Market Making and Proprietary Trading in the US Corporate Bond Market

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Abstract

I study broker-dealers' trading activity in the US corporate bond market. I find evidence of broker-dealer market making when customers both buy and sell a bond in a day, which happens half of the time: as predicted by market making theories with adverse selection or inventory costs, prices go down (up) as customers sell (buy). Otherwise, evidence is in favor of proprietary trading as in limits of arbitrage theories: prices go up (down) when customers sell (buy), and dealers buy (sell) bonds that are relatively cheap (expensive). Proprietary trading is reduced after the crisis. Relatedly I show that before the crisis, large broker-dealers borrowed and sold Treasury bonds in amounts similar to their corporate bond holding, but not after. I give suggestive evidence that they were subject to a severe tightening of their margin constraints as early as July 2007, in particular following increased Treasury bond volatility.

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1 Introduction

How broker-dealers trade is core to ongoing regulatory debates. These intermediaries in financial markets are often viewed as *market makers*: they buy or sell on customer demand, which does not seem to call for prudential regulation. But the macro-finance literature suggests that they also trade actively, engaging in *proprietary trading*.[1] The crisis has suggested they took excessive risk that called for regulation, some seeing proprietary trading as the source of the problem: as a result, the Volcker rule bans proprietary trading but permits market making by bank-affiliated broker-dealers, which has caused intense discussion.[2] Is a distinction between proprietary trading and market making possible? What are broker-dealers trading strategies? What are the associated risks?

To answer these questions I empirically study transaction-level data from the US corporate bond market. I show that about half of bond$\times$day observations contradict predictions of market making theories: prices tend to go up (down) when broker-dealers' customers sell (buy). Moreover, for these observations, broker-dealers buy (sell) more bonds that were relatively cheap (expensive) as in limits of arbitrage theories. The other half are consistent with market making. I also give suggestive evidence that proprietary traders' financing constraints generate risks for proprietary traders which materialized at the onset of the crisis, in July 2007, without any obvious link to a prop trading strategy.

I use customer-to-dealer transaction data for a large sample of liquid, investment grade bonds from FINRA's TRACE reporting system. On top of having macroeconomic relevance[3] the US corporate bond market also allows to focus on broker-dealer trades. In other markets like equity markets, isolating broker-dealer trades is generally impossible because the type of trader behind a given order is not disclosed.

Theories of market making and of proprietary trading give two testable predictions. The first prediction is about the correlation between short-term price changes and customer trades. Theories of market making predict that prices go down (up) when customers sell (buy). This is because a customer can be informed so his trade signals asset value,[4] or because risk averse market makers require a higher expected return to hold more risk.[5] By contrast, under dealer proprietary trading prices should go up when dealers buy, *i.e.* when customers sell, and conversely. I understand proprietary trading very broadly as dealers comparing prevailing asset prices to their private or public information, then trading on it. For instance two assets may trade at different prices that dealers think not justified by fundamentals: they

[1] See for instance Adrian and Shin (2009, 2010), Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017) and Gilchrist and Zakrajsek (2012).

[2] Critiques argue the rule failed and inefficiently impeded market making; regulators are about to drop the distinction in 2020.

[3] Corporate-Treasury spreads forecast economic activity and recessions: *cf.* in particular Philippon (2009), Gilchrist and Zakrajsek (2012), Gilchrist and Mojon (2017), López-Salido, Stein, and Zakrajsek (2017).

[4] Kyle (1985), Glosten and Milgrom (1985)

[5] Stoll (1978), Ho and Stoll (1981), Grossman and Miller (1988).

may buy the cheaper asset and sell the more expensive asset and expect a profit. This is the situation described by theories of limits of arbitrage,[6] with proprietary traders being the analogs of arbitrageurs.

Theories of limits of arbitrage give a second prediction: when dealers buy (sell), they buy a cheap (expensive) bond i relative to other bonds, given bond i's and other bonds' characteristics. I do not assess whether a low price is *too* low.

As first suggestive evidence of broker-dealer proprietary trading, figure 1 plots corporate bonds and Treasury bonds holding of Primary Dealers, *i.e.* large broker-dealers for which the New York Fed releases inventory data, and corporate-to-Treasury spreads indices for A and BBB bonds.[7] Primary Dealer trading activity is in my TRACE sample. Strikingly before the crisis, the large net corporate holdings were mirrored by negative net Treasury holdings, a fact not reported in the literature: it means Primary Dealers borrowed and sold Treasury bonds, *i.e.* held a short position. If this was proprietary trading, Treasury bond prices should go down and corporate bond prices should go up: this is what corporate spreads indicate. The BBB index even decreases as Primary Dealers holdings go up. After the crisis, the long/short position is not rebuilt, while spreads are higher and more volatile.

Thus I expect broker-dealers to do both proprietary trading and market making: to distinguish between the two, I find an intuitive criterion and check whether it holds in the data. The criterion is as follows. Suppose that on a given day for a given bond, order flow is a *partial* or *full roundtrip*: customers both buy and sell within a day. This may reveal that dealers have, say, bought bonds from customers but are unwilling to hold them so start to re-sell them within the day: this suggests market making. By contrast, suppose order flow is *one-way*: customers only buy or sell. This may be either because they they are making market but are not able to reverse the trade quickly, or because they are actually willing to hold the position because it enters a proprietary trading strategy.

To test the prediction about price changes and customer trades, I use price impact regressions, a standard tool in empirical market microstructure: I regress price changes on customer daily purchases net of daily sales, controlling for plausible determinants of these changes including stock return, long and short rate changes.

I find that the coefficient for one-way order flow is as predicted by limits of arbitrage theories, except during the crisis, while it is as consistent with market making on days with partial roundtrips. Running the price impact regression without distinguishing between one-way and partial roundtrips, the coefficient is consistent with market making, which suggests raw price impact regressions may mislead to a conclusion that broker-dealers are always passive market makers. Quantitatively, on average a $1 million customer net sale is associated with a price increase by 1.5 basis point. To explore heterogeneity within one-way observations, I add interactions

[6] *Cf.* Gromb and Vayanos (2002, 2010, 2018).

[7] Median spread in bonds from my sample with 4-6 years residual maturities. The spread is the log price difference between a fictitious risk-free price of a bond with the same cash flows discounted with the Treasury yield curve.

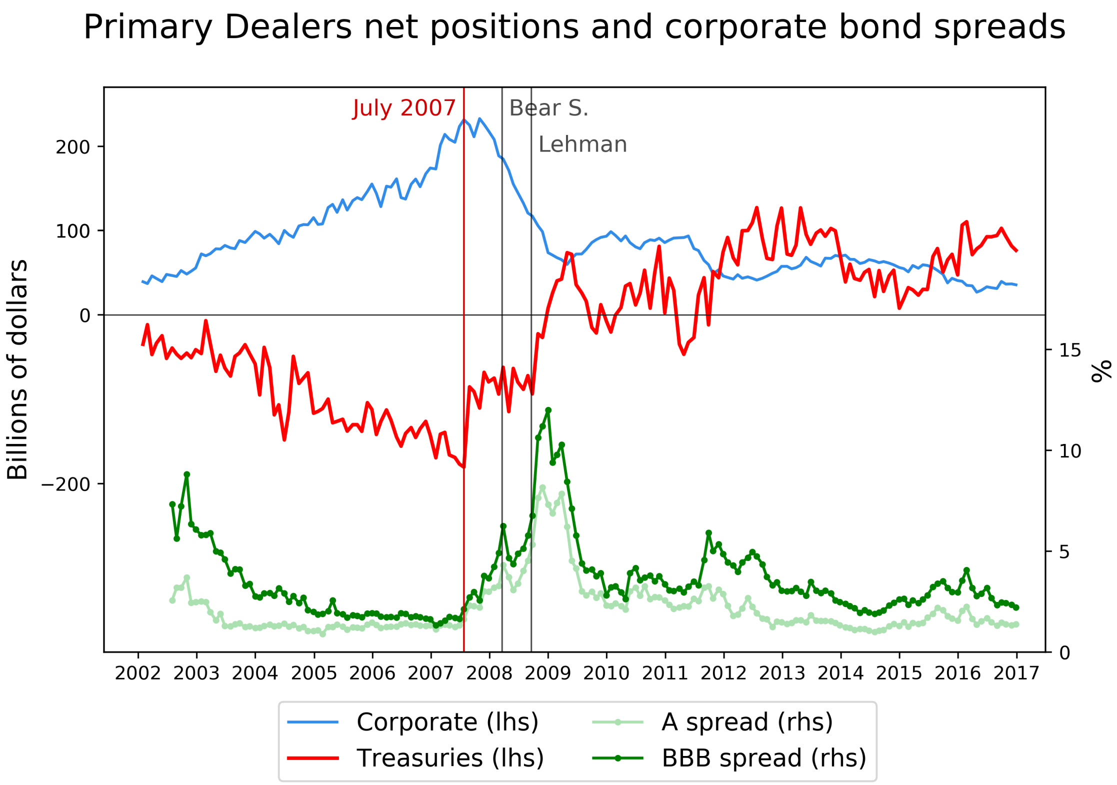

Figure 1 – Primary Dealers holdings in corporate bonds and Treasury bonds (all maturities above 3 months), and corporate-Treasury spreads for A and BBB bonds with 4-6 years residual maturity. Holding data are from the New York Fed, spreads computed from my sample, all data are as of the last Wednesday of each month (holding data are published weekly as of Wednesday).

with dummies for the bond's initial or residual maturity, or its age, being less than 10 years: I find that proprietary trading is concentrated on bonds with initial or residual maturity less than 10 years, or on bonds younger than 10 years.

I look at the evolution through time. I interact one-way and partial rountrip with dummies for time periods: I find that one-way order flow has coefficients consistent with proprietary trading both before and after the crisis; before the crisis, customer sales by \$1 million come with an increase by 5 basis points, while it reduces to 1.7 basis point after the Dodd-Frank Act. During the crisis, estimates are consistent with market making and higher than for partial roundtrip order flow, suggesting that dealers were not willing to hold the bonds they bought (or hold the inventory deficit) for long, but expected to be unable to re-sell (or repurchase) them quickly.

I also discuss endogeneity concerns. In particular to address the concern that there are common drivers of order flow and price changes, I control for risk-free rate changes and credit risk changes through stock return, two main sources of corporate bond price change and likely of customer willingness to trade.

Then I test the second prediction, by regressing customer order flow on lagged measures of bond cheapness, controlling for lagged order flow, lagged price changes and market factors. The cheapness measures are spreads between baskets of bonds.

I first test a measure in which a bond's spread to an equivalent Treasury is compared with the median spread in a basket of bonds with similar maturity, credit rating and callability (presence or absence of an embedded call). This measure captures idiosyncratic component of the bond spread. I further split one-way and roundtrip order flow based on bond age, bond initial or residual maturity being more or less than 10 years. Then I find that the measure is significant for one-way order flow and in the expected direction for bonds younger than 10 years, and more so for bonds with initial or residual maturity less than 10 years. The estimates imply that an increase by one percentage point in the measure is associated with dealer purchases being higher by 12%, and conversely.

Then I add three measures of cheapness in the regression, which are differences in median corporate-to-Treasury spreads of different baskets of bonds. The first additional measure captures a bond's cheapness relative to bonds with similar maturity irrespective of their credit risk and callability, having controlled for idiosyncratic components. The second additional measure captures arbitrage between bonds of different maturities, having controlled for its credit risk and callability. The third additional measure captures corporate bond cheapness with respect to Treasuries: the former may be more expensive than the latter even after controlling for credit risk, because of liquidity or other services they provide. It may be on average profitable to sell Treasury bonds to buy corporate bonds. I call this measure the Treasury convenience yield component. Primary Dealers appear to exploit it on figure 1.

I find significant effects on the credit risk/callability component, and on the Treasury convenience yield component. When I further distinguish by age or maturity, I find unchanged effect for the idiosyncratic component, and highly significant effects for the credit risk/callability and Treasury convenience yield components for bonds with age or maturity below 10 years. The maturity component does not appear exploited by dealers. For roundtrip order flow, coefficients are zero or small in absolute value, consistently with price impact regressions. Quantitatively, I find that an increase in the credit risk/callability measure by one percentage point for a bond with maturity lower than 10 years is associated with higher dealer purchases by 24%. For the Treasury convenience yield component, the effect is 15%. Running the regression across subperiods reveals a drop of proprietary trading after the crisis, in line with figure 1.

These results suggest that 1) broker-dealers do proprietary trading on top of market making and 2) my measures distinguish the former from the latter, which is useful for existing regulation and 3) proprietary trading was weaker after the crisis. But they do *not* imply that prop trading is socially inefficient or deserves regulation.

In fact I give suggestive evidence from the 2007-2009 crisis that a crucial proprietary trading risk is not obviously linked with the underlying strategy, but comes from margin requirements or regulatory capital requirements. Figure 1 shows that Primary Dealers' net Treasury position shrank by half in July 2007, months before major crisis events. If concerns were about the corporate-Treasury position, lenders would probably have imposed scaling down of both legs: this is not the case. Instead, I show that the short position cut occured a few weeks after 1) the historical volatility of daily return on Treasuries increased with respect to the previous 18 months and 2) Primary Dealers' CDSs, a proxy for their perceived default risk, abruptly rose. By contrast corporate bond volatility did not vary much and the corporate bond position was not cut. Primary Dealers also faced financing constraints: I show that the long and short position were funded independently through short-term repurchase agreements, which imply haircuts. Another hypothesis, with equivalent effect, is that regulatory capital requirements, computed with statistical models for large dealers. This suggests that Primary Dealers faced financing constraints that increasing in asset volatility and their own default risk:[8] a tightening of the short side occured in July 2007.

This evidence suggests that the Volcker rule does not address an important proprietary trading risk. The assumption underlying the Volcker rule is that bank-affiliated dealers anticipated that the public sector would not let large banking groups fail, so that they had limited sensitivities to their trading losses: they would thus take excessive proprietary trading risk. Instead, the tightening of financing constraints seems independent from broker-dealers belonging to a banking group or not - a similar mechanism was at play during the LTCM crisis in 1998 - while it was crucial by its timing and its scale in the 2007-2009 crisis in the corporate bond market. Gromb and Vayanos (2002) give a first step in the regulatory discussion: they show that prop traders take too large positions because of a pecuniary externality generated by price-dependent financing constraints. Whether this calls for regulation is unclear, however, and beyond the scope of this paper.[9]

[8]Which may come from other activities than prop trading, *e.g.* mortgage-backed securities.

[9]Biais, Heider, and Hoerova (2019) observe that forward contracts mitigate the margin con-

Literature review. Several question the assumption that broker-dealers are always passive, as Choi and Huh (2019): I further show that broker-dealers initiate trades also to buy relatively cheap and sell expensive bonds. An (2019) shows that broker-dealers initiate trades to build excessively large inventories of different bonds, to offer a wide menu of asset to match buyers' preferences. Effects described in his and my papers are fully compatible; empirically, he focuses on reversals within 15 minutes, while I focus on reversals within a day.

Other papers hint at broker-dealer proprietary trading but do not test the hypothesis. Adrian et al. (2017) show that before the crisis, bond market liquidity was positively related with broker-dealer leverage, but negatively after the crisis. As proprietary trading often implies leverage through long-short positions which I exhibit for Primary Dealers, my findings explain this fact. In FX markets, Du et al. (2018) show that covered interest parity deviations are stronger when the corresponding arbitrage positions appear on quarterly financial statements.

This paper is also connected to the literature assessing post-crisis regulation. Many papers focus on broker-dealer market making activity, showing that dealers tend to hold position for shorter periods of time, Bessembinder et al. (2018) Schultz (2017); Duffie (2018) and Saar, Jian, Yang, and Zhu (2019) suggest this is not necessarily a bad thing. Bao et al. (2018) and Dick-Nielsen and Rossi (2018) show that abnormal returns surrounding bond downgrades to speculative grades have increased after the crisis. Dick-Nielsen and Rossi (2018) also mentions decreased Primary Dealers' corporate bond inventories: I connect this pattern with the Treasury short position. Overall my contribution with respect to these papers is to separate proprietary trading from market making.

Goldstein and Hotchkiss (2020) show that for the *least* traded bonds, in about 60% of the cases, inventory holding is less than one day. While I look at *most* traded bonds for which proprietary trading is more likely, the fact they uncover is the basis of my identification. Some papers look at dealer networks (Di Maggio et al. 2017, Friewald and Nagler 2019, Li and Schuerhoff 2019). Overall I confirm that a large fraction of broker-dealer trading activity is market making, but I show that broker-dealer also provide liquidity through prop trading.

Price impact regressions have seldom been run on the US corporate bond market.[10] With a different focus, Rapp (2016) does it and finds that the price impact of customer trades goes as expected from market makers. I find qualitatively similar results on average, but I isolate a subset of proprietary trading transactions.

This paper also relates to the macro-finance literature on broker-dealers, which does not explore broker-dealer trading strategies. Adrian and Shin (2009, 2010) show that broker-dealers' leverage ratio is positively correlated with asset prices, and in particular with the market price of risk. Gilchrist and Zakrajsek (2012) show

straint problem, making regulation useless in their model.

[10]Possibly because pre-trade quotes are not available. In other markets price impact regressions are standard: in the stock market, seminal papers include Glosten and Harris (1988), Hasbrouck (1991), Madhavan and Smidt (1993), Huang and Stoll (2015). In FX market, cf. Lyons (1995), Evans and Lyons (2002). *Cf.* Collin-Dufresne, Junge, and Trolle (2018) in the index CDS market.

that negative shocks to Primary Dealers' equity is translated in higher corporate bond/Treasury bond yield spread. Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017) show that Primary Dealer leverage is an important factor explaining asset prices. The link I make with limits to arbitrage theories both explains the link between broker-dealer balance sheet and risk premia, and raises regulatory questions related to financing constraints.

The paper is divided as follows. Section 2 develops the empirical hypotheses. Section 3 gives institutional background and presents the main dataset with summary statistics. Section 4 presents the price impact regressions results. Section 5 studies the relationship between customer order flow and bond cheapness measures. Section 6 suggests that the end of Primary Dealers' long-short strategy shown by figure 1 was caused by a tightening of the margin requirement on the short Treasury position. Section 7 discusses the implications for financial regulation and for safe asset production by the private sector. Section 8 concludes.

2 Empirical hypotheses

2.1 Theoretical predictions

Market making and proprietary trading appear complementary activities that are hard to separate, leading practioners and some academics (*e.g.* Duffie 2012) to make no difference between the two. Indeed both activities are in the end about buying low from investors eager to sell, selling high to investors eager to buy: both are thus liquidity provision.

