Whose asset sales matter?

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Abstract

We study the price impact of sales in bond markets. Using novel data on the transactions of financial firms in corporate and government bonds in the UK, we develop a new measure of non-fundamental selling pressure. We instrument for firms' sales of a bond with their sales of bonds *other than the bond in question* and exploit within issuer-time variation to identify selling pressure that is unrelated to the bond's fundamentals. The price impact of a sale depends critically on who is selling the asset: sales by dealers and hedge funds generate significantly larger impacts than sales of the same size by other investor types. Our results suggest that more attention should be devoted to risks to financial stability stemming from these impactful sellers.

Keywords: Price impact, fire sales, liquidity.

JEL Codes: G12, G21, G23.

When an asset is sold, what happens to its price? Various key economic and financial stability issues depend on the answer to this question, including the existence and impact of asset fire sales, the real effects of financial market fluctuations, and the determinants of market liquidity.

We answer this question by developing a new measure of selling pressure that is unrelated to an asset's price-relevant fundamentals. The key insight is that we can identify exogenous variation in investors' sales of an asset using their sales of other, unrelated assets. We apply this measure to granular data on trading in bonds by all types of investor, and show that selling pressure has significant impacts on bond prices that last for weeks, and are greater in less liquid bonds and times of stress. Most importantly, we show that the extent of the impact depends critically on who is selling the asset, with sales by dealers and hedge funds generating significantly larger impacts than other investor types. To the best of our knowledge, we are the first to document this dependence of price impacts on investor type.

Our paper is built around the following intuition: researchers studying the impact of asset sales are confronted with a basic problem of endogeneity. Suppose we observe an individual investor selling an asset: we do not know if the sale was because they needed to sell the asset, or because they received a signal about the asset's value. If, however, at the same time as selling the asset the agent is selling off many other unrelated assets – their house, their car, etc. – the sale is more likely driven by the trader's condition rather than the particular features of the asset. It follows that investors' sales of other unrelated assets can be used as an instrumental variable for their sales of a given asset. The rest of this paper formalises and applies this intuition to study the impact of sales in bond markets.

The starting point for our work is regulatory data on transactions in corporate and government bonds by financial firms in the United Kingdom from 2019 to 2020. The key advantage of this dataset, relative to others that are commonly used, is that it includes the trades of all types of firms that trade bonds, not just a single type of trader. Specifically, our dataset covers trades by dealers, non-dealer banks, hedge funds, asset managers (including mutual funds) and other types of firm.

To study the price impact of market participants' sales of bond i we define a new measure of selling pressure – *outside selling pressure* – based on these market participants' net sales of bonds *other than bond i*. To control for correlated shocks to bond i and other related bonds we follow Choi et al. (2020) by including issuer-time fixed effects as controls, along with bond fixed effects and the time since the bond was issued. We then use our selling pressure measure as an instrumental variable for their sales of bond i. To build intuition, consider two bonds issued by Dell: Dell A and Dell B. If those traders selling Dell A are net sellers of other bonds to a greater extent than are the sellers of Dell B, our instrumental variable will identify Dell A as facing greater selling pressure than Dell B. The exclusion restriction is that any correlation between the fundamentals of Dell bonds and other bonds is swept up by our fixed effects and controls. If this assumption is satisfied, Dell A has received an exogenous shock to its demand relative to Dell B, and we can use this to identify the price impact of sales.

We document the properties of outside selling pressure. We show that it is highly positively correlated with observed asset sales, and that it peaked during the 'dash-for-cash' in March 2020. We show that when we compute the selling pressure measure solely for funds, it is positively correlated with existing measures of fire-selling pressure based on mutual fund flows (Coval and Stafford, 2007; Wardlaw, 2020). This suggests that, to some extent, the non-fundamental sales our measure picks up are fire sales by firms looking to offload assets.

We then study how our measure of selling pressure impacts prices. We show that it has statistically and economically significant impacts on bond prices: moving from the 5^{th} to the 95^{th} percentile of outside selling pressure is associated with a 25 basis point fall in bond prices. These effects persist for a month, but by five weeks after the shock the effects have disappeared. Price impacts are greater in corporate than government bonds, and greater during the dash-for-cash than in the rest of our sample period. These findings support the exogeneity of our pressure measure, as sales in response to news about a bond's fundamentals would have permanent price effects. They are also consistent with our approach successfully isolating non-fundamental selling by firms.

The key innovation of our paper is that our combination of novel data and new selling pressure measure enables us to study the causal impact of sales by different types of investors. We do this by regressing prices on sales by investors of a particular type (and controls), instrumenting for their sales using our selling pressure measure. We show that the price impacts of dealers' selling is larger than that of any other sector, with hedge funds the second most impactful sector. All else equal, sales by the asset management companies that house mutual funds have relatively minor effects.

We then discuss the variation that underlies our selling pressure measure, and how this varies across firms. Our identification strategy isolates non-fundamental sales by investors that are correlated across bonds. This likely comes from a number of sources. For example, these sales could represent fire sales – forced sales of assets by firms in distress. Alternatively, they could capture investors seeking to shrink their inventories, or sell assets to raise their cash buffers. Existing research into the trading behavior of different investors would suggest the balance between these two types of sales – fire sales and other non-fundamental sales that are correlated across bonds – likely varies across investors. In particular, dealers were typically not thought to be engaging in large fire sales of assets over our sample period, while there is evidence that dealers in recent years have become more reluctant to intermediate markets and hold large inventories (Adrian et al., 2017). The variation in outside selling pressure for these investors thus likely represent non-fundamental sales that are not fire sales. There is evidence of other types of investors engaging in fire sales – in particular mutual funds (Ma et al., 2022) and hedge funds (Barth and Kahn, 2021) – and for these investors our pressure measure likely picks up these fire sales.

Why is the price impact of a sale a function of who is selling? We offer two explanations. The first relates to information. Whilst our empirical approach enables us to identify selling that is unrelated to fundamentals, the counterparties to the selling do not have this knowledge, and hence demand a price discount when trading with counteparties they believe might have private information, either about the fundamentals of the asset or future trading in the asset. Dealers' business models give them access to private information about trading flows and the financial conditions of bond issuers, whilst hedge funds' business models are based around gaining and benefiting from an informational advantage. As a result, when these informed traders sell assets, price impacts are greater.

The second explanation for these differential price impacts comes from the roles that dealers and hedge funds play in markets. Both are thought to typically supply liquidity to markets, dealers by 'leaning against the wind' (Weill, 2007) and hedge funds via their arbitrage activities (Jylhä et al., 2014). When these roles reverse and these investors demand liquidity, liquidity must be supplied by other investors who are less suited to it, and who thus demand greater price discounts.[1]

Our results have clear implications for policymakers tasked with monitoring risks from fire sales in financial markets, and preventing them from crystallising. Much of the policy and academic attention on fire sales to date has focused on mutual funds (Baranova et al., 2017). There is sound logic to this, as the structure of these funds means they may be forced into sales of illiquid assets in order to satisfy redemptions, and these redemptions may suffer

[1] This logic is consistent with the model of Shleifer and Vishny (1992).

from a first-mover advantage whereby investors have an incentive to redeem before others do (Feroli et al., 2014; Goldstein et al., 2017). But policymakers should also consider the *impact* of fire sales once they are triggered, even when the probability of them happening seems small. We show that the sales of dealers and hedge funds have greater impacts on prices than other investors. Policymakers concerned about risks to financial stability that operate via the prices of financial assets should, all else equal, pay particularly close attention to these impactful sellers.

