost. We also include in the model additional explanatory variables related to the maturity and the credit ratings of each bond, as the dependent variable is not somehow "adjusted" to reflect any differentiation in their impact. Our results pertaining to the excess returns enjoyed by each investor category across all the horizons examined are presented in table 5 Panels B1 & B2. Overall, our findings remain qualitative the same with the ones under section 3.2.1, verifying once again that informed investors earn more often than not while uninformed investors lose more often than not both in subsequent and preceding horizons around the trade day.

3.2.3. Identifying the corporate bond excess returns stemming from systematic trading strategies, earned by institutional and retail investors

In this subsection we test whether the excess returns earned by various investors can be attributed not only to their bond picking abilities, but also to their systematic trading strategies. In particular, we examine whether certain investor categories do earn statistical significant excess returns via the trading of corporate bonds that belong to market segments that share similar maturity or/and credit rating characteristics. It is not uncommon for institutional investors to adopt an investment strategy oriented towards trading bonds with specific credit rating or/and maturity profiles, rather than focusing on particular bonds. Such a strategy is less costly to implement since it entails an analysis of the overall macroeconomic conditions rather than of a particular bond issuer. Moreover, it enables investors to create diversified portfolios with small "name" concentration. Hence, it is more often than not preferred by investors who want to get exposed to a particular market segments without being over-exposed to single names.

Taking all the above into account, we include into the set of regressors a new variable that combines the excess return of the matched by rating and maturity value weighted benchmark sub-portfolio ($ExRet_{M,t}$) with the position undertaken by each investor category. That is, it takes the value of the sub-portfolio excess return over risk free rate for the horizon examined in case a certain investor category traded at (t), else it is set to zero. The coefficient of this variable serves as an indicator for the magnitude of excess returns enjoyed by each investor category that are driven by the returns of the respective market segment. Both the market excess returns slope dummy coefficients as well as the investor category fixed effect dummies are presented in table 5 Panel C for all time horizons examined. We next present the respective equations for the t+1 horizon.

Institutional Investors

$$
\begin{aligned}
ExRet(Rf)_{i,t+1} \\
&= b_0 + b_1 C_{i,t} + b_2 AMT_{i,t} + b_3 FN_{i,t} + b_4 AGE_{i,t} + b_5 COC_{i,t} \\
&+ b_6 DOM_{i,t} + b_7 EUR_{i,t} + b_8 MK_{i,t} + b_9 SEC_{i,t} \\
&+ b_{10} SN_{i,t} + b_{11} MAT_{i,t} + b_{12} RAT1_{i,t} + b_{13} RAT2_{i,t} + b_{14} RAT3_{i,t} \\
&+ b_{15} LIQ_{i,t} + b_{16} ABV_{i,t} + b_{17} VOL_{i,t} + b_{18} RET_{i,t} + b_{19} RET1_{i,t} \\
&+ b_{20} RET2_{i,t} + b_{21} RET3_{i,t} + b_{22} NTI_{i,t} + b_{23} ExRet_{M,t+1} InstBuy_{i,t} \\
&+ b_{24} ExRet_{M,t+1} InstSell_{i,t} + b_{25} InstBuy_{i,t} + b_{26} InstSell_{i,t}
\end{aligned}
$$

Retail Investors

$$
\begin{aligned}
ExRet(Rf)_{i,t+1} \\
&= b_0 + b_1 C_{i,t} + b_2 AMT_{i,t} + b_3 FN_{i,t} + b_4 AGE_{i,t} + b_5 COC_{i,t} \\
&+ b_6 DOM_{i,t} + b_7 EUR_{i,t} + b_8 MK_{i,t} + b_9 SEC_{i,t} \\
&+ b_{10} SN_{i,t} + b_{11} MAT_{i,t} + b_{12} RAT1_{i,t} + b_{13} RAT2_{i,t} + b_{14} RAT3_{i,t} \\
&+ b_{15} LIQ_{i,t} + b_{16} ABV_{i,t} + b_{17} VOL_{i,t} + b_{18} RET_{i,t} + b_{19} RET1_{i,t} \\
&+ b_{20} RET2_{i,t} + b_{21} RET3_{i,t} + b_{22} NTI_{i,t} + b_{23} ExRet_{M,t+1} RetBuy_{i,t} \\
&+ b_{24} ExRet_{M,t+1} RetSell_{i,t} + b_{25} RetBuy_{i,t} + b_{26} RetSell_{i,t}
\end{aligned}
$$

(Equation 3)

The excess returns earned both by institutional and retail investors are positively related to the returns of the relevant sub-portfolio, as indicated by the statistical significant positive coefficients in almost all horizons examined. Not surprisingly, the part of the excess returns earned by institutional investors that is attributed to systematic trading is much higher compared to retail investors. In particular, the coefficients capturing the influence of the sub-portfolio returns are much higher for institutional than for retail investors, indicating the higher dependence of institutional investors' returns on the returns of the respective market segments. For example, the excess returns earned by institutional investors have a market sub-portfolio sensitivity of 0.57 in the (t+2) horizon, while for the retail investors the respective sensitivity coefficient is only 0.34.

Institutional investors pursue both diversifications and superior returns. This is to be expected because their trades include both market-neutral and index tracking strategies. On the other hand, retail investors do not even follow systematic trends. Specifically, the bond picking strategies of retail investors confirm that they lose both in buying and in selling up to (t+2) horizon while keep losing when they buy up to (t+5) horizon. However, they earn positive excess returns when selling for the (t+3) up to (t+5) horizons, possibly reflecting their lagged response in falling markets.

From another perspective, we examine the decision making process of different market participants. That is, we investigate how realized excess bond returns affect the probability of a trade being initiated by each investor category. To this end we perform a random-effects logistic regression in which the dependent variable is a dummy indicating the dominant investor category. The independent variables include bond-specific and market sub-portfolio excess returns along with a series of bond specific attributes. The analysis is performed over a series of horizons (h) that cover the period both before and after the trade day. Below we present the respective equations for retail investors' buying and selling side trades in the t+h horizon.

<u>Retail Investors</u>

$$\begin{aligned} RetailBuy_{i,t} = {} & b_0 + b_1 C_{i,t} + b_2 AMT_{i,t} + b_3 FN_{i,t} + b_4 AGE_{i,t} + b_5 COC_{i,t} \\ & + b_6 DOM_{i,t} + b_7 EUR_{i,t} + b_8 MK_{i,t} + b_9 SEC_{i,t} \\ & + b_{10} SN_{i,t} + b_{11} LIQ_{i,t} + b_{12} ExRetBond_{i,t+h} + b_{13} ExRetMarket_{t+h} \end{aligned}$$

$$RetailSell_{i,t} = b_0 + b_1C_{i,t} + b_2AMT_{i,t} + b_3FN_{i,t} + b_4AGE_{i,t} + b_5COC_{i,t} + b_6DOM_{i,t} + b_7EUR_{i,t} + b_8MK_{i,t} + b_9SEC_{i,t} + b_{10}SN_{i,t} + b_{11}LIQ_{i,t} + b_{12}ExRetBond_{i,t+h} + b_{13}ExRetMarket_{t+h}$$

where h = -5, -4, -3, -2, -1, +1, +2, +3, +4, +5, reflects the number of days included in the calculation of cumulative excess returns relative to the trade day [before (-) or after (+)].

(Equation 4)

Our results, presented in table 5 panels D1 and D2, indicate that bond purchases by institutional investors are associated, more often than not, with subsequent positive excess returns for the underlying bonds, so that institutional investors appear to be the informed in the market. In particular, the higher the excess returns of a bond or/and of the market sub-portfolio following the trade day (panel D1), the higher the probability of an institutional investor to be the dominant buyer at (t). Whereas, we identify no such a relation for retail investors, so we confirm their characterization as uninformed. Retail investors neither consistently buy the bonds the prices of which increase nor their trading patterns are affected by market returns. The respective coefficients for retail investors are either not statistically significant or much smaller in magnitude relative to the ones for institutional investors.

As far as the selling side trades following the trade day is concerned, our results confirm once again the asymmetry in the information held by institutional relative to retail investors. We find that the more negative the excess returns for a bond and for the market sub-portfolio, the higher the probability both for an institutional and for a retail investor to be the dominant seller at (t). However, the coefficients for institutional investors are in most cases much higher in magnitude and in statistical significance relative to the ones for retail investors, signaling once again that subsequent bond specific and market segment excess returns are indeed linked to the institutional investors' trading behavior at (t).

During the period before the trade day (panel D2), institutional investors appear to offer liquidity while retail investors often seem to buy liquidity following the momentum. In particular, the buying side trades of institutional investors are affected only by bond specific returns, reflecting again that they buy bonds the prices of which have decreased over the previous days. Whereas, retail investors appear to buy bonds in market segments the prices of which have increased over the previous days, possibly expecting an even higher subsequent price rise. Regarding the selling side trades before the trade day, our results suggest that both institutional and retail investors somehow attempt to lock their profits. That is, we observe that the more positive the excess returns of a bond and of the market sub-portfolio for the t-3 up to t-5 horizons, the higher the probability both for an institutional and for a retail investor to be the dominant seller at (t).

All in all, the analysis in the last 3 subsections verifies that dealers are indeed right in identifying retail investors as noise traders and institutional investors as value traders, as the former consistently lose while the latter consistently benefit around the trade day.

3.3. Hypothesis 3: What happens to the dealers? Does this strategy enhance their profits?

What matters the most for the dealers is neither the profits nor the losses of their clients, but rather the potential impact of their quote-setting strategies on their own daily P&L. The efficient quote-setting strategy leads to the fast discovery of the supply-demand equilibrium. The faster this happens, the lower is the cost that dealers will have to pay to informed traders. Theory says that dealers lose to the informed traders and receive their compensation from the uninformed. Indeed, the effects of the dealers' pre-classification strategy on their daily P&L are not easy to guess. Dealers may lose part of their bid/ask spread by overreacting to uninformed orders of traders they have pre-classified as "informed". If this is the case, pre-classification will be damaging to the dealers' P&L and makes no sense. However, it may be that by distinguishing their clients into informed and uniformed categories in a correct way more often than not, they obtain part of the information premium the value traders enjoy. To this end, we study under the third hypothesis whether the pre-classification strategy that dealers follow improves their daily P&L or not.