In this paper I choose to make a difference between the two, based on clear theoretical predictions and because it sheds new light on what broker-dealers do. For convenience I borrow the terminology from the Volcker rule, which does *not* imply any stance on the optimality of the Volcker rule, which is neither the only way nor necessarily the best way to regulate proprietary trading: such assessment is beyond the scope of this paper.

Price changes and order flow. Theories of market making and proprietary trading give opposite predictions regarding the correlation between short-term price changes and customer trades. Theories of market making predict that customer sales (purchases) are associated with price decreases (increases). This is because a customer can be informed and his trade may signal asset value (Kyle 1985, Glosten and Milgrom 1985) or because risk averse market makers require a higher expected return to hold more risk (Stoll 1978, Ho and Stoll 1981, Grossman and Miller 1988).

By contrast, under dealer proprietary trading prices should go up when dealers buy, i.e. customers sell. I understand dealer proprietary trading as dealers comparing prevailing asset prices to their private or public information, and then trade on it. Dealer information can be private, in which case the dealer plays the role of the informed trader within market making theories. Dealer information can also be public, as when there is a spread between two publicly listed assets that appears not justified by fundamentals, but which persists because of some market frictions. In this case dealers are expected to buy the cheaper asset and sell the more expensive asset: except that the strategy possibly involves risk over the strategy's terminal payoff, this is exactly the situation described by theories of limits of arbitrage (Gromb and Vayanos 2002, 2010, 2018) with proprietary traders being the analogs of arbitrageurs.

Drivers of transactions. Theories of limits of arbitrage therefore give a second prediction: dealers should buy (sell) more a bond i that trade at low (high) price with respect to other bonds, given bond i's and other bonds' respective characteristics. In this paper I test this prediction giving up on whether a low price is indeed *too* low.

However, proprietary traders may have other strategies that those predicted by theories of limits of arbitrage: dealers may be informed on the issuer's credit risk or on order flow. I do not test it in this paper however.

2.2 One-way and Roundtrip days

I expect broker-dealers to do both market making and proprietary trading, which should correspond to different subsets of transactions.

To identify these subsets I separate days where large order flow goes only one way − only customer buys or only customer sells − from days where large order flow results from partial or full roundtrip − a customer buy is partially or fully offset by a customer sell − as illustrated by Figure 2.

I expect days with partial Roundtrip order flow to be associated with market making. A market maker expects to re-sell (repurchase) a security he has bought (sold) at some horizon. Partial Roundtrip order flow suggests that dealers were not willing to hold inventory deviations from their target overnight, and that they were able to revert part of customer initial transactions to get closer to the target.

This hypothesis is consistent with evidence by Goldstein and Hotchkiss (2020) on the least liquid US corporate bonds: dealers tend to revert transactions within a day in 58.2% of the roundtrips they study. In a related way, Li and Schuerhoff (2019) show in the US municipal bond market that when some customers demand immediacy, dealers match them more directly with other customers, meaning that a customer-to-dealer is more quickly associated with other customer-to-dealer trades in the other direction. Thus if my hypothesis is true, this means that customers initiate the trades and dealers accommodate, meaning these trades correspond to market making by dealers.

By contrast, I expect days with One-way order flow to be associated with proprietary trading. In principle One-way order flow could reflect one of two events. Either dealers are willing to hold the bonds they have purchased from customers, because it enters a proprietary trading strategy. Or dealers are unwilling to hold the

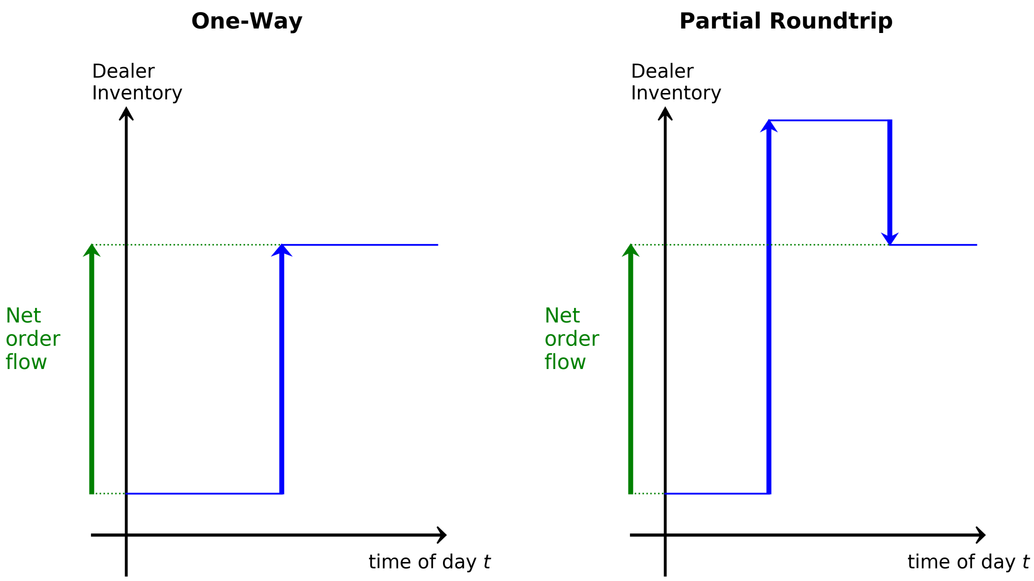

Figure 2 – **One-Way *vs.* Partial Roundtrip order flow.** This figure illustrates how some days, customer net order flow may result from transactions all in the same direction (only customers buys or only customer sales) as in the left panel, or in both directions as in the right panel. Partial Roundtrip order flow is likely to correspond to market making, because it suggests dealers were unwilling to hold bonds sold by customers for long; One-way order flow is likely to correspond to dealer proprietary trading because it suggests dealers were willing to hold all bonds sold by customers.

position overnight, but they are not able to start to revert their position because none of their customers is willing to buy on short notice: in this case it corresponds to market making. Thus I expect the first motive to dominate.

2.3 Hypotheses

Crossing the theoretical predictions from subsection 2.1 with the hypothesis that One-way order flow is associated with prop trading, and Roundtrip order flow with market making, I formulate the following testable hypotheses.

Hypothesis 1. *On days with one-way order flow in a given bond, price increases (decreases) are correlated with customer net sales (buys).*

On days with partial roundtrip order flow in a given bond, price increases (decreases) are associated with customer net buys (sales).

Hypothesis 2 (Limits of arbitrage)**.** *On days with one-way order flow, dealers tend to buy (sell) bonds that are cheap (expensive) compared with other bonds.*

In this paper I understand "cheap" and "expensive" in a broad and agnostic way. Broad, because bonds with very different risk level or maturity, for instance, can be said to be cheap relative to one another after adjustment for risk or maturity: one bond can have a risk premium deemed "too large" compared with the other. Agnostic, because I am not interested in whether a spread between two bonds is justified from a theoretical point of view or not: I am simply interested in the positive fact that dealers take some spreads into account or not.

3 Data

3.1 Background: broker-dealers, and the US corporate bond market

Broker-dealers. Broker-dealers are institutions that trade a lot in financial markets: they include banks' activities in financial market, such as Barclays Capital, Citigroup Global Markets, Goldman Sachs & Co. or JP Morgan Securities, and other non-bank large players such as Citadel Securities.[11] More precisely, a *dealer* is a person or company "engaged in the business of buying and selling securities for his own account" (Section 3(a)(5)(A) of the Securities Exchange Act of 1934) as a regular business.[12] A *broker* is "any person engaged in the business of effecting transactions in securities for the account of others". A *broker-dealer* is thus a person or company that acts as a broker and/or as a dealer. In this paper I am interested only in the dealer activity of broker-dealers.

[11] A much more complete list of broker-dealers can be found on FINRA's website: https://www.finra.org/about/firms-we-regulate.

[12] Most information in this paragraph comes from Security and Exchange Commission's website: https://www.sec.gov/reportspubs/investor-publications/divisionsmarketregbdguidehtm.html

Dealers are often viewed as market makers. But the SEC definition is broader, as the following are typical examples of dealer activities:

- Market making: "a person who holds himself out as being willing to buy and sell a particular security on a continuous basis;"
- Proprietary trading or arbitrage: "a person who runs a matched book of repurchase agreements" (in appendix D I describe how long-short positions are implemented through repurchased agreements).
- Securitization: "a person who issues or originates securities that he also buys and sells".

A central point of this paper is to show that broker-dealers follow strategies consistent with proprietary trading.

Broker-dealers have to register with the SEC, and have to join a "Self-Regulatory Organization" (SRO) such as the FINRA and national securities exchanges: a SRO is a professional association that assist the SEC in regulating the activities of broker-dealers. Becoming a member of FINRA is mandatory for dealers who trade outside exchanges, such as in the US corporate bond market.[13]

The US corporate bond market The US corporate bond market is over-the-counter: investors do not trade through exchanges, but with individual broker-dealers. It is thus unlike equity markets where trading occurs through limit-order book markets. Most often, customers use telephone and messaging systems to request quotes from dealers, or dealers may contact investors to make them offers. The content of the conversations between dealers and their customers is not available in the US corporate bond market: in particular, quotes offered by dealers, which may be customer-specific, are not disclosed.

Some platforms have emerged to allow investors to request quotes from several dealers at once (Hendershott and Madhavan 2015), but this does not change the fact that investors can choose to trade with a dealer A and not with another dealer B even if dealer B would be willing to trade.

In July 2002, dealers were requested to report all their transactions in quasi real time in the TRACE system, which is managed by FINRA. These reports would be instantaneously released to market participants to give them *ex post* market transparency.

Broker-dealer reporting of transactions. FINRA requires all its members, that is all broker-dealers who trade in the US corporate bond market, to report all their transactions, both as broker and as dealer, in the corporate bond market through TRACE system.

Therefore all transactions in the US corporate bond market that involve a broker-dealer are in TRACE. However, it is not required by broker-dealers to enter the

[13] https://www.sec.gov/reportspubs/investor-publications/divisionsmarketregbdguidehtm.html#III.

type of activity the transaction is involved in such as market making or proprietary trading, or the party who initiated the trade.

3.2 Data and sample selection

Data I use US corporate bonds transaction data from FINRA's enhanced TRACE engine, which I retrieved through WRDS. The sample runs from July 1st, 2002 to December 31st, 2014. Each transaction report in my version of the dataset contains a bond identifier (CUSIP), the date and time of the transaction, the transaction price, the transaction size in terms of par value traded, whether the reporting dealer was a buyer or a seller, and whether the trading counterparty was another dealer or a customer. I clean the data with usual procedures described in appendix A.

Daily Treasury yield curves come from Gurkaynak, Sack, and Wright (2007) and updates by the Fed. Other financial indicators (LIBOR, TYVIX, ...) come from various usual providers.

Sample selection I select customer-to-dealer transactions for dollar-denominated corporate bonds with characteristics available in Mergent FISD database, with issuer common stock to match with using WRDS CRSP-TRACE linking suite. I drop bonds with principal value different from $1000 as these are usually non-standard, whose payoff depend on an index (with "-linked" in their name), and with issue size less than $10 million, as all these bonds are likely to be very illiquid. I keep bonds with embedded options (call, put).

I focus on most actively traded bonds: I keep bonds for which there are customer-to-dealer trades at least 75% of its relevant business days, *i.e.* between first trade and last trade, like Bao, Pan, and Wang (2011). I drop transactions for bonds with residual maturities less than one year, as the trading patterns are special. I drop trades that occur until 7 days after the bond's offering date, as these are likely related to the primary market. I drop bonds that have less than 50 observations, to exclude bonds that are traded only a few days and then disappear.

Finally, I keep observations for investment-grade bonds. Ratings are by S&P, Fitch and Moody's, accessed through Mergent. When ratings from several agencies are available, I retain the worst nonmissing one. If a bond is not rated, then I consider it with a worse rating than any other rating.

This procedures leaves 3080 unique bonds corresponding to 546 issuers as identified by Mergent FISD.

3.3 Variables definitions

I study daily order flow in parallel with daily price changes. For bond i and day t, I retain the price $p_{i,t}$ of the last transaction. I also keep the size $q_{i,t}$ of this transaction, with the convention that $q_{i,t} > 0$ if it is a customer buy, $q_{i,t} < 0$ if it is a customer sale.

Order flow I define customer order flow for bond i on day t as the sum of the sizes of customer large buys minus the sum of the sizes of customer large sells. Large transactions are those for which there is at least \$100,000 of par value traded at once: these trades are generally considered as of institutional size and comprise 97% of trading volume in my sample. Formally, denoting $q^1_{i,t}, q^2_{i,t}, ..., q^n_{i,t}, ...$ the 1st, 2nd, ..., nth large transaction in bond i and day t, the order flow is

$$OF_{i,t} = \sum_n q^n_{i,t} \ \mathbb{1}_{|q^n_{i,t}|>\$100{,}000}$$

It includes the last transaction of day t if this last transaction is large. As shown in the summary statistics subsection 3.4, the distribution of order flow has fat tails. To avoid large observations driving the regression estimates, I use the following:

$$\widetilde{OF}_{i,t} = \text{sign}\left(OF_{i,t}\right) \times \log_{10} |OF_{i,t}|$$

which allow to reduce the tails of the order flow distribution while keeping track of the sign of order flow.

I will also need to distinguish between One-way and Partial Roundtrip order flow, and sometimes with a further split between bond maturity being more or less than a cutoff. Thus I define

$$\widetilde{OF}^{OneWay}_{i,t} = \begin{cases} \widetilde{OF}_{i,t} & \text{if One-Way order flow} \\ 0 & \text{otherwise.} \end{cases}$$

and I define $\widetilde{OF}^{Roundtrip}_{i,t}$ for Partial Roundtrip order flow in a similar way. I also define in an analogous way

$$\widetilde{OF}^{OneWay,M\leq 10y}_{i,t} = \begin{cases} \widetilde{OF}_{i,t} & \text{if One-Way order flow and maturity } \leq 10y \\ 0 & \text{otherwise.} \end{cases}$$

and similarly for One-way order flow and bond maturity above 10 years, and Partial Roundtrip with bond maturities above and below 10 years.

Bond spreads. I compute bond spreads in a way similar to Gilchrist and Zakrajsek (2012): for each bond i, I compute a risk-free price as the sum of its theoretical cash-flows (coupons + principal at maturity, maturity being the theoretical maturity for callable bonds) each discounted by the fitted Treasury yield curve of Gurkaynak et al. (2007), and adjusted for accrued interest. The spread is the log of the ratio of the risk free price to the observed price.

Subperiods In some sections of the paper I test the predictions over several subperiods, defined as follows:

1. *Opaque*, from TRACE inception (first observation on July 1st, 2002) to February 7th, 2005. During this period, TRACE data were released for a limited number of bonds only, so that post-trade transparency was limited for other bonds for which data were not released to market participants. On February 8th all transactions were disclosed. One expects a different dealer behavior during this period.

2. *Pre-Crisis*, from February 8th, 2005 to June 30th, 2007.

3. *Crisis*, from July 1st, 2007 to April 30, 2009. The crisis dates (June 30th, 2007 to April 30, 2009) are borrowed from Bessembinder et al. (2018). Making the crisis start in July 2007 is consistent with the increase in bond spread and Primary Dealers' short Treasury position cut in July 2007.

4. *Post-Crisis*, from May 1st, 2009 to July 20th, 2010. This period ends the day before the Dodd-Frank Act was passed. The Dodd-Frank Act in particular contained the Volcker rule, although the implementation details were not written at this time. However, Bessembinder et al. (2018) show large investment banks announced they shut down their proprietary trading desks, suggesting anticipatory effects of the rule.

5. *Dodd-Frank*: from July 21st 2010 to the end of the sample, corresponding to the period when the Dodd-Frank Act was voted.

3.4 Summary statistics

3.4.1 Whole sample

Bond characteristics. Table 1 provides a few summary statistics for the sample of bonds. The first line indicates an average issue size of one billion dollars, above the median which stands at 800 million: issues are in general large. At issuance, bonds have an average maturity of 10.6 years, with the median and the 75th percentile being at 10 years. As suggested by the table, most bonds have initial maturity 10 years (31.7%), 5 years (27.0%) or 30 years (9.4%), and 78.9% of bonds have initial maturity less than or equal to 10 years. Finally, more than half of the bonds in the sample have an embedded call as shown by the last line.

Transaction-level. Figure 3 gives the share of total volume that transactions of given size represent over the whole sample. For instance transactions between $1 million and $5 million represent close to 40% of total trading volume in my sample. The distribution does not change much across my subperiods. Large transactions, with par value traded above $100,000, represent 97% of total trading volume.

Daily observations. This paragraph gives summary statistics about bond $\times$ day observations. Table 2 shows that out of the 2.2 million observations, 1.5 million have

	Mean	Std. Dev.	p5	p10	p25	p50	p75	p90	p95
Issue size ($mn)	1,026	793	268	350	500	800	1,250	2,000	2,500
Initial maturity	10.6	8.5	3	5	5	10	10	30	30
Maturity $\leq$ 10y	78.9%	-	-	-	-	-	-	-	-
Callable	57.8%	-	-	-	-	-	-	-	-

Table 1 – Distribution of bond characteristics across the 3,080 bonds in the sample: issue size in millions of dollats, maturity at issuance, and for the last two lines the fraction of bonds with initial maturity less than 10 years, and of bonds with an embedded call giving the bond issuer the opportunity to redeem his bond before maturity.

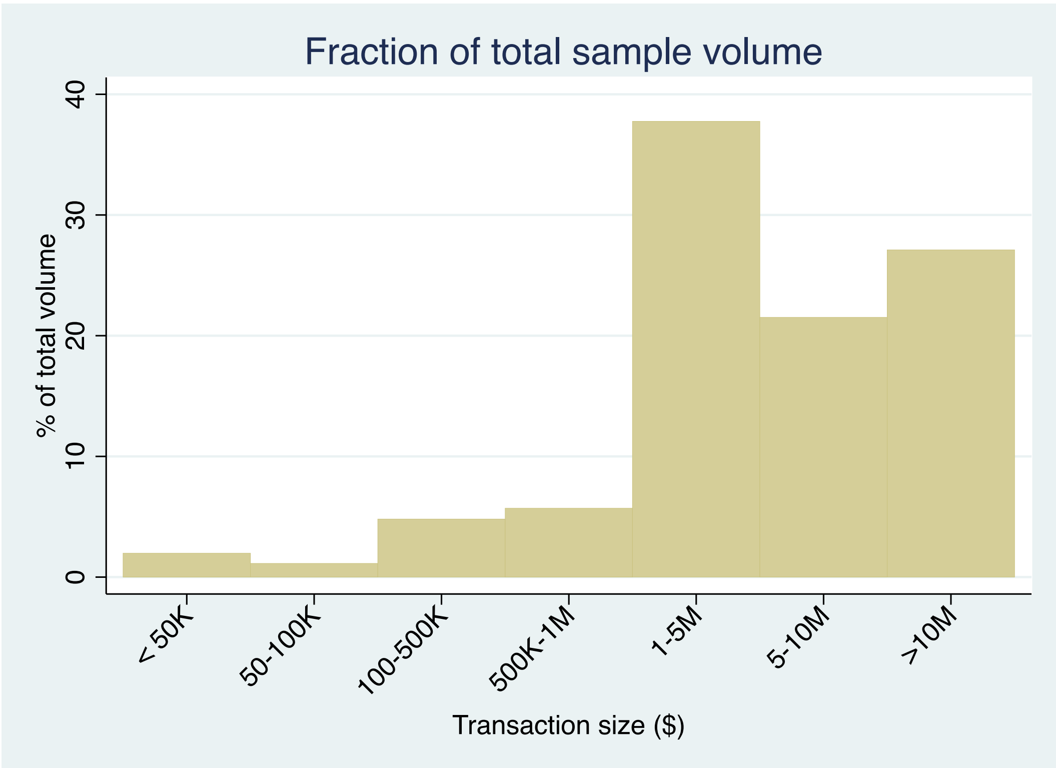

Figure 3 – Share of total trading volume of transactions in various size buckets.

