Corporate Bond Liquidity During the COVID-19 Crisis[*]

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Abstract

We study liquidity conditions in the corporate bond market during the COVID-19 pandemic, and the effects of the unprecedented interventions by the Federal Reserve. We find that, at the height of the crisis, liquidity conditions deteriorated substantially, as dealers appeared unwilling to absorb corporate debt onto their balance sheets. In particular, we document that the cost of risky-principal trades increased by a factor of five, forcing traders to shift to slower, agency trades. The announcements of the Federal Reserve's interventions coincided with substantial improvements in trading conditions: dealers began to "lean against the wind" and bid-ask spreads declined. To study the causal impact of the interventions on market liquidity, we exploit eligibility requirements for bonds to be purchased through the Fed's corporate credit facilities. We find that, immediately after the facilities were announced, trading costs for eligible bonds improved significantly while those for ineligible bonds did not. Later, when the facilities were expanded, liquidity conditions improved for a wide range of bonds. We develop a simple theoretical framework to interpret our findings, and to estimate how the COVID-19 shock and subsequent interventions affected consumer surplus and dealer profits.

KEYWORDS: Corporate bonds, liquidity, intermediation, SMCCF, COVID-19

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1 Introduction

The COVID-19 pandemic has wrought havoc on the global economy. To cope with this unprecedented economic shock, many large US corporations turned to the $10 trillion corporate bond market. However, with the prospect of downgrades and possible defaults, along with widespread outflows from corporate bond funds, reports of illiquidity began to surface: in mid-March, 2020, former Federal Reserve chairs Bernanke and Yellen described the corporate bond market as "under significant stress" (Bernanke and Yellen, 2020), while a report from Bank of America deemed the market "basically broken" (Idzelis, 2020). In response, the Federal Reserve introduced several facilities designed to bolster liquidity and reduce the costs and risks of intermediating corporate debt, including the Primary Dealer Credit Facility (PDCF) and the Primary and Secondary Market Corporate Credit Facilities (PMCCF and SMCCF, respectively). The latter two facilities represented a particularly bold intervention, in that they allowed the Fed, for the first time, to make outright purchases of investment-grade corporate bonds issued by US companies, along with exchange-traded funds (ETFs) that invested in similar assets.

The purpose of this paper is to study trading conditions in the US corporate bond market in response to the large economic shock induced by the COVID-19 pandemic, as well as the unprecedented interventions that followed. Given the nature of the shock, set against the backdrop of a well-capitalized financial sector, this episode offers a unique opportunity to study how dealers respond to a massive, exogenous surge in selling pressure, and the subsequent implications for transaction costs, liquidity, consumer surplus, and dealer profits.

In assessing market conditions during this tumultuous period, we find that it is important to consider both the *cost* and the *quality* of intermediation services being provided. More specifically, we distinguish between two types of transactions offered by dealers: "risky-principal" trades, in which a dealer offers a customer-seller immediacy by purchasing the asset directly and storing it on his balance sheet until finding a customer-buyer; and "agency" trades, in which the customer-seller retains the asset while waiting for a dealer to find a customer-buyer to take the other side of the trade. We think of the former as a higher quality transaction service, since the customer is able to sell immediately, and the latter as lower quality since the customer has to wait. Importantly, this distinction not only offers a more complete assessment of market liquidity—one that incorporates both the cost of trading and the time it takes to trade—but it also offers a window into the frictions that can generate illiquidity during periods of high selling pressure, and the channels through which interventions can ease these frictions. In particular, our analysis suggests that, at the height of the COVID-19 panic, dealers were reluctant to absorb inventory onto their balance sheets via risky-principal trades, and this was a key factor in the dissolution of market liquidity. As dealers shied away from traditional market-making activity, we find that the Federal Reserve's decision to intervene as a "market-maker of last resort" played a significant role in reducing transaction costs and increasing the quality of intermediation services.

While the main contribution of our analysis is empirical, we start, in Section 3, by developing a simple theoretical framework that guides our exploration of the data. More specifically, we consider a model in which customers with fixed-size demand purchase transaction services from dealers. These transaction services come in two varieties: low-quality, meant to capture agency trades; and high-quality, meant to capture risky-principal trades. Customers prefer high-quality transaction services, but they are more costly for dealers to produce. Within this framework, we derive a number of testable predictions regarding the impact of a surge in demand for transaction services—as experienced during the COVID-induced crisis—on the equilibrium prices and quantities of low- and high-quality trades. In particular, in response to an increase in demand, the model predicts that the price of all transaction services will rise, but that the price of high-quality, risky-principal trades will increase more than the price of lower-quality, agency trades. As a result, in equilibrium customers will shift their consumption bundle from the former to the latter.

With these predictions in mind, in Section 4 we turn to our empirical analysis of trading conditions in the corporate bond market in response to the panic of mid-March and the Fed's interventions that followed. As a first step, using data from the Trade Reporting Compliance Engine (TRACE), we construct time series to measure the costs of risky-principal and agency trades in the corporate bond market.[1] As the theory predicts, we find that the cost of risky-principal trades increased significantly during the COVID-induced panic, reaching a peak of more than 200 basis points (bps), while the cost of agency trades increased much more modestly. Hence, when selling pressure surged, it appears that dealers were highly reluctant to absorb inventory onto their own balance sheet, or to "lean against the wind" (Weill, 2007).

As the premium paid for risky-principal trades increased, we document that the fraction of total volume executed as agency trades increased by as much as 15% at the height of the sell-off. This implies that the average trade was not only more expensive, but also more likely to be slower, hence of lower quality. Taken together, these results highlight the importance of studying both the cost and quality of intermediation services: simply measuring the behavior of average transaction costs during this period would underestimate the deterioration in market liquidity. We return to this point later when we use our theoretical framework to quantify the impact of shocks on consumer surplus.