In testing the third hypothesis we have to compare the realized dealers' P&L margin relative to the P&L margin that the dealers would have earned in case they had responded to all investors as if they were uninformed (retail). In other words, should the dealers had not followed an a-priory classification of their clients as informed and uninformed, but rather considered all of their clients as uninformed, what would have been their P&L. To get an estimate of the dealers' P&L we implement the following approach. Given the large cross sectional dimension of our sample, we can assume without material loss of precision that all trades are executed at the average price[19] between their opening and their closing price on a given day. Multiplying the price change by the net daily volume for a given bond we get the

[19] This assumption results into a conservative estimate for the dealers' daily P&L, since it is possible that dealers might trade all the volume in the closing price (one-off quote adjustment) in cases they are faced by informed investors asking for trading high volumes.

dealers' daily P&L. Next, we divide the daily P&L for each bond for which there is a trade on a given day by the gross volume traded to derive an estimate of the dealers' P&L margin for each bond. Finally, we average all the daily P&L margins for all bonds available in the sample to end up with the dealers' average P&L margin per bond issue[20].

Our results, exhibited in table 6, show that dealers' all-sample mean P&L margin amounts to 4.7 b.p. with a median of 0.84 b.p.. Furthermore, we can note that the P&L margin extracted from institutional investors (6.5 b.p.) is higher than the all-sample mean P&L margin, signaling the dealers' higher adverse selection risk charges to the investors they classify as informed.

The P&L margin in case dealers had responded to all investors as if they were uninformed (retail) can be estimated by the following steps:

i. Estimate the regression under H1 (Equation 1) so as to get the residuals ($Res_{i,t}$).

$$
\begin{aligned}
\Delta y_{i,t} = b_0 &+ b_1 C_{i,t} + b_2 AMT_{i,t} + b_3 FN_{i,t} + b_4 AGE_{i,t} + b_5 COC_{i,t} + b_6 DOM_{i,t} \\
&+ b_7 EUR_{i,t} + b_8 MK_{i,t} + b_9 SEC_{i,t} + b_{10} SN_{i,t} + b_{11} MAT_{i,t} \\
&+ b_{12} RAT1_{i,t} + b_{13} RAT2_{i,t} + b_{14} RAT3_{i,t} + b_{15} LIQ\_B_{i,t} \\
&+ b_{16} LIQ\_S_{i,t} + b_{17} \Delta VOL1_{i,t} + b_{18} \Delta VOL2_{i,t} + b_{19} \Delta VOL3_{i,t} \\
&+ b_{20} RET1_{i,t} + b_{21} RET2_{i,t} + b_{22} RET3_{i,t} + b_{23} \Delta NTI_{i,t} \\
&+ b_{24} InstBlock\_Buy\_Vol_{i,t} + b_{25} InstBlock\_Sell\_Vol_{i,t} \\
&+ b_{26} Retail\_Buy\_Vol_{i,t} + b_{27} Retail\_Sell\_Vol_{i,t}
\end{aligned}
$$

[20] We didn't use volume-weights in our calculation of the average, because this would likely produce biased estimates towards few large issues.

These residuals reflect the unexplained part of the model, that is, the part of the yield changes that cannot be attributed to the explanatory variables employed.

ii. Consider that all investors in the sample are uninformed (retail) by:

a) Using the values for the dummies referring to informed investors (institutionals) along with the dummies for uninformed investors (retail). That way, we apply the dealer's sensitivities (i.e. regression coefficients) of uninformed investors (retail) to the informed investors (institutionals) as well.

b) Setting all the values of the dummies referring to informed investors (institutionals) to zero, so as for the sensitivities of informed (institutional) investors not to be applied to any investor category.

iii. Estimate the projected bond yield changes ($\Delta y_{i,t}^{PrUn}$) using equation 1, while considering the amendments in the values of the investor category dummies described under step (ii).

iv. Generate the total bond yield change ($\Delta y_{i,t}$) by summing the unexplained part of the regression under H1 (step (i)) and the explained part of the regression as if all investors were uninformed (step (iii)).

$$\Delta y_{i,t} = Res_{i,t} + \Delta y_{i,t}^{PrUn}$$

v. Multiply the total bond yield change by the modified duration (MD), by the bond price at t-1 (P_{t-1}) and by the net volume at (t) and divide the product by two, which accounts for the fact that all trades are considered to be executed at their average price between their opening and their closing price for a given day, so as to derive the dealers' P&L for each bond.

$$P\&L_{i,t} = \frac{\Delta y_{i,t} \times MD \times P_{t-1} \times NetVolume_t}{2}$$

vi. Then, divide the daily P&L for each bond (step (v)) by its gross volume traded so as to calculate the daily P&L margin.

$$P\&L\ Margin_{i,t} = \frac{P\&L_{i,t}}{Gross\ Volume_{i,t}}$$

vii. Finally, average all the daily P&L margins for all bonds to get the all-sample average P&L margin as if the dealers considered all investors as uninformed.

Our results, presented in table 6, reveal that in case dealers had considered all investors as being uninformed, they would have earned an average and a median profit margin of only 0.87 b.p. and -0.04 b.p. respectively, against the much higher realized mean and median profit margins that amount to 4.7 b.p. and 0.84 b.p. respectively. Therefore, our analysis provides evidence that indeed the a-priory classification of investors as informed and uninformed proves to be profitable for the dealers. Furthermore, we also present in table 6 the dealers' median and mean P&L margin for transacting with institutional investors. Not surprisingly, the dealers' P&L margin is higher when institutional investors are on the selling-side, reflecting the higher compensation that the dealers require for bearing a higher adverse selection risk.

3.4. Hypothesis 4: Dealers dominate the public information profits

Dealers profit by following a pre-classification strategy of their clients, though, the volatility in their daily P&L is found to be rather high. Seeing that dealers' profits are not uniformly distributed across their bond trades, it might be the case that dealers' profits are rather concentrated around trades executed under certain conditions. In other words, it might be the case that dealers do earn above their average P&L margin when trading under conditions for which they have a competitive advantage over investors.

New information can be either publicly announced or private. The former can pertain either to a macroeconomic (Green 2004, Brenner 2005, Pasquariello 2007) or to a firm-specific announcement. Whereas, the latter can stem from asymmetric information (Fricke 2011, Li et al. 2009, Lyons 2001) or from heterogeneity in the decoding of publicly available information (Brandt 2004, Green 2004) or from particular security characteristics that an investor prefers (clientele effect) compared to another security of similar risk. Publicly announced information is continuously flowing into the market, spurring market participants in continuously updating the prices they are willing to pay or to ask for buying or selling a security respectively. Dealers are continuously monitoring the markets and are experienced enough so as to interpret almost faultlessly any new public information, so that they may have a competitive advantage over other market participants. Indeed, being the market makers, we expect that dealers are the fastest and most efficient news-traders. As such, we anticipate that they are the ones benefiting most from the trades propelled by public information releases. To this end, we are developing the forth hypothesis so as to explore whether the dealers do indeed earn more on the days of public news releases.

To put our hypothesis into test, we need to define what the "news" events are in our sample. We define as public information events all the trades the direction of which can be observed in isolated days. That is, single-day buys and single-days sell followed by the opposite direction on the next day. Furthermore, in order for a public information event to be classified as such we also require that the traded volume exceeds the average trading volume for that particular security, that is, we require that the abnormal volume is positive. Those trades are captured in our analysis through the use of a fixed effect dummy variable named DM single trade. We acknowledge that those trades are most likely motivated by public information, though, with possibly a few utilitarian trades contaminating them. However, the prerequisite for a higher than average volume in order for a day to be classified as a "news" day, precludes from the news identification process all these days in which retail investors, which are mostly driven by exogenous to the market considerations, dominate the market by trading at lower than average volumes.

We also define as public information all those sequences of unidirectional trades of which the magnitude of the yield change registered on that first day is larger than the magnitude of the cumulative yield change registered over the following days of the sequence. The idea is that whenever public information is released, day (t) is news trading, i.e. trading on the direction of the news. We expect this pattern to be especially prevalent in illiquid bonds, causing large price adjustments. During the rest of the days, (t+1) up to (t+N), value traders and arbitrageurs speculate about the exact level of the new, updated price. This fine-tuning is not of such a high interest for the dealers, thus, we expect that dealers winning on the first day of a sequence and perhaps losing little after that. The first day of a sequence is captured in the analysis through the use of a fixed effect dummy variable named DM Δyield 1st day, while the remaining days of the sequence are captured by a fixed effect dummy named DM Δyield rest.

Before moving in formulating a model specification so as to test the hypothesis, we present some summary statistics of the dealers' P&L margin on those "news" days. In table 7 we present the median and mean P&L margin for each one of the abovementioned news days. Our results indicate that the dealers realize indeed a higher than their average profit margin both in the single trade days (7.1 b.p.) and in the days in which yield change registered on that first day is larger than the magnitude of the cumulative yield change registered over the following days of a sequence (17.6 b.p.). Whereas, as expected dealers make a relatively small loss on the rest days of a sequence (-2.2 b.p.). We also apply a simple t-statistic so as to verify that the mean P&L margin is indeed statistically different from zero, and that it is significantly positive for the first and the second case while it is significantly negative in the third case. Overall, the simple summary statistics' analysis provides preliminary evidence for the dealers dominating the public information profits, as their P&L margin significantly increase in these "news" days.