In the following section we discuss related literature. In section 2 we describe the data we use. In section 3 we set out our empirical approach. In section 4 we set out our results and in section 5 we discuss them. We conclude in section 6.

1 Related literature

Our work contributes to four strands of literature. Firstly, and most importantly, it contributes to a literature studying the impacts of forced sales on asset prices. Secondly, it contributes to a literature on the provision of liquidity in over-the-counter markets. Thirdly, it contributes to a literature studying asset price dynamics in times of stress, and in particular during the 'dash-for-cash' episode during the Covid-19 pandemic. Fourthly, it contributes to a literature modelling and simulating fire sales and their impact.

A large empirical literature studies the impact of forced sales of assets on prices and other asset or firm outcomes (for example Falato et al. (2021), Edmans et al. (2012), Kundu (2021), Kundu (2023) and Dessaint et al. (2019)). Much of this literature is based on the initial insight of Coval and Stafford (2007) that flows from mutual funds can be used to identify non-discretionary sales by funds, and shows that such sales can have large impacts on price. In recent years work by Wardlaw (2020) and Choi et al. (2020) has disputed this, suggesting that, after resolving certain issues with the methodology in earlier works and including more restrictive controls, the price impacts of flow-induced trading seem smaller. Ellul et al. (2011) study fire sales of insurance motivated by corporate bond downgrades.

Work in this area has tended to focus on a particular type of trader in a particular setting, partly due to data constraints and partly because their method for identifying exogenous sales was closely motivated by the institutional features of a particular trader. Our innovation relative to this literature is to propose a new measure of selling pressure which can be applied consistently across all types of traders, and to apply this to a dataset that, unlike many of the datasets used in this literature, includes trades by all types of traders. Our contribution is to show that selling by dealers and hedge funds is more impactful than selling by other investor types, including mutual funds. We believe further attention in this literature should be devoted to these sectors.[2]

A second literature studies the changing nature of liquidity in over-the-counter markets in recent years. Various papers have pointed to a decrease in the willingness of dealers – the traditional suppliers of liquidity in over-the-counter markets – to intermediate (Duffie, 2020; He et al., 2022). Post-crisis regulation, and in particular the leverage ratio, is often cited as an explanation for this (Duffie, 2018). Recent literature has highlighted that the traditional view of over-the-counter markets, where dealers only supply liquidity and everybody else only demands liquidity, may no longer apply, with non-dealers playing a significant role in supplying liquidity (Choi et al., 2023). Our contribution to this literature is to connect it with the literature on fire selling, and show that the types of traders we typically expect to provide liquidity are those who have the greatest impact on asset prices when they sell. This points to the propensity of traditional liquidity suppliers to become liquidity demanders – whether due to fire sales or sales for other non-fundamental reasons like inventory management – as a key determinant of liquidity and overall market functioning. This is in the spirit of early models (Shleifer and Vishny, 1992) where price falls following asset sales are determined by the extent to which 'natural' buyers of assets are constrained or unwilling to buy the assets sold. Much of the recent empirical work on fire sales has focused only on sellers' behavior, and not its interaction with the supply of liquidity.

A third literature studies prices, liquidity (Kargar et al., 2021; Haddad et al., 2020; Schrimpf et al., 2020) and selling behaviour (Barth and Kahn, 2021; Czech et al., 2021a,c) during stress episodes and in particular during the dash-for-cash.[3] These papers typically either study aggregate market conditions, the role of a particular trader in contributing to distress, or in the case of Czech et al. (2021a) the extent to which different investor types sold assets during the turmoil. Our contribution is different: we highlight the importance of *who* is selling in determining the extent of price falls. We also have a broader focus, studying trading behavior across all market participants in both government and corporate bonds.

[2]We note that which traders 'matter most' for fire sales depends not just on the impact of their selling, but also their propensity to engage in fire sales. Our results speak to the former only.

[3]Pinter (2023) studies the causes and impacts of fire selling during the 2022 gilt market crisis.

A fourth literature builds stress testing models that simulate fire sales and estimate the resulting losses for financial institutions.[4]. An important but challenging component of these models is the estimation of the price impact of asset sales. Our findings suggest that price impacts in these models should vary according to the type of the seller. Our findings also have implications for which types of investor this literature should focus on.

2 Data & institutional setting

The core dataset we use is the universe of transactions in government and corporate bonds by entities regulated by the Financial Conduct Authority (FCA). These data are required to be submitted under the MiFID II directives. In practice, this includes nearly all financial firms operating in the UK, including subsidiaries of foreign firms. Note that only one counterparty in each transaction needs be regulated by the FCA in this way, so many non-FCA-regulated entities feature in the data. The bonds traded include those of both British and foreign issuers and include bonds denominated in sterling and other currencies.

The data contain detailed information on each transaction, such as the timestamp, volume, price, instrument traded and the identity of the two counterparties. We match the data with a hand-collected mapping that associates to each counterparty a financial sector (i.e., dealers, funds, banks, hedge funds and others). It should be noted that funds includes a wide range of fund types. This is due to the fact that in our transaction-level data we can identify only asset management firms, who might be trading on behalf of mutual funds as well as other fund types.

Table 1 displays summary statistics on the bonds and traders in our sample. Around 85% of the bonds in our sample are corporate bonds, with the remainder government bonds. Government bonds are traded more frequently, and account for slightly over half the trades in our sample. These statistics highlight the relative turnover of government and corporate bonds, with corporate bonds being traded less despite accounting for the largest majority of instrument captured in our dataset. 80% of the instruments and over 90% of the trades are in sterling, euro or dollar instruments. 3% of traders are dealers but they account for half of total trading. The rest of trading is accounted for largely by funds, banks and others, which includes trading services firms such as brokerage firms. This is consistent with the fact that

[4]See, for example, Coen et al. (2019) and Baranova et al. (2019)

both government and corporate bonds are mainly traded bilaterally over-the-counter (OTC), and rely on dealers to intermediate between buyers and sellers.[5][6] Dealers are therefore key players as they observe the order flow of a wide range of sectors, whilst their clients may be less informed due to the lack of transparency in the market.[7]

Our dataset covers the period from 1st January 2019 to 1st July 2020. This includes March 2020, which was a time of high volatility and low liquidity for financial markets following the onset of the COVID-19 pandemic,[8] and more benign periods before and after.

We adopt a much finer observation frequency than is typical in the literature (which is at quarterly or monthly frequency) in aggregating trade data to the weekly frequency. Table 2 summarises trading in our weekly dataset. A large number of unique bonds and traders trade each week.[9] Each trader on average trades 78 bonds a week, and each bond is traded by 10 traders each week conditional on being traded at all that week. These features of trading – the fact that on average several traders trade the same bond in a week and each trader trades several bonds in a week – will be critical for our approach to identifying exogenous selling pressure in a bond.

We merge the trading data with bond-level information from Eikon Fixed Income data, providing key characteristics of the securities. These characteristics will feature as controls in our analysis.

In complementary analysis (see the end of section 3), we also make use of data on mutual funds to replicate some of the price pressure measures associated with mutual fund outflows that have been developed in the literature. Specifically, we use data on total net assets, net flows and portfolio holdings data of mutual funds from Morningstar to construct fund-based price pressure measures between 2019 Q3 and 2020 Q2. The funds selected in Morningstar

[5]In the sterling government bond (gilt) market there are designated market-makers called Gilt-edged Market Makers (GEMMs) that are required to make markets in all conditions. For more information see the UK Debt Management Office website. The firms we identify as dealers include GEMMs as well as other large US dealer-banks.