As trading shifted from risky-principal to agency transactions, we show that, somewhat astonishingly, the dealer sector as a whole absorbed *no* inventory, on net, during the most tumultuous period of trading. Hence, when the demand for transaction services surged, it was customers themselves that ultimately stepped up to provide additional liquidity. In fact, it was only after the

[1]The TRACE data is made available by the Financial Industry Regulation Authority (FINRA).

announcement of the Federal Reserve's interventions that dealers began to absorb inventory onto their balance sheets, and trading conditions started to improve. Indeed, after the announcement of the Fed's credit facilities, the quantity of corporate debt held by dealers more than doubled, relative to pre-COVID levels. At the same time, the cost of risky-principal trades decreased significantly, to approximately double the levels observed before the pandemic.

While these observations establish the coincidence of key interventions and improvements in market liquidity, they do not establish a causal relationship. To further explore the effect of interventions on market liquidity, we exploit restrictions on the types of bonds that could be purchased through the Fed's corporate credit facilities. In particular, using a standard difference-in-differences approach, we use restrictions on bond ratings and time-to-maturity to identify the change in trading cost induced by the announcement of the SMCCF. We find that, immediately after the announcement of the SMCCF, the cost of trading bonds that were eligible for purchase by the Fed decreased substantially, while the cost of trading ineligible bonds was essentially unchanged. For example, our results suggest that the initial announcement of the SMCCF reduced the cost of risky-principal trades for eligible bonds by approximately 50 bps. Later, when the program was expanded in both size and scope, we show that the trading costs of all bonds fell. Hence, our results suggest that the initial announcement induced dealers to purchase eligible bonds at a lower cost, while the expansion of the corporate credit facility appears to have relaxed balance sheet constraints more generally, making dealers less reluctant to purchase any bond.

Finally, in Section 5, we combine derivations from our parsimonious theoretical framework with the empirical results described above to assess consumer surplus and dealer profits during the March panic and the recovery that followed. To the best of our knowledge, despite the explosion of research on financial markets during the COVID-19 crisis, this is the first attempt to quantify the impact of these events on the payoffs of consumers and dealers.

Again, we find that considering both the cost and the quality of trades—i.e., the distinction between risky-principal and agency trades—reveals new insights. On the consumer side, our estimates suggest that the large drop in consumer surplus early in the crisis was largely due to increased transaction costs. However, as the crisis evolved and consumers shifted towards low-quality agency trades, we find that increased transaction costs only account for about half of the loss in consumer surplus; the remaining decline in consumer surplus can be attributed to lower quality, slower trades. This exercise highlights the value of interpreting our empirical results through the lens of a model, in that we are able to quantify the extent to which studying average transaction costs alone would lead one to underestimate the impact of the COVID-19 pandemic on consumers.

On the dealer side, our estimates suggest that profits spiked during the height of the crisis, reflecting the large increase in transaction costs (i.e., bid-ask spreads). However, despite transaction costs (and thus revenue) remaining elevated throughout the recovery, our estimates suggest that profits returned to pre-crisis levels, as dealers' cost of providing more intermediation services remained elevated as well. We also study how our results would change if the large increase in the price of transaction services was driven by a supply shock, such as a rise in dealers' funding costs, instead of a surge in demand. Under this scenario, the model infers that profits increased less during the height of the panic, relative to the demand-driven benchmark, but remained elevated during the recovery stage. Intuitively, the model now rationalizes the observed decline in post-intervention trading costs as a positive supply shock, which increases dealers' profits.

1.1 Related literature

Given the size of the COVID-19 shock, and the historic nature of the Federal Reserve's response, it is not surprising that a number of recent papers have emerged to study financial market activity since the onset of the pandemic. Our paper belongs to the literature focused on the corporate bond market, which we discuss in greater detail below, but shares much in common with studies of other markets, including the market for Treasuries and other government debt (Duffie, 2020; He, Nagel, and Song, 2020; Fleming and Ruela, 2020; Schrimpf, Shin, and Sushko, 2020), as well as the market for asset-backed securities (Foley-Fisher, Gorton, and Verani, 2020; Chen, Liu, Sarkar, and Song, 2020). For example, like our analysis, He, Nagel, and Song (2020) emphasize the importance of dealers' balance sheet constraints on their willingness to absorb selling pressure, and the subsequent effects on prices and trading activity.

In the corporate bond market, Falato, Goldstein, and Hortaçsu (2020) focus on the effects of the pandemic on outflows from bond mutual funds, and the role that the Fed's corporate credit facilities played in reversing these outflows. Ma, Xiao, and Zeng (2020) also explore outflows in fixed-income mutual funds, including those that invest in corporate bonds and Treasuries. They derive a pecking order theory of liquidation, which helps to explain why selling pressure was strongest in the most liquid sectors of these markets. More closely related to our paper is work by Haddad, Moreira, and Muir (2020), Nozawa and Qiu (2020), and D'Amico, Kurakula, and Lee (2020), who focus primarily on the behavior of credit spreads throughout the crisis, and attempt to identify the mechanism through which the Fed's interventions appear to have improved market conditions.

However, our paper is most closely related to contemporaneous work by O'Hara and Zhou (2020) and Boyarchenko, Kovner, and Shachar (2020), who also investigate liquidity conditions in the corporate bond market during the COVID-19 crisis, and the effects of the Fed's interventions. Despite some overlap, the three papers differ (and complement one another) in several important ways. For example, using the regulatory version of TRACE with dealer identities, O'Hara and Zhou (2020) document the heterogeneous response of different dealers to the Fed's interventions.