We next proceed in testing the forth hypothesis by developing an econometric model for the determinants of the dealers' P&L. The dependent variable is the daily P&L margin (PL) for each bond traded, which is calculated as described under section 3.3. The independent variables we employee include both static and volume related bond characteristics, equity specific variables as well as the aforementioned "news" days dummies defined above. These "news" day dummies capture premiums in the dealers' P&L margin attributed especially to those public information days, so that their sign and statistical significance will confirm or refute our forth hypothesis. We use panel data analysis to estimate the equation presented below:

$$PL_{i,t} = b_0 + b_1 C_{i,t} + b_2 AMT_{i,t} + b_3 FN_{i,t} + b_4 AGE_{i,t} + b_5 COC_{i,t} + b_6 DOM_{i,t} + b_7 EUR_{i,t} + b_8 MK_{i,t} + b_9 SEC_{i,t} + b_{10} SN_{i,t} + b_{11} MAT_{i,t} + b_{12} RAT1_{i,t} + b_{13} RAT2_{i,t} + b_{14} RAT3_{i,t} + b_{15} LIQ_{i,t} + b_{16} AbnVol_{i,t} + b_{17} VOL1_{i,t} + b_{18} RET1_{i,t} + b_{19} RET2_{i,t} + b_{20} RET3_{i,t} + b_{21} NTI_{i,t} + b_{22} SingleTrade_{i,t} + b_{23} \Delta yield1st_{i,t} + b_{24} \Delta yieldRest_{i,t}$$

(Equation 5)

Our results, presented in table 8, suggest that dealers dominate public information profits since both the "Single Trade" and the "Δyield 1st day" dummy coefficients are positive and highly statistical significant. In other word, our results indicate that dealers do earn more than their mean P&L margin on these public news days, thus, suggesting that they act as the news traders in the market. As anticipated, dealers lose on the rest days of a sequence following a news trade, since they do not participate in the fine tuning process pertaining to the determination of the exact level of the updated bond's price. Overall, Wald X^2 indicates that the model is overall highly statistical significant with an explanatory power of 4.8%. Our findings also point that dealers profit less for higher credit quality bonds, whereas, they profit more for longer maturity bonds. Not surprisingly, the dealers' less intense quote adjustments when trading in highly liquid bonds results into a smaller profit margin. In particular, the negative coefficient of the outstanding amount and of the liquidity score reflect the lower premium required by the dealer for trading in liquid bonds. In a sense, liquid bonds lead to a more intense competition.

4. Robustness checks

In view of the large cross sectional dimension of our dataset, the use of the Fama-MacBeth (1973) algorithm will ensure that any correlation across issuers included in the panel haven't affected the robustness of our results. This two-stage process involves performing cross sectional regression analysis for every single day in the first step, and subsequently averaging the estimated coefficients across time. Our results remain qualitative the same and none of our conclusions is changed.

5. Conclusions

We study a large cross-sectional dataset of investment grade corporate bonds that ranges from January 2012 up to June 2013 and includes daily bond level market data coupled with a wide range of bond specific attributes. Our findings verify that any adverse selection risks are indeed incorporated into dealers' price discovery process by contemporaneously adjusting their quotes to capture the level of potential private information possessed by various investors. Particularly, our analysis suggests that bond dealers do utilize the information pertaining to the investor category of their counterparty, thus, a-priory classifying their clients into informed (institutional) and uninformed (retail) so as to update their expectations regarding the price of a security, and so, share in the value traders profits. We theoretically support our findings by extending the Easley O'Hara model (1992) so as to incorporate the customer type in the quote setting strategy followed by the dealers. Our simulation exercise implies that the extended model (CV) outperforms relative to EO, in terms of the P&L that it generates for the dealers.

Our empirical analysis also unveils that dealers are right in pre-classifying their customer as informed and uniformed, since institutional investors appear to be on the “correct” side of the market more often than not, while retail investors appear to consistently lose in the time horizons examined. Furthermore, we find that the dealers’ P&L margin is significantly improved by following this a-priory classification strategy relative to a simplistic strategy that would treat all investors as uniformed. Last but not least, our results denote that dealers dominate the public information profits, being unequivocally the fastest and most efficient news traders.

Tables of Results

Table 1: Country, sector & credit rating profile of our sample

Panel A

Country	Numb. Of Issuers	Percentage of Observations (%)
Australia	7	0.52
Belgium	4	0.99
Brazil	7	0.68
Canada	29	4.14
Switzerland	14	1.67
Chile	2	0.02
China	4	0.05
Colombia	2	0.18
Germany	2	0.41
Denmark	1	0.01
Spain	1	0.04
France	10	1.07
United Kingdom	13	2.72
Greece	1	0.01
Ireland	2	0.22
Israel	4	0.26
Italy	1	0.02
Japan	3	0.27
Mexico	6	0.90
Netherlands	6	0.45
Norway	2	0.42
Sweden	3	0.16
United States	474	84.79
Other	3	0.01
Total	601	100.00

Panel B

Sector	Numb. Of Issuers	Percentage of Observations (%)
Banks	86	18.88
Basic Industries	50	7.20
Capital Goods	39	4.19
Consumer	70	10.42
Diversified	3	0.53
Energy	74	9.81
Healthcare/Pharmaceuticals	54	9.85
Insurance	44	7.20
Media Entertainment	21	6.04
Property Real Estate	23	1.53
Retail	31	6.81
Technology	44	7.68
Telecoms	14	4.99
Transportation	14	2.11
Utilities	34	2.77
Grand Total	601	100.00

Panel C

Credit Rating	Numb. Of ISINs	Percentage of Observations (%)
AAA	16	1.17
AA	59	7.07
A	2,095	37.16
BBB	609	54.60
Total	2,779	100.00

Panel A, Panel B and Panel C of Table 1 present the country, sector and the credit rating profile of our sample respectively. There are 394,675 observations in our sample covering the period from January 2012 up to June 2013. Our sample contains investment grade corporate bond data of firms located in 26 countries.

Table 2: Descriptive statistics of variables

	Excess return	Yield change (%)	Coupon (%)	Outstanding amount (in mio)
Mean	-0.000041	-0.0025	4.89	966.47
Median	-0.000111	-0.0025	5.12	750.00
Maximum	0.227550	2.6600	10.20	5,545.00
Minimum	-0.240110	-4.2200	0.45	300.00
Std. Dev.	0.005361	0.0948	1.76	692.21
Skewness	0.787030	-0.8484	-0.16	1.98
Kurtosis	106.11	68.2954	2.74	7.97
Observations	388,805	388,805	388,805	388,805
	Age	**Liquidity score**	**Debt to market capitalization**	**Net trade flow imbalance**
Mean	3.38	14.16	1.38	0.0074
Median	2.55	14.37	0.38	0.0000
Maximum	23.60	16.10	36.97	1.0000
Minimum	0.01	8.33	0.00	-1.0000
Std. Dev.	3.10	1.43	2.98	0.8356
Skewness	1.83	-0.82	4.20	-0.0039
Kurtosis	8.00	3.53	26.47	1.3025
Observations	388,805	388,805	388,084	388,805

In table 2 we display descriptive statistics for the variables that are used in the analysis whether included as dependent or as independent variables. Our sample contains 388,805 observations covering the period from January 2012 up to June 2013.

Table 3: Dealers' yield change response

Random-effects GLS regressions with robust cluster standard errors			
Number of obs:	267,632		
Num. of groups:	2,703		
Wald X^2 / Prob > X^2 :	2592.81 / 0		
Overall R^2 :	8.6%		
Δyield (t)	**Coefficient (x 100)**	**z-statistics**	**p-value**
Coupon	-0.0767	-3.29	0.001
Outstanding Amount	0.0265	0.50	0.618
Financial	-0.3002	-5.56	0.000
Age	-0.0040	-0.32	0.748
Coc	0.0808	1.27	0.203
Domestic	0.1422	2.11	0.035
Euro area	-0.1297	-1.21	0.227
Market	-0.0136	-0.05	0.963
Secured	-0.8584	-1.24	0.215
Seniority	-0.0490	-0.31	0.756
Remaining Maturity	0.0171	6.81	0.000
Rating AAA	0.3154	2.57	0.010
Rating AA	0.3741	2.56	0.011
Rating A	0.4421	2.42	0.016
Liquid Bond - Buy side	0.9734	9.23	0.000
Liquid Bond - Sell side	-0.7065	-8.07	0.000
$\Delta(\text{EqVolat})_{(t-1)}$	0.0083	0.35	0.730
$\Delta(\text{EqVolat})_{(t-2)}$	0.0175	0.89	0.372
$\Delta(\text{EqVolat})_{(t-3)}$	-0.0296	-0.97	0.331
$\text{EqRet}_{(t-1)}$	-0.1791	-4.12	0.000
$\text{EqRet}_{(t-2)}$	-0.1042	-6.12	0.000
$\text{EqRet}_{(t-3)}$	-0.1247	-5.68	0.000
Δ(Net Trade Flow Imbalance)	-1.5191	-21.61	0.000
Institutional (Buying-side volume)	-0.1095	-7.99	0.000
Institutional (Selling-side volume)	0.1712	15.58	0.000
Retail (Buying-side volume)	0.0671	3.62	0.000
Retail (Selling-side volume)	0.0425	3.29	0.001
Constant	-0.8227	-1.88	0.061
σ (u)	1.6%		
σ (e)	8.4%		
ρ	3.6%		

Table 3 illustrates the determinants of yield changes. The regressors include static bond characteristics, bond level liquidity, lagged volatility changes, lagged equity returns as well as changes in net trade flow imbalances. Furthermore, dummies that combine the dominant investor category along with the direction and the logarithm of the traded volume are also included so as to unveil any a-priory adjustments that a bond dealer might consider when transacting with a given investor category.