[6]For more details on the gilt market see Benos and Žikeš (2018). For more details on the sterling corporate bond market see Coen and Coen (2022), Mallaburn et al. (2019) and Czech and Roberts-Sklar (2019).

[7]We note that whilst in US fixed income markets the Trade Reporting and Compliance Engine (TRACE) gives post-trade transparency, there is no equivalent in the UK. For more details and a comparison on trade reporting in the US and the UK we refer to Ivanov et al. (2020).

[8]For further details on this episode see Czech et al. (2021a) for sterling markets; and Kargar et al. (2021), Ma et al. (2022) and Schrimpf et al. (2020) for US markets.

[9]Unique bonds are defined by their International Securities Identification Number (ISIN) and unique traders by their Legal Entity Identifier (LEI).

hold between 38-52% of bonds traded in our transaction dataset, as shown in Table A4.[10]

3 Research design

Let us imagine that we have been able to identify bonds that are 'unrelated', in the sense that their price-relevant fundamentals are uncorrelated. If an investor trading bond i at time t is selling many other unrelated assets at the same time, then it suggests that her trades in i are driven, to a large degree, by the investor's condition, rather than by any idiosyncratic properties of bond i. Conversely, if an investor is trading bond i for purely idiosyncratic (to the bond) reasons then, on average, her sales of other assets should be zero.

Let $s_{i,j,t}$ be the net sales of bond i by trader j at time t, where $s_{i,j,t} > 0$ indicates the trader is net selling the asset, and let iss_i be the issuer of bond i. For bond i and trader j at time t we first define net sales ($z^{NS}_{i,j,t}$) and transactions ($z^{T}_{i,j,t}$) of bonds k issued by entities other than iss_i:

$$
\begin{aligned}
z^{NS}_{i,j,t} &= \sum_k \mathbf{1}(iss_i \neq iss_k) s_{k,j,t} \\
z^{T}_{i,j,t} &= \sum_k \mathbf{1}(iss_i \neq iss_k) |s_{k,j,t}|
\end{aligned}
$$

where $\mathbf{1}()$ is the indicator function. We then compute our measure of selling pressure – *outside selling pressure* $z_{i,t}$ – as the percentage net sales of bonds other than those issued by iss_i by all investors $j \in \mathcal{J}$ that are selling bond i:

$$
z_{i,t,\mathcal{J}} = \frac{\sum_{j \in \mathcal{J}} \mathbf{1}(s_{i,j,t} > 0) z^{NS}_{i,j,t}}{\sum_{j \in \mathcal{J}} \mathbf{1}(s_{i,j,t} > 0) z^{T}_{i,j,t}} \qquad (1)
$$

where $\mathcal{J}$ is a set of investors of a particular type. In our initial regressions we take $\mathcal{J}$ to be all traders in our data, and in our sector-level analysis we split traders up into dealers, banks, funds, hedge funds, and others.

In our analysis below, we run two types of regressions. The first is a two-stage least

[10] For further details on this analysis, see section 3 and the Appendix.

squares specification, where the equation we are estimating is:

$$p_{i,t} = \sum_{\mathcal{J}} \beta_{\mathcal{J}} s^V_{i,t,\mathcal{J}} + X_{i,t}\gamma + \epsilon_{i,t} \tag{2}$$

where $s^V_{i,t,\mathcal{J}}$ denotes sales of i at time t by investor type $\mathcal{J}$ as a percentage of the average weekly trading volume in that bond, where this average is taken over all weeks on which that bond trades, $p_{i,t}$ denotes the bond's price, $X_{i,t}$ is a set of control variables and $\epsilon_{i,t}$ is an error term.

We use our selling pressure measure $z_{i,t,\mathcal{J}}$ as an instrumental variable for these sales $s^V_{i,t,\mathcal{J}}$. The coefficient $\beta_{\mathcal{J}}$ can then be interpreted as the marginal causal effect of sales by sector $\mathcal{J}$ on prices.

Our instrumental variable approach can be thought of as solving two classic problems with estimating a regression like equation (2) using OLS. The first is a problem of simultaneity: price and quantity are jointly determined by the interaction of demand and supply, and simply regressing price on quantity does not recover any structural parameters. To identify structural parameters one needs an exogenous shifter. This is what outside selling pressure gives us: an exogenous shift in a set of traders' demand for a bond. The second issue is that of endogeneity or reverse causality discussed above: perhaps sales were driven by a signal about the bond's value. This problem is solved by having an instrumental variable for sales. Again, this is provided by outside selling pressure.

The second type of specification we run is the reduced-form of our two-stage least squares regressions:

$$p_{i,t} = \sum_{\mathcal{J}} \delta_{\mathcal{J}} z_{i,t,\mathcal{J}} + X_{i,t}\eta + \nu_{i,t} \tag{3}$$

Here $\delta_{\mathcal{J}}$ is the marginal effect of *outside selling pressure* from sector $\mathcal{J}$ on prices.

We reiterate that in all our analysis our pressure measure for bond i is computed based on investors' net sales of bonds *other* than i. As such, we use minimal information about investors' behavior with respect to bond i while capturing the natural requirement that they be reducing their position in the bond. This minimal use of information (other than the sign of the trade) on bond i protects against concerns that our pressure measure is directly related to i's fundamentals. Furthermore, in our regressions we use notional net sales of bonds rather than value-based measures, helping us to avoid mechanical correlations of the sort identified by Wardlaw (2020).

Clearly the requirement that the other bonds being sold are 'unrelated' to i is unlikely to be satisfied by simply considering bonds that are issued by a different issuer. One can easily envisage how net sales of securities from different issuers may reflect shared time varying factors that both induce sales *and* are tied to price-relevant fundamentals. For example, an investor may have acquired a portfolio featuring similar bonds, perhaps from the same industry, so that sales in other assets may reflect the effects of time-varying industry fundamentals. If an investor is heavily selling bonds issued by Acer, and bond i is issued by Dell, then it is plausible - indeed likely - that z_{it} encodes price-relevant fundamental information regarding i.

We include a set of demanding fixed effects and controls to eliminate these endogeneity concerns.[11] Specifically, in each regression we include issuer-time fixed effects. That is, we exploit within issuer-time variation, such that even if $z_{i,t}$ encodes confounding variation about the issuer, this variation should be absorbed. This powerful approach, following Choi et al. (2020), means that we only exploit variation that is obtained by contrasting returns from, for example, Dell Bond A vs Dell Bond B in the same period. Any source of fundamental variation in sales that is issuer-level (or, *a fortiori*, industry level) is stripped out.

It is difficult to think of remaining fundamental variation that would survive this fixed effect, though not impossible. For this reason, we include instrument fixed effects and control for the time since issuance of the bond. Once we have added our fixed effects and the aforementioned controls, our identification assumption is $cov(z_{i,t}, \epsilon_{i,t}|X_{i,t}) = 0$.

At this point, the main concern with the specification is perhaps whether we retain enough non-absorbed variation to allow us to assess the effect of non-fundamental sales. However, as shown below in our results section, we retain ample non-fundamental variation for precise estimation of the effects of non-fundamental sales.