This allows them to control for dealer fixed effects, and to distentangle the effects of the PDCF and the SMCCF, among other things. Boyarchenko, Kovner, and Shachar (2020) also use the regulatory version of TRACE, along with data on the volume of bonds (or shares of ETFs) purchased by the Fed's corporate credit facilities. This allows them to decompose the effects of the Fed's interventions into direct "purchase effects" and indirect "announcement effects."

While our paper makes a number of distinct contributions relative to these contemporaneous studies, we highlight two aspects of our methodology that are particularly important. First, our approach to measuring trading conditions takes into account that there are multiple channels through which market liquidity can deteriorate: customers can face higher transaction costs or longer waiting times for executing a trade. Hence, by measuring the cost and the frequency of risky-principal and agency trades separately, our analysis provides a multi-dimensional assessment of market liquidity, and offers new insights into the frictions that dealers face and the effects of the Fed's interventions on dealers' behavior. Second, exploiting our empirical results in conjunction with our theoretical framework, we are able to construct quantitative estimates of the effects of the COVID-19 crisis (and ensuing interventions) on consumer surplus and profits. Crucially, this allows us to map easily quantifiable objects, such as trading costs and the fraction of risky-principal vs. agency trades, into the (harder to measure) objects of primary concern to policymakers—namely, the surplus of customers and the profits of dealers.

2 Background

The COVID-19 Shock. Despite reports of a potentially lethal virus spreading in China, US equity markets reached all-time highs on February 19, 2020. Just two weeks later, as the scope of the COVID-19 coronavirus and the duration of its effects became apparent, financial markets around the world entered a period of turmoil. For example, between March 5 and March 23, the S&P 500 fell more than 25%. In the corporate bond market, the ICE Bank of America AAA US Corporate Index Option-Adjusted spread increased by about 150 bps over this same period, while the corresponding spread for high-yield (HY) corporate debt increased by more than 500 bps.[2]

As the price of equities and debt plummeted, reports of illiquidity in key financial markets emerged.[3] Such reports were especially troubling in the corporate bond market, as many large US firms would almost surely need access to capital in light of the impending shocks to their balance

[2]See Ebsim, Faria-e Castro, and Kozlowski (2020) for a more comprehensive analysis of credit spreads during this time period.

[3]In fact, reports of trading difficulties even reached the market for Treasuries, in what one journalist described as a "stunning lack of liquidity in whats often billed as the worlds deepest and most liquid bond market." (Chappatta, 2020)

sheets. However, as investors pulled out of corporate bond funds in droves,[4] and selling pressure surged, market participants reported that dealers were unwilling to absorb corporate debt onto their balance sheet. In a *Wall Street Journal* article titled "The Day Coronavirus Nearly Broke the Financial Markets," Baer (2020) writes:

> [W]hen Mr. Rao called senior executives for an explanation on why [broker-dealers] wouldnt trade, they had the same refrain: There was no room to buy bonds and other assets and still remain in compliance with tougher guidelines imposed by regulators after the previous financial crisis [...] One senior bank executive leveled with him: We cant bid on anything that adds to the balance sheet right now."

Assessing Liquidity Conditions in the Corporate Bond Market. The sentiment expressed in the quote above was not an anomaly; even before the COVID-induced crisis, both market participants and academics alike had argued that dealers' balance sheet concerns posed a threat to market liquidity. According to this argument, the implementation of post-2008 banking regulations—including the Basel III capital requirements and the ban on proprietary trading codified in the Dodd-Frank Act—increased dealers' cost of holding inventory on their balance sheets, and hence made them less willing to provide liquidity directly to their customers, especially in times of stress.[5] These concerns seemed to be validated by the fact that the share of outstanding corporate bonds held by the dealer sector as a whole declined significantly in the post-2008 period, from approximately 3% to less than 1%.[6]

Yet, despite this evidence, detecting and measuring illiquidity in the corporate bond market proved to be a challenge, as common metrics that are easily available in equity markets, like bid-ask spreads, are difficult to construct for corporate debt. However, several recent studies have offered guidance on "where to look" for signs of illiquidity in this crucial market. In particular, these studies have highlighted the important distinction between risky-principal trades, in which dealers offer immediacy by using their own balance sheet space, and agency trades, in which dealers simply locate other customers to provide liquidity, usually at a delay. For example, Bao et al. (2018) document that dealer-banks subject to the Volcker rule shifted a considerable amount of trades from fast, risky-principal trades to slower, agency trades after the implementation of

[4] For example, according to Scaggs (2020), funds investing in investment-grade corporate bonds faced withdrawals of almost $100 billion alone in mid-March. In a more comprehensive analysis, Falato et al. (2020) report that, between the months of February and March, the average corporate bond fund experienced cumulative outflows of approximately 9% of net asset value, which constitutes by far the largest outflows in the last decade.

[5] See, e.g., Duffie (2012) and Thakor (2012) for discussions of how post-2008 financial regulation could hurt market liquidity. Bao, O'Hara, and Zhou (2018), Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), Dick-Nielsen and Rossi (2019), and Choi and Huh (2018) provide empirical evidence to support the erosion of liquidity, particularly during episodes of sudden, increased selling pressure.

[6] See Kargar, Lester, and Weill (2020), who document this fact using data from Table L.213 of the federal Reserve's Flow of Funds.

post-2008 banking regulations. Choi and Huh (2018), meanwhile, document that the cost of risky-principal trades increased substantially during this time period, while the cost of agency trades did not. Taken together, these observations suggest that conventional measures of trading costs provide an incomplete assessment of market liquidity; as the composition of trades shift from more expensive, faster risky-principal trades to less expensive, slower agency trades, average trading costs can appear essentially unchanged despite significant deterioration in the *time* it takes for customers to trade. This is why, as we explore the effects of the COVID-19 crisis, we are careful to distinguish between the price of these two different types of transaction services.