Table 4: Excess returns earned by different investor categories

Random-effects GLS regressions with robust cluster standard errors

	Institutional			Retail		
Number of obs:	316,250			316,250		
Num. of groups:	2,718			2,718		
Wald X^2 / Prob > X^2 :	3517.71 / 0			3679.65 / 0		
Overall R^2 :	6.0%			6.1%		
Excess Returns (t+1)	**Coefficient (x 10.000)**	**z-statistics**	**p-value**	**Coefficient (x 10.000)**	**z-statistics**	**p-value**
Coupon	0.2200	2.39	0.017	0.2190	2.36	0.018
Outstanding Amount	0.2790	1.08	0.280	0.3910	1.51	0.132
Financial	1.6570	4.71	0.000	1.6890	4.72	0.000
Age	0.3750	4.12	0.000	0.3680	4.04	0.000
Coc	-0.1140	-0.41	0.685	-0.0993	-0.35	0.723
Domestic	-1.7980	-3.47	0.001	-1.7340	-3.35	0.001
Euro area	-0.5940	-0.93	0.353	-0.5670	-0.91	0.364
Market	-5.0940	-2.20	0.028	-4.8030	-2.04	0.041
Secured	3.4830	1.23	0.218	3.2950	1.15	0.250
Seniority	0.2320	0.16	0.876	0.0874	0.06	0.953
Liquidity Score	-1.4270	-11.72	0.000	-1.4480	-11.72	0.000
Abnormal Volume	0.4300	5.28	0.000	0.4140	5.15	0.000
Equity Volatility	-0.0486	-1.98	0.048	-0.0466	-1.90	0.057
$EqRet_{(t)}$	2.1780	7.54	0.000	2.1810	7.57	0.000
$EqRet_{(t-1)}$	1.3900	7.72	0.000	1.3910	7.68	0.000
$EqRet_{(t-2)}$	0.9980	10.73	0.000	1.0010	10.72	0.000
$EqRet_{(t-3)}$	0.6640	5.64	0.000	0.6600	5.69	0.000
Net Trade Flow Imbalance	6.6430	17.10	0.000	19.8210	50.12	0.000
Dominant Buyer	13.8360	18.01	0.000	-16.4710	-18.62	0.000
Dominant Seller	-8.3250	-14.64	0.000	11.0090	19.48	0.000
Constant	20.0000	5.52	0.000	21.9670	5.80	0.000
σ (u)	0.1%			0.1%		
σ (e)	0.6%			0.6%		
ρ	2.2%			2.2%		

Table 4 reports the coefficients for the variables that are examined as potential determinants of corporate bond excess returns. The independent variables include both static bond characteristics as well as market based indicators. Furthermore, we have introduced dummies to accommodate for any differentiation in the impact of net traded flows placed by different investor categories on corporate bond excess returns. T-statistics above 2.576 (in absolute terms) mean significance at 1% confidence level, t-statistics above 1.96 (in absolute terms) mean significance at 5% confidence level and t-statistics above 1.645 (in absolute terms) mean significance at 10% confidence level. * Denotes significance at 5%.

Table 5: Excess returns earned by different investor categories across different investment horizons

Random-effects GLS regressions with robust cluster standard errors

Panel A1		**Excess returns over a mapped by rating & maturity portfolio**							
		Institutional				**Retail**			
Investment Horizons	**Position Dummies**	Coef. (x10.000)	t	P>t	Gain/ Lose	Coef. (x10.000)	t	P>t	Gain/ Lose
ExRet over Rm (t+1)	**Buy**	13.84	18.01	0	**G**	-16.47	-18.62	0	**L**
	Sell	-8.33	-14.64	0	**G**	11.01	19.48	0	**L**
ExRet over Rm (t+2)	**Buy**	9.32	14.63	0	**G**	-11.51	-17.11	0	**L**
	Sell	-2.57	-5.07	0	**G**	4.52	8.3	0	**L**
ExRet over Rm (t+3)	**Buy**	7.93	13.27	0	**G**	-9.60	-14.72	0	**L**
	Sell	-1.13	-1.97	0.049	**G**	2.53	4.38	0	**L**
ExRet over Rm (t+4)	**Buy**	7.85	12.14	0	**G**	-9.03	-12.98	0	**L**
	Sell	-0.21	-0.34	0.731	**-**	1.07	1.65	0.099	**-**
ExRet over Rm (t+5)	**Buy**	7.26	11.35	0	**G**	-8.15	-11.43	0	**L**
	Sell	0.20	0.31	0.756	**-**	0.42	0.58	0.562	**-**
ExRet over Rm (t+30)	**Buy**	3.01	2.82	0.005	**G**	-1.64	-1.41	0.159	**-**
	Sell	-3.94	-3.94	0	**G**	4.33	4.03	0	**L**

Panel A2		**Excess returns over a mapped by rating & maturity portfolio**							
		Institutional				**Retail**			
Investment Horizons	**Position Dummies**	Coef. (x10.000)	t	P>t	Gain/ Lose	Coef. (x10.000)	t	P>t	Gain/ Lose
ExRet over Rm (t-1)	**Buy**	-0.71	-2.57	0.01	**G**	0.63	2.14	0.033	**L**
	Sell	0.24	0.82	0.411	**-**	-0.09	-0.25	0.801	**-**
ExRet over Rm (t-2)	**Buy**	-0.65	-1.78	0.075	**-**	0.36	0.94	0.346	**-**
	Sell	0.45	1.23	0.217	**-**	-0.13	-0.3	0.763	**-**
ExRet over Rm (t-3)	**Buy**	-0.46	-1.05	0.294	**-**	0.30	0.59	0.555	**-**
	Sell	0.79	1.81	0.07	**-**	-0.78	-1.63	0.103	**-**
ExRet over Rm (t-4)	**Buy**	-0.07	-0.14	0.892	**-**	-0.36	-0.63	0.528	**-**
	Sell	1.12	2.29	0.022	**G**	-0.96	-1.78	0.075	**-**
ExRet over Rm (t-5)	**Buy**	-0.29	-0.51	0.611	**-**	-0.17	-0.26	0.797	**-**
	Sell	1.50	2.88	0.004	**G**	-1.57	-2.69	0.007	**L**
ExRet over Rm (t-30)	**Buy**	-1.92	-1.59	0.111	**-**	0.92	0.65	0.514	**-**
	Sell	1.81	1.45	0.146	**-**	-1.08	-0.83	0.407	**-**

Panel B1		Excess returns over risk free rate							
		Institutional				Retail			
Investment Horizons	Position Dummies	Coef. (x10.000)	t	P>t	Gain/ Lose	Coef. (x10.000)	t	P>t	Gain/ Lose
ExRet over Rf (t+1)	**Buy**	14.29	19.15	0	**G**	-16.99	-19.57	0	**L**
	Sell	-7.82	-13.92	0	**G**	10.45	18.58	0	**L**
ExRet over Rf (t+2)	**Buy**	10.49	16.31	0	**G**	-12.81	-18.53	0	**L**
	Sell	-1.70	-3.43	0.001	**G**	3.65	7.04	0	**L**
ExRet over Rf (t+3)	**Buy**	9.54	15.44	0	**G**	-11.31	-16.49	0	**L**
	Sell	0.03	0.05	0.958	**-**	1.29	2.28	0.023	**L**
ExRet over Rf (t+4)	**Buy**	9.45	14.06	0	**G**	-10.77	-14.55	0	**L**
	Sell	1.10	1.89	0.058	**-**	-0.29	-0.46	0.648	**-**
ExRet over Rf (t+5)	**Buy**	8.66	12.57	0	**G**	-9.71	-12.47	0	**L**
	Sell	1.47	2.34	0.019	**L**	-0.87	-1.22	0.224	**-**
ExRet over Rf (t+30)	**Buy**	6.77	5.19	0	**G**	-5.01	-3.58	0	**L**
	Sell	-1.08	-0.93	0.353	**-**	0.88	0.7	0.485	**-**

Panel B2		Excess returns over risk free rate							
		Institutional				Retail			
Investment Horizons	Position Dummies	Coef. (x10.000)	t	P>t	Gain/ Lose	Coef. (x10.000)	t	P>t	Gain/ Lose
ExRet over Rf (t-1)	**Buy**	-0.86	-3.13	0.002	**G**	0.59	2.02	0.043	**L**
	Sell	0.16	0.57	0.572	**-**	-0.02	-0.05	0.96	**-**
ExRet over Rf (t-2)	**Buy**	-1.31	-3.65	0	**G**	0.68	1.79	0.073	**-**
	Sell	0.15	0.38	0.703	**-**	0.16	0.37	0.712	**-**
ExRet over Rf (t-3)	**Buy**	-1.28	-2.74	0.006	**G**	0.69	1.34	0.181	**-**
	Sell	0.36	0.8	0.426	**-**	-0.35	-0.72	0.471	**-**
ExRet over Rf (t-4)	**Buy**	-0.75	-1.32	0.185	**-**	-0.27	-0.45	0.654	**-**
	Sell	0.53	1	0.319	**-**	-0.28	-0.5	0.616	**-**
ExRet over Rf (t-5)	**Buy**	-0.48	-0.71	0.478	**-**	-0.84	-1.14	0.254	**-**
	Sell	0.95	1.66	0.097	**-**	-0.82	-1.33	0.184	**-**
ExRet over Rf (t-30)	**Buy**	-4.38	-2.95	0.003	**G**	1.50	0.87	0.387	**-**
	Sell	-2.02	-1.41	0.158	**-**	2.34	1.59	0.111	**-**

The excess returns are calculated over a mapped by rating & maturity portfolio in panels A1 and A2 of table 5, while in panels B1 and B2 the excess returns are estimated over the risk free rate. Panels A1 and B1 present the excess returns realized by each investor category following a trade, while panels A2 and B2 introduce the excess returns earned by each investor category before a trade takes place. For panels A1 and B1, the coefficients are interpreted as follows. If following a purchase of a bond on day (t) its price rises the next days (+ve coefficient), then the holder of the bond gains, while if its price decreases (-ve coefficient) the next days then the holder losses. On the other hand, if following a sale of a bond on day (t) its price decreases (-ve coefficient) the next days, then the investor gains while if its price subsequently increases (+ve coefficient) then the investor losses. For panels A2 and B2 the interpretation is the opposite one, that is, a positive coefficient indicates a loss for the buyer and a gain for the seller, while a negative coefficient indicates a gain for the buyer and a loss for the seller.