	Nr observations	% Callable	% One-way
With large trades	1,464,701	52.1	50.4
All	2,220,248	53.6	33.0

Table 2 – Percentage of observations with callable bonds; percentage of observations with One-way order flow (only large customer buys or only large customer sells), for the subsample with large trades (1st line) and for all observations (2nd line).

large transactions. Slightly more than half observations are with callable bonds, in line with the proportion of callable bonds shown in table 1.

Table 3 shows the distribution of several variables. The distribution of order flow $OF_{i,t}$ is symmetric, with a mean equal to the median at 0. The distribution has fat tails, with more than 20% of the observations having absolute value above \$4 million: this motivates the use of the signed logarithm of order flow $\widetilde{OF}_{i,t}$ in the regressions, to compress the distribution. Conditional on order flow being one-way, order flow is slightly skewed towards customer buys with positive mean and median. Quantiles of one-way order flow are slightly smaller in absolute value than for the unconditional distribution, but the order of magnitude remains the same.

The distribution of log price changes if also symmetric around zero. Log price changes are multiplied by 100, so that they are expressed in percentage points. The volatility of these daily price changes is suprisingly large, but mitigated in the longer run by reversals.

The mean of residual maturity when bonds are traded is lower than the mean bond maturity at issuance, which is partly mechanical due to the fact that residual maturity decreases through time. Interestingly, the distribution of bond ages suggests that most observations are for relatively young bonds, with a mean and median close to 3 years, while the 95th percentile is at 8.2 years, suggesting bond older than 10 years are seldom traded.

Finally, the last two lines show the distribution of the number of transactions per bond $\times$ day observation. The mean of 7.5 is low compared to equity markets for instance; the lower median at 4 transactions suggests the mean is driven by a few observations with many transactions. Over all observations, the number of large transactions (more than \$100,000 traded) is even lower, with a median at 1 transaction and a mean at 1.7 transaction.

3.4.2 Evolution through time

Table 4 plots the percentage of One-way order flow across observations by subperiod, with a further split by initial maturity. I use the further split by maturity in the order flow regressions in section 5, to better identify proprietary trading.

There is no striking change from before to after the crisis: the proportion of One-way order flow is slightly higher during the Pre-Crisis and Dodd-Frank periods, as is the proportion for One-way order flow and maturity below 10 years.

	Mean	Std. dev.	p5	p10	p25	p50	p75	p90	p95
$OF_{i,t}$ ($ million)	0	11.2	-8.7	-4.2	-.7	0	.9	4	7.9
$OF_{i,t}$ if One-way	.1	7.1	-5.7	-2.9	-.6	.2	.8	3	5.8
$\Delta \log p_{i,t} \times 100$	0	1.85	-2.36	-1.51	-.53	0	.54	1.53	2.38
Years to maturity	7.8	8.1	1.4	1.8	2.9	5	8.5	23.7	27.7
Age (years)	3.3	2.7	.4	.7	1.4	2.6	4.5	6.9	8.2
# trades (all sizes)	7.5	13.4	1	1	2	4	8	15	22
# trades (large)	1.7	2.6	0	0	0	1	2	4	6

Table 3 – Sample distribution of order flow $OF_{i,t}$, order flow conditional on it being One-way, of residual maturity and age *conditional on having large transactions* (> \$100,000) in bond i on day t. The distribution of log price changes $\Delta \log p_{i,t}$ and of the number of trades are *unconditional*. Order flow is positive when customers are net buyers.

Subperiod	One-Way	One-Way $M \leq 10$y	OneWay $M > 10$y
Opaque	47	38	9
Pre-Crisis	56	44	11
Crisis	49	38	11
Post-Crisis	44	34	10
Dodd-Frank	51	39	13

Table 4 – Percentage of One-way order flow and further breakdown by initial maturity M, conditional on observations having large transactions.

4 Price changes and order flow

In this section I test hypothesis 1 on the correlation between price changes and customer order flow. To do this I regress daily log price changes on customer order flow, controlling for other plausible determinants of price changes. These regressions allow to determine whether broker-dealers act only as market makers, or if they also follow other strategies. I also discuss potential endogeneity concerns in subsection 4.3

4.1 Specifications

Here I present three different specifications: one with order flow with no distinction between One-way and Partial Rountrip, one with the distinction, and one with the distinction and an interaction with a dummy for the post-Lehman crisis. I present estimation results in the next subsection.

4.1.1 Baseline

Here I present a benchmark specification where I do not distinguish between One-way and Roundtrip order flow. A first limit to measuring price impact is that pre-trade quotes are not available. These would allow to separate actual quote movements, which are what I am interested in, from one-shot order processing costs that are charged without impact on subsequent prices. Inspired by Foucault, Pagano, and Roell (2014) and as in Rapp (2016) I circumvent the issue raised by the absence of pre-trade quotes issue by aggregating transactions at daily level, so that the price impact component of the spread can be isolated from other order processing costs and rents.

Thus I compute the log price difference between the last transaction of day t and the last transaction of day $t-1$, and regress it on large customer order flow, controlling for small order flow, measures of order processing costs and various controls. Thus I estimate the following equation:

$$\Delta \log p_{i,t} = \alpha + \beta\, \widetilde{OF}_{i,t} + \gamma' X_{i,t}^{(p)} + \epsilon_{0,i,t} \tag{4.1}$$

Market making theories predict $\beta > 0$. As reviewed in subsection 2.1, under dealer inventory costs and/or customer private information about bond value, one expects customer sales (resp. purchases) to be associated with price decreases (resp. increases): a customer sell either signals bad news about the asset value, or imposes more risk on the dealer's balance sheet - both of which leading the dealer to trade at a lower price.

$X_{i,t}^{(p)}$ is a vector of controls that contains the following variables. First, I control for order processing costs: each price $p_{i,t-1}, p_{i,t}$ is the price of an actual transaction that can be a customer buy at the ask price, or a customer sell at the bid price lower than the ask price. Thus I include the directions $d_{i,t-1}, d_{i,t}$ of the the corresponding transactions, equal to $+1$ for customer buys and -1 for customer sells. The empirical microstructure literature in the US corporate bond market also suggest that order processing costs may decrease with the size of the order because larger customers get better terms: to the direction of the last transaction I add their signed log sizes, $\text{sign}(q_{i,t-1}) \log_{10} |q_{i,t-1}|$ and $\text{sign}(q_{i,t}) \log_{10} |q_{i,t}|$, with the log again to prevent the largest observations to drive the results.

I also control for the bond issuer's stock return, for changes in the 10 years US Treasury yield, changes in the 3 months LIBOR, changes in rating, TYVIX (an implied volatility index for 10 years Treasury futures) and changes in TYVIX. All changes are daily, using closing prices.

Log price changes are $\Delta \log p_{i,t} = \log(p_{i,t}/p_{i,t-1})$. Therefore $\Delta \log p_{i,t} = 0.01$ means the price has changed by 1 percent. To express price changes in percentage points, in the regressions I replace $\Delta \log p_{i,t}$ by $\Delta \log p_{i,t} \times 100$ as in table 3.

Both trades and price changes may be driven by information related to the bond issuer. Therefore I cluster standard errors by bond issuer. In the appendix I also compute standard errors clustered by bond issuer, by maturity and by calendar month.

4.1.2 One-way *vs.* Roundtrip

Now I distinguish between One-way and Partial Roundtrip order flow: I replace the order flow measure by a one-way order flow measure and a partial roundtrip order flow measure:

$$\Delta \log p_{i,t} = \alpha + \beta_1 \widetilde{OF}_{i,t}^{OneWay} + \beta_2 \widetilde{OF}_{i,t}^{Roundtrip} + \gamma X_{1,i,t}^{(p)} + \epsilon_{1,i,t} \tag{4.2}$$

$\widetilde{OF}_{i,t}^{OneWay}$ equals $\widetilde{OF}_{i,t}$ if order flow in bond i was One-way on day t; it equals zero otherwise. Similarly $\widetilde{OF}_{i,t}^{Roundtrip}$ equals $\widetilde{OF}_{i,t}$ if order flow in bond i on day t was a partial roundtrip, and zero otherwise. Hypothesis 1 formally reads

$$\beta_1 < 0 \quad \text{and} \quad \beta_2 > 0.$$

Splitting order flow in the previous way is equivalent to putting an interaction of order flow with the dummy for order flow being One-way: I include this dummy in the vector of controls $X_{1,i,t}^{(p)}$, which otherwise contains the same controls as in equation (4.1). Again $\log p_{i,t}$ is multiplied by 100 to express it in percentage points. I cluster standard errors by bond issuer similarly to regression (4.1).

4.1.3 One-way *vs.* Roundtrip outside post-Lehman crisis

The financial crisis period has been special regarding prop trading: after Lehman Brothers' failure on September 15th, 2008, markets were reportedly highly illiquid, which may have induced dealers to stop proprietary trading. Therefore One-way order flow during this period may reflect only market making; in addition, market making costs may have been very high: this would tend to bias the coefficient β_1 up in equation 4.2.

Therefore I interact both measures of order flow with the dummy $Lehman_t$ that equals 1 between September 15th, 2008 and April 30th, 2009, *i.e.* for 7.5 months out of the 12.5 years of my sample. The equation becomes:

$$\begin{aligned}\Delta \log p_{i,t} = \alpha &+ \beta_1 \widetilde{OF}_{i,t}^{OneWay} + \beta_2 \widetilde{OF}_{i,t}^{Roundtrip} \\ &+ \beta_3 \widetilde{OF}_{i,t}^{OneWay} \times Lehman_t + \beta_4 \widetilde{OF}_{i,t}^{Roundtrip} \times Lehman_t \\ &+ \beta_0 Lehman_t + \gamma X_{2,i,t}^{(p)} + \epsilon_{2,i,t} \end{aligned} \tag{4.3}$$

The vector of controls $X_{2,i,t}^{(p)}$ includes the dummy for one-way order flow, the $Lehman_t$ dummy and the interaction between the two. Otherwise it contains the same controls as in specifications 4.1 and 4.2.

4.2 Results

Table 5 presents the estimation results for equations 4.1, 4.2 and 4.2.

The first column reports the estimation result for the baseline regression 4.1. The coefficient is positive and highly significant, consistently with market making: running the price impact regression without distinction thus legitimates the idea that broker-dealers are pure market makers. The estimates imply that customer net buys by 1 million are on average associated with a price increase by $\log_{10}(1,000,000) \times .0033 = .02$ percentage points, that is, 2 basis points. It may appear small, but this is not my point: I distinguish between theories that imply positive or negative coefficients, with potentially broader, systemic implications.

The second column reports the results for One-way and Partial Roundtrip order flow separately. The coefficient for One-way order flow is 7 times smaller that the coefficient for partial Roundtrip order flow, and the difference is statistically significant (not shown); it is however positive and just significant at 5% level. The difference between the two coefficients is already striking.

The third column reports the estimation results for the main effects of One-way and Roundtrip order flow, *i.e.* for these measures outside the crisis post-Lehman. The coefficient for one-way order flow is now negative and highly significant, while the other is significantly positive: this validates hypothesis 1.

4.3 Endogeneity concerns and robustness checks

One may be concerned about endogeneity when interpreting correlations in price impact regressions as reflecting one class of theories or the other. Endogeneity is certainly there, but I claim that 1) it does not raise significant concerns for my purpose and 2) I already control for plausible sources of endogeneity.

4.3.1 Direction of causality

A first concern is about the direction of causality: one does not know whether prices decrease because dealers sell (i.e. customers sell), or whether customers buy

Table 5 – Regression of daily log price changes on customer order flow and controls. $\widetilde{OF}_{i,t}$ is the sign of order flow times the logarithm of the absolute value of order flow. Order flow is the sum of customer large buys minus the sum of customer large sells. A customer buy or sell is large its size is above \$100,000. $\widetilde{OF}_{i,t}^{OneWay}$ equals $\widetilde{OF}_{i,t}$ if order flow in bond i on day t is one-way (only customer buys or only customer sells), and zero otherwise. $\widetilde{OF}_{i,t}^{Roundtrip}$ equals $\widetilde{OF}_{i,t}$ if order flow is not One-way, *i.e.* (partial) roundtrip, and zero otherwise. Controls are issuer stock return, changes in 10 years Treasury yield, changes in 3-months LIBOR, TYVIX, an implied volatility index for Treasury futures, and changes in TYVIX. In the second and third column, a dummy $OneWay_{i,t}$for one-way order flow is included. $Lehman_t$ is a dummy that equals 1 if t is between September 15th, 2008 and April 30th, 2009. In the third column, the interaction $OneWay_{i,t} \times Lehman_t$ is included.

	Baseline	One-way *vs.* Roundtrip	One-way *vs.* Roundtrip Lehman interaction
$\widetilde{OF}_{i,t}$	0.0033***		
	(10.68)		
$\widetilde{OF}_{i,t}^{OneWay}$		0.0008*	**-0.0025*****
		(2.05)	**(-6.12)**
$\widetilde{OF}_{i,t}^{Roundtrip}$		0.0056***	0.0040***
		(13.67)	(11.65)
Interaction with $Lehman_t$	N	N	Y
Constant and controls	Y	Y	Y
R^2	0.24	0.24	0.24
N	2,220,248	2,220,248	2,220,248

Standard errors clustered by bond issuer

* (p<0.05), ** (p<0.01), *** (p<0.001)

because they see a low price. One would view the second case as a sign dealer proprietary trading. One may view the first direction as consistent with market making behavior, with dealers decreasing their quotes to liquidate inventory they have just purchased.

I view the market making interpretation as misled. It is true that a market maker willing to re-sell inventory he has just bought is quoting low price to induce customer purchases. However this does not imply that the market maker is systematically willing to *decrease* his quotes to induce customer purchases: indeed such statement implies the market maker would systematically buy at a high price and sell at a low price, and thus make a systematic market making loss that would drive him out of business.

In fact, a profitable pure market maker anticipates that the re-sell price will have to be low as well when he buys, thus buys at a lower price. This predicts that customer buys are associated with price increases.

Therefore observing a correlation between customer buys (sales) and price decrease (increase) does not require any stand on the direction of causality to conclude that it corresponds to proprietary trading. However, one may worry that common drivers of customer net trades and price changes drive the results. I review these concerns in what follows.

4.3.2 Common drivers for price changes and customer trades

One may also be concerned that there are common drivers for price changes and customer trades: for instance public bad news may induce both prices to decrease and customers to sell. In this case the correlation does not seem to reflect market making effects such as adverse selection and dealer inventory costs.

I see the reverse correlation as less problematic for my interpretation. If bad news induce both price drops and dealer sells or customer buys, it means that dealers are more willing to sell than their customers, who thus provide liquidity to dealers.

In any case I control for plausible common drivers of order flow and price changes, which I review now.

Credit and risk-free rate risks. I address this endogeneity concern by controlling for proxies for public information. Relevant information should be primarily about issuer's credit quality and interest rates. Regarding credit risk, I add control for stock return: informed traders should also trade in the stock market, as bond credit risk and stocks valuation are both about the issuer's asset side valuation. Regarding interest rate movements, I control for changes in the 10 years Treasury yield, and for the 3-months LIBOR. The LIBOR captures both short-term interest rate movements and changes in credit risk concerns in the banking sector; including changes in the 3-months Treasury bill instead does not change the results.

Cheapness measures One may also worry that cheapness measures forecast both dealer purchases and price increases. I address this concern in appendix B.1, in which

I show that estimates of order flow are unaffected.

Predicted order flow I also assess in appendix B.2 whether other predictors of order flow are driving the results: previous price changes, lags of order flow and lagged stock return and interest rate changes. To do this I compute a predicted and an unexpected component of order flow, separately for One-way and Partial Rountrip order flow, as described in the appendix. I am interested in the unexpected component. Again the estimates are unchanged.

4.3.3 Robustness to more conservative standard errors

My results are robust to additional layers of clustering: one may be concerned that order flow is correlated with price changes within a maturity bucket, or within a calendar month. In appendix B.3 I re-run the price impact regression by computing standard errors with various multiway clustering, following the methodology by Cameron et al. (2011), and including the cheapness measures as in subsection 4.3.2 to check full robustness. The estimates remain significant at 5% level even with three-way clustering by bond issuer, maturity and calendar month.

4.4 Proprietary trading: refinements

Table 5 shows that outside the crisis, One-way order flow corresponds on average to proprietary trading, while it does not during the crisis. One may wonder whether such average effect hide some heterogeneity: sometimes dealers buy and do not sell and conversely because they are willing to hold the position, sometimes it may be because they were not able to find a counterparty sufficiently quickly.

Here I re-run regressions of price changes over One-way and Partial Roundtrip order flow, by further distinguishing by three different criteria: bond age, bond maturity at issuance (initial maturity) and bond residual maturity at the time of trade. I split the sample with according to whether the criterion is below or above 10 years. The generic specification for criterion $Z = Age$, $InitialMaturity$, $ResidualMaturity$ is thus

$$\begin{aligned}\Delta \log p_{i,t} = \alpha &+ \beta_1 \, \widetilde{OF}_{i,t}^{OneWay,Z\leq 10y} + +\beta_2 \, \widetilde{OF}_{i,t}^{OneWay,Z>10y} \\ &+ \beta_3 \, \widetilde{OF}_{i,t}^{Roundtrip,Z\leq 10y} + \beta_4 \, \widetilde{OF}_{i,t}^{Roundtrip,Z>10y} \\ &+ \sum_k LehmanInteractionTerms_{k,i,t} + Lehman_t + \gamma X_{2,i,t}^{(p)} + \epsilon_{2,i,t}\end{aligned} \tag{4.4}$$

where the $LehmanInteractionTerms_{k,i,t}$ are interaction terms of each of the four measures of order flow with the dummy $Lehman_t$.