Federal Reserve Interventions. Given reports that dealers were unwilling to absorb assets onto their own balance sheet, the Federal Reserve introduced several new facilities designed to bolster liquidity and reduce trading costs. On the evening of March 17, the Federal Reserve introduced the aforementioned PDCF, offering collateralized overnight and term lending to primary dealers. By allowing dealers to borrow against a variety of assets on their balance sheets, including investment-grade corporate debt, this facility intended to reduce the costs associated with holding inventory and intermediating transactions between customers.[7]

On March 23, the Federal Reserve proposed even more direct interventions in the corporate bond market through the PMCCF and SMCCF. These facilities were designed to make outright purchases of corporate bonds issued by investment-grade US companies with remaining maturity of five years or less. The facilities were also allowed to purchase shares in US-listed exchange-traded funds (ETFs) that invested in US investment-grade corporate bonds. On April 9, these corporate credit facilities were expanded in size and extended to allow for purchases of ETFs that invested in high-yield corporate bonds.[8] Interestingly, though many of the effects of these corporate credit facilities were observed immediately after they were announced (and expanded), the Federal Reserve did not actually begin purchasing bonds until May 12. We provide a more detailed description of this timeline, and of the Federal Reserve's facilities, in Appendix C.

[7] In addition to the facilities that we highlight in our analysis here, it is also noteworthy that the Federal Reserve temporarily relaxed the supplementary leverage ratio (SLR) rule—first on April 1 and again on May 15, 2020—to ease balance sheet constraints and increase banks' ability to lend to households and businesses. By excluding US Treasury securities and reserves from the calculation of the SLR rule for holding companies, the rule change was primarily intended to increase liquidity in the Treasury market. However, to the extent that it relaxed dealers' balance sheet constraints, the effects could clearly extend to the corporate bond market as well, as we discuss later in the text. To read more about the rule change, see the April 1, 2020 and the May 15, 2020 press releases.

[8] The April 9 update also allowed the SMCCF to make direct purchases of bonds that had been downgraded from investment-grade to high-yield status (so-called "fallen angels") after March 22. The facility also allowed purchasing of high-yield ETFs.

3 A simple theoretical framework

In this section, we develop a parsimonious theoretical framework to study equilibrium prices and quantities for two distinct types of transaction services, meant to capture risky-principal and agency trades. To guide and interpret our exploration of the data, we use the model to analyze the effects of an exogenous shock to the aggregate demand for transaction services, which we think captures the key feature of the COVID-19 crisis in the corporate bond market, i.e., the surge in selling pressure. At this stage, we do not consider contemporaneous supply shocks to dealers' cost of providing transaction services; that is, we assume these costs derive from factors put in place before the COVID-19 crisis, such as banking regulations, and do not change significantly during the crisis itself.[9] Later, in Section 5, we also use our framework to offer empirical measures of consumers' surplus and the dealer sector's extra profits during the first two quarters of 2020, relative to an early January baseline. When we do so, we also extend our analysis to consider the effects of shocks to the supply of intermediation services.

3.1 The model

There are two types of agents: a measure N of customers and a measure one of dealers, all of whom are price takers. Each customer seeks to trade one share of an asset, and we do not distinguish between purchases and sales; this simplification allows us to study the determinants of transaction costs, though it is worth noting that our model is silent on the determinants of the asset's price. Since there are N customers with unit demand, the aggregate demand for transactions is exogenous and equal to N. However, while the total number of transactions is exogenous, the composition is not. Namely, we assume that customers demand vertically differentiated transaction services supplied by dealers at a convex cost: low-quality transaction services, interpreted as agency trades, and high-quality transaction services, interpreted as risky-principal trades.

Customers have quasi-linear utility for transaction services and for cash. Specifically, the problem of a customer is to choose how much low- and high-quality transaction services to demand from dealers in order to maximize

$$u(x_l, x_h) - p_l x_l - p_h x_h,$$

subject to the constraint that the total number of transactions (per customer) adds up to the exogenously desired level, $x_l + x_h = 1$. We assume that $u(x_l, x_h)$ is increasing, concave, twice continuously differentiable, and satisfies $u_h(x_l, x_h) - u_l(x_l, x_h) \geq 0$, where the h and l subscripts

[9] Notice that, during the COVID-19 crisis, the price (transaction cost) and quantity (trading volume) of transaction services increased at the same time, which is suggestive of demand, not supply, shocks.

denote first partial derivatives with respect to x_h and x_l, respectively. This condition simply means that the customer values high-quality transaction services more than low-quality transaction services.

Assuming interior solutions, the first-order optimality condition of the customer is

$$u_h(x_l, x_h) - u_l(x_l, x_h) = p_h - p_l, \quad \text{where} \quad x_l + x_h = 1.$$

On the other side of the market, dealers choose their supply of transaction services, X_l and X_h, in order to maximize profits,

$$p_l X_l + p_h X_h - C(X_l, X_h),$$

where $C(X_l, X_h)$ is some continuous, convex, and twice continuously differentiable cost function. This leads to the first-order optimality conditions

$$p_l = C_l(X_l, X_h) \quad \text{and} \quad p_h = C_h(X_l, X_h).$$

Finally, the market clearing conditions for transaction services are simply

$$X_l = N x_l \quad \text{and} \quad X_h = N x_h.$$

Given some level of aggregate transaction demand, N, an equilibrium is thus a tuple $(x_l, x_h, X_l, X_h, p_l, p_h)$ solving the first-order optimality conditions of customers and dealers, and the market clearing conditions.

3.2 The impact of a shock to aggregate transaction demand

The immediate consequence of the COVID-19 crisis in the corporate bond market was a surge in selling pressure, as investors withdrew money from bond funds en masse and financial institutions made a "dash for cash."[10] In fact, according to TRACE, customer trading volume rose sharply during the crisis, by about 50%.[11] In our model, we represent this large, sudden increase in the demand for transaction services by an increase in N, the measure of customers who arrive to the market. The following proposition characterizes the impact of this shock on the equilibrium prices and quantities of low- and high-quality transaction services. The proof is in Appendix A.