We now briefly discuss properties of our outside selling pressure measure $z_{i,t}$. Table 3 summarises the distribution of prices $p_{i,t}$, outside selling pressure $z_{i,t}$ and sales $s^V_{i,t}$. In Figure 1 we plot the distribution of outside selling pressure $z_{i,t}$ through time for all traders. We emphasise at this point, however, that our identification draws on the enormous cross sectional

[11]An alternative would be to refine z_{it} by adopting a selection rule that filters the trades of 'other bonds' that feature in the calculation of z_{it}, exploiting information about the traders, bonds or the context of the trade. However, we choose not to adopt this approach for the purpose of isolating exogenous, non-fundamental variation in sales. The approach relies on observable criteria, such that there would always be the concern that some unobserved factor might correlate with sales and price-relevant information.

dimension of our data, rather than the time series alone. Notwithstanding this, it is reassuring that our measure exhibits a spike during the 'dash for cash' in March 2020 period which, anecdotally and in aforementioned academic studies, has been argued was associated with fire selling pressure.[12]

In addition, our measure is positively correlated with various measures of fire selling pressure in the literature derived from mutual fund flows. Table 4 shows the correlation between outside selling pressure – calculated only for funds – with the flow-induced pressure measure introduced in Coval and Stafford (2007) and the 'flow-to-stock' (F2S) and 'flow-to-volume' (F2V) measures constructed in Wardlaw (2020). The correlation between outside selling pressure measure and these measures is positive and generally statistically significant, indicating that there is some common variation between outside selling pressure and these measures. This is indicative that some of the variation in outside selling pressure comes from fire sales, and also that the sales by the asset management firms in our transaction data – who we label funds – reflects the trading of the mutual funds they contain. However, we note that there is no requirement for our measure to be strongly correlated with these proxies – and their utility is even questioned in Wardlaw (2020) – to be considered an effective measure of non-fundamental sales, as the demanding set of fixed effects we use likely absorbs fire-selling pressure by these mutual funds, and because our measure will include other non-fundamental trading by mutual funds that is not linked to flows.

4 Results

In this section we use our new measure of selling pressure to study the price impacts of selling. We first study how aggregate selling pressure from all sectors affects asset prices, how this varies across assets and according to financial market conditions. We then study how the price impact of selling depends on the type of investor that is doing the selling.

[12]The dispersion of selling pressure also increases at the end of the calendar year. Trading activity tends to drop around the end of the year, so this could partly be an artifact of relatively few trades. Alternatively, it could represent firms seeking to 'window dress' their balance sheets at the end of the year, a process which is facilitated by other traders (Kotidis and Van Horen, 2018; Morey and O'Neal, 2006).

4.1 Price impacts

Table 5 shows results from our reduced-form regression of equation (3) of asset prices on the selling pressure of all traders, plus controls.[13] Selling pressure has a statistically significant negative impact on asset prices. The magnitudes are meaningful: moving from the 5^{th} to the 95^{th} percentile of selling pressure causes a fall in price of $0.37 \times 0.68 = 0.25\%$, so 25 basis points. This is a meaningful effect relative to the median absolute weekly change in the price of a bond, which is 70 basis points. The significance of these effects is striking given the extremely demanding set of fixed effects we include in our regressions.

Table 6 shows how the impact of selling pressure varies across bonds and across time periods. A natural division within fixed income is between corporate and government bonds. In the first two columns, we show results distinguishing between these two types of securities. The coefficient on pressure for corporate bonds is over four times greater than that for government bonds, which is not statistically different from zero. This is consistent with the view that liquid assets should not exhibit as much of a price effect when sold. Indeed, various models (for example Coen et al. (2019)) suggest that this is precisely why liquid assets might be sold by distressed firms, before less liquid assets where they might be forced to realise a loss due to fire sale-depressed prices.

Various models of fire selling and liquidity suggest the price impact of forced selling will depend on the financial condition of traders and assets as a whole. The final two columns of Table 6 show how the coefficient on selling pressure differs between the 'dash for cash' episode in March 2020 and the rest of the sample. The coefficient during the dash-for-cash was 50% greater than the coefficient in the rest of the sample period. Again, this lends support to the idea that non-fundamental sales do matter for prices, and their impacts on prices are as models predict.

Figure 2 shows how the price impacts of selling pressure persist through time. In particular, we run the following version of our reduced-form regression:

$$p_{i,t+\tau} = \delta z_{i,t} + X_{i,t}\eta + \nu_{i,t} \tag{4}$$

where $\tau = 0, 1, ..., 6$ weeks and $z_{i,t}$ is computed for all investor types.[14]

[13] Note that we cannot run the two-stage least squares specification here, as the sales of all investor types by definition sum to zero, meaning there is no variation in the main regressor of interest.

[14] To ensure we have a consistent sample of bonds and weeks for these regressions, we only include

The coefficient dies away over time: after 2 weeks the effect of an increase in selling pressure halves relative to the contemporaneous effect, and after 5 weeks the effect of selling pressure on prices is statistically insignificant. Non-fundamental sales should not have permanent effects, as they by definition should not reveal anything about the future cashflows of the bond. By contrast, sales based on a bond's fundamentals should have permanent effects. As a result, Figure 2 provides reassuring evidence that our measure isolates non-fundamental trading, as it is inconsistent with *any* alternative rationale for our sales that is based on the bond's fundamentals.

4.2 Whose sales impact prices?

In the previous section we showed that non-fundamental selling can have large impacts on asset prices, and that the nature of these price impacts are consistent with the sales being unrelated to the fundamentals of the bond: they have greater impacts in stress and in less liquid bonds, and their impact on prices dies away over time. How can this be reconciled with recent studies based on mutual funds showing sales induced by fund outflows have relatively modest impacts on price (Wardlaw, 2020; Choi et al., 2020)? In this section we seek to answer that question, by showing that sales by different types of firm have radically different impacts on price. In section 5 we discuss why this might be.

To do this, we run two-stage least squares specifications as set out in equation (2), where we instrument for sectors' sales of a bond using outside selling pressure measure $z_{i,t}$.[15] As in all our specifications, we include issuer-time and instrument fixed effects as well as controlling for the time since the bond was issued.

Figure 3 shows the estimated price impact coefficients for each sector.[16] To facilitate interpretation, summary statistics of sales and selling pressure are given in Table 7. These coefficient estimates can be interpreted as the marginal impact on price of an extra unit of sales of an asset (scaled by the asset's average trading volume) by a given sector.

There is a clear ordering across sectors: non-fundamental sales by dealers have the largest

observations where a bond was traded (at least) 7 weeks in a row. As a result the coefficient for $\tau = 0$ does not need to match the coefficient in Table 5.

[15]We are able to do this for the sector-level regressions as there is variation in sales across instruments and time. By contrast, when we include all traders in our specifications, total sales are by definition zero.

[16]The underlying regression table is shown in Table A1 in the appendix. The first-stage regressions – regressing sector-level sales on sector-level pressure – and the reduced-form regressions – regressing price directly on sector-level pressure $z_{i,t}$ – are shown in Tables A2 and A3 in the appendix.

impact on price, followed by hedge funds and banks, followed by funds and other firms. The magnitudes for the most impactful sectors are substantial: a one standard deviation increase in dealers' net sales of a bond decreases its price by $0.10 \times 69 = 6.9$pp, which is greater than one standard deviation of prices. The *differences* are also large: a sale by funds has a 9 times smaller impact than sales by a dealer.

In the following section we discuss these results in more details, in particular in terms of what drives selling pressure and why it matters who is selling.