Table 6 shows the results, which are clear: proprietary trading is concentrated on younger bonds (less than 10 years old), on bonds with initial maturity 10 years, and

Table 6 – Regression of price changes on One-way and Partial Roundtrip order flow, further distinguishing order flow on whether a criterion $Z_{i,t}$ is below or above 10 years. Criteria Z are bond age (time since issuance), bond maturity at issuance (initial maturity), bond residual maturity at the time of trade. Each column reports the estimation with a different criterion. Controls are issuer stock return, changes in 10 years Treasury yield, changes in 3-months LIBOR, TYVIX, an implied volatility index for Treasury futures, and changes in TYVIX. In the second and third column, a dummy $OneWay_{i,t}$for one-way order flow is included. $Lehman_t$ is a dummy that equals 1 if t is between September 15th, 2008 and April 30th, 2009. Dummy main effects are included, as well as relevant interactions terms between dummies.

	Age	Initial Maturity	Residual Maturity
$\widetilde{OF}_{i,t}^{OneWay,Z\leq 10y}$	-0.0029***	-0.0050***	-0.0045***
	(-6.72)	(-9.83)	(-10.17)
$\widetilde{OF}_{i,t}^{OneWay,Z>10y}$	0.0109***	0.0066***	0.0093***
	(5.32)	(6.87)	(7.50)
$\widetilde{OF}_{i,t}^{Roundtrip,Z\leq 10y}$	0.0039***	0.0029***	0.0031***
	(11.21)	(8.94)	(9.98)
$\widetilde{OF}_{i,t}^{Roundtrip,Z>10y}$	0.0093**	0.0085***	0.0090***
	(3.28)	(10.97)	(9.13)
Interaction with $Lehman_t$	Y	Y	Y
Constant and controls	Y	Y	Y
R^2	0.24	0.24	0.24
N	2,220,248	2,220,248	2,220,248

Standard errors clustered by bond issuer

* (p<0.05), ** (p<0.01), *** (p<0.001)

on bonds with residual maturity 10 years. Otherwise the coefficients are consistent with market making.

Overall it seems that older bonds, or bonds with longer maturity (initial or residual), one-way order flow corresponds to market making and dealers' inability to revert inventory quickly towards the target. These bonds are likely less liquid, so the results are also in line with the results by Goldstein and Hotchkiss (2020) who find on their sample of illiquid bonds that 42% of customer trades are *not* reversed within one day.

4.5 Evolution through time

I ran the previous regressions over the whole sample, covering plausibly very different environments from before the crisis to after. Here I add interaction of one-way and partial roundtrip order flows with dummies for the subperiods defined in section 3.

Formally, I estimate the following, where $Period_t^k$ is a dummy for one of the above periods *Opaque*, *Bear Stearns to Lehman*, *Lehman to end of crisis*, *Post-Crisis*, *Post Dodd-Frank*, the base level being the Pre-Crisis period (the base level choice does not affect the results):

$$\begin{aligned}\Delta \log p_{i,t} = \alpha &+ \beta_1\, \widetilde{OF}_{i,t}^{OneWay} + \beta_2\, \widetilde{OF}_{i,t}^{Roundtrip} \\ &+ \sum_k \left(\beta_{k,OW}\, \widetilde{OF}_{i,t}^{OneWay} \times Period_t^k + \beta_{k,R}\, \widetilde{OF}_{i,t}^{Roundtrip} \times Period_t^k\right) \\ &+ \sum_k \beta_{k,0} Period_t^k + \gamma X_{2,i,t}^{(p)} + \epsilon_{2,i,t} \end{aligned} \tag{4.5}$$

I plot the total effects of this regression for each period, for One-way and Partial Roundtrip coefficients separately, in figure 4. I scale the coefficients so that they correspond to the price change in basis points associated with net customer purchases by \$1 million. The original coefficients are in table 13 in the appendix.

Proprietary trading, as shown by negative coefficients, is present before the Crisis in the Opaque and Pre-Crisis periods, and also after the crisis in the Dodd-Frank period. The coefficient on One-way order flow is positive during the Crisis and strikingly higher than the coefficient on Partial Roundtrip order flow. This likely comes from the fact that one-way order flow corresponds to positions dealers are not willing to hold, but cannot start to offload within a day: as they probably expect to hold these positions for longer, they entail higher price impact, for instance associated with higher inventory holding costs.

It is also striking that coefficients before the crisis are much strongly more negative than after the Dodd-Frank Act was passed: this suggests that post-crisis regulation, the Volcker rule in particular, decreased the strength of proprietary trading.

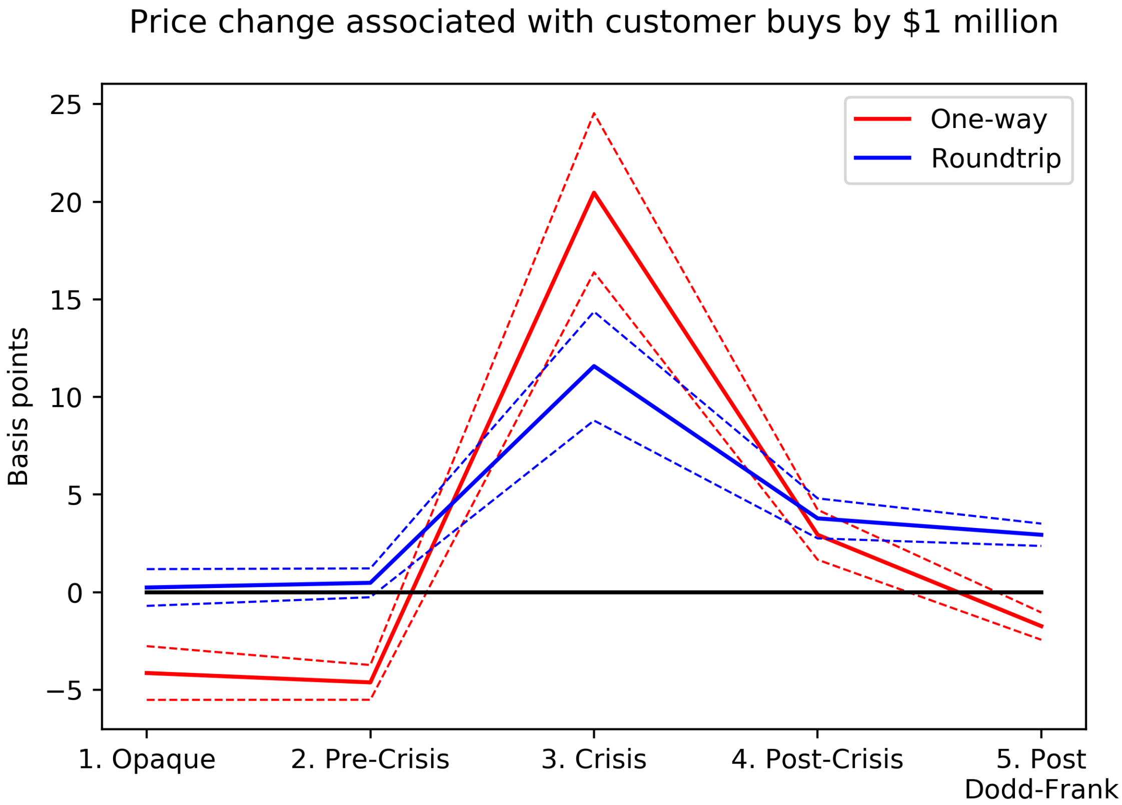

Figure 4 – Regression-implied log price changes associated with customer net purchases by $1 million across sample subperiods, for One-way (red) and Roundtrip(blue) order flow. Dashed lines are the 95% confidence intervals for each coefficient. The Opaque period when not all TRACE transactions were disclosed to market participants starts on July 1st, 2002 and stops on February 7th, 2005. The Pre-Crisis period starts on February 8th, 2005 and stops on June 30th, 2007. The Xrisis period goes from July 1st, 2007 to April 30th, 2009 (a conventional date used in other papers). The Post-Crisis period goes from May 1st, 2009 to July 20, 2010. The Post Dodd-Frank goes from July 21st (Dodd-Frank Act voted) to the end of the sample.

5 Order flow and lagged cheapness

In this section I test hypothesis 2. If dealers tend to buy (sell) bonds that were cheap (expensive) the day before, it reveals prop trading activities by dealers.[14] I first focus on a simple of bond cheapness. I introduce individual corporate-to-Treasury spreads, *i.e.* the spread between the bond's yield and the yield of a fictitious bond with the same contractual cash flows discounted with the Treasury yield curve. Then I compare this spread to the median spread of all bonds with the same maturity, credit risk and callability features: this is a proxy for an idiosyncratic component of the bond's individual spread. I find that broker-dealers indeed tend to purchase (sell) bonds with maturity below (above) 10 years.

Then I add three spread components related to credit risk and callability given residual maturity, to maturity and to differences between corporate bonds as a whole and Treasury bonds. The four measures are a model-free decomposition of the spread: it only looks at relative price differences between various subsets of bonds. The analysis shows that broker-dealers arbitrage corporate bonds within maturities (thus across ratings/callability) and as an asset class with respect to Treasuries.

There are potentially many proprietary trading opportunities in the corporate bond market and in related markets, and I do not try to be exhaustive: documenting that broker-dealers exploit at least some price differentials is enough for my purposes. Furthermore, I proxy cheapness with various price differentials, that may or may not be justified from a normative viewpoint: I am only interested in the fact that broker-dealers react to these differentials, which likely shows that dealers perceive them as mispricings.

5.1 A narrow measure of relative cheapness

5.1.1 The measure

I compute spreads as indicated in section 3: they are the log difference between the observed clean bond price and a fictitious "risk-free" bond price. The latter price is the price of a fictitious bond that has the same contractual coupons and principal, but with these cash flows discounted with the Treasury yield curve.

There are two spurious correlations I have to avoid. First, by regressing customer order flow on *contemporaneous* last spread of the day, one may simply capture the price impact of market making trades: customer sales (purchases) would be associated with price decrease (increase) and misleadingly be interpreted as dealers purchasing cheap bonds. To limit this and other potential endogeneity concerns, I regress order flow on *lagged* spread.

Second, the raw spread may capture mechanical effects related to the bid-ask bounce. The problem is as follows. If the last transaction of day t was a customer

[14] Although this reveals nothing about their leverage.

sale, it was executed at a lower price than if it was a customer buy just because of a positive bid-ask spread. I may therefore capture spurious explanatory power of day $t-1$ bond spread: if 1) a customer buy at the end of day $t-1$ is correlated with customer sale at the end of day $t-1$, and 2) a customer buy at the end of day t is correlated with overall customer buys during day t, then the forecasting power of the bond spread simply captures some mechanical features of customer order flow, and not dealer proprietary trading. Averaging over past business days solves the problem.

Thus to address both concerns I consider the average $y_{i,t-1}$ of the last bond spreads of the seven previous business days $t-7$ to $t-1$ in cheapness measures. The choice of 7 days is conservative, while results do not materially change if I do not average at all over business days.

I first consider a simple strategy that is close to arbitrage: bonds with similar time until maturity, with similar credit rating and with or without an embedded call can be viewed as close substitutes, and from this perspective should have very similar prices.[15] Therefore I group bonds by integer part of years to maturity, by credit rating category (AAA/AA, A, BBB) and by callability. The difference between a bond's average spread $y_{i,t}$ and the median in its group $y_{i,t}^{sim}$ is the cheapness measure that captures this quasi arbitrage, and is a proxy for the idiosyncratic component of the bond's spread to Treasuries:

$$Idiosync_{i,t} = y_{i,t} - y_{i,t}^{sim}$$

This measure is positive if bond i is cheap, *i.e.* its spread is higher than the median in the basket of similar bonds.

5.1.2 Baseline specification

Again I distinguish between One-way and Partial Rountrip order flow. To do it I regress order flow on my measure of cheapness interacted with a dummy $Roundtrip_{i,t}$ equal to 1 if order flow is a partial roundtrip on day t for bond i.

$$\begin{aligned} \widetilde{OF}_{i,t} = \alpha + \nu_1 \; Idiosync_{i,t-1}^{OneWay} + \nu_2 \; Idiosync_{i,t-1}^{Roundtrip} \\ + \beta' X_{1,i,t-1}^{q} + \eta_{i,t} \end{aligned} \tag{5.1}$$

Dealers tend to purchase bonds that are cheap with respect to bonds that are similar to it on One-way days if $\nu_1 < 0$. The same happens on Partial Roundtrip days if $\nu_2 < 0$.

The regression includes controls for 10 lags of log order flow, for 10 lags of past price changes, and the vector $X_{1,i,t-1}^{q}$ contains 3 lags of issuer stock return, lagged

[15] Assets with similar expected payoff and variance may have different prices because of different covariances with the market portfolio. For investment grade bonds, this should come from the credit risk component, and I do not expect the covariance between credit risk to play such a big role with respect to other components - interest rate risk, systematic component of credit spreads, ...

10 years Treasury yield change and lagged changes in 3 months LIBOR. I exclude contemporaneous controls to avoid an endogeneity concern: the cheapness measure may predict both order flow and the contemporaneous controls such as stock return and rate changes. It also contains the dummy $OneWay_{i,t}$ for the order flow on day t in bond i being one-way. I estimate equation 5.1 through OLS and cluster standard errors by issuer as for price impact regressions.

5.1.3 Refined specification with age or maturity criteria

I regress the signed logarithm of order flow on derived cheapness measures: for instance $Idiosync_{i,t}^{OneWay,Maturity\leq 10y}$ equals $Idiosync_{i,t}$ if bond i has residual maturity less than 10 years on day t, and day t order flow is One-way in bond i; it equals zero otherwise. Similarly, for Roundtrip order flow and for residual maturities above 10 years. Order flow can also be split according to an age, or an initial maturity criterion.

I thus estimate the following equation for each criterion Z being bond age, bond initial maturity and bond residual maturity:

$$\begin{aligned}\widetilde{OF}_{i,t} = \alpha &+ \nu_1 \; Idiosync_{i,t-1}^{OneWay,Z\leq 10y} + \nu_2 \; Idiosync_{i,t-1}^{OneWay,Z>10y} \\ &+ \nu_3 \; Idiosync_{i,t-1}^{Roundtrip,Z\leq 10y} + \nu_4 \; Idiosync_{i,t-1}^{Roundtrip,Z>10y} \\ &+ \beta' X_{Z,i,t-1}^{q} + \eta_{i,t} \end{aligned} \tag{5.2}$$

Bond lagged cheapness is associated with dealer purchases for criterion Z less than 10 years and One-way order flow if $\nu_1 < 0$: then a higher spread (cheaper bond) is associated with more customer sales ($\widetilde{OF}_{i,t} < 0$), *i.e.* dealer purchases. A similar reasoning applies to ν_2, ν_3, ν_4. The vector $X_{Z,i,t-1}^{q}$ includes the same controls as as for regression 5.1 and adds a dummy for the criterion Z being lower than 10 years, and its interaction term with the dummy $OneWay_{i,t}$ for order flow being One-way on day t.

5.1.4 Results

Table 7 shows the results. To save space I hide coefficients for Roundtrip order flow, which are never significant.

The coefficient for $Idiosync_{i,t-1}^{OneWay}$ is not significant in the first column, although it is negative as expected. In the second column, I show the estimates of regression 5.2 for the age criterion: the coefficient is negative (weakly) significant for bonds older than 10 years, and negative insignificant for bonds younger than 10 years.

The maturity criteria work better: the coefficient is negative significant for shorter maturity bonds, whether initial (third column) or residual (fourth column). Spreads are computed as log price differences multiplied by 100. The estimate for the initial maturity criterion implies that a one point increase in the $Idiosync_{i,t-1}$ measure is associated with a .0550 decrease in log customer purchases, meaning that customer purchases vary by $10^{-0.0550} - 1 = -12\%$, *i.e.* dealer purchases increase by

Table 7 – Order flow regressed on lagged measure of cheapness $CheapInSim$, equal to the bond spread to a fictitious Treasury bond with the same cash flows and discounted with the Treasury yield curve of the day, minus the median of these spreads in the basket of bonds with the same credit rating, maturity and callability. Controls include the main effects for the dummy $OneWay_{i,t}$ for one-way order flow, and in the 2nd, 3rd and 4th columns the main effect for the criterion $Crit$ (bond age, initial maturity and residual maturity) being less than 10 years, and its interaction with $OneWay_{i,t}$. Additional controls are 10 lags of order flow, 10 lags of bond price changes, 3 lags of stock return and lagged 10 years Treasury yield changes. To save space only the coefficient for $Idiosync$ for One-way order flow are shown. Coefficients for Roundtrip order flow are never significant.

Z	None	Age	InitMaturity	ResidMaturity
$Idiosync_{i,t-1}^{OneWay}$	-0.0114			
	(-1.54)			
$Idiosync_{i,t-1}^{OneWay,Age\leq 10y}$		-0.0100	**-0.0550*****	**-0.0541*****
		(-1.29)	**(-4.06)**	**(-4.26)**
$Idiosync_{i,t-1}^{OneWay,Age>10y}$		**-0.0209***	0.0095*	0.0121*
		(-2.06)	(2.03)	(2.55)
Roundtrip order flow	Y	Y	Y	Y
Constant and controls	Y	Y	Y	Y
R^2	0.00	0.00	0.00	0.00
N	2,316,162	2,316,162	2,316,162	2,316,162

Standard errors clustered by bond issuer
* (p<0.05), ** (p<0.01), *** (p<0.001)

12%. The estimate is similar for the residual maturity criterion. For longer maturity bonds (by both measures) the estimate is slightly positive significant, suggesting customer proprietary trading.

5.2 More general proprietary trading strategies

In this section I investigate additional arbitrage strategies by decomposing the bond spread in four model-free components including that of section 5.1. The decomposition brings stronger evidence of dealer proprietary trading and isolates three relevant broker-dealer trading strategies:

- between similar bonds as in subsection 5.2
- between bonds of similar maturities, irrespective of their credit rating/maturities
- between corporate bonds and Treasury bonds, which is consistent with figure 1.