[10] See Ma et al. (2020), along with the references cited in Footnote 4.

[11] See TRACE Market Aggregate Information from FINRA.

Proposition 1 *Let $(x_l^\star, x_h^\star, X_l^\star, X_h^\star, p_l^\star, p_h^\star)$ be an equilibrium for a given N. If*

$$\frac{\partial}{\partial N}\left[C_h\left(Nx_l^\star, Nx_h^\star\right)\right] \geq \frac{\partial}{\partial N}\left[C_l\left(Nx_l^\star, Nx_h^\star\right)\right] \geq 0, \tag{1}$$

then, in response to a marginal increase in N:

- *The cost of all transaction services go up: both $p_h^\star$ and $p_l^\star$ increase;*
- *The cost of high-quality transaction services go up by more: $p_h^\star - p_l^\star$ increases;*
- *Customers substitute towards low-quality transaction services: $x_h^\star$ decreases.*

The sufficient condition in (1) has a natural interpretation: it means that, holding the composition of low- and high-quality transaction services fixed, an increase in N increases the marginal cost of all transaction services, but more so for the marginal cost of high-quality transaction services. Of course, one may be concerned about whether this condition is likely to be satisfied, so it is worth noting that condition (1) is true for *all* (x_l, x_h) and N under a number of standard cost functions. For example, this condition is always satisfied if $C(X_l, X_h) = (\alpha X_l + \beta X_h)^k$ for some $k > 1$ and any $\beta > \alpha > 0$.

To understand the impact of an increase in N on equilibrium prices and allocations, we can combine the first-order conditions of the customers and the dealers, together with the market-clearing condition, to get

$$u_h(1-x_h, x_h) - u_l(1-x_h, x_h) = p_h - p_l = C_h(N(1-x_h), Nx_h) - C_l(N(1-x_h), Nx_h).$$

The left-hand side of this equation, represented by the orange solid curve in the left panel of Figure 1, defines a downward-sloping schedule for the per-customer demand of high-quality intermediation services, x_h, as a function of the difference in prices, $p_h - p_l$. The right-hand side, represented by the blue solid curve, defines an upward-slopping supply schedule.[12] The intersection of the two curves determines the equilibrium quantities of high- and low-quality transaction services, along with the premium paid for high-quality services, given some level of aggregate transaction demand, N.

The sufficient condition in (1) ensures that the supply schedule shifts up in response to an increase in N, i.e., from the blue solid supply curve to the green dashed supply curve. Since per-customer demand is independent of N, the demand curve is unchanged. Using a loose, dynamic interpretation of the model, the "short run" effect of an increase in N is a rise in the premium

[12]Notice that both schedules are defined by differences in marginal values and marginal costs; this is because each customer has a fixed total demand for intermediation services, so a marginal increase in the demand for high-quality services induces a corresponding decrease in the demand for low-quality services.

$p_h - p_l$ along the vertical red arrow. In response to this change in relative prices, of course, customers substitute towards low-quality transaction services and $x_h^\star$ falls (the third bullet point in Proposition 1). The premium $p_h - p_l$ decreases along the diagonal red arrow, but remains elevated relative to its pre-shock level (the second bullet point).

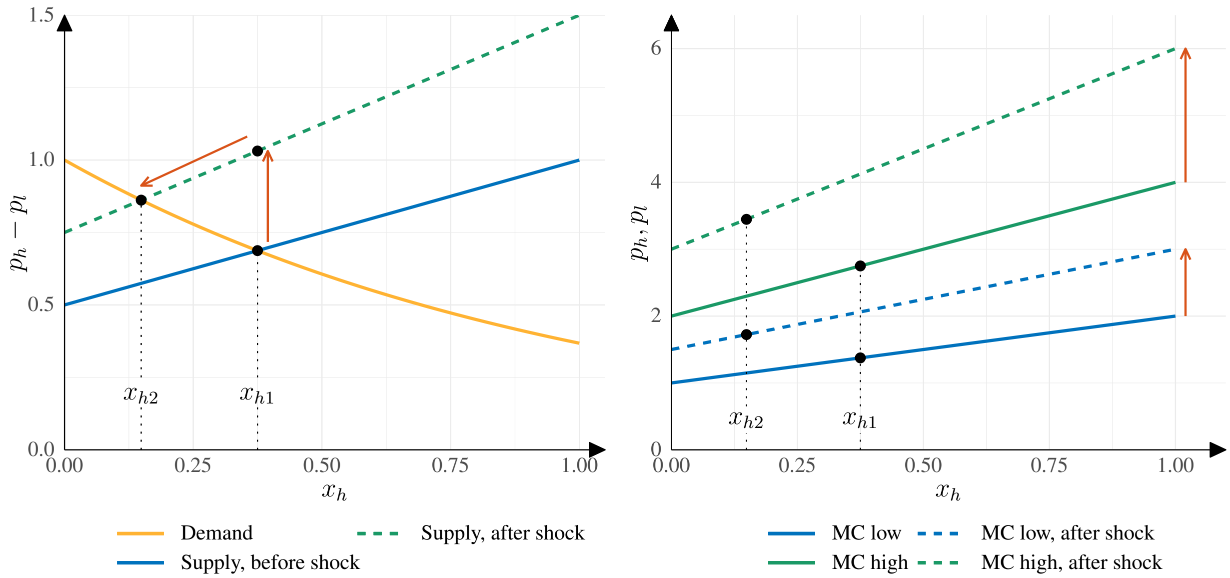

Figure 1. Equilibrium prices and quantities of high- and low-quality transaction services.