Panel C			Excess returns over risk free linked to systematic trading and bond picking strategies							
			Institutional				Retail			
Investment Horizons		Position Dummies	Coef.	t	P>t	Gain/Lose	Coef.	t	P>t	Gain/Lose
(t+1)	**ExRet Rm**	**Buy**	0.2793	21.62	0		-0.0023	-0.15	0.882	
		Sell	0.2684	18.55	0		0.0324	2.77	0.006	
	ExRet over Rm	**Buy**	0.0013	17.77	0	**G**	-0.0017	-19.64	0	**L**
		Sell	-0.0009	-15.82	0	**G**	0.0010	18.43	0	**L**
(t+2)	**ExRet Rm**	**Buy**	0.5686	27.64	0		0.3367	16.4	0	
		Sell	0.5516	24.86	0		0.2895	15.79	0	
	ExRet over Rm	**Buy**	0.0006	8.87	0	**G**	-0.0015	-21.98	0	**L**
		Sell	-0.0006	-12.47	0	**G**	0.0002	3.3	0.001	**L**
(t+3)	**ExRet Rm**	**Buy**	0.6431	26.5	0		0.4409	20.61	0	
		Sell	0.6524	23.41	0		0.3856	20.39	0	
	ExRet over Rm	**Buy**	0.0003	3.87	0	**G**	-0.0015	-22.28	0	**L**
		Sell	-0.0007	-13.28	0	**G**	-0.0002	-4.19	0	**G**
(t+4)	**ExRet Rm**	**Buy**	0.7229	26.28	0		0.5065	20.71	0	
		Sell	0.7204	22.91	0		0.4724	20.62	0	
	ExRet over Rm	**Buy**	0.0000	0.17	0.866	**-**	-0.0016	-20.58	0	**L**
		Sell	-0.0009	-13.33	0	**G**	-0.0006	-9	0	**G**
(t+5)	**ExRet Rm**	**Buy**	0.7714	26.27	0		0.5631	20.91	0	
		Sell	0.7807	24.16	0		0.5147	21.39	0	
	ExRet over Rm	**Buy**	-0.0003	-3.15	0.002	**L**	-0.0017	-19.76	0	**L**
		Sell	-0.0010	-13.46	0	**G**	-0.0008	-10.57	0	**G**

Panel C of table 5 illustrates how the excess returns over the risk free rate (equation 3) realized by each investor category are related to the returns of the particular rating-maturity segment (ExRet Rm) that each bond belongs (systematic trading), and to any incremental excess returns arising from investors' bond picking abilities (ExRet over Rm), which pertain to the selection of a particular security. Again, G reflects that the investor gains while L that the investor losses following a trade.

Panel D1			Institutional				Retail			
Position	**Investment Horizons**		Coef.	t	P>t	Increase/ Decrease	Coef.	t	P>t	Increase/ Decrease
Buy	**(t+1)**	**ExRet over Rm**					0.38	0.6	0.578	**-**
		ExRet Rm					9.76	5.0	0	**I**
	(t+2)	**ExRet over Rm**	41.96	89.7	0	**I**	-1.04	-1.9	0.061	**-**
		ExRet Rm	39.75	44.6	0	**I**	2.81	2.2	0.03	**I**
	(t+3)	**ExRet over Rm**	27.36	67.4	0	**I**	-0.83	-1.7	0.09	**-**
		ExRet Rm	21.79	31.7	0	**I**	-1.03	-1.0	0.311	**-**
	(t+4)	**ExRet over Rm**	20.53	54.6	0	**I**	-0.77	-1.7	0.094	**-**
		ExRet Rm	14.51	24.5	0	**I**	-1.23	-1.4	0.16	**-**
	(t+5)	**ExRet over Rm**	16.80	46.5	0	**I**	-0.44	-1.0	0.319	**-**
		ExRet Rm	11.22	21.0	0	**I**	-0.16	-0.2	0.84	**-**
Sell	**(t+1)**	**ExRet over Rm**					-14.72	-21.7	0	**I**
		ExRet Rm					-13.38	-7.2	0	**I**
	(t+2)	**ExRet over Rm**	-25.96	-55.8	0	**I**	-7.60	-14.4	0	**I**
		ExRet Rm	-6.81	-7.5	0	**I**	-4.73	-3.9	0	**I**
	(t+3)	**ExRet over Rm**	-14.83	-35.7	0	**I**	-5.78	-12.3	0	**I**
		ExRet Rm	-0.88	-1.2	0.215	**-**	-2.87	-3.0	0.003	**I**
	(t+4)	**ExRet over Rm**	-10.30	-26.5	0	**I**	-4.77	-10.8	0	**I**
		ExRet Rm	2.45	4.0	0	**D**	-2.31	-2.8	0.006	**I**
	(t+5)	**ExRet over Rm**	-7.82	-21.0	0	**I**	-4.27	-10.1	0	**I**
		ExRet Rm	2.60	4.7	0	**D**	-1.36	-1.8	0.074	**-**

Panel D2			Institutional				Retail			
Position	**Investment Horizons**		Coef.	t	P>t	Increase/ Decrease	Coef.	t	P>t	Increase/ Decrease
Buy	**(t-1)**	**ExRet over Rm**	-3.06	-5.3	0	**I**	1.07	1.5	0.135	**-**
		ExRet Rm	4.98	3.6	0	**D**	4.54	2.3	0.023	**D**
	(t-2)	**ExRet over Rm**	-3.13	-6.7	0	**I**	0.18	0.3	0.746	**-**
		ExRet Rm	-0.37	-0.4	0.684	**-**	3.77	2.8	0.005	**D**
	(t-3)	**ExRet over Rm**	-3.39	-8.1	0	**I**	-0.63	-1.3	0.212	**-**
		ExRet Rm	-0.46	-0.6	0.52	**-**	2.41	2.3	0.022	**D**
	(t-4)	**ExRet over Rm**	-3.60	-9.2	0	**I**	-1.39	-2.9	0.003	**I**
		ExRet Rm	0.11	0.2	0.851	**-**	0.73	0.8	0.419	**-**
	(t-5)	**ExRet over Rm**	-3.10	-8.2	0	**I**	-1.14	-2.5	0.012	**I**
		ExRet Rm	-0.11	-0.2	0.843	**-**	-1.62	-2.0	0.047	**I**
Sell	**(t-1)**	**ExRet over Rm**	0.07	0.1	0.903	**-**	0.85	1.3	0.212	**-**
		ExRet Rm	-2.35	-1.6	0.1	**-**	2.25	1.2	0.228	**-**
	(t-2)	**ExRet over Rm**	0.54	1.1	0.261	**-**	0.63	1.2	0.236	**-**
		ExRet Rm	-1.01	-1.1	0.28	**-**	1.59	1.3	0.202	**-**
	(t-3)	**ExRet over Rm**	2.43	5.7	0	**I**	1.24	2.6	0.009	**I**
		ExRet Rm	-1.87	-2.5	0.011	**D**	-0.24	-0.3	0.805	**-**
	(t-4)	**ExRet over Rm**	2.53	6.3	0	**I**	1.33	3.0	0.003	**I**
		ExRet Rm	0.30	0.5	0.637	**-**	2.23	2.6	0.009	**I**
	(t-5)	**ExRet over Rm**	3.38	8.7	0	**I**	1.45	3.4	0.001	**I**

Panels D1 and D2 of table 5 illustrate how the trading patterns of institutional and retail investors are linked with the bond specific (ExRet over Rm) and market sub-portfolios (ExRet Rm) excess returns (equation 4). Specifically, we use a random-effects logistic regression so as to identify how the probability of trading by a particular investor class is affected (I = Increase, D = Decrease) by the excess bond returns both after (Panel D1) and before (Panel D2) the trade day.

Table 6: Dealers' P&L margin due to a-priory classification of their clients

	Realized P&L Margin (in bp)		Estimated P&L as if all clients were uninformed (in bp)		Difference	
	Median	Mean	Median	Mean	Median	Mean
All trades	0.84	4.70	-0.04	0.87	0.87	3.83
Trades with institutionals (Buying-side)	2.00	6.51	-0.31	0.40	2.31	6.11
Trades with institutionals (Selling-side)	1.85	6.58	-0.07	1.72	1.92	4.86

Table 6 displays the realized P&L margin of the dealers as well as the estimated P&L margin as if the dealers had treated all of their clients as uninformed.

Table 7: Dealers' P&L margin on public news days

	Realized P&L Margin (in bp)				
	Median	Mean	Observations	St.Dev	Mean P&L different from zero (t-test)
DM single trade	1.75	7.11	55,558	23.80	Yes
DM Δyield 1st day	8.00	17.60	53,333	28.20	Yes
DM Δyield rest	-0.24	-2.16	98,093	18.08	Yes

Table 7 exhibits various summary statistics for the realized P&L margin of the dealers on public information days.