5.2.1 A model-free spread decomposition

A given bond can enter proprietary trading strategies because of one or several of its characteristics. Broker-dealers could arbitrage between highly similar bonds in terms of maturity, credit rating and embedded options; or between bonds that have similar maturities, irrespective of their credit rating and embedded options; or between baskets of bonds of similar maturities; or between corporate bonds and Treasury bonds as asset classes. To capture possibly perceived trading opportunities along each of these dimensions, for each bond i I decompose its spread at the end of day t (averaged over the past 7 business days up to t) as the sum of four bond cheapness measures:

$$y_{i,t} = \underbrace{(y_{i,t} - y_{i,t}^{sim})}_{\mathbf{Idiosync_{i,t}}} + \underbrace{(y_{i,t}^{sim} - y_{i,t}^{\tau})}_{\mathbf{CreditCall_{i,t}}} + \underbrace{(y_{i,t}^{\tau} - y_{i,t}^{1-7})}_{\mathbf{Maturity_{i,t}}} + \underbrace{y_{i,t}^{10}}_{\mathbf{TreasuryConv_{i,t}}} \tag{5.3}$$

where:

- $y_{i,t}^{sim}$ is the median of $y_{i,t}$ in the group of bonds with the same rating category (AAA/AA, A, BBB), the same residual maturity rounded to the year and the same callability (presence or absence of an embedded call) as bond i;
- $y_{i,t}^{\tau}$ is the median of $y_{i,t}$ in the group of bonds with the same residual maturity τ (rounded to the year) as bond i;
- $y_{i,t}^{10}$ is the median spread of bonds with residual maturity less than 10 years if it is the case for bond i, and the median spread for bonds with residual maturity more than 10 years otherwise.

Each term between parenthesis in (5.3) is a spread differential that captures one of the strategies described above, in isolation from the others.

To visualize the components of spread from equation 5.3, I consider a "spread curve", by analogy with a yield curve for Treasury bonds: as illustrative examples, Figure 5 plots bond spreads as a function of residual maturity, for randomly chosen dates. Each component in equation 5.3 reflects an aspect of figure 5:

- $Idiosync_{i,t}$ - *Scatter thickness within rating category/callability*:[16] a bond is considered cheap (expensive) with respect to similar bonds as assessed through credit risk, maturity, and the presence of embedded call or not[17]); it thus capture a bond idiosyncratic component of its yield;
- $CreditCall_{i,t}$ - *Scatter thickness across ratings/callability*: bonds with similar credit risk maturity and callability are considered overall cheap (expensive) with bonds of similar maturity τ; it thus jointly captures credit risk and callability components of the spread, controlling for maturity;
- $Maturity_{i,t}$ - *Scatter slope*: bonds of a given maturity τ are considered cheap (expensive) with respect to bonds of another maturity τ';
- $TreasConv_{i,t}$ - *Scatter level*: bonds within a broad maturity bucket are considered cheap (expensive) with respect to Treasuries. It captures safe asset demand arbitrage.

I regress order flow on each of the terms in parenthesis in (5.3) separately for the three criteria $Z = Age, InitMaturity, ResidMaturity$ below and above 10 years, interacting cheapness measures with the dummy $OneWay_{i,t}$ used in the price impact regressions, and controlling lags of order flow, lags of price changes and other lagged market factor changes:

$$\widetilde{OF}_{i,t} = \alpha + \sum_x \big(\nu_1^x Idiosync_{i,t-1}^x + \nu_2^x CreditCall_{i,t-1}^x + \nu_3^x Maturity_{i,t-1}^x + \nu_4^x TreasConv_{i,t-1}^x\big) + \beta' X_{i,t-1}^q + \eta_{i,t} \quad (5.4)$$

with

$$\begin{aligned} x = &(OneWay, Z \leq 10y), (OneWay, Z > 10y), \\ &(Roundtrip, Z \leq 10y), (Roundtrip, Z > 10y). \end{aligned}$$

For consistency I stick to the previous convention that customer buys correspond to positive order flow, and vice-versa. If dealers are also arbitrageurs, then we expect them to buy cheap bonds and sell expensive bonds to customers.

[16] Callability is not distinguished on Figure 5.

[17] Callable corporate bonds, i.e. with an option to the issuer to redeem the bond before maturity, are highly frequent. The option to call the bond *e.g.* to reissue at lower rate should be priced and incorporated into the bond spread.

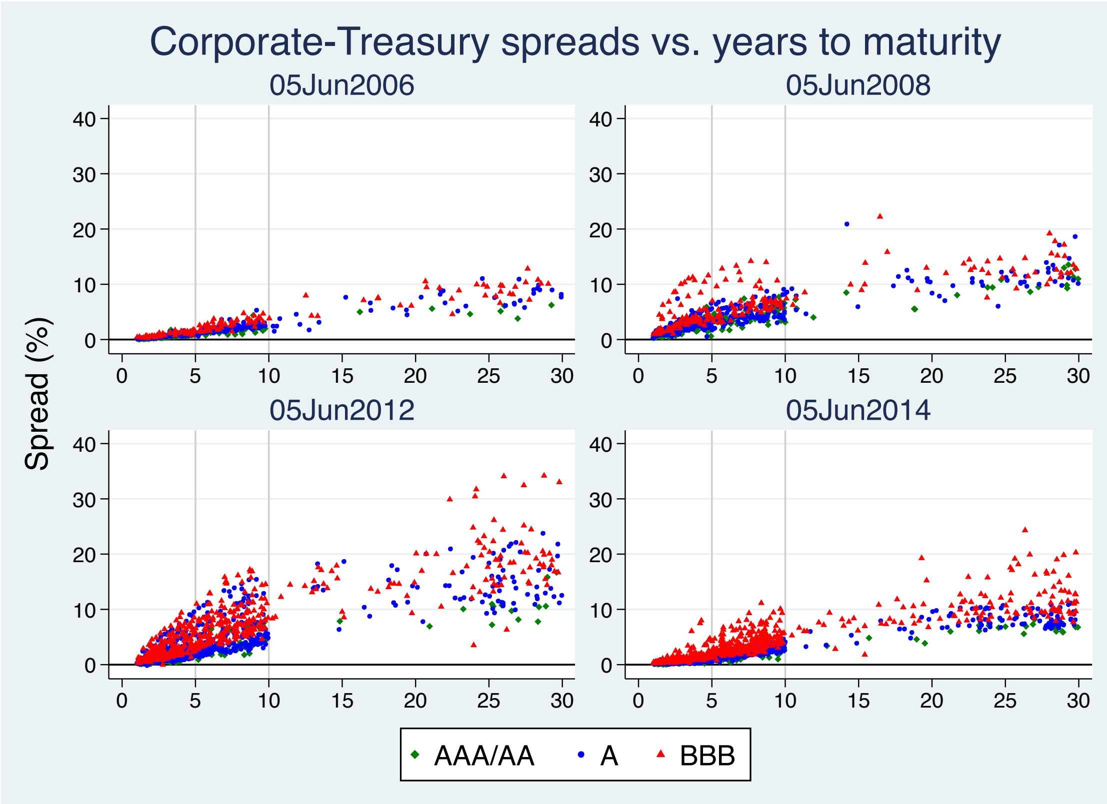

Figure 5 – *Visualizing potential proprietary trading opportunities.* Bond spreads as a function of residual maturity for four randomly chosen dates, by rating category (bonds with maturity more than 30 years not shown). These graphs illustrate four trading opportunities that could be perceived by broker-dealers or their customers. The first two ones show up as the scatter's thickness: bonds within the same rating category and callability (not distinguished) may have spreads considered too different (upper right and lower left panels); and bonds within the same maturity (irrespective of rating/callability) may have different spread. The third one is related to the slope of the scatter: bonds of different maturities may trade at spreads considered too different. The fourth one relates to the level of the scatter: corporate bonds as an asset class may be considered cheap with respect to Treasuries. Strategies involve selling bonds considered expensive and buying bonds considered cheap.

Dealer proprietary trading again implies $\nu_k^x < 0$ for at least one measure; I also expect the coefficient for one-way order flow and criterion $Z \leq 10$ years to be the largest in absolute terms and the most significant. For instance bonds that are cheap with respect to similar ones are those with high spread with respect to the median in its similarity group ($y_{i,t-1} - y_{i,t-1}^{sim} > 0$) and are expected under dealer arbitrage to be associated with more customer sales: thus we expect a negative coefficient ν_1.

5.2.2 Results

Table 8 shows the estimation results for One-way order flow, while table 14 in the appendix shows them for Partial Roundtrip order flow.

The first column in table 8 gives a negative significant coefficient for the $CreditCall$ component of the spread and a highly significant for the $TreasConv$ component: dealers appear to manage bonds by maturity bucket irrespective of rating and callability; similarly they buy corporate bonds as long as they are overall cheap with respect to Treasury bonds. In table 14, in the first column only the $TreasConv$ component is negative significant, to a weak level. The second column, where observations are split according to bond age, gives similar results.

The results are more striking when observations are split according to bond initial maturity or residual maturity: the $CheapInSim$ measure becomes highly significant, as the $CreditCall$ and $TreasConv$ components. For shorter maturities, dealers appear to buy (sell) more bonds that are cheap (expensive) with respect to similar bonds in terms of rating, maturity and callability, with respect to bonds of the same maturity, and with respect to Treasury bonds. The $CreditCall$ component appears especially strong: the coefficient implies that a one percentage point increase in this measure is associated with an increase by $-(10^{-.1211} - 1) = 24\%$ in dealer purchases.

5.3 Evolution through time and plausible impact of regulation

In this section I run regression (5.4), splitting by age and maturity being below or above 10 years on the same subperiods as for price impact regressions.

Tables 9 gives the results with the split over initial maturities (results are very similar with residual maturity). To save space and focus on proprietary trading behavior I show only coefficients for one-way order flow and bonds with initial maturity $M \leq 10$ years. I show the other coefficients in table 15 in appendix.

The evolution across periods is clear: before the crisis, the coefficients are larger in absolute value than during the Post-Dodd-Frank period, especially for the $CreditCall$ and $TreasConv$ measures that are the most relevant. If the $CreditCall$ measure for a shorter maturity bond (2nd line) is one percentage point higher, dealers tend to buy it more by $10^{-.4542} - 1 = 65\%$ during the Pre-Crisis period (second column), while it falls to 15% after the crisis (sixth column). For the $TreasConv$ measure, the effects of a one percentage point increase are 62% more dealer purchase before

Table 8 – Order flow regressed on four lagged measures of cheapness. $Idiosync$ is the difference between the bond's spread $y_{i,t}$ to an equivalent Treasury bond minus the median $y_{i,t}^{sim}$ of these spreads in the basket of bonds with the same credit rating, maturity and callability. $CreditCall_{i,t}$ is equal to $y_{i,t}^{sim}$ minus the median spread for all bonds with the same maturity $y_{i,t}^{\tau}$. $Maturity_{i,t}$ is equal to $y_{i,t}^{\tau}$ minus the median $y_{i,t}^{10}$, the median spread of all bonds that have residual maturity below 10 years if it is the case for bond i, or above 10 years otherwise. Controls include the dummy $OneWay_{i,t}$ for one-way order flow, and where applicable the dummy for the criterion Z (bond age, initial maturity and residual maturity) being less than 10 years, and its interaction with $OneWay_{i,t}$. Additional controls are 10 lags of order flow, 10 lags of bond price changes, 3 lags of stock return and lagged 10 years Treasury yield changes. To save space **only the coefficients for One-way order flow are shown**. Coefficients for Roundtrip order flow are shown in table 14.

	NoCrit	Age	InitMaturity	ResidMaturity
$Idiosync_{i,t-1}^{OneWay}$	-0.0127			
	(-1.83)			
$Idiosync_{i,t-1}^{OneWay,Z\leq 10y}$		-0.0116	**-0.0496*****	**-0.0492*****
		(-1.62)	**(-4.58)**	**(-4.82)**
$Idiosync_{i,t-1}^{OneWay,Z>10y}$		-0.0265	0.0095*	0.0132**
		(-1.96)	(2.04)	(2.77)
$CreditCall_{i,t-1}^{OneWay}$	**-0.0176***			
	(-2.08)			
$CreditCall_{i,t-1}^{OneWay,Z\leq 10y}$		**-0.0206***	**-0.1211*****	**-0.1215*****
		(-2.19)	**(-11.46)**	**(-12.36)**
$CreditCall_{i,t-1}^{OneWay,Z>10y}$		-0.0100	0.0119*	0.0179**
		(-0.71)	(2.11)	(3.13)
$Maturity_{i,t-1}^{OneWay}$	0.0156***			
	(3.55)			
$Maturity_{i,t-1}^{OneWay,Z\leq 10y}$		0.0181***	0.0321***	0.0270***
		(3.75)	(3.91)	(3.53)
$Maturity_{i,t-1}^{OneWay,Z>10y}$		-0.0055	0.0082	0.0088
		(-0.51)	(1.59)	(1.63)
$TreasConv_{i,t-1}^{OneWay}$	**-0.0443*****			
	(-9.12)			
$TreasConv_{i,t-1}^{OneWay,Z\leq 10y}$		**-0.0449*****	**-0.0733*****	**-0.0664*****
		(-8.31)	**(-5.77)**	**(-5.84)**
$TreasConv_{i,t-1}^{OneWay,Z>10y}$		-0.0017	**-0.0155***	**-0.0587*****
		(-0.18)	**(-2.38)**	**(-5.86)**
Constant and controls	Y	Y	Y	Y
R^2	0.00	0.00	0.00	0.00
N	2,316,162	2,316,162	2,316,162	2,316,162

Standard errors clustered by bond issuer

* ($p<0.05$), ** ($p<0.01$), *** ($p<0.001$)

Table 9 – Order flow regressed on four lagged components of bond spread $Idiosync_{i,t-1}$, $CreditCall_{i,t-1}$, $Maturity_{i,t-1}$ and $TreasConv_{i,t-1}$ (see table 8 for details on the components), broken down by One-way / partial Rountrip order flow and bond initial maturity M being below or above 10 years. Controls include the dummy $OneWay_{i,t}$ for one-way order flow, and where applicable the dummy for bond initial maturity M being less than 10 years, and its interaction with $OneWay_{i,t}$. Additional controls are 10 lags of order flow, 10 lags of bond price changes, 3 lags of stock return and lagged 10 years Treasury yield changes. To save space **only the coefficients for one-way order flow and bonds of maturity $M \leq 10$ years are shown**. Other coefficients are in table 15

	Opaque	Pre-Crisis	Crisis	Post-Crisis	Dodd-Frank
$Idiosync_{i,t-1}^{OneWay,M\leq10y}$	-0.0886**	-0.0528	-0.1188***	-0.0243	-0.0029
	(-3.02)	(-0.67)	(-7.79)	(-1.61)	(-0.24)
$CreditCall_{i,t-1}^{OneWay,M\leq10y}$	-0.1310***	-0.4542***	-0.1315***	-0.0865***	-0.0717***
	(-3.94)	(-6.79)	(-7.67)	(-3.38)	(-3.49)
$Maturity_{i,t-1}^{OneWay,M\leq10y}$	0.0391	-0.0134	0.0440*	0.0511*	0.0235*
	(0.88)	(-0.26)	(2.24)	(2.16)	(2.36)
$TreasConv_{i,t-1}^{OneWay,M\leq10y}$	-0.1493**	-0.4195***	-0.1140***	-0.1039***	-0.0830***
	(-3.16)	(-6.70)	(-5.16)	(-4.04)	(-4.51)
R^2	0.00	0.01	0.01	0.00	0.00
N	327,389	328,629	276,026	242,140	1,141,978

Standard errors clustered by bond issuer.

* (p<0.05), ** (p<0.01), *** (p<0.001)

the crisis, and 17% after the crisis.

This is likely to be related to post-crisis regulation, what was indeed intended by the Volcker rule: it seems that prop trading was reduced. The Volcker rule was fully enforced in 2015, after the end of my sample. As widely noticed in the literature, it may have had effects well before 2015: it was announced as the Dodd-Frank act was voted on July 21st, 2010, and Bessembinder et al. (2018) noticed that many large investment banks shut their proprietary trading desks as early as 2011-2012.

5.4 Consistency with evidence on Primary Dealers

In order flow regression results, the measure $TreasConv$ comes with a high and highly significant coefficient: broker-dealers thus appear to purchase more corporate bonds to the extent they are cheap with respect to Treasury bonds, possibly even after adjustment for risk. Primary Dealers trading activity is included in my sample, as Primary Dealers are registered as broker-dealers. This is consistent with evidence from Primary Dealers in figure 1: Primary Dealers accumulated bond inventories, while they borrowed Treasury bonds to sell them; figure 1 also suggests this compressed corporate bond spreads.

In addition, the coefficient on the measure $TreasConv$ sharply decreases at the onset with the crisis and remains stable until after the crisis: this is again consistent with figure 1, as Primary Dealers short Treasury position was cut at the onset of the crisis, and did not reconstruct their long corporate, short Treasury position. The coefficient on $TreasConv$ is not zero after the crisis however: this simply suggests that broker-dealers other than Primary Dealers are exploiting corporate-to-Treasury spreads. This also suggests that Primary Dealers had a comparative advantage in this strategy, either because of their Primary Dealer status (they underwrite and make markets for Treasury bonds) or to the bank status many Primary Dealers have, or for another reason.

6 Why proprietary trading stopped in July 2007: the plausible role of margin constraints and capital requirements

As shown by figure 1, Primary Dealers were net long in corporate bonds, and net short in Treasury bonds before the crisis. However, in July 2007 the Treasury position was cut by half, leaving Primary Dealers with an unhedged interest rate exposure on their corporate bond holdings. Primary Dealers started shrinking their corporate bond inventory only months later, in January 2008.

In the following I explore plausible causes for this. First I give suggestive evidence that Primary Dealers were facing separate financing constraints for each leg of the strategy, with two origins. Second, I give suggestive evidence that Primary Dealers' short Treasury position shrinkage in July 2007 was related to a tightening of the financing constraint on the Treasury side. Overall, the evidence appears consistent with the assumption made in Gromb and Vayanos (2002) on arbitrageurs' financing contraints.

6.1 Financing constraints #1: repos and reverse repos

A proprietary trader's long and short positions are implemented as follows: the long positions are implemented with repurchase agreements (repos) and the short by reverse repos - Primary Dealers lend cash to their counterparties so that they get the desired collateral, and sell this collateral. I give more details in appendix D and what a proprietary traders' balance sheet looks like (figure 11).

Repo financing of corporate bonds. Together with corporate bond net outright position (solid thin blue line), Figure 6 plots Primary Dealers' net financing positions for corporate bonds (solid thick blue line). Net financing are net funds received with an opposite transfer of corporate bonds for financing purposes: repos and reverse repos, security lending and borrowing, collateralized borrowing and loans, *etc.*, that we generically label "net repo position" for convenience. It is positive if PD are net cash borrowers, *i.e.* net security lenders.

It also plots the position in such contracts that are easily "runnable" (dashed red line): with overnight maturity or on a continuing basis, *i.e.* with no specific maturity but that can be ended on demand. The difference between the solid thick line (all repos) and the dashed line (overnight repos) is thus net amount of repos with maturity of at least two days. The match of both curves with corporate bond net outright position is good, suggesting that most of Primary Dealers' corporate bond position was indeed financed with runnable repos, and that corporate bonds were mainly used as collateral for the outright position purpose.