The right panel of Figure 1 illustrates the effect of an increase in N on p_l and p_h separately. Drawing on the dealers' first-order conditions, the prices p_l and p_h must equal the marginal cost of providing low- and high-quality transaction services (represented by the solid-blue and solid-green curves, respectively), evaluated at the equilibrium quantities implied by x_h. In response to an increase in N, when (1) is satisfied, the marginal cost curves shift up and x_h declines, leading to an increase in both prices (the first bullet point in Proposition 1).

To summarize, the comparative statics derived from this reduced-form theoretical framework provide straightforward, testable predictions. In particular, drawing the analogy that p_l and p_h represent the cost of agency and risky-principal trades, respectively, our model predicts that $p_l < p_h$ before the shock to aggregate demand. Upon impact, both p_l and p_h should spike, but the magnitude of the p_h spike should be larger. In the new equilibrium, p_l should remain only slightly elevated, while the increase in p_h should be more pronounced. Finally, these price movements should coincide with a decrease in risky-principal trades.

4 Trading conditions during the pandemic

In this section, we describe how market conditions evolved from the sanguine conditions of mid-February through the freefall of mid-March to the post-intervention recovery of April and May. Guided by the theoretical results derived above, we first construct time series for several variables of interest: the cost of risky-principal trades, the cost of agency trades, and the fraction of each type of transaction services. We document that, at the height of the selling pressure, dealers appeared unwilling to absorb assets onto their balance sheets, as the cost of risky-principal trades surged and the fraction of such trades dropped significantly. Conditions improved immediately after the Fed's announcement of the corporate credit facilities, with dealers providing liquidity directly, via risky-principal trades, at significantly lower prices. To test the causal relationship between the Fed's interventions and market liquidity, we exploit the eligibility requirements for bond purchases by the SMCCF. We find that, after the initial announcement, trading costs for eligible bonds fell substantially, while trading costs for ineligible bonds were little changed. Later, after the program was expanded in both size and scope, we document more significant declines in trading costs for all bonds.

4.1 Data and key dates

To construct our sample, we combine the standard TRACE data set (for 2020Q1) with the End-of-Day version (for 2020Q2). We first filter the report data following the standard procedure laid out in Dick-Nielsen (2014). We merge the resulting data set with the TRACE master file, which contains bond grade information, and with the Mergent Fixed Income Securities Database (FISD) to obtain bond fundamental characteristics. Following the bulk of the academic literature, we exclude variable-coupon, convertible, exchangeable, and puttable bonds, as well as asset-backed securities, and private placed instruments. We also exclude newly-issued and foreign securities.

The filtered dataset covers the period from January 2 to June 5, 2020, and contains 7.4 million trades and 40,279 unique bonds. Approximately 61% of the transactions are identified as customer-dealer and 39% as interdealer trades. The average trade size is $225,727 across all transactions, with average total daily volumes for customer-dealer and interdealer trades of $8.26 billion and $3.52 billion, respectively. It is worth noting that, in both the standard and End-of-Day versions of TRACE, the trade size for investment-grade and high-yield bonds is top-coded at $5 million and $1 million, respectively. For a typical bond, the median time-to-maturity is 4.95 years and the mean (median) number of daily trades is 7.2 (4) across all dates.

In all of our plots below, we include vertical dashed lines to highlight several key dates mentioned above: February 19, when stock markets reached their all-time peaks; March 5, which marks the beginning of the extended fall in equity prices and rise in corporate credit spreads; March 18, the first day of trading after the announcement of the PDCF; March 23, the day that the PMCCF and SMCCF were announced; April 9, the day that the size and scope of the corporate credit facilities were expanded; and May 12, the date that bond purchases commenced.[13]

4.2 The cost of trading, fast and slow

To capture the average transaction cost for risky-principal trades, we use the measure of bid-ask spreads proposed by Choi and Huh (2018), CH hereafter. To construct this measure, we first calculate, for each customer trade, the spread

$$2Q \times \frac{\text{traded price} - \text{reference price}}{\text{reference price}},$$

where Q is equal to $+1$ for a customer buy from and -1 for a customer sell to a dealer, and the reference price is taken to be the volume-weighted average price of interdealer trades larger than $100,000 in the same bond-day. Importantly, we restrict our sample so that it only includes trades in which the dealer who buys the bond from a customer holds it for more than 15 minutes. In doing so, we leave out those trades where the dealer had pre-arranged for another party (either a customer or another dealer) to buy the bond immediately.[14] The measure of risky-principal trading costs is then calculated at the trade level, and at the bond-day level by taking the volume-weighted average of trade level spreads. Finally, this measure is calculated at the daily level by taking the average in each day across all bonds, weighted by bonds daily total volume of customer trades where the CH measure is available.

To capture the average transaction cost of agency trades, we calculate a modified version of the Imputed Roundtrip Cost measure described in Feldhütter (2012). To construct this modified imputed roundtrip cost (or "MIRC"), we first identify imputed roundtrip trades (IRT) by matching a customer-sell trade with a customer-buy trade of the same size that takes place within 15 minutes of each other.[15] We do not include interdealer trades in constructing IRTs, so that each IRT only includes one customer-buy trade and one customer-sell trade. Then, to compute the MIRC, we calculate

$$\frac{P_{max} - P_{min}}{P_{max}},$$

[13] To start, the SMCCF purchased shares of ETFs that held a portfolio of corporate bonds. The first purchases of individual bonds did not occur until June 16.

[14] Likewise, in calculating reference prices, we follow CH and exclude interdealer trades executed within 15 minutes of a customer-dealer trade.