5 Discussion

5.1 What drives selling pressure?

We have used our measure of outside selling pressure to isolate exogenous selling pressure in a bond, and used this to study the price impacts of sales. At this point, one might ask what is the nature of this selling pressure? If these sales are not related to the fundamentals of a bond, what is driving them? Does this differ depending on who is selling?

It is perhaps useful to interpret sales of an asset as coming from three sources: (a) 'fundamentals' trading, where firms trade based on news about the asset's future cashflows; (b) 'noise' trading, where firms trade assets randomly, for reasons uncorrelated with *anything*; and (c) 'correlated' trading, where firms trade assets in a way that is correlated across assets, but for reasons unrelated to the asset's fundamental value. Our measure of outside selling pressure, when combined with our demanding set of controls and fixed effects, removes variation related to fundamentals trading. It also removes pure noise trading: sales of an asset that are completely random will not be correlated with trading in other assets,[17] and thus will not show up in our pressure measure. The variation that's left is from correlated, non-fundamental trading.

What drives this correlated, non-fundamental trading? Fire sales are perhaps the clearest example of how correlated trading of assets arises, in that because a firm faces binding constraints or distress, they sell a host of assets, such that $z_{i,t}$ becomes 'large'. There are, however, other sources of correlated trading. For example, suppose a trader wishes to shrink its inventory to decrease its leverage: this would lead to correlated selling of assets. Similarly,

[17]This includes trading that relates to individual bonds being downgraded, which has been used in the literature to identify non-fundamental selling (Ellul et al., 2011).

suppose a trader anticipates future financial volatility and wishes to increase its cash buffers: this too could lead it to sell a number of assets simultaneously. In practice, our selling pressure measure likely captures a combination of each of these types of variation.

The balance between fire sales and other correlated sales is likely to vary across different types of firm. There is a large literature documenting the tendency of firms like mutual funds to engage in fire sales: they face outflows and are forced to sell assets quickly as a result (Coval and Stafford, 2007). These types of mechanisms have been documented in our sample period for corporate bonds (Ma et al., 2022). The fact our pressure measure for funds is positively correlated with fund-flow based measures of pressure (Table 4) suggests they are picking up some common variation. There is also evidence of other types of firms engaging in fire sales in recent years, such as UK liability-driven investors during the 2022 gilt crisis (Pinter, 2023).

Hedge funds have also been documented fire selling in various recent episodes. Ben-David et al. (2012) find evidence of forced sales of stocks by hedge funds in the global financial crisis. Barth and Kahn (2021), Schrimpf et al. (2020) and Kruttli et al. (2023) show that hedge funds using relative value basis trade strategies were forced to sell US Treasuries during the 'dash for cash' in March 2020. Our instrumental variables approach, will capture the effects of such fire sales, along with other correlated, non-fundamental selling that hedge funds undertake in our sample period.

Dealers, however, are not typically thought of as being prone to fire sales, at least in our sample period. They were typically well capitalised and had significant liquidity buffers (International Monetary Fund, 2020), so were not facing the distress associated with fire sales. For these firms, the sales more likely represent non-fundamental trading that would not be considered fire sales, for instance sales related to inventory management or to other costs linked to their market making role. This is consistent with evidence in the literature on how dealers behaved in our sample period. For example, in the US corporate bond market at the height of the Covid-19 crisis dealers sold assets and shrank their inventories (O'Hara and Zhou, 2021), and prices fell and liquidity conditions deteriorated (Kargar et al., 2021). Similarly, dealer constraints played a role in driving deteriorating liquidity conditions in US Treasury markets in the same period (Duffie, 2020; He et al., 2022). Similar dynamics can be seen in non-stressed periods. For example, Pinter et al. (2022) find that dealers sell government bonds to clients before monetary policy announcements, and interpret this as stemming from balance sheet constraints limiting their risk-bearing capacity.

5.2 Why does it matter who sells a bond?

Our key result is that a sale of an asset can have a very different impact on the asset's price depending on who is selling it. Why? We offer two explanations: the first relates to how informed different types of trader are thought to be, and the second relates to the roles certain types of trader have as liquidity suppliers and arbitrageurs in markets.

The key innovation of our instrumental variables approach is that it identifies selling that we, the econometrician, know to be unrelated to the asset's fundamentals. However, the counterparties to this selling – and the market as a whole – do not know this. Indeed, sellers of an asset would always like to convince their counterparty the sales are non-fundamental, as this would enable them to sell at a better price. The counterparty is then faced with an inference problem, where they must establish the extent to which this sale – which we know to be non-fundamental but they do not – reveals some private information.

In principle, a sale could reveal two types of information (Farboodi and Veldkamp, 2020). The first is information about the fundamental value of the asset – the classic asymmetric information setup in Kyle (1985). The second is information about future trading in the asset: does this agent selling the asset signal there will be further sales of the asset in the future, either by this agent or other market participants?

Our results are consistent with both these stories. Dealers have many informational advantages over other investors. They may have direct lending relationships with the issuers of the bonds they are trading, from which they can gather information about their probability of default. They may also have been involved in underwriting the initial issuance of the bond in question. As shown by Goldstein et al. (2021), underwriters benefits from the informational advantage gained during the bookbuilding process which extends to secondary markets. Dealers also get to observe a large portion of the order flow for the bonds in which they trade, given much of the trading occurs via them. This has been shown to give dealers an informational advantage over other traders in opaque over-the-counter markets (Bessembinder et al., 2006; Kondor and Pinter, 2022; Pagano and Röell, 1996). This is particularly important for the OTC bond markets we consider where transactions are not publicly reported.[18]

As a result of these informational advantages, when another trader observes a sale by a dealer, it is reasonable for them to conjecture that this potentially encodes significant

[18] We note that this is different from the US markets where transactions are publicly reported in TRACE. For more details and a comparison on trade reporting in the US and the UK we refer to Ivanov et al. (2020).

information both about the fundamentals of the asset and the future trading in that asset, and to demand a discount as a result.

Similarly, hedge funds are typically considered to be informed traders. Indeed, Czech et al. (2021b) show that hedge funds trade in a manner that suggests informational advantages regarding future trading flows and bond fundamentals. In a sense, our result for hedge funds is an implication of this informational advantage: a trader who has read Czech et al. (2021b) should demand a higher discount to buy from a hedge fund than a less informed trader.

An alternative explanation for the large price impacts of dealers' and hedge funds' sales comes from the roles they typically play in markets. Dealers are traditionally market makers, seeking to link buyers of assets with sellers of assets, and 'leaning against the wind' when other sectors sell assets (Weill, 2007). Hedge funds are traditionally arbitrageurs in markets, seeking to exploit mispricing of securities and seeking to profit when other firms are forced to sell assets (Jylhä et al., 2014). Each of these roles entails supplying liquidity, and buying assets (at a discount) when other traders want to sell. Our results suggest that the largest price impacts of sales are when these liquidity suppliers change role and demand liquidity. Given the other types of trader are less able or inclined to make markets or absorb sales, the price discounts necessary for them to do so are greater. This is consistent with the model of Shleifer and Vishny (1992), where sales trigger price falls if 'specialists' are unable to buy assets and 'non-specialists' are forced to do so instead.

6 Conclusion

We have combined granular data on all firms' trading activity in corporate and government bonds with a new strategy for identifying non-fundamental sales to study how bond sales impact prices. We have shown that sales have significant impacts on bond prices, that are greater in less liquid markets and during stressed periods, and dissipate through time. This is consistent with the intuition behind how markets should react to non-fundamental sales.