Drop in net reverse repos financing of Treasury bond. Figure 7 plots the same graph for Treasury positions. The thick line shows that Primary Dealers are structurally net Treasury borrowers (they lend funds and receive Treasury securities as collateral), and that they borrowed more securities than they sold short as comparison with the outright position shows. The securities borrowed that were not sold were likely to be kept as collateral for loans provided by Primary Dealers to their customers. After the crisis, Primary Dealers were still net Treasury borrowers, while they held Treasury bonds outright.

The July 2007 cut in the short position was associated with a cut of similar magnitude in the total net repo position. The *overnight* net repo position (dashed line) exhibits a similar break of comparable magnitude; it also increases a few months ahead (end of 2006) without a similar pattern in total position: this suggests that security lenders gradually shortened the maturity of their loans before they started to run on the security lending contracts.

Therefore it is likely that Primary Dealers' financing constraint on the reverse repo position became more binding in July 2007, which imposed a reduction in the

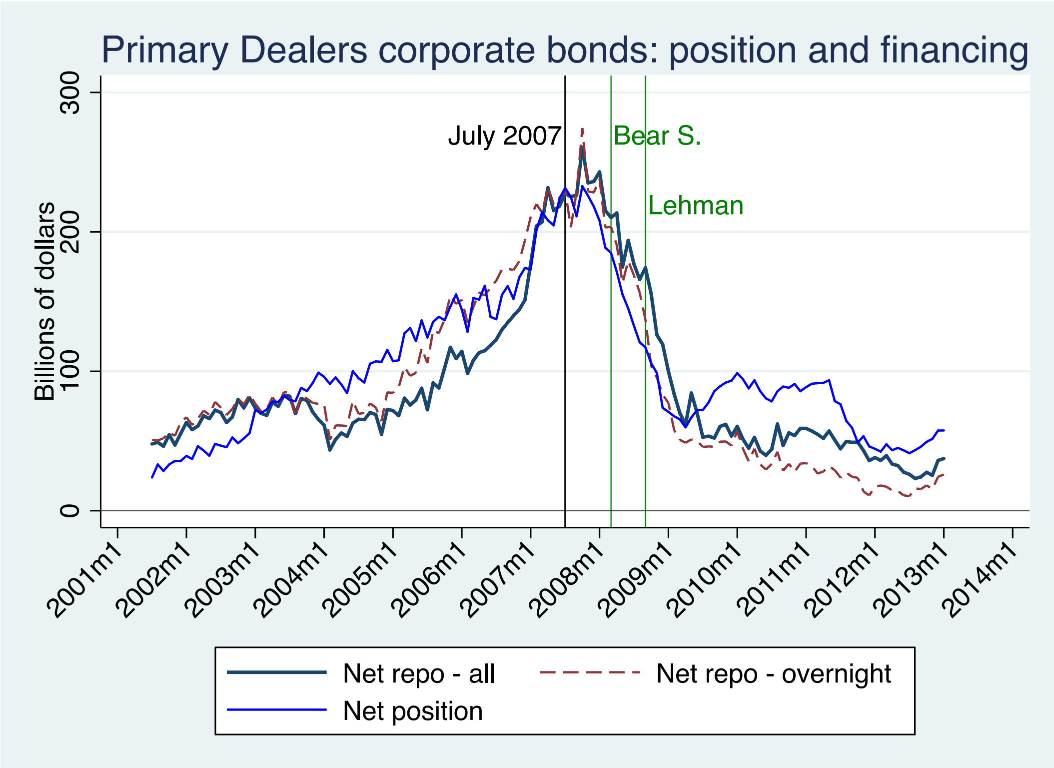

Figure 6 – **Repo financing of Primary Dealers' corporate bond inventories.** This graph plots Primary Dealers corporate bond inventory (solid, thin blue line), together with net borrowing collateralized by corporate bonds (thick, solid black line) and net borrowing with overnight maturity (dashed red line). The good fit between the three curves before the crisis suggests that most corporate bond inventories were funded through very short-term repos.

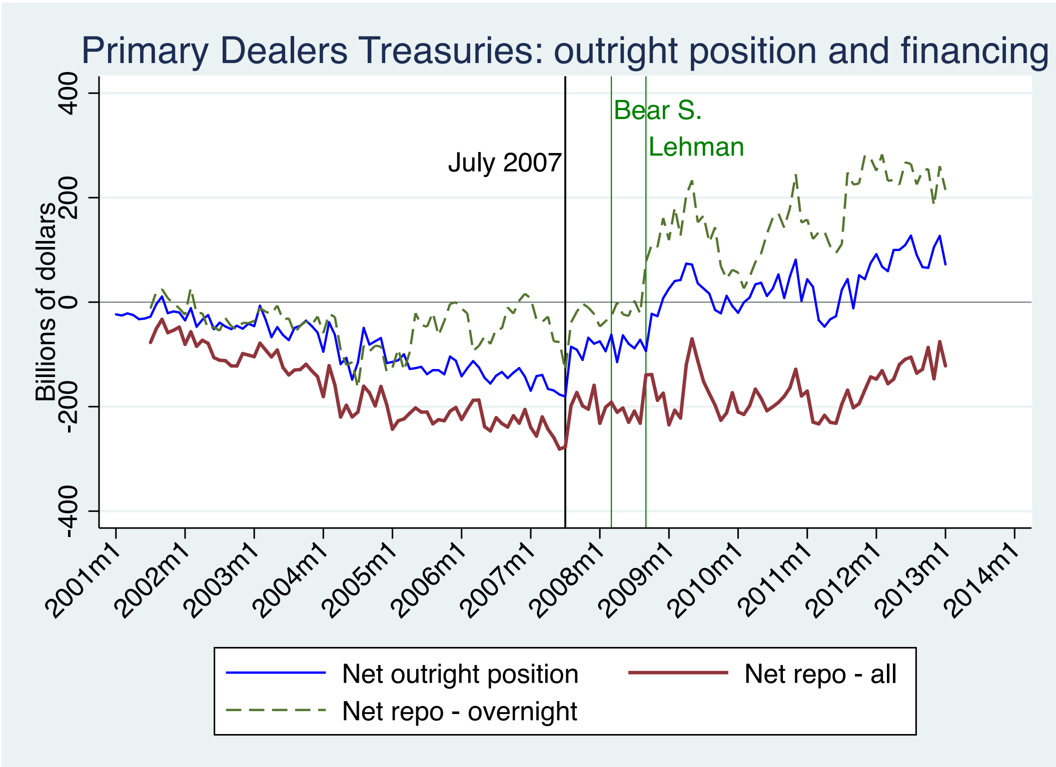

Figure 7 – **Reverse repo funding of Treasuries and run.** This graph plots Primary Dealers net inventories in Treasury securities (excluding inflation-protected and T-Bills), together with net collateralized borrowing with Treasuries as collateral (thick, solid brown line) and net collateralized borrowing collateralized by Treasuries that are overnight (dashed green line)

Treasury short position. However, similar constraints stem from regulatory capital requirements, as exposed in the next subsection.

6.2 Financing constraints #2: regulatory capital requirements

Broker-dealers also face capital requirements set by the Securities Exchange Act of 1934 and implemented by their regulator, the Security and Exchange Commission.[18] The most important points for my purpose here are the following:

- these capital requirements have to be met at all times,[19] and the broker-dealer has to notify the SEC or the FINRA immediately when it is approaching the limit. In practice, it seems that daily mark-to-market is the lowest frequency of computation admitted by FINRA.[20]
- Broker-dealer equity, net of haircuts on securities long and on short positions, is higher than a fraction of dealer indebtedness
- The haircuts can be computed using dealers' own internal statistical models

6.3 Financing constraints at the onset of the 2007-2009 crisis: suggestive evidence

The July 2007 drop in the short Treasury position may have been caused by a tightening of haircuts on the Treasury borrowing contracts, a supply effect. By contrast, it could also be Primary Dealers who reduced their demand for Treasury borrowing because they were willing to reduce the short position. I am not able to unambiguously test one hypothesis against the other because I am not aware of dataset on haircuts over the period, but several elements point to Primary Dealers undergoing a tightening of haircuts.

First, after July 2007 Primary Dealers had a new exposure to interest rate risk on half of their corporate bond inventories, as shown on figure 1: they subsequently liquidated these inventories, suggesting that this new exposure was not desired. Lehman's collapse in September 2008 and a further drop in the Treasury short position came just the long-short position became balanced.

Second, I give suggestive evidence that the position cut was associated with an increase in haircut on Treasury reverse repos. Haircuts for Primary Dealers are likely to increase with the underlying asset volatility (as a proxy for the risk of price decrease for repo, or increase for reverse repo) and with Primary Dealers' default risk.

[18] Capital requirements are defined in Rule 15c3-1 of the Securities Exchange Act of 1934, commonly referred to as the "Net Capital Rule" dates back to 1975.

[19] Including intraday

[20] https://www.finra.org/rules-guidance/key-topics/portfolio-margin/faq

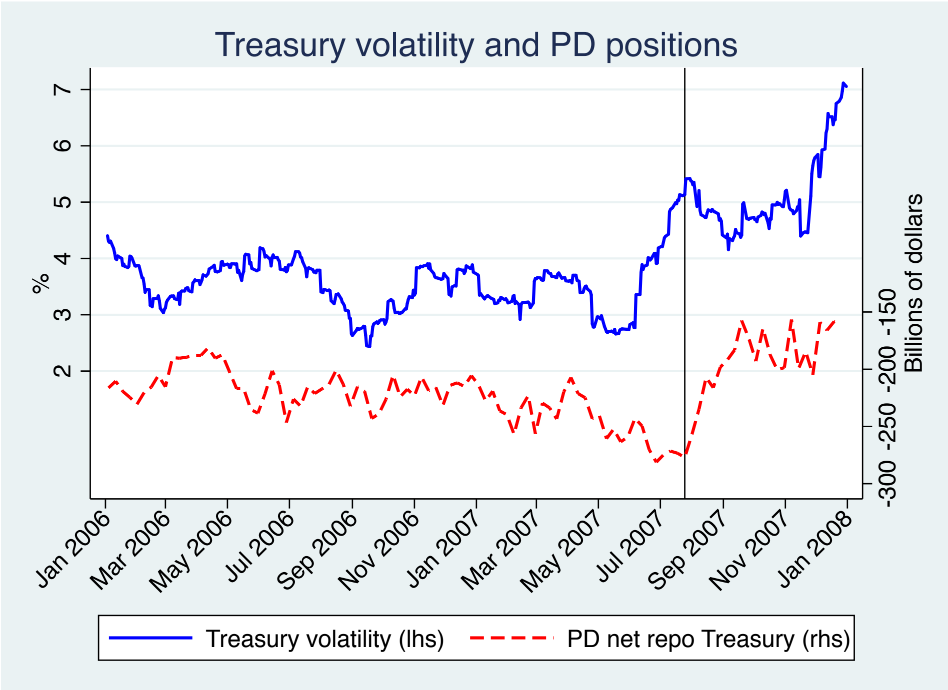

Figure 8 – This graph plots the 2-months rolling-window standard deviation of 10 years Treasury yield daily changes and Primary Dealers' (PDs') net reverse repo position in US Treasuries, *i.e.* minus the amount of Treasuries borrowed by Primary Dealers. The black vertical line is on July 25th, 2007 when PDs' outright position in Treasuries began to shrink in absolute terms: it coincides with a decrease in the PD Treasury borrowing. The volatility of the 10 years yield increased by half in June 2007.

Regarding asset volatilities, figures 8 and 9 plot the two-month rolling-window volatility of daily changes in the 10 years Treasury yield, and on the cross-sectional median two-month rolling-window volatility of daily returns on a portfolio of corporate bonds. The portfolio retains bonds within my sample whose maturity is between 4 and 6 years and whose rating is at least AA. This relatively tight subsample avoids volatility related to slope and thickness of the spread curve, but the results carry over when the portfolio is broadened.

These figures show that the volatility of 10 years bond clearly increased in June 2007, from a recent history average level between 3 and 4% to about 5.5%, and increase by roughly 50%. By contrast, the historical volatility of corporate bonds did not appear to rise much with respect to the levels observed in the previous 18 months.

However, earlier in the sample the volatility of 10 years Treasury bonds was higher, up to 6%. This suggests that asset volatility is not the only driver of haircuts. Another potential determinant is PD default risk, as argued by Copeland et al. (2010) from data starting in March 2008. Figure 10 plots an equal-weighted index of 7 Primary Dealers CDS (the major investment banks with US parents), as a proxy

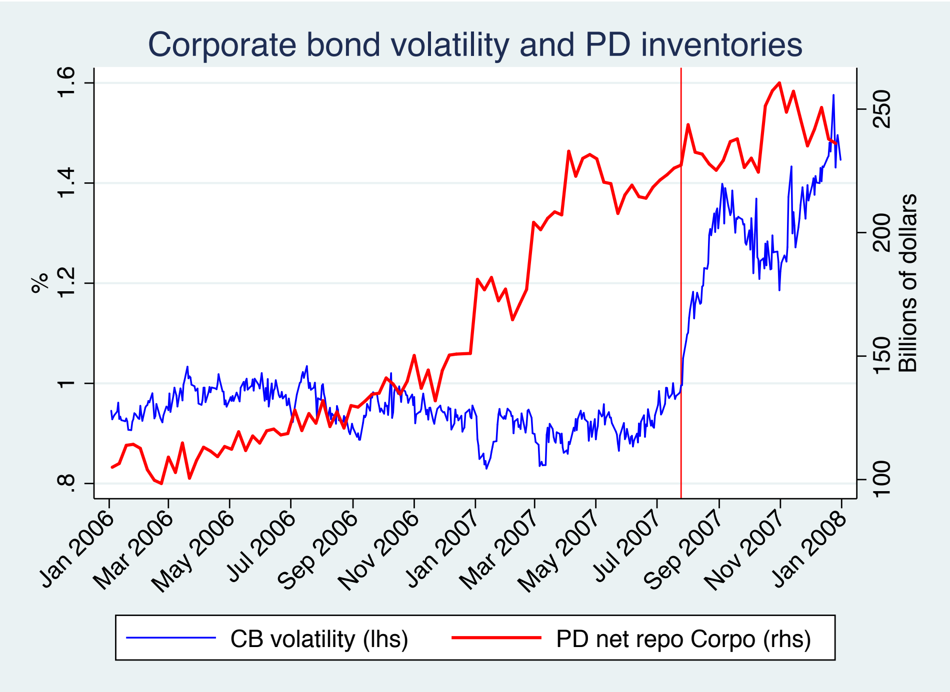

Figure 9 – 2 month rolling-window volatility of corporate bonds (returns on the median price of a portfolio investment grade, maturities between 4 and 6 years) and Primary Dealers' net position in repo contracts involving corporate bonds. The vertical line marks 25th July 2007 when PDs started shrinking the net short Treasury position. The graph shows basically no connection between the two even during the weeks before July 2007. It also shows that corporate bond volatility rose right after the short Treasury position cut.

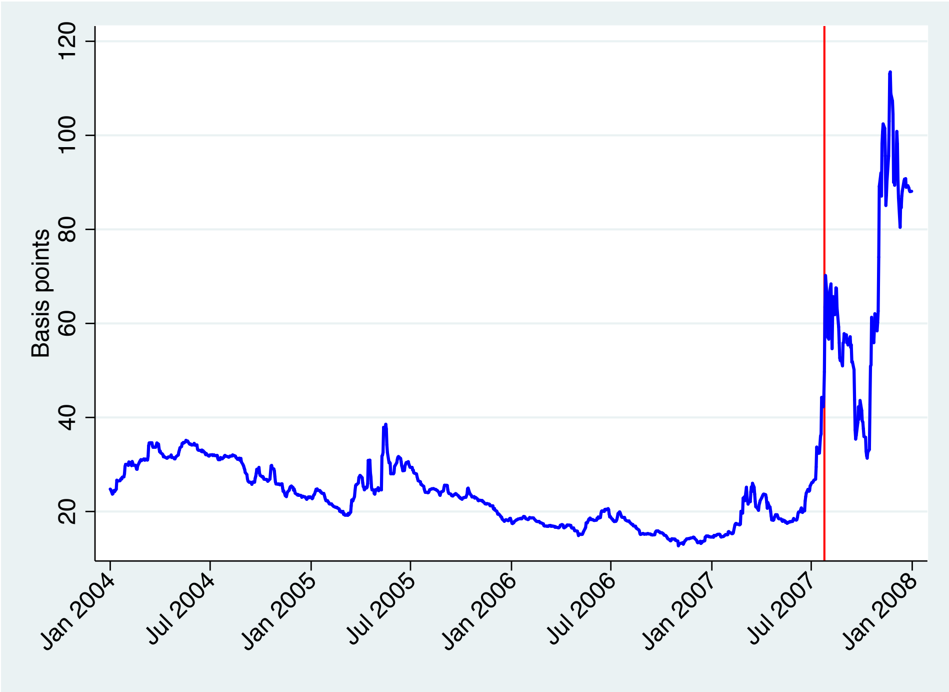

Figure 10 – CDS index for 7 Primary Dealers with US parent. This graph plots and equal-weighted five years CDS index for all Primary Dealers with available CDS in US dollars, for senior unsecured debt except Bear Stearns (subordinated debt). These include the major US investment banks. Individual CDS movements are broadly parallel. The vertical line is on July 25th, 2007, when Primary Dealers' aggregate short Treasury position began to shrink.

for default risk (individual movements are broadly parallel): CDS spreads increased sharply in July 2007.

However, default risk alone cannot explain haircut increases, as these should also have impacted repos involving corporate bonds and thus simultaneous shrinkage of both the long corporate position and the short Treasury position.

Overall this suggests that lender may begin to start revising haircuts when default risk becomes more of a concern. Default risk may arise because of other Primary Dealer activities than the proprietary trading strategy I document.

7 Implications for financial regulation and safe asset production

7.1 Financial regulation

The results in my paper show that dealers are not only market makers, but also proprietary traders who exploit price spreads they think not justified by fundamentals. The Volcker rule bans the latter for bank-affiliated dealers, while in principle still allowing the former.

Proprietary trading is not *per se* bad. By uncovering some proprietary trading strategies, I do not mean to say what regulation is optimal, if regulation is needed. Proprietary trading as described by theories of limits of arbitrage is to some extent liquidity provision, and bears many similarities with market making as described by above theories. In both cases, the market is fragmented, and market makers or prop traders bridge the gap between investors eager to sell and investors eager to buy, which is a priori improving social welfare of all market participants.[21]

The macro-finance literature suggests that when broker-dealers buy, this compresses risk premia (Adrian and Shin 2009, Adrian et al. 2014). Again this does not necessarily means that they take excessive risk: if markets are fragmented before broker-dealers enter, risk-sharing is limited and asset risk premia are high. When broker-dealers enter, they may improve risk sharing, so that all investors are more willing to take risk and compress equilibrium risk premia: in this case this is socially optimal.