[15] In other words, as in earlier papers, we assume that customer-buys and customer-sells that occur in rapid succession are likely to be agency trades. Indeed, in an agency trade, dealers search for counterparties on behalf of customers. When counterparties are found, the two customers are matched by dealers, and two customer-to-dealer trades are recorded in a short time window.

where P_{max} is the largest price in the IRT and P_{min} is the smallest price in the IRT. Within each bond and day, we calculate the daily average roundtrip cost as the average of the bond's MIRC on that day, weighted by trade size. Finally, a daily estimate of average roundtrip cost is the average of roundtrip costs on that day across all bonds, weighted by bonds' total daily trading volumes in the matched IRTs.

Figure 2 plots the two time series. The two measures of transaction costs are relatively stable through February 19, with risky-principal trades approximately twice as expensive as agency trades. Upon realization of the COVID-induced shock, as our theory predicts, the cost of risky-principal trades rises dramatically, while the cost of agency trades is more muted. In particular, between Thursday, March 5, and Monday, March 9, the cost of risky-principal trades roughly triples, to approximately 100 bps; over these three trading days, the S&P 500 Index declined more than 12%. A week later, during the most tumultuous period of March 16-18, this series continues to rise, reaching a peak of more than 250 bps, before beginning a steady decline after the announcement of the SMCCF on March 23. The MIRC measure of agency trading costs, in contrast, increases from a baseline around 8 bps to approximately 28 bps, before receding slightly after the Fed's intervention.

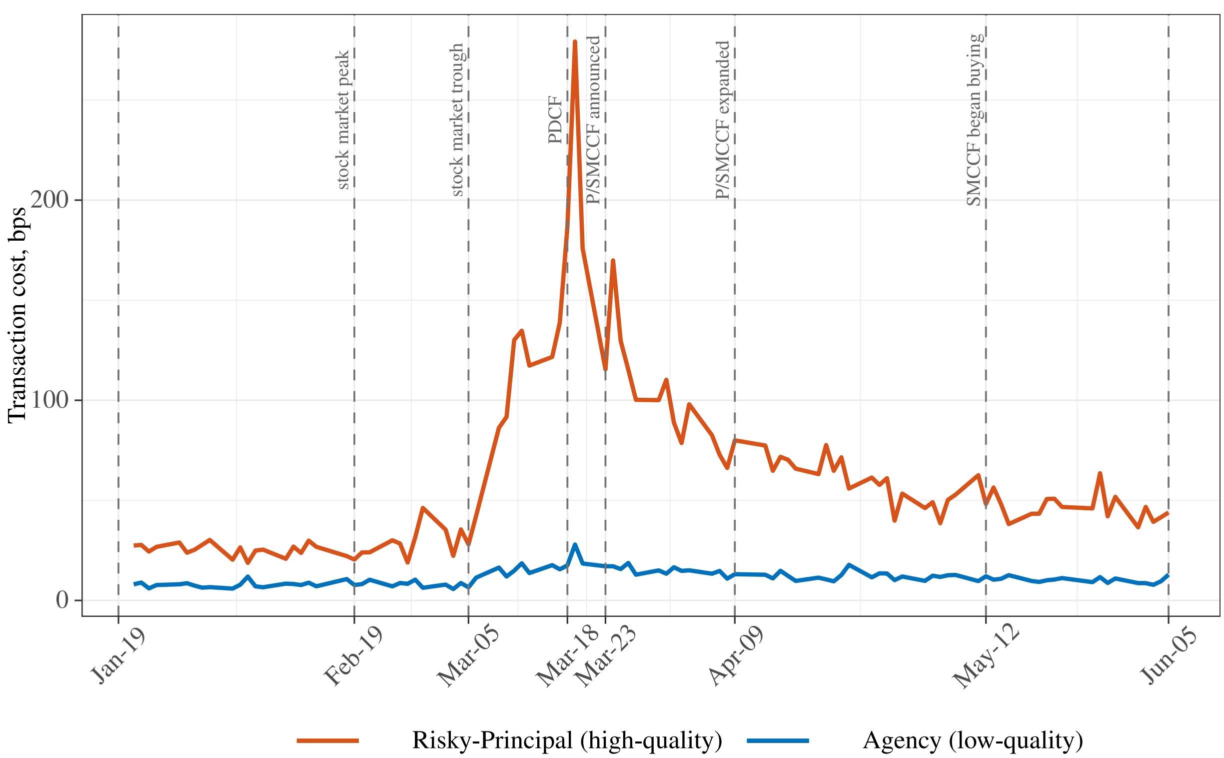

Figure 2. Transaction costs: Risky-principal vs. agency trades.

To highlight the relative costs of risky-principal and agency trades, we plot the difference between the two series in Figure 3. One can see that the cost of trading immediately was considerably more responsive to both the heightened selling pressure induced by the pandemic in mid-March and the Fed's interventions which followed. Moreover, despite considerable improvement in both metrics during the month of April, note that the price of trading immediately remained elevated through early June, which suggests that liquidity conditions remained somewhat strained well after the markets appear to have calmed.