Table 8: Determinants of dealers' P&L on public news days

Random-effects GLS regressions with robust cluster standard errors			
Number of obs:	331,477		
Num. of groups:	2,719		
Wald X^2 / Prob > X^2 :	2239.71 / 0		
Overall R^2 :	4.8%		
P&L Margin (t)	**Coefficient (x 100)**	**z-statistics**	**p-value**
Coupon	0.0043	6.43	0.000
Outstanding Amount	-0.0094	-5.04	0.000
Financial	-0.0041	-1.53	0.125
Age	-0.0001	-0.27	0.787
Coc	0.0014	0.56	0.578
Domestic	-0.0046	-0.92	0.360
Euro area	0.0078	0.89	0.372
Market	-0.0049	-0.48	0.634
Secured	0.0125	0.78	0.435
Seniority	-0.0010	-0.13	0.896
Remaining Maturity	0.0033	19.26	0.000
Rating AAA	-0.0160	-2.89	0.004
Rating AA	-0.0052	-1.54	0.124
Rating A	-0.0041	-1.79	0.074
Liquidity Score	-0.0022	-2.92	0.003
Abnormal Volume	0.0003	1.12	0.265
$EqVolat_{(t-1)}$	0.0001	1.31	0.189
EqRet(t-1)	0.0005	1.62	0.105
EqRet(t-2)	0.0001	0.34	0.733
EqRet(t-3)	-0.0008	-2.41	0.016
Net Trade Flow Imbalance	0.0043	4.92	0.000
DM single trade	0.0321	20.14	0.000
DM Δyield 1st day	0.1418	36.87	0.000
DM Δyield rest	-0.0695	-36.66	0.000
Constant	0.0982	5.53	0.000
σ (u)	0.0%		
σ (e)	0.3%		
ρ	2.6%		

Table 8 exhibits the coefficients of the regressors examined as potential determinants of the dealers' P&L margin. These include both static bond characteristics as well as market based indicators. Furthermore, we have introduced dummies to accommodate for any differentiation in the dealers' P&L on public information days.

Figure 1: Event Tree

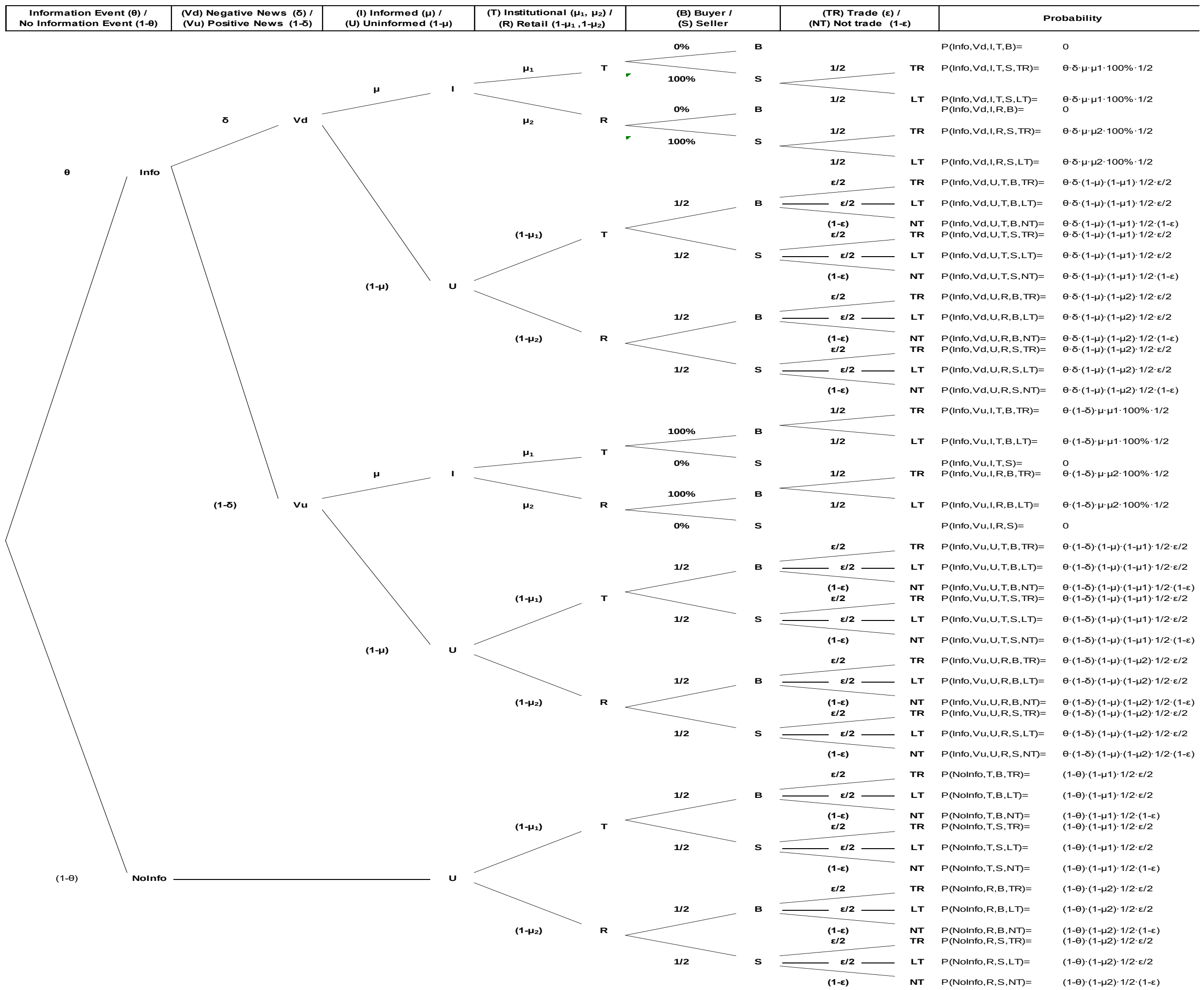
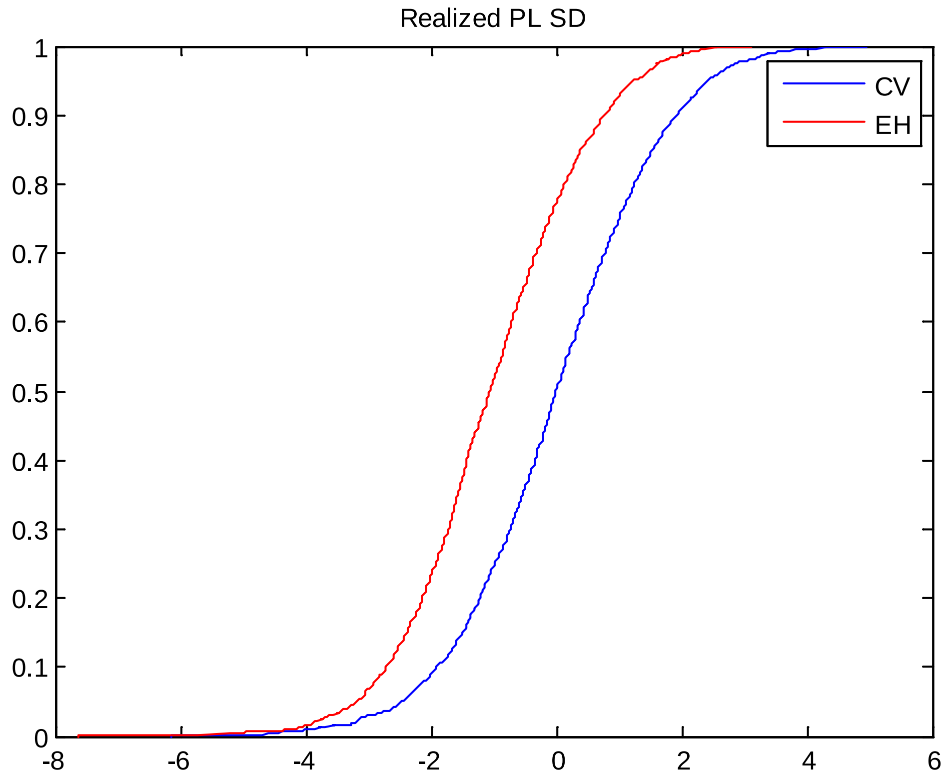


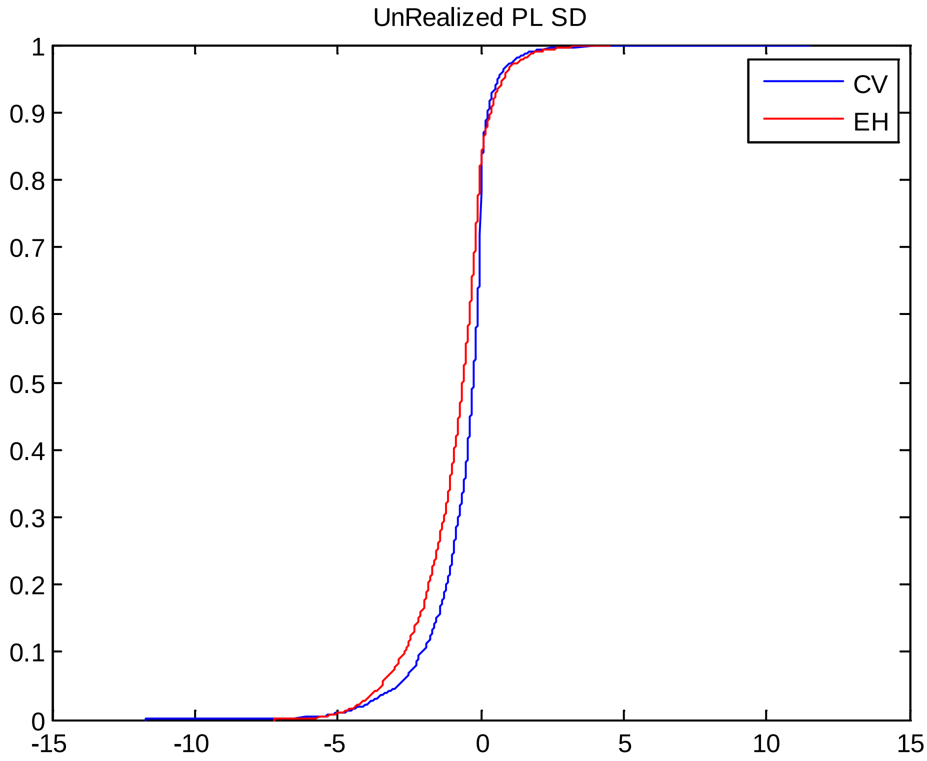
Figure 1 present the event tree of the extended model relative to Easley O'Hara (1992), which includes the investor category (i.e. institutional, retail) as an extra parameter that dealers consider under their quote setting strategy. The last column shows the probability assigned to each potential outcome of the event tree.