Most strikingly, we have shown that the price impact of an asset sale depends critically on the type of institution selling. Dealers' sales have the largest price impacts, with hedge funds the second largest. Mutual funds' sales have been the subject of much interest in academia and policy, but appear to have smaller impacts on price. All else equal, our results suggest more attention should be devoted to risks stemming from the sales of these impactful sellers.

Our results show that the impact of an institution selling a given amount of an asset varies according to the type of institution that is selling. It does not address the *propensity* of different institutions to engage in selling. It is the combination of these two factors – the propensity to sell and the impact of selling – that governs how much different types of institution can affect asset prices, and how much scrutiny they should receive from policymakers monitoring risks from fire sales. We believe that the interaction between these two factors – the propensity to sell and the impact of selling – is worthy of further investigation, but we leave this to future work.

Our method can be applied to transaction-level data on any OTC market where traders have identifiers – even in anonymised. As a result, we hope this work can be of use to researchers looking to quantify the price impacts of asset sales, either as an end in itself or as an input into quantitative models of asset sales and their impacts on price.

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Figures

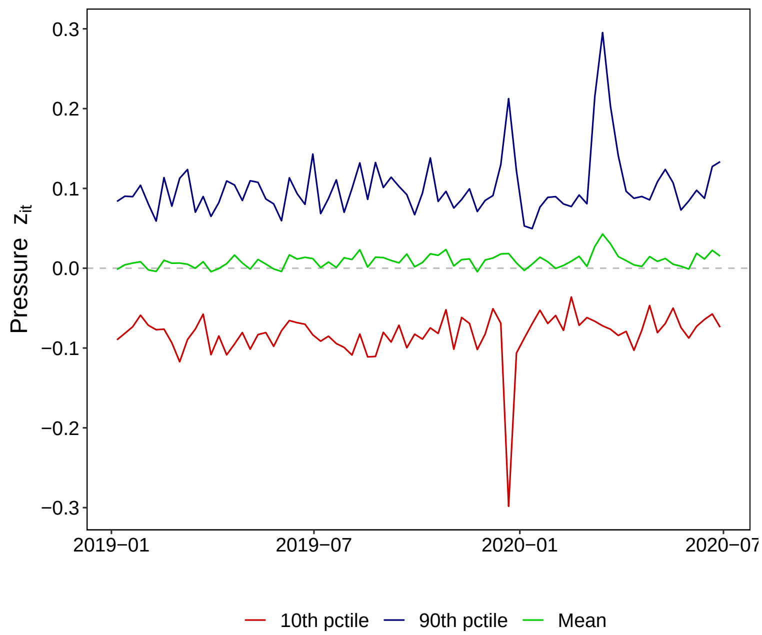

Figure 1: Outside selling pressure through time

Note: This figure summarises the distribution of outside selling pressure $z_{i,t}$ through time. For each week we compute the mean, 10^{th} and 90^{th} percentiles of $z_{i,t}$ across bonds, where $z_{i,t}$ is computed across all traders. We then plot these series through time.

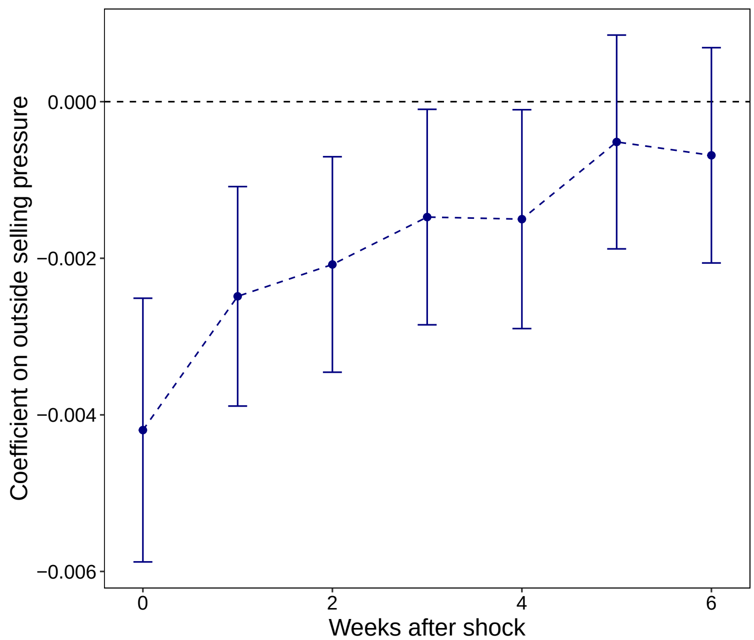

Figure 2: Price impacts through time

Note: This figure shows the duration of the price effects of outside selling pressure $z_{i,t}$. In particular we run regressions as set out in 4, where we related price at time $t + \tau$ to pressure and controls at time t. The x-axis plots τ and the y-axis plots the coefficient estimate δ. To ensure we have a consistent sample of bonds and weeks for these regressions, we only include bonds that are traded on (at least) 7 consecutive weeks. As a result the coefficient for $\tau = 0$ need not match the coefficient in Table 5.

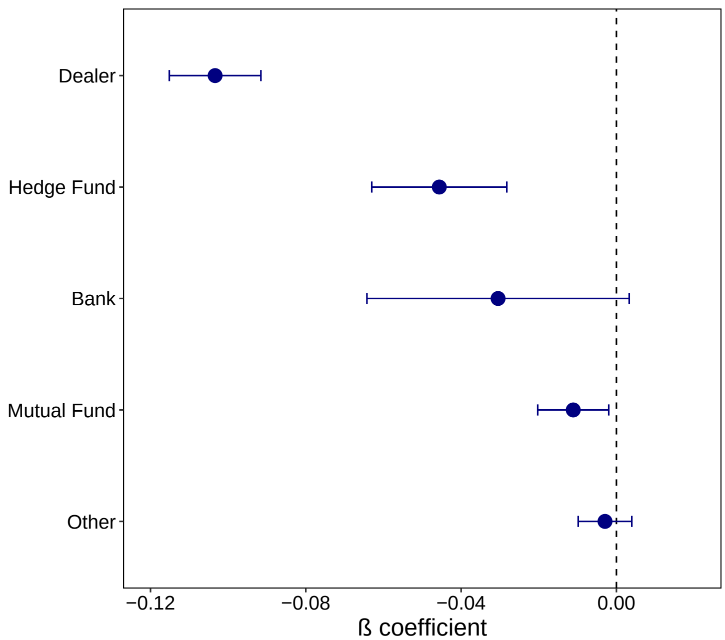

Figure 3: Price impact by sector

Note: This figure shows the price impact of sales by different types of investor. The x-axis shows the estimated coefficient β in equation 2, and can be interpreted as the marginal effect of increasing the sales of asset i by a given sector on the asset's price. Prices are expressed as a percentage of par. Sales are net sales by investors of a given type as a percentage of average trading volume in the instrument. Controls include issuer-time and instrument fixed effects as well as the time since a bond was issued.

Tables

Table 1: Summary Statistics

	Share	Trade Share
PANEL A: BONDS		
Type		
Corporate	85	44
Government	15	56
Currency		
GBP	7	11
EUR	26	44
USD	47	39
Other	20	6
Maturity		
0-5 years	45	21
6-10 years	37	44
11-20 years	7	12
21+ years	11	24
PANEL B: TRADERS		
Sector		
Fund	44	15
Bank	11	14
Dealer	3	51
Hedge Fund	6	2
Other	37	18

Note: This table summarises the instruments traded and the types of traders in the dataset. The first numeric column shows raw shares, for example the percentage of bonds that are corporate vs. government, or the percentage of traders that are asset managers. The second numeric column shows the percentage of total trades accounted for by each bond and trader type. 'Other' traders include pensions funds, liability-driven investment funds, central counterparties, principal trading firms, brokerage firms, and sovereign wealth funds, among other firm types.