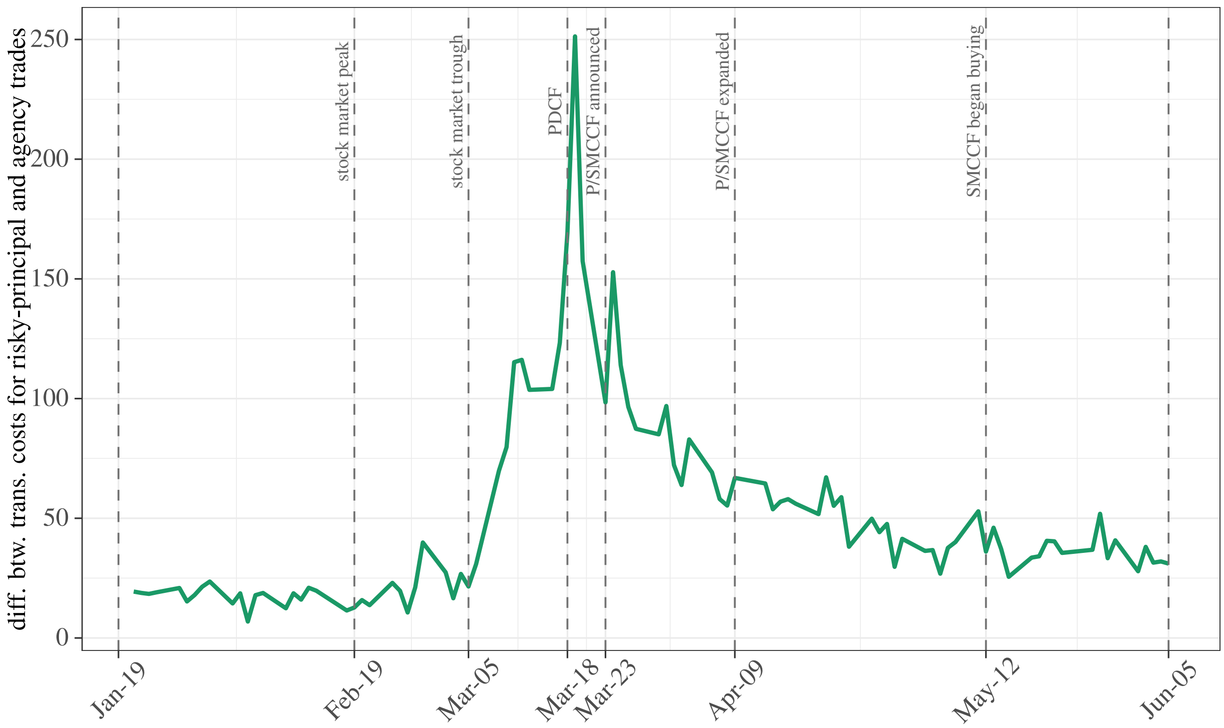

Figure 3. Difference between transaction costs for risky-principal and agency trades.

Of course, the change in spreads could be driven by a change in the composition of bonds that were traded during this period of distress. For example, perhaps trading volume was unusually high for retail-size trades of illiquid bonds, which typically involve higher transaction costs. Thus, to further clarify the impact of the crisis and ensuing interventions on the cost of risky-principal and agency trades, we turn to formal regressions that allow us to control for bond- and trade-level fixed effects. We consider the following specification

$$y_{ijt} = \alpha_i + \alpha_s + \beta_1 \times \text{Crisis}_t + \beta_2 \times \text{Intervention}_t + \varepsilon_{ijt}. \tag{2}$$

The dependent variable, y_{ijt}, represents the transaction cost for a type $j \in \{\text{risky-principal, agency}\}$ trade of bond i on day t. The dummy variables Crisis_t and Intervention_t allow us to distinguish between three sub-periods: (i) Pre-crisis, which corresponds to dates before March 5, 2020; (ii) Crisis, which covers the period March 5–23, 2020; and (iii) Intervention, which covers the period after March 23. Hence, the coefficients β_1 and β_2 measure transactions costs relative to the pre-crisis period. Finally, α_i and α_s represent bond and trade size fixed effects, respectively. Bond fixed effects capture bond characteristics that are fixed over time such as industry, par amount, etc.[16] For trade size fixed effects we consider three categories: less than $100,000, between $100,000 and $1 million, and larger than $1 million.[17]

Table 1 presents the results for all bonds, as well as the sub-sample of bonds issued by US firms.[18] We include bond and size category fixed effects and cluster standard errors at the bond and day levels in all regressions to account for correlation over time within a bond and across bonds in a given day. From columns (1) and (3), we observe that during the crisis period of March 5-23, average bond-level trading costs for risky-principal and agency trades increased by approximately 107 bps and 10 bps, respectively, relative to the pre-crisis period. After the Fed's interventions on March 23, trading costs for risky-principal trades fell by approximately 55 bps—more than half the initial spike—while transaction costs for agency trades declined much more modestly. These results are consistent with the aggregate results we present in Figure 2. From columns (2) and (4), we see that the sub-sample of US-issued bonds was roughly the same as the behavior of all bonds, though the cost of agency trades for US-issued bonds increased slightly more during the crisis period.

4.3 Substituting agency trades for risky-principal trades

As the premium for risky-principal trades increased, our theory predicts that customers respond by substituting towards agency trades. Figure 4 confirms that this was indeed the case during the most tumultuous weeks of trading in mid-March.[19] For example, between March 5 and March 23, the fraction of agency trades measured by both number (left axis) and volume (right axis) increased by as much as 15 percentage points, trough to peak, before receding after the March 23 announcement of the corporate credit facilities. Again, this shift toward agency trades has important implications for assessing market liquidity. In particular, if one were simply to measure trading costs across all

[16]We do not have access to the latest credit rating data for all bonds in our sample, just the binary IG/HY classification provided by TRACE. For the sub-sample of bonds where the credit rating is available, we include a credit rating fixed effect in specification (2) to control for potentially time-invariant nature of bond credit ratings. From Table 6 in Appendix D, we see that controlling for bond credit rating leads to very similar results to the ones from Table 1.

[17]Bao et al. (2018) show that trades with dealers that are affected by more stringent regulation following the global financial crisis (GFC), such as the Volcker rule, can exhibit higher trading costs after the GFC. Hence, one would ideally include dealer fixed effects in specification (2) as well. Unfortunately, the standard and end-of-day versions of TRACE data that we use do not include dealer identities available in the regulatory and academic versions.

[18]One reason we include the results for the US sub-sample is to demonstrate that the trading cost patterns are similar to the full sample. This is helpful later, in Section 4.5, when we focus on the US sub-sample exclusively.

[19]We discuss how we identify agency trades in depth in Appendix B.

Table 1. Trading costs