Figure 2: Realized P&L



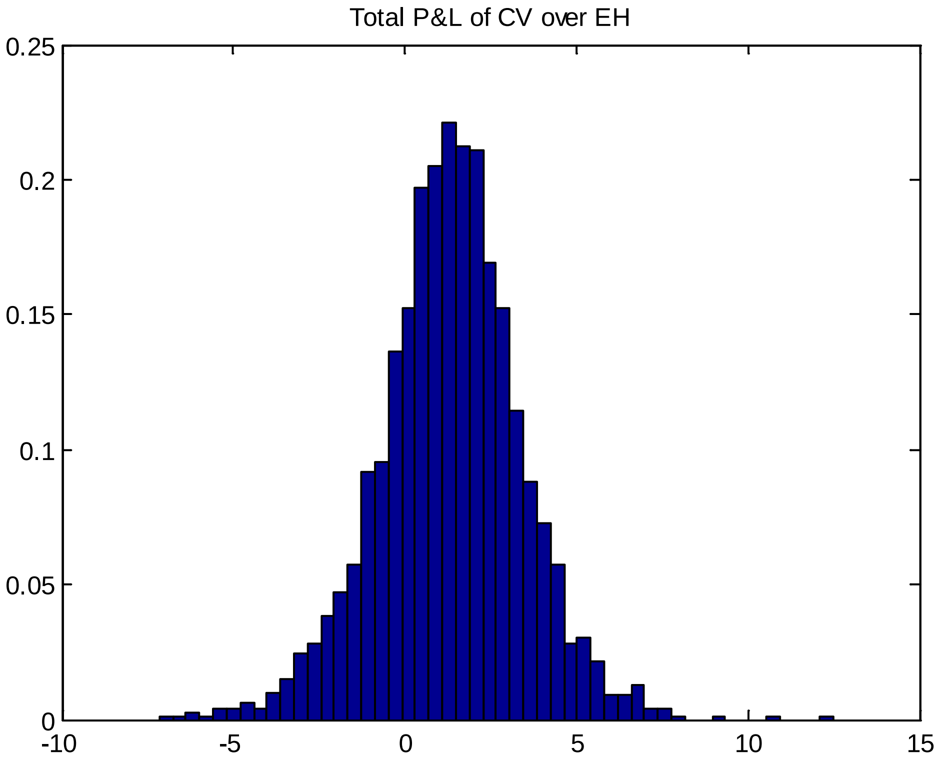
Figures 2 displays the empirical cumulative realized P&L distribution of our extended model (CV) relative to the model proposed by Easley O'Hara (1992) (EO). In the y axis the cumulative proportion of the sample is reflected, while x axis indicates the P&L. The more to the right the curve, the higher the P&L enjoyed by the dealer that utilizes the respective model.

Figure 3: Unrealized P&L



Figures 3 displays the empirical cumulative unrealized P&L distribution of our extended model (CV) relative to the model proposed by Easley O'Hara (1992) (EO). In the y axis the cumulative proportion of the sample is reflected, while x axis indicates the P&L. The more to the right the curve, the higher the P&L enjoyed by the dealer that utilizes the respective model.

Figure 4: Total P&L comparison



Figures 4 displays the histogram based on the empirical cumulative distribution function for the total P&L generated by the CV model over the model of EO.

Appendix A. Market microstructure background

In efficient markets with no information asymmetries and frictions we expect that prices at any point in time capture all the available information, so that each security price reflects its expected value, in a sense, following a random walk. However, market frictions and asymmetric information can result into a deviation from the abovementioned random walk process. This is the point where market microstructure intervenes so as to facilitate our understanding of the price discovery process. Roll (1984) developed a simplistic model of a dealer market with fixed transaction cost so as to illustrate how the bid-ask spread is set by the dealer. Transactions costs (c) are derived from the square root of the covariance between consecutive changes in trade prices (Δp), as presented in following equation:

$$c = \sqrt{-cov(\Delta p_t, \Delta p_{t-1})}$$

Indeed, Roll (1984) develops a model that makes use of observed trading prices so as to calculate the cost of transactions in case bid-ask data are not available. Thus, a dealer has to set the range of his bid-ask spread to 2c. Hasbrouck (2006) denotes that the bid-ask spread derived by Roll model (0.01$/share) underestimates the realized average bid-ask spread for NYSE (0.022$/share) on 2/7/2003. She interprets this difference on the grounds of potential sampling errors as well as on the fact that some of the model's assumptions do not hold.

To overcome the simplistic assumptions inherent in the Roll's model, a series of generalizations have been developed in the literature. One of the most important being the Glosten and Milgrom (1985) model that allows transaction costs (c) to be endogenous to the efficient price, which is the price that captures all the available information and would have been equal to the trading price in the absence of transactions costs.

The model developed by Glosten and Milgrom (1985) belongs to the class of asymmetric information models. It assumes that traders arrive in the market randomly, sequentially and independently. In particular, the value of a security at the end of a day can be either high (V^H) or low (V_L) with probabilities (δ) and (1-δ) respectively. Traders can be informed (I) or uninformed (U), with the former comprising a fixed percentage (μ) of the population and knowing about the terminal value of a security (V). Furthermore, the unconditional expectation of the terminal security value is noted as V^E. The models works as follows:

- The dealer set his bid (B) and ask (A) quotes.
- A trader is selected randomly from the population.
    - If he is informed (μ probability), the trader buys (Buy) if the price of the security is expected to rise at the end of the day, while he sells (Sell) if the price of the security is expected to decrease at the end of the day.
    - If he is uninformed (1-μ probability), he undertakes a long or a short position randomly with equal probability (50%).

Therefore, all the potential outcomes can be illustrated via an event tree that attributes to each state a certain probability.

A market maker's ask price is determined as the expected value of a security following the arrival of a purchase order.

$$A = V^H \Pr(\text{ I} \mid \text{Buy}) + V^E \Pr(\text{ U} \mid \text{Buy})$$

The above equation implies that the market maker provides quotes subject to the direction of the trade. That is, he provides an ask price for traders' buying orders and a bid price for traders' selling orders. In other words, the market maker provides a quote knowing not only the available public information but also the trade direction itself. The quoted bid-ask spread has to be proportional to the information asymmetry and to the level of uncertainty regarding an asset's true value. Therefore, a market maker has to set his quotes so that any gains arising from his trades with uninformed traders to offset any losses from informed traders.

The class of asymmetric information models also includes strategic trade models (Kyle 1985), in which a single informed trader acts strategically and transacts many times before the information he possesses become known to the public. It is not uncommon to consider that it is traders' common practice to distribute their orders over time and across dealers so as to minimize the impact of their trades on security prices. That is, a trader has to determine his trade size by considering any abrupt price adjustment spurred by large volumes.

On the other hand, the market maker determines a price after considering the net order flow, in a sense, functioning as an order processor setting the settlement prices. Under Kyle's model there is not bid and ask prices, but rather all the trades are cleared at a single market price, reflecting all the available information. Kyle's model can be considered as a linear equation in which the price of a security at time t (p_t) is a function of the market maker's perceived security price the previous time point (μ_{t-1}) and the observed net order flow imbalance at time t (q_t).

$$p_t = \mu_{t-1} + \lambda \times q_t$$

The coefficient λ can be considered as a measure of illiquidity, which affects how an informed trader behaves. Specifically, the higher the value for λ the less an informed trader trades.

All in all, under asymmetric information models trades are the means for conveying any private information in the market. Hence, market makers adjust their quotes so as to price this information asymmetry. That is, the higher the information asymmetries the wider the bid-ask spreads set by market makers.

Appendix B. Extension of the Easley O'Hara (1992) model

We assume that dealers have some internal estimates, based on their experience, of the probability (μ) that an informed trader will arrive, of the probability of an institutional investor being informed (μ1) and of the probability of a retail investor being informed (μ2). Then, we use the structure of the tree so as to extract the probability of (θ) and of (δ) based on the observed trades (buy-side (B), sell-side (S), not trade (NT)) as well as based on the type of the counterparty (Institutional (T), Retail (R)). The formulas for adjusting (θ) are the following:

$$\boldsymbol{\theta(B,T)} = \frac{\boldsymbol{P(Info \cap B \cap T)}}{\boldsymbol{P(B \cap T)}} = \frac{\theta * (\varepsilon * (\mu - 1 + \mu 1) + \mu * \mu 1 * (-2 + 2 * \delta - \varepsilon))}{\varepsilon * (\mu 1 - 1 + \mu * \theta) + \mu * \mu 1 * \theta * (-2 + 2 * \delta - \varepsilon)}$$

$$\boldsymbol{\theta(B,R)} = \frac{\boldsymbol{P(Info \cap B \cap R)}}{\boldsymbol{P(B \cap R)}} = \frac{\theta * (\varepsilon * (\mu - 1 + \mu 2) + \mu * \mu 2 * (-2 + 2 * \delta - \varepsilon))}{\varepsilon * (\mu 2 - 1 + \mu * \theta) + \mu * \mu 2 * \theta * (-2 + 2 * \delta - \varepsilon)}$$

$$\boldsymbol{\theta(S,T)} = \frac{\boldsymbol{P(Info \cap S \cap T)}}{\boldsymbol{P(S \cap T)}} = 1 - \frac{\varepsilon * (\theta - 1) * (\mu 1 - 1))}{\varepsilon * (1 - \mu 1 - \mu * \theta) + \mu * \mu 1 * \theta * (2 * \delta + \varepsilon)}$$

$$\boldsymbol{\theta(S,R)} = \frac{\boldsymbol{P(Info \cap S \cap R)}}{\boldsymbol{P(S \cap R)}} = 1 - \frac{\varepsilon * (\theta - 1) * (\mu 2 - 1))}{\varepsilon * (1 - \mu 2 - \mu * \theta) + \mu * \mu 2 * \theta * (2 * \delta + \varepsilon)}$$

$$\boldsymbol{\theta(NT)} = \frac{\boldsymbol{P(Info \cap NT)}}{\boldsymbol{P(NT)}} = 1 - \frac{\theta - 1}{\mu * \theta - 1}$$