Table 2: Instruments & Traders per week

	Number
Instruments	23,588
Traders	2,922
Instruments per Trader	78
Traders per Instrument	10

Note: This table summarises the number of traders and instruments traded per week. Each statistic in the table is calculated for reach week, including only instruments and traders that traded at least once in that week, and excluding traders with missing trader IDs. The table shows averages of the statistics across the weeks in the sample.

Table 3: Returns, Sales & Pressure

	Mean	Std. dev.	95^{th} - 5^{th} pctile
Prices $p_{i,t}$	99.82	4.86	5.65
Sales $s_{i,t}^{V}$	0.36	67.73	144.06
Pressure $z_{i,t}$	0.02	0.22	0.68

Note: This table summarises the distributions of asset prices, sales, and selling pressure. Prices $p_{i,t}$ are expressed as a percentage of par. Sales $s_{i,t}^{V}$ are net sales as a percentage of average trading volume in the instrument. Pressure $z_{i,t}$ is defined in equation 1, and takes values between -1 and 1. The distributions of prices are within-bond distributions. For example, to compute the standard deviation of prices we first compute the standard deviation of weekly prices for each bond i, and then take the average of this across bonds.

Table 4: Outside selling pressure and fund-flow-based measures

	Fund outside selling pressure $z^F_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Coval-Stafford	0.049***			0.007***		
	(0.001)			(0.002)		
Wardlaw F2V		0.018***			0.0002	
		(0.0005)			(0.0007)	
Wardlaw F2S			0.019***			0.003***
			(0.0005)			(0.0008)
R^2	0.005	0.002	0.002	0.38	0.30	0.30
Observations	335,335	830,292	830,292	335,335	830,292	830,292
Issuer-Week fixed effects	No	No	No	Yes	Yes	Yes
Instrument fixed effects	No	No	No	Yes	Yes	Yes

Note: This table summarises the positive correlation between outside selling pressure – computed solely for funds – and various measures of selling pressure induced by mutual fund flows defined in the literature. The Coval-Stafford measure is the measure introduced by Coval and Stafford (2007). The two Wardlaw measures are introduced by Wardlaw (2020), with F2V denoting his flow-to-volume measure and F2S denoting his flow-to-stock measure. We multiply each measure by -1 such that a large positive number entails positive selling pressure. For each week, we then take the percentile rank of each measure, such that each week our regressors are distributed between 0 and 1. For further details on the pressure measures see the appendix.

Table 5: Price changes and selling pressure

	Price (%)
	(1)
Pressure $z_{i,t}$	-0.3727***
	(0.0506)
R^2	0.89582
Observations	1,514,387
Issuer-Week fixed effects	Yes
Instrument fixed effects	Yes

Note: This table shows the results of our reduced-form regression of prices on selling pressure and controls, where pressure is computed for all types of investor. Time since issuance is included as an additional control.

Table 6: Heterogeneity: bond type and stressed periods

	Price (%)			
	Corporate	Government	March 2020	Rest of sample
	(1)	(2)	(3)	(4)
Pressure $z_{i,t}$	-0.468***	-0.102	-0.593***	-0.402***
	(0.055)	(0.114)	(0.176)	(0.052)
R^2	0.89	0.90	0.97	0.90
Observations	1,193,684	320,703	80,541	1,433,846
Issuer-Week fixed effects	Yes	Yes	Yes	Yes
Instrument fixed effects	Yes	Yes	Yes	Yes

Note: This tables summarises how the price impacts of selling pressure vary according to the type of bond and the state of the economy. The first column runs our reduced-form regression only for corporate bonds, and the second column includes only government bonds. The third column runs the regression only for March 2020, a time of great financial stress, and the fourth runs the regression for all periods except March 2020. Time since issuance is included as an additional control.

Table 7: Sector sales & pressure

Sector	Mean	Std dev	95^{th} - 5^{th} pctile
Sales $s^V_{i,t}$			
Bank	-0.6	46.0	66.5
Dealer	-0.5	68.7	149.8
Fund	0.5	48.3	78.4
Hedge fund	0.1	14.4	3.5
Other	0.3	42.6	52.4
Pressure $z_{i,t}$			
Bank	-0.01	0.14	0.40
Dealer	0.00	0.07	0.12
Fund	0.01	0.16	0.40
Hedge fund	0.00	0.07	0.00
Other	0.01	0.16	0.32

Note: This table summarises the distributions of sales and selling pressure by investor type. Sales $s^V_{i,t}$ are net sales by investors of a given type as a percentage of average trading volume in the instrument. Pressure $z_{i,t}$ is defined in equation 1 as the net selling of bonds other than i by investors of a given type, and takes values between -1 and 1.

A Appendix

A.1 Additional Results

In this section we include analysis supporting our main findings on price impacts by sector, given in section 4.2. Table A1 shows the full results of the regressions underlying Figure 3, which are two-stage least squares regressions of prices on sector-level sales and controls, where we instrument for sales using outside selling pressure. The most impactful sales are by dealers, followed by hedge funds, followed by banks.

Table A2 summarises the results of the first stages of these regressions. The first stages for dealers and hedge funds are particularly strong, and are moderately strong for banks and funds. The first stage for other traders is weak.

Table A3 shows the results of reduced-form regressions of price directly on sector-level outside selling pressure. These reduced-form results can be rationalised with the two-stage least squares results as follows: dealer selling pressure is associated with around a 25 times greater price effect than fund pressure (Tabel A3). Dealer selling pressure is also associated with greater asset sales than fund pressure, though this difference is smaller than the price effects (Table A2). Together these are consistent with the greater price impact per unit sold for dealers than funds found using our two-stage least squares regressions (Table A1).

A.2 Mutual fund selling pressure

We use our data on mutual fund holdings to construct three measures of fire-selling pressure induced by fund flows that are commonly used in the literature, introduced by Coval and Stafford (2007) and Wardlaw (2020). Each of these approaches results in an instrument-level measure of selling pressure, which we then compare to our instrument-level pressure measure based only on transactions data. As Table A4 shows, on average funds in our fund holdings data hold between one-third and one-half of the instruments observed in our transactions data, though they hold only a small percentage of the total amount issued.

A.2.1 Coval and Stafford (2007) selling pressure measure

Coval and Stafford (2007) develop a selling pressure measure using data on mutual fund holdings. For a given instrument the measure is defined as the difference between total purchases of that instrument by mutual funds that experience extreme inflows and total sales of that instrument by mutual funds that experience extreme outflows, normalised by lagged trading volume. Sales and purchases are evaluated using changes in holdings between two consecutive time periods. Extreme outflows and inflows are defined as those below the 10^{th} percentile and above the 90^{th} percentile of the distribution of flows, respectively.