"Risk-shifting" and "margin constraint" problems Indeed, Volcker (2010) asserts that proprietary trading is socially useful even if risky. The assumption underlying the Volcker rule is that broker-dealers that are in large banking groups have access to public bailouts or liquidity backstops by the Fed: thus they do not internalize the downside risk of their strategies, leading them to take excessive risk. In what follows I label this assumption the "risk-shifting problem".

The results in section 6 suggest that a problem with dealer proprietary trading is with margin constraints becoming more binding before the trading strategy pays off, as in Gromb and Vayanos (2002). This paper shows that these constraints *generate* some inefficiency: liquidation prices decrease when market participants' *ex ante* exposures in the asset increase, which they do not internalize when they invest - fire sale prices are thus inefficiently low. In addition, these constraints make arbitrageurs withdraw liquidity provision at times when liquidity is needed the most. The effect thus relies on a pecuniary externality on a collateral constraint, as in Lorenzoni (2008) and Stein (2012). I label the associated issue the "margin constraint problem".

The Volcker rule does not adress the margin constraint problem. The margin constraint problem is likely to arise even outside the banking sector: the externality of a dealer's large positions is on its *competitors*. In the risk-shifting case, bank-affiliated dealers take excessive risk because the perspective of bank public bailout make them insensitive to losses: the externality is on bank's creditors. Therefore it is largely unclear that the Volcker rule in its principle has prevented the financial system from proprietary trading-related risks.

[21]Although Hart (1975) shows that welfare improvement is warranted only if market makers or prop traders *fully* complete the markets.

If proprietary trading needs regulation, then regulation should address the margin constraint problem. This is beyond the scope of this paper.

7.2 Safe assets production and "recirculation"

An important literature, starting with Caballero, Farhi, and Gourinchas (2008, 2017) and Gorton, Lewellen, and Metrick (2012) suggests a mismatch between a specific demand for safe assets and the supply, inducing the private sector to fill the gap with potential inefficiencies (Stein 2012). The private sector production of safe assets is usually thought as short term bank debt and deposits, or asset-backed securities that extract a seemingly safe component from risky assets.

Here I highlight another channel by which the private sector exploits safe asset low yields or not: dealers borrowed Treasury bonds from investors likely out of the market, and sold them; in parallel they bought corporate bonds, and were more eager to do so to the extent that by short-selling Treasury bonds, they hedged interest rate risk on corporate bonds. This seems to have raised corporate bond prices with respect to Treasury bonds.

In the case of deposit or asset-backed securities, the private sector *produced* new safe assets, by issuing relatively safe debt at a low interest rate and investing in riskier assets. In the proprietary trading channel I document, for the specific long corporate, short Treasury strategy, it looked more like broker-dealer *re-circulating* safe assets that held who are inframarginal but willing to lend their securities.

8 Conclusion

In this paper I show that not all broker-dealers in the US corporate bond market is market making as described by traditional theories, but resembles theories of limits of arbitrage, what I call proprietary trading.

On days when customers only buy or only sell, *i.e.* the customer order flow is one-way, which account for 50% of bond×day observations, I observe a correlation between price changes and net customer trades that is opposite to what market making theories predict but in line with theories of limits of arbitrage. On days with both customer buy and customer sells, the correlation is in line with market making theories.

Second, I show that the observations with one-way order flow also correspond to dealers purchasing (selling) bonds that were cheaper (more expensive) the day before. As measures of bond relative cheapness I decompose the bond spread into four components reflecting cheapness with respect to similar bonds (credit risk, maturity, callability), cheapness of the group of similar bonds with respect to bonds with similar maturity, cheapness of the group of similar maturities with respect to other maturity group, and overall cheapness of corporate bonds with respect to Treasuries.

Broker-dealers appear to be responsive mainly to spreads between bonds of similar maturity, and to the spread between Treasury bonds and corporate bonds, likely reflecting Treasury bonds' convenience yield.

The Treasury/corporate bond strategy is confirmed by looking at Primary Dealers' inventory positions: I show that large corporate bond inventories before the crisis, peaking around $200bn, were mirrored by symmetric negative net inventories in Treasury bonds, echoing the results in the regressions. This suggests broker-dealers re-circulated safe assets that were held by inframarginal investors.

Moreover, proprietary trading appears to come with constraints that began to bind at the onset of the crisis, likely triggering the corporate bond market crisis. I show that the net Treasury position was abruptly reduced by half in July 2007, leaving Primary Dealers with new exposure to interest rate risk on $100bn corporate bonds. This coincided with a similar reduction in PDs' Treasury security lending contracts; in addition, Primary Dealers' default risk as assessed through their CDS sharply increased in June 2007, while the volatility of Treasuries also increased at abnormal levels with respect to the previous 18 months standards, a combination of which should lead to a tightening of haircuts.

This evidence suggests that the Volcker rule may fail to address an important risk: dealers may have taken excessively large positions, exposing themselves to a run analogous to a funding liquidity risk, because of their margin constraints (Gromb and Vayanos 2002). The Volcker rule bans proprietary trading in the banking sector: but the margin constraints problem is likely to arise even outside the banking sector, as illustrated by the 1998 LTCM crisis.

A Data

Cleaning. For each bond, I drop transactions within 7 days before and 7 days after the bond's offering date, because primary market transaction are very specific.

TRACE includes transaction information with prices, quantity, the direction of the trade (buy or sell) and whether the counterparty to the reporting dealer is a customer or another dealer. I clean the data following Dick-Nielsen (2014) to remove explicit reporting errors, when-issued transactions and special trading under special circumstances. I remove interdealer transactions.

I remove transactions with price lower than 80% or higher than 120% of the median price of the day, or with price lower than \$1 or higher than \$500. I remove transactions with amounts lower than the par value of one bond, or higher than the offered amount for the bond are removed.

Stock prices and returns. I retain bonds for which a stock price is available (average of end-of-day bid and ask), using the WRDS Bond-CRSP linking suite at PERMCO (company) level for CRSP. I use common stocks (CRSP share code's first digit equal to 1); whenever there are several common stock classes for a single company, I use the average common stock prices weighted by the number of shares outstanding. I do not adjust stock returns are not adjusted for dividend payment or annoucement: dividend decisions may have an impact on the company's perceived credit risk.

B More on testing hypothesis 1

B.1 Regression with cheapness measures

To address the concern that cheapness measures defined in equation (5.3) may forecast both dealer purchases (sales) and price decreases (increases), I add these measures in regression (4.3), interacting them with the $Lehman_t$ dummy.

$$\begin{aligned}
\Delta \log p_{i,t} = \alpha &+ \beta_1\, \widetilde{OF}_{i,t}^{OneWay} + \beta_2\, \widetilde{OF}_{i,t}^{Roundtrip} \\
&+ \beta_3\, \widetilde{OF}_{i,t}^{OneWay} \times Lehman_t + \beta_4\, \widetilde{OF}_{i,t}^{Roundtrip} \times Lehman_t \\
&+ \sum_x \big(\nu_1^x Idiosync_{i,t-1}^x + \nu_2^x CreditCall_{i,t-1}^x \\
&\qquad + \nu_3^x Maturity_{i,t-1}^x + \nu_4^x TreasConv_{i,t-1}^x \big) \\
&+ \sum_k LehmanInteractionTerms_{i,t} \\
&+ \gamma X_{2,i,t}^{(p)} + \epsilon_{3,i,t}
\end{aligned} \tag{B.1}$$

where the $LehmanInteractionTerms$ are the cheapness measures $Idiosync_{i,t-1}^{OneWay}$, $Idiosync_{i,t-1}^{Roundtrip}$, $CreditCall_{i,t-1}^{OneWay}$, *etc.* times the dummy $Lehman_t$, and

$$x = OneWay, Roundtrip$$

I also include the $Lehman_t$, $OneWay_{i,t}$ dummies and their interaction in the vector of controls $X_{3,i,t}^{(p)}$.

Table 10 shows that the coefficient on One-way order flow is unaffected by the presence of the cheapness measures: it stands at 0.0024, while it was at 0.0025 in table 5

B.2 Regression with predicted order flow

I also assess whether other predictors or order flow are driving the results: previous price changes, lags of order flow and lagged stock return and interest rate changes. To do this I compute a predicted and an unexpected component of order flow, separately for One-way and Partial Rountrip order flow, as follows:

$$\widetilde{OF}_{i,t}^{x} = \underbrace{\alpha_x + \sum_{k=1}^{10} \rho_k \widetilde{OF}_{i,t-k} + \sum_{k=1}^{10} \mu_k \Delta \log p_{i,t-k} + \gamma X_{1,i,t-1}}_{\widehat{\widetilde{OF}}_{i,t}^{x}} + \eta_{i,t}^{x}$$

where the vector $X_{1,i,t-1}$ includes lagged stock return and interest rate changes.

Then I regress price changes on the predicted and unpredicted components of order flow, still with the interaction with the $Lehman_t$ dummy as in the main regression:

$$\begin{aligned}
\Delta \log p_{i,t} = \alpha &+ \beta_1 \, \widehat{\widetilde{OF}}_{i,t}^{OneWay} + \beta_2 \, \widehat{\widetilde{OF}}_{i,t}^{Roundtrip} \\
&+ \beta_3 \, \widetilde{OF}_{i,t}^{OneWay} \times Lehman_t + \beta_4 \, \widetilde{OF}_{i,t}^{Roundtrip} \times Lehman_t \\
&+ \beta_0 Lehman_t + \gamma X_{2,i,t}^{(p)} + \epsilon_{2,i,t}
\end{aligned}$$

The regressor of interest are the unexpected components of order flow $\eta_{i,t}^{OneWay}$ and $\eta_{i,t}^{Roundtrip}$.

Table 11 presents the results. The coefficient on $\eta_{i,t}^{OneWay}$ and $\eta_{i,t}^{Roundtrip}$ are very close to the estimates of One-Way and Partial Roundtrip order flow in table 5, which were at -0.0025 and 0.0040 respectively.

B.3 Robustness to multiway clustering

I re-run regression B.1, computing standard errors in more conservative ways: I allow clustering by the number of years to bond maturity, and by calendar month, following the methodology by Cameron et al. (2011). One concern with the maturity clustering is that the number of clusters along this dimension is close to 30, which may not be sufficient. In any case the results are robust, as shown by table 12.

Table 10 – Regression of daily log price changes on customer order flow, cheapness measures and controls. $\widetilde{OF}_{i,t}$ is the sign of order flow times the logarithm of the absolute value of order flow. Order flow is the sum of customer large (above \$100,000) buys minus the sum of customer large sells. $\widetilde{OF}_{i,t}^{OneWay}$ equals $\widetilde{OF}_{i,t}$ if order flow in bond i on day t is one-way (only customer buys or only customer sells), and zero otherwise. $\widetilde{OF}_{i,t}^{Roundtrip}$ equals $\widetilde{OF}_{i,t}$ if order flow is not One-way, *i.e.* (partial) roundtrip, and zero otherwise. Cheapness measures are defined in equation (5.3). Controls are issuer stock return, changes in 10 years Treasury yield, changes in 3-months LIBOR, TYVIX, an implied volatility index for Treasury futures, and changes in TYVIX. In the second and third column, a dummy $OneWay_{i,t}$for one-way order flow is included. $Lehman_t$ is a dummy that equals 1 if t is between September 15th, 2008 and April 30th, 2009. The interaction $OneWay_{i,t} \times Lehman_t$ is included.

	$\Delta \log p_{i,t}$
$\widetilde{OF}_{i,t}^{OneWay}$	**-0.0024*****
	(-6.10)
$\widetilde{OF}_{i,t}^{Roundtrip}$	0.0041***
	(11.82)
$CheapInSim_{i,t-1}^{OneWay}$	0.0014
	(1.37)
$CreditCall_{i,t-1}^{OneWay}$	0.0023
	(1.79)
$Maturity_{i,t-1}^{OneWay}$	-0.0009
	(-0.88)
$TreasConv_{i,t-1}^{OneWay}$	0.0045***
	(5.83)
$CheapInSim_{i,t-1}^{Roundtrip}$	0.0040**
	(2.69)
$CreditCall_{i,t-1}^{Roundtrip}$	0.0019*
	(2.52)
$Maturity_{i,t-1}^{Roundtrip}$	0.0014
	(1.79)
$TreasConv_{i,t-1}^{Roundtrip}$	0.0022***
	(4.37)
Interaction with $Lehman_t$	Y
Constant and controls	Y
R^2	0.24
N	2,203,723

Standard errors clustered by bond issuer

* (p<0.05), ** (p<0.01), *** (p<0.001)

Table 11 – Regression of daily log price changes on customer order flow, cheapness measures and controls. $\widetilde{OF}_{i,t}$ is the sign of order flow times the logarithm of the absolute value of order flow. Order flow is the sum of customer large (above \$100,000) buys minus the sum of customer large sells. $\widetilde{OF}_{i,t}^{OneWay}$ equals $\widetilde{OF}_{i,t}$ if order flow in bond i on day t is one-way (only customer buys or only customer sells), and zero otherwise. $\widetilde{OF}_{i,t}^{Roundtrip}$ equals $\widetilde{OF}_{i,t}$ if order flow is not One-way, *i.e.* (partial) roundtrip, and zero otherwise. Controls are issuer stock return, changes in 10 years Treasury yield, changes in 3-months LIBOR, TYVIX, an implied volatility index for Treasury futures, and changes in TYVIX. In the second and third column, a dummy $OneWay_{i,t}$ for one-way order flow is included. $Lehman_t$ is a dummy that equals 1 if t is between September 15th, 2008 and April 30th, 2009. The interaction $OneWay_{i,t} \times Lehman_t$ is included.

	$\Delta \log p_{i,t}$
$\eta_{i,t}^{OneWay}$	-0.0027***
	(-6.47)
$\eta_{i,t}^{Roundtrip}$	0.0037***
	(11.01)
$\widetilde{OF}_{i,t}^{OneWay}$	-1.5375***
	(-7.17)
$\widetilde{OF}_{i,t}^{Roundtrip}$	3.4071***
	(7.50)
R^2	0.24
N	2,212,269

Standard errors clustered by bond issuer
* (p<0.05), ** (p<0.01), *** (p<0.001)

Table 12 – Regression of daily log price changes on customer order flow and controls, clustering standard errors by the variable indicated in column header. $\widetilde{OF}_{i,t}$ is the sign of order flow times the logarithm of the absolute value of order flow. Order flow is the sum of customer large buys minus the sum of customer large sells. A customer buy or sell is large its size is above \$100,000. $\widetilde{OF}_{i,t}^{OneWay}$ equals $\widetilde{OF}_{i,t}$ if order flow in bond i on day t is one-way (only customer buys or only customer sells), and zero otherwise. $\widetilde{OF}_{i,t}^{Roundtrip}$ equals $\widetilde{OF}_{i,t}$ if order flow is not One-way, *i.e.* (partial) roundtrip, and zero otherwise. Controls are bond cheapness measures, issuer stock return, changes in 10 years Treasury yield, changes in 3-months LIBOR, TYVIX, an implied volatility index for Treasury futures, and changes in TYVIX. In the second and third column, a dummy $OneWay_{i,t}$for one-way order flow is included. $Lehman_t$ is a dummy that equals 1 if t is between September 15th, 2008 and April 30th, 2009. The interaction $OneWay_{i,t} \times Lehman_t$ is included.

	Issuer/Month	Issuer/Mat	Issuer/Month/Mat
$\widetilde{OF}_{i,t}^{OneWay}$	-0.0024**	-0.0024***	-0.0024*
	(-2.73)	(-4.36)	(-2.50)
$\widetilde{OF}_{i,t}^{Roundtrip}$	0.0041***	0.0041***	0.0041***
	(9.19)	(6.78)	(5.44)
Cheapness measures	Y	Y	Y
Interaction with $Lehman_t$	Y	Y	Y
Constant and controls	Y	Y	Y
R^2	0.24	0.24	0.24
N	2,203,723	2,203,723	2,203,723

Standard errors clustered by bond issuer
* (p<0.05), ** (p<0.01), *** (p<0.001)

B.4 Estimation table for regression through time

Table 13 shows the estimation results of regression 4.5. I plot the coefficients for each subperiods in figure 4.

Table 13 – Regression of daily log price changes on customer order flow and controls, interacted with subperiod dummies. Coefficients are plotted on figure 4 $\widetilde{OF}_{i,t}$ is the sign of order flow times the logarithm of the absolute value of order flow. Order flow is the sum of customer large buys minus the sum of customer large sells. A customer buy or sell is large its size is above $100,000. $\widetilde{OF}_{i,t}^{OneWay}$ equals $\widetilde{OF}_{i,t}$ if order flow in bond i on day t is one-way (only customer buys or only customer sells), and zero otherwise. $\widetilde{OF}_{i,t}^{Roundtrip}$ equals $\widetilde{OF}_{i,t}$ if order flow is not One-way, *i.e.* (partial) roundtrip, and zero otherwise. Controls are issuer stock return, changes in 10 years Treasury yield, changes in 3-months LIBOR, TYVIX, an implied volatility index for Treasury futures, and changes in TYVIX. In the second and third column, a dummy $OneWay_{i,t}$for one-way order flow is included. $Lehman_t$ is a dummy that equals 1 if t is between September 15th, 2008 and April 30th, 2009.

Opaque	
$\widetilde{OF}_{i,t}^{OneWay}$	-0.0069***
	(-6.02)
$\widetilde{OF}_{i,t}^{Roundtrip}$	0.0004
	(0.51)
Pre-Crisis	
$\widetilde{OF}_{i,t}^{OneWay}$	-0.0077***
	(-10.38)
$\widetilde{OF}_{i,t}^{Roundtrip}$	0.0008
	(1.30)
Crisis	
$\widetilde{OF}_{i,t}^{OneWay}$	0.0341***
	(10.04)
$\widetilde{OF}_{i,t}^{Roundtrip}$	0.0193***
	(8.31)
Post-Crisis	
$\widetilde{OF}_{i,t}^{OneWay}$	0.0049***
	(4.60)
$\widetilde{OF}_{i,t}^{Roundtrip}$	0.0063***
	(7.38)
Post-Dodd-Frank	
$\widetilde{OF}_{i,t}^{OneWay}$	-0.0029***
	(-4.98)
$\widetilde{OF}_{i,t}^{Roundtrip}$	0.0049***
	(10.28)***
R^2	0.24
N	2,220,248

Clustered by bond issuer

* (p<0.05), ** (p<0.01), *** (p<0.001)

C More on testing Hypothesis 2

C.1 General proprietary trading strategies: coefficients for Roundtrip order flow

Table 14 complements table 8 by showing coefficients for the four components of the bond spread for Partial Roundtrip order flow. The coefficients are less significant than for One-Way order flow, and in any case of smaller magnitude.