Accordingly, the formulas for updating (δ) are presented below:

$$\boldsymbol{\delta(B,T)} = \frac{\boldsymbol{P(Vd \cap B \cap T)}}{\boldsymbol{P(B \cap T)}} + \boldsymbol{\delta} * \frac{\boldsymbol{P(NoInfo \cap B \cap T)}}{\boldsymbol{P(B \cap T)}} =$$

$$\delta - \frac{2 * \delta * \mu * \mu 1 * \theta * (\delta - 1)}{\varepsilon * (\mu 1 + \mu * \theta * (1 - \mu 1) - 1) - 2 * \mu * \mu 1 * \theta * (1 - \delta)}$$

$$\boldsymbol{\delta(B, R)} = \frac{\boldsymbol{P(Vd \cap B \cap R)}}{\boldsymbol{P(B \cap R)}} + \boldsymbol{\delta} * \frac{\boldsymbol{P(NoInfo \cap B \cap R)}}{\boldsymbol{P(B \cap R)}} =$$

$$\delta - \frac{2 * \delta * \mu * \mu 2 * \theta * (\delta - 1)}{\varepsilon * (\mu 2 + \mu * \theta * (1 - \mu 2) - 1) - 2 * \mu * \mu 2 * \theta * (1 - \delta)}$$

$$\boldsymbol{\delta(S, T)} = \frac{\boldsymbol{P(Vd \cap S \cap T)}}{\boldsymbol{P(S \cap T)}} + \boldsymbol{\delta} * \frac{\boldsymbol{P(NoInfo \cap S \cap T)}}{\boldsymbol{P(S \cap T)}} =$$

$$\delta + \frac{2 * \delta * \mu * \mu 1 * \theta * (1 - \delta)}{\varepsilon * (1 - \mu 1 - \mu * \theta) + \mu * \mu 1 * \theta * (2 * \delta + \varepsilon)}$$

$$\boldsymbol{\delta(S, R)} = \frac{\boldsymbol{P(Vd \cap S \cap R)}}{\boldsymbol{P(S \cap R)}} + \boldsymbol{\delta} * \frac{\boldsymbol{P(NoInfo \cap S \cap R)}}{\boldsymbol{P(S \cap R)}}$$

$$= \delta + \frac{2 * \delta * \mu * \mu 2 * \theta * (1 - \delta)}{\varepsilon * (1 - \mu 2 - \mu * \theta) + \mu * \mu 2 * \theta * (2 * \delta + \varepsilon)}$$

Lastly, dealers adjust their Bid and Ask quotes by using the following equations:

$$\boldsymbol{Ask = EV * P(U/B) + Vu * P(I/B)}$$

$$\boldsymbol{Ask} = EV - \frac{2 * \mu * \theta * (\mu 1 + \mu 2) * (EV - Vu) * (\delta - 1)}{2 * \mu * \theta * (\delta - 1) * (\mu 1 + \mu 2) + \varepsilon * (\mu 1 + \mu 2 + \mu * \theta * (2 - \mu 1 - \mu 2) - 2)}$$

$$\boldsymbol{Bid = EV * P(U/S) + Vd * P(I/S)}$$

$$\boldsymbol{Bid} = EV - \frac{2 * \mu * \theta * (\mu 1 + \mu 2) * (EV - Vd) * \delta}{2 * \mu * \theta * \delta * (\mu 1 + \mu 2) - \varepsilon * (\mu 1 + \mu 2 + \mu * \theta * (2 - \mu 1 - \mu 2) - 2)}$$

where: $\boldsymbol{EV = \theta * \delta * Vd + \theta * (1 - \delta) * Vu + (1 - \theta) * V_0}$

Appendix C. Determinants of the proprietary liquidity score

The bond-specific liquidity variables that have been found in the literature to affect bond yield spreads can be classified into two broad categories. The first category includes static bond characteristics (Longstaff 2005, Houweling et al. 2005, Chen 2007, Bao 2011, Friewald 2012, Kalimipalli 2012 among others) such as, coupon (Elton et al. 2001), time to maturity, age (on-the-run), outstanding amount (Fisher 1959), issuer type (financial vs. non-financial firms), seniority, secured, market of issuance as well as other bond covenants (Nashikkar 2008). Whereas, the second category is comprised by liquidity-specific measures that are estimated from bond market data (Chen 2007, Nashikkar 2008, Friewald 2012, Bao 2011, Beber 2009, Kalimipalli 2012 among others), such as bid-ask spreads, volumes, number of trades, % of zeros, LOT measure, latent liquidity, Amihud measure, Roll measure, price dispersion measures, liquidity indices, limit-order book depth, volatilities of liquidity measures etc.

Bao et al. (2011) regress an illiquidity measure on bond characteristics and find that older bonds as well as bonds with lower issuance amounts have higher illiquidity. Furthermore, Nashikkar (2011) points that the higher the coupon the higher the latent liquidity of a bond. Finally, to test for consistency among bond-specific liquidity measures that are derived from market data, Chen et al. (2007) regress one liquidity measure on the others, after controlling for static bond characteristics and bond credit risk.

The current literature provides evidence that bond specific liquidity also depends on the credit standing of the issuer. Ericsson (2006) and Friewald (2012) note that as a firm approaches default, the part of its yield spread that is attributed to a decrease in liquidity increases. Similarly, Huang and Huang (2012) quantify the amount of yield spreads that is attributed to credit risk and find that for high-rated bonds a small portion of the total yield spread is due to credit risk, while for low-rated bonds a bigger part of the yield spread is due to credit risk. On the other hand, Longstaff et al. (2005) point that even for high rated bonds, a material part of the yield spread (above 50%) is attributed to default risk. To sum up, it becomes evident that a bond's credit rating plays an important role in the formation of its liquidity score.

The same value of a liquidity specific measure that is calculated from bond's market data can indicate different levels of liquidity at different points in time and in different markets, depending on the aggregate level of market liquidity. What is more, since investors evaluate the liquidity of a particular asset relative to the liquidity of another asset with similar risks characteristics, liquidity risk becomes, as Beber (2009) aptly notes, a "relative concept". Therefore, to control for this "relativity" of liquidity we apply the Fama-MacBeth (1973) approach so as for the sensitivities of the regressors to be fitted along the cross-sectional dimension of the sample.

In identifying the determinants of liquidity score we consider all the relevant bond characteristics that are available in our sample across the cross section of securities. The volume related variables that are used in the estimation are the following:

i. Price Variability (PrVar). Average price variability over the last 30 days, where price variability is calculated daily as total return change over total trading volume.
ii. Average Turnover (TURN). Average turnover over the last 30 days, where turnover is defined as traded volume over outstanding issue amount. (Bao 2011)

iii. Percentage of Trading Days (TrDays). Calculated as the percentage of trading days during the last month, i.e. the number of days with non-zero trading volume (Bao 2011).

The fitted equation has an explanatory power of 70%, while the regressor coefficients are illustrated in the equation below:

$$
\begin{aligned}
LS_{i,t} = 659 - 6.53 \times C_{i,t} + 93.4 \times AMT_{i,t} + 0.16 \times FN_{i,t} - 5.66 \times AGE_{i,t} + 0.28 \\
\times COC_{i,t} - 13.89 \times DOM_{i,t} - 1.87 \times EUR_{i,t} + 6.13 \times MK_{i,t} \\
+ 1.29 \times SEC_{i,t} - 9.79 \times SN_{i,t} + 1.67 \times MAT_{i,t} - 32.65 \times RAT1_{i,t} \\
- 23.85 \times RAT2_{i,t} - 18.99 \times RAT3_{i,t} - 300.8 \times PrVar_{i,t} \\
+ 150 \times TURN_{i,t} + 178 \times TrDays_{i,t}
\end{aligned}
$$

All coefficients are multiplied by 100, apart from: PrVar that is divided by 10.000 and TURN that is left as such.

Table C: Determinants of the liquidity score

Fama-MacBeth (1973) Two-Step procedure			
Number of obs:	799,370		
Num. time periods:	268		
F(17, 267) / Prob > F :	89,300.36 / 0		
Overall R^2 :	69.6%		
Liquidity Score	**Coefficients**	**z-statistics**	**p-value**
Coupon	-6.5305	-61.01	0.000
Outstanding Amount	93.4056	211.98	0.000
Financial	0.1622	0.38	0.706
Age	-5.6635	-90.91	0.000
Coc	0.2764	1.01	0.314
Domestic	-13.8895	-53.55	0.000
Euro area	-1.8651	-2.69	0.008
Market	6.1317	2.68	0.008
Secured	1.2943	1.81	0.071
Seniority	-9.7903	-15.85	0.000
Remaining Maturity	1.6663	55.81	0.000
Rating AAA	-32.6547	-32.01	0.000
Rating AA	-23.8543	-42.01	0.000
Rating A	-18.9943	-40.60	0.000
Mean Price Variability	-300.8192	-53.00	0.000
Turnover	150.1554	63.03	0.000
Percentage of trading days	178.2392	111.78	0.000
Constant	659.2516	209.06	0.000

In table 5.C the determinants of liquidity score are examined.

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