We evaluate the pressure measure developed by Coval and Stafford (2007) at weekly frequency using weekly data on mutual fund total net assets (TNA) and quarterly data on mutual fund holdings. Specifically, for a given bond i and week t we evaluate:

$$Press_{it}^{CS} = \frac{\sum_j \big(\max(0, purchases_{jit})|f_{jt} > 90^{th} \text{ pctile}\big) - \max(0, -sales_{jit})|f_{jt} < 10^{th} \text{ pctile}\big)}{AvgVol_{iq_t}},$$

where $f_{jt} = F_{jt}/TNA_{jt-1}$ are mutual fund j's weekly flows as a percentage of lagged total net assets; weekly purchases and sales of bond i by mutual fund j are evaluated from weekly data on TNAs and quarterly portfolio weights w_{jiq_t} as follows:[19]

$$sales_{ijt}^{(1)} = \Delta TNA_{jt} w_{jiq_t} \quad \text{when } \Delta TNA_{jt} = TNA_{jt} - TNA_{jt-1} < 0, \tag{5}$$
$$purchases_{ijt}^{(1)} = \Delta TNA_{jt} w_{jiq_t} \quad \text{when } \Delta TNA_{jt} = TNA_{jt} - TNA_{jt-1} > 0; \tag{6}$$

w_{jiq_t} are portfolio weights as in the previous quarter of any time t; and $AvgVol_{iq_t}$ is the average weekly volume traded in the previous quarter estimated using transaction level data. As in Coval and Stafford (2007) we assume that there should be at least 10 mutual funds that hold a given bond i.

When identifying mutual funds with extreme inflows and outflows we treat each fund separately—namely, funds with extreme inflows and outflows are determined relative the 10^{th} and 90^{th} of the distribution of their own flows in the sample period, and not those of the whole population of funds.

Following Coval and Stafford (2007) bonds with fire sales are those with $Pressure_{it}^{CS}$ in the lowest decile of its distribution across bonds and time periods.

[19]Following Coval and Stafford (2007) Equation 5 and Equation 6 are derived as weekly changes in asset holdings assuming that weekly portfolio weights are constant in a given quarter, and equal to those at the end of the previous quarter. Therefore we are not including discretionary sales or purchases.

A.2.2 Wardlaw (2020) selling pressure measures

Wardlaw (2020) shows that the measure introduced by Edmans et al. (2012) might include a monotonically increasing function of asset returns when the variables used to evaluate it—the amount held in the portfolio and volumes—are marked to market. He suggests two alternative measures that measure holdings and volumes in nominal terms. We follow his approach and evaluate the two alternative measures he proposes as follows:

1. The *flow-to-stock* measure:

$$Press_{it}^{F2S} = \sum_j \frac{F_{jt} shares_{ijq_t}}{TNA_{jt-1} OutShare_{it}} = \sum_j \frac{f_{jt} shares_{ijq_t}}{OutShare_{it}}, \tag{7}$$

   where $OutShare_{it}$ is the amount outstanding of bond i at time t, and $shares_{ijq_t}$ are the portfolio weights as in the previous quarter q_t.[20]

2. The *flow-to-volume* measure

$$Press_{it}^{F2V} = \sum_j \frac{F_{jt} shares_{ijq_t}}{TNA_{jt-1} VolShare_{it}} = \sum_j \frac{f_{jt} shares_{ijq_t}}{VolShare_{it}}, \tag{8}$$

   where again $shares_{ijq_t}$ are the portfolio weights as in the previous quarter q_t and $VolShare_{it}$ is the total volume of bond i traded expressed in units terms. Namely, we can evaluate it from our transaction level data by dividing the traded volume expressed in monetary units by the par value of bond i.

In both Equation 7 and Equation 8 only mutual funds in distress carrying out fire sales are included in the summation. Similarly to Coval and Stafford (2007) we identify mutual funds doing fire sales as those experiencing extreme outflows—namely, with outflows below the 10$^{\text{th}}$ percentile of their distribution.

[20] In the original definition of Wardlaw (2020) $shares_{ijq_t}$ are defined to be linked to the quarterly portfolio weights $w^*_{ijq_t}$ and quarterly prices PRC_{iq_t} by the following equation: $w^*_{ijq_t} TNA_{jq_t} = shares_{ijq_t} PRC_{iq_t}$.

Appendix Figures & Tables

Table A1: Prices & sector-level sales: two-stage least squares results

	Price (%)				
	(1)	(2)	(3)	(4)	(5)
Dealer sales	-0.1034***				
	(0.0071)				
Bank sales		-0.0305			
		(0.0194)			
Fund sales			-0.0111**		
			(0.0053)		
Hedge fund sales				-0.0456***	
				(0.0105)	
Other sales					-0.0029
					(0.0039)
R^2	0.68722	0.88544	0.89221	0.89152	0.89323
Observations	1,591,470	1,591,470	1,591,470	1,591,470	1,591,470
Issuer-Week fixed effects	Yes	Yes	Yes	Yes	Yes
Instrument fixed effects	Yes	Yes	Yes	Yes	Yes

Note: This table shows the results of two-stage least squares regressions of prices on sales by different investors and controls. The coefficient estimates show the estimated coefficient β in equation 2, and can be interpreted as the marginal effect of increasing the sales of asset i by a given sector on the asset's price. Prices are expressed as a percentage of par. Sales are net sales by investors of a given type as a percentage of average trading volume in the instrument. Time since issuance is included as an additional control.

Table A2: First stage summary: sales & pressure

Sector	Coeff. on $z_{i,t}$	t-stat	R-squared	F-stat
Dealer	22.7	21.1	0.25	1,125.7
Hedge fund	6.6	40.8	0.27	35.0
Bank	1.9	6.8	0.28	4.4
Fund	6.2	23.3	0.29	7.5
Other	8.0	34.8	0.28	0.9

Notes: This table summarises the first stage of the two-stage least squares regressions in equation 2. The first column shows the estimated coefficient on the pressure in a regression of sector-level sales on sector-level pressure and fixed effects, where the sector is given by the row. The 2nd shows the t-statistic. The 3rd shows the R-squared on this regression, and the final column reports the F-statistics for these first-stage regressions.

Table A3: Prices and selling pressure

	Price (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Dealer pressure	-2.147***					-2.147***
	(0.1050)					(0.1050)
Bank pressure		-0.0615*				-0.0579*
		(0.0349)				(0.0349)
Fund pressure			-0.0889***			-0.0861***
			(0.0326)			(0.0326)
Hedge fund pressure				-0.3509***		-0.3496***
				(0.0674)		(0.0674)
Other pressure					-0.0647**	-0.0625**
					(0.0314)	(0.0314)
R^2	0.88798	0.88791	0.88791	0.88791	0.88791	0.88798
Observations	1,864,873	1,864,873	1,864,873	1,864,873	1,864,873	1,864,873
Issuer-Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Instrument fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table summarises the results of reduced-form regressions of prices on sector-level pressure and controls. The coefficient estimates show the estimated coefficients $\delta_{\mathcal{J}}$ shown in equation 3, and can be interpreted as the marginal effect of increasing the selling pressure in asset i for a given sector on the asset's price. Prices are expressed as a percentage of par. Time since issuance is included as an additional control.

Table A4: Funds Data Coverage

	Percentage of instruments held by mutual funds	Percentage of issuance held by mutual funds
2019 Q3	50.1	1.3
2019 Q4	52.1	1.3
2020 Q1	37.8	0.5
2020 Q2	48.0	0.6

Notes: Table shows the percentage of bonds traded in our transactions data held by funds in our mutual fund data. For each quarter-end we compute the number of bonds in our transactions data that are in issue at that time, and the aggregate amount issued of these bonds. We then compute the percentage of these bonds that are recorded as held by mutual funds in our mutual fund holdings data, and the aggregate holdings of these bonds by mutual funds as a percentage of the amount issued.