C.2 Evolution through time

C.2.1 Initial maturity: other regression coefficients

Table 15 complements table 9 by giving the coefficients on One-way order flow and initial maturities more than 10 years, and for Partial Roundtrip order flow. Coefficients are not not often significant and in any case of lower magnitude than for one-way order flow and shorter maturities.

C.2.2 Results with residual maturity

Table 16 and 17 show the results of running regression 5.2 by subperiod with a breakdown by bond *residual* maturity.

The results are qualitatively similar to the results with the split by initial maturity. The coefficient for the $TreasConv$ measure for one-way order flow, bonds with maturities below 10 years, is however weaker, although still strongly negative significant. The evolution through time is still in the direction of decreased proprietary trading after the crisis.

Table 14 – Order flow regressed on four lagged measures of cheapness. $Idiosync$ is the difference between the bond's spread $y_{i,t}$ to an equivalent Treasury bond minus the median $y_{i,t}^{sim}$ of these spreads in the basket of bonds with the same credit rating, maturity and callability. $CreditCall_{i,t}$ is equal to $y_{i,t}^{sim}$ minus the median spread for all bonds with the same maturity $y_{i,t}^{\tau}$. $Maturity_{i,t}$ is equal to $y_{i,t}^{\tau}$ minus the median $y_{i,t}^{10}$, the median spread of all bonds that have residual maturity below 10 years if it is the case for bond i, or above 10 years otherwise. Controls include the dummy $OneWay_{i,t}$ for one-way order flow, and where applicable the dummy for the criterion $Crit$ (bond age, initial maturity and residual maturity) being less than 10 years, and its interaction with $OneWay_{i,t}$. Additional controls are 10 lags of order flow, 10 lags of bond price changes, 3 lags of stock return and lagged 10 years Treasury yield changes. To save space **only the coefficients for Roundtrip order flow are shown**. Coefficients for One-way order flow are shown in table 8.

	NoCrit	Age	InitMaturity	ResidMaturity
$Idiosync_{i,t-1}^{Roundtrip}$	0.0014			
	(1.20)			
$Idiosync_{i,t-1}^{Roundtrip,Z\leq 10y}$		0.0016	0.0030	0.0029
		(1.24)	(1.41)	(0.28)
$Idiosync_{i,t-1}^{Roundtrip,Z>10y}$		0.0037	0.0007	0.0003
		(1.55)	(0.60)	(1.46)
$CreditCall_{i,t-1}^{Roundtrip}$	-0.0019			
	(-1.58)			
$CreditCall_{i,t-1}^{Roundtrip,Z\leq 10y}$		-0.0025	**-0.0137*****	**-0.0117*****
		(-1.78)	**(-3.52)**	**(-3.44)**
$CreditCall_{i,t-1}^{Roundtrip,Z>10y}$		0.0023	0.0005	0.0002
		(0.97)	(0.43)	(0.16)
$Maturity_{i,t-1}^{Roundtrip}$	0.0004			
	(0.33)			
$Maturity_{i,t-1}^{Roundtrip,Z\leq 10y}$		0.0006	0.0080**	0.0069**
		(0.51)	(2.74)	(2.84)
$Maturity_{i,t-1}^{Roundtrip,Z>10y}$		0.0020	0.0003	0.0003
		(0.90)	(0.30)	(0.29)
$TreasConv_{i,t-1}^{Roundtrip}$	**-0.0033***			
	(-2.36)			
$TreasConv_{i,t-1}^{Roundtrip,Z\leq 10y}$		**-0.0034***	0.0027	0.0020
		(-2.21)	(0.77)	(0.68)
$TreasConv_{i,t-1}^{Roundtrip,Z>10y}$		0.0016	0.0016	0.0023
		(1.13)	(1.30)	(1.20)
Constant and controls	Y	Y	Y	Y
R^2	0.00	0.00	0.00	0.00
N	2,316,162	2,316,162	2,316,162	2,316,162

Standard errors clustered by bond issuer

* ($p<0.05$), ** ($p<0.01$), *** ($p<0.001$)

Table 15 – Order flow regressed on four lagged components of bond spread $Idiosync_{i,t-1}$, $CreditCall_{i,t-1}$, $Maturity_{i,t-1}$ and $TreasConv_{i,t-1}$ (see table 8 for details on the components), broken down by One-way / partial Rountrip order flow and bond initial maturity M being below or above 10 years. Controls include the dummy $OneWay_{i,t}$ for one-way order flow, and where applicable the dummy for bond initial maturity M being less than 10 years, and its interaction with $OneWay_{i,t}$. Additional controls are 10 lags of order flow, 10 lags of bond price changes, 3 lags of stock return and lagged 10 years Treasury yield changes. To save space **only the coefficients for one-way order flow and bonds of maturity $M > 10$ years, and for Partial Roundtrip order flow, are shown**.

	Opaque	Pre-Crisis	Crisis	Post-Crisis	Dodd-Frank
$Idiosync_{i,t-1}^{OneWay,M>10y}$	-0.0190	0.0122*	-0.0011	0.0065	0.0223***
	(-1.92)	(2.18)	(-0.11)	(0.54)	(3.34)
$CreditCall_{i,t-1}^{OneWay,M>10y}$	0.0015	0.0221	-0.0046	0.0199	0.0211**
	(0.19)	(1.52)	(-0.59)	(1.51)	(2.73)
$Maturity_{i,t-1}^{OneWay,M>10y}$	-0.0250**	0.0320***	0.0111	-0.0004	0.0074
	(-2.97)	(3.53)	(1.11)	(-0.03)	(0.94)
$TreasConv_{i,t-1}^{OneWay,M>10y}$	-0.0063	-0.0314	-0.0582***	0.0345*	0.0017
	(-0.30)	(-1.30)	(-6.03)	(2.57)	(0.22)
$Idiosync_{i,t-1}^{Roundtrip,M\leq 10y}$	0.0018	-0.0040	-0.0045	0.0076	0.0135*
	(0.15)	(-0.43)	(-1.25)	(1.76)	(2.52)
$CreditCall_{i,t-1}^{Roundtrip,M\leq 10y}$	-0.0338**	-0.0802**	-0.0100	0.0034	-0.0024
	(-2.79)	(-3.06)	(-1.79)	(0.33)	(-0.36)
$Maturity_{i,t-1}^{Roundtrip,M\leq 10y}$	0.0324*	0.0077	0.0050	0.0088	0.0052
	(2.12)	(0.39)	(0.76)	(1.00)	(1.55)
$TreasConv_{i,t-1}^{Roundtrip,M\leq 10y}$	-0.0209	-0.0042	0.0067	-0.0092	-0.0014
	(-1.16)	(-0.20)	(1.13)	(-0.85)	(-0.27)
$Idiosync_{i,t-1}^{Roundtrip,M>10y}$	-0.0060	0.0004	0.0015	0.0042*	0.0012
	(-1.88)	(0.45)	(1.06)	(2.09)	(0.39)
$CreditCall_{i,t-1}^{Roundtrip,M>10y}$	0.0020	-0.0003	0.0018	0.0073*	-0.0030
	(1.11)	(-0.12)	(0.83)	(2.01)	(-1.21)
$Maturity_{i,t-1}^{Roundtrip,M>10y}$	-0.0040	-0.0011	0.0015	0.0084**	0.0000
	(-1.09)	(-0.69)	(0.68)	(2.80)	(0.02)
$TreasConv_{i,t-1}^{Roundtrip,M>10y}$	0.0104*	0.0023	0.0014	-0.0065	0.0022
	(2.06)	(0.46)	(0.60)	(-1.25)	(1.19)
R^2	0.00	0.01	0.01	0.00	0.00
N	327,389	328,629	276,026	242,140	1,141,978

Standard errors clustered by bond issuer.
* (p<0.05), ** (p<0.01), *** (p<0.001)

Table 16 – Order flow regressed on four lagged components of bond spread $Idiosync_{i,t-1}$, $CreditCall_{i,t-1}$, $Maturity_{i,t-1}$ and $TreasConv_{i,t-1}$ (see table 8 for details on the components), broken down by One-way / partial Rountrip order flow and bond **residual maturity** T being below or above 10 years. Controls include the dummy $OneWay_{i,t}$ for one-way order flow, and where applicable the dummy for bond residual maturity T being less than 10 years, and its interaction with $OneWay_{i,t}$. Additional controls are 10 lags of order flow, 10 lags of bond price changes, 3 lags of stock return and lagged 10 years Treasury yield changes. To save space **only the coefficients for One-way order flow are shown.**

	Opaque	Pre-Crisis	Crisis	Post-Crisis	Dodd-Frank
$Idiosync_{i,t-1}^{OneWay,T\leq 10y}$	-0.0843*	-0.0497	-0.1171***	-0.0259	-0.0005
	(-2.60)	(-0.73)	(-8.00)	(-1.92)	(-0.04)
$CreditCall_{i,t-1}^{OneWay,T\leq 10y}$	-0.1459***	-0.4025***	-0.1299***	-0.0957***	-0.0711***
	(-4.05)	(-6.03)	(-8.12)	(-3.83)	(-3.52)
$Maturity_{i,t-1}^{OneWay,T\leq 10y}$	0.0316	-0.0025	0.0293	0.0363	0.0228*
	(0.77)	(-0.05)	(1.70)	(1.67)	(2.37)
$TreasConv_{i,t-1}^{OneWay,T\leq 10y}$	-0.0534	-0.1784***	-0.1072***	-0.0994***	-0.0724***
	(-1.57)	(-3.58)	(-5.07)	(-4.12)	(-3.93)
$Idiosync_{i,t-1}^{OneWay,T>10y}$	-0.0231*	0.0136*	0.0066	0.0096	0.0217**
	(-2.22)	(2.27)	(0.62)	(0.79)	(3.26)
$CreditCall_{i,t-1}^{OneWay,T>10y}$	0.0081	0.0243	0.0017	0.0245	0.0251**
	(1.09)	(1.68)	(0.22)	(1.73)	(3.19)
$Maturity_{i,t-1}^{OneWay,T>10y}$	-0.0201**	0.0332***	0.0139	0.0006	0.0026
	(-2.61)	(3.65)	(1.31)	(0.04)	(0.35)
$TreasConv_{i,t-1}^{OneWay,T>10y}$	-0.0835**	-0.0684	-0.0765***	0.0687*	-0.1135***
	(-2.61)	(-1.01)	(-5.69)	(2.23)	(-7.20)
R^2	0.00	0.01	0.01	0.00	0.00
N	327,389	328,629	276,026	242,140	1,141,978

Clustered by firm, month, years to maturity
* (p<0.05), ** (p<0.01), *** (p<0.001)

Table 17 – Order flow regressed on four lagged components of bond spread $Idiosync_{i,t-1}$, $CreditCall_{i,t-1}$, $Maturity_{i,t-1}$ and $TreasConv_{i,t-1}$ (see table 8 for details on the components), broken down by One-way / partial Rountrip order flow and bond **residual maturity** T being below or above 10 years. Controls include the dummy $OneWay_{i,t}$ for one-way order flow, and where applicable the dummy for bond residual maturity T being less than 10 years, and its interaction with $OneWay_{i,t}$. Additional controls are 10 lags of order flow, 10 lags of bond price changes, 3 lags of stock return and lagged 10 years Treasury yield changes. To save space **only the coefficients for Partial Roundtrip order flow are shown.**

	Opaque	Pre-Crisis	Crisis	Post-Crisis	Dodd-Frank
$Idiosync^{Roundtrip,T\leq 10y}_{i,t-1}$	-0.0004	-0.0048	-0.0034	0.0080	0.0125**
	(-0.04)	(-0.73)	(-0.99)	(1.93)	(2.64)
$CreditCall^{Roundtrip,T\leq 10y}_{i,t-1}$	-0.0294**	-0.0522**	-0.0094	0.0065	-0.0001
	(-2.71)	(-2.72)	(-1.82)	(0.70)	(-0.02)
$Maturity^{Roundtrip,T\leq 10y}_{i,t-1}$	0.0289*	0.0023	0.0013	0.0094	0.0053
	(2.14)	(0.15)	(0.25)	(1.26)	(1.86)
$TreasConv^{Roundtrip,T\leq 10y}_{i,t-1}$	-0.0072	-0.0090	0.0027	-0.0100	0.0009
	(-0.58)	(-0.66)	(0.54)	(-1.12)	(0.23)
$CheapInSim^{Roundtrip,T>10y}_{i,t-1}$	-0.0063	0.0000	0.0013	0.0035*	0.0005
	(-1.95)	(0.01)	(0.85)	(2.11)	(0.17)
$CreditCall^{Roundtrip,T>10y}_{i,t-1}$	0.0020	-0.0014	0.0017	0.0059	-0.0041
	(1.16)	(-0.61)	(0.72)	(1.72)	(-1.53)
$Maturity^{Roundtrip,T>10y}_{i,t-1}$	-0.0040	-0.0016	0.0012	0.0075*	0.0003
	(-1.09)	(-1.02)	(0.51)	(2.43)	(0.14)
$TreasConv^{Roundtrip,T>10y}_{i,t-1}$	0.0023	0.0246	0.0067	-0.0090	-0.0010
	(0.24)	(1.66)	(1.65)	(-1.05)	(-0.20)
R^2	0.00	0.01	0.01	0.00	0.00
N	327,389	328,629	276,026	242,140	1,141,978

Clustered by firm, month, years to maturity

* (p<0.05), ** (p<0.01), *** (p<0.001)

D Repos, reverse repos, long and short positions

Repos or collateralized loans are ways for an investor with limited capital to fund the acquisition of an asset: the investor borrows cash up to some horizon and gives the asset as collateral to the lender. In general the lender does not finance the full amount of the purchase, so that the investor has to complete the purchase amount with his capital. This ensures that if the borrower fails, the lender can sell the collateral and recover a high fraction of his loan even if the asset price has decreased. The ratio between the amount of investor's own capital required to fund the asset and the market value of the asset is called the *haircut*. Haircuts are thus financing constraints.

Reverse repos go in the opposite direction: instead of borrowing cash, the investor borrows a security and gives cash as collateral to the security lender. Similarly to repos, the security lender may require an amount of cash collateral that is higher than the market value of the asset, so that the investor has to find cash, typically from his own funds, to finance the cash collateral. For reverse repos I call haircut the ratio of the value of the cash collateral that is funded on the investor's own funds, to the market value of the security when the loan is made.

Repos and reverse repos are mirror images of each other: a repo for the investor is a reverse repo from the perspective of his (cash) lender. Positive haircuts from the perspective of one agent correspond to negative from the perspective of the other agent. Therefore the definition of haircuts depends on which agent one considers: here I define haircuts from the perspective of Primary Dealers.

In a reverse repo, the investor can sell the security he has borrowed as long as he comes back with an identical security at the expiration of the contract. In the interim period, the security borrowed and sold becomes a liability. The investor who sells the security makes a loss if he repurchases the asset at a higher price, and gains if he repurchases at a lower price. Reverse repos are thus used to implement short-selling.

In the definition I adopt here, arbitrage involves long and short position in correlated assets. A long position, consists in buying and holding an asset for some period of time and being exposed to the risk of a low payoff. A short position is the short-selling of a security as described above, so that the investor carrying a short position is exposed to the risk of a high payoff. When securities on the long and short legs of the strategy comove, the risks associated with each leg are partially or completely offset.

Implementing a long-short strategy naturally leads to using a combination of a repo to fund the long leg and a reverse repo to fund the short leg, as illustrated on figure 11. An investor with limited capital is willing to borrow a security: he has to finance the cash collateral, which is a loan to the security lender. To do this he benefits from an unsecured loan L, presumably from a clearing agent who knows his positions and thus his ability to reimburse well. Then the investor receives the security borrowed, for a lower value than the loan he grants reflecting the haircut. By selling the security borrowed, the investor gets cash, while he still owes the security at expiration of the security lending contract which now appear as a liability. With the cash he could purchase the asset on the long side of the strategy: then the unsecured lender may require to have it as collateral for the initial loan L, which would improve its terms; or he could equivalently redeem the loan L with the cash, and enter a separate repo to implement the long side. Both imply a repo and a reverse repo. In the following subsection I show that Primary Dealers appeared to implement their strategies in this way.

Such implementation implies distinct financial contraints for each leg of the long-short strategy, as each leg involves potentially different haircuts.

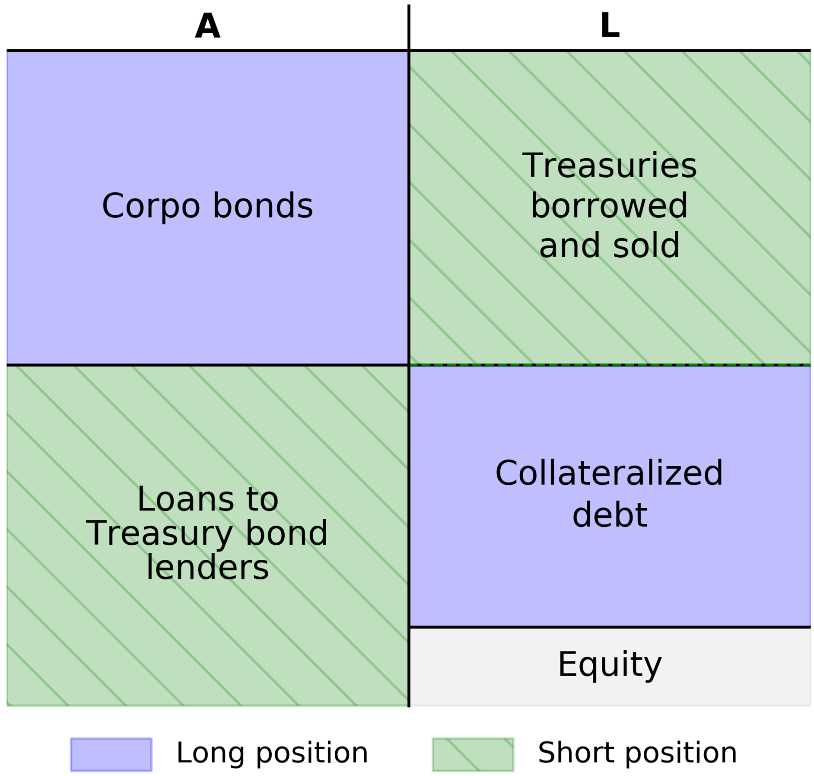

Figure 11 – **Simplified balance sheet of an arbitrageur.** The long position (blue, without hatches), in corporate bonds for illustrative purpose, is funded through collateralized debt or repo contracts. The short position (green, with hatches), in Treasuries for illustration, is funded through a reverse repo: Treasury securities are borrowed from security lenders, the arbitrageur granting a loan to the security lender as collateral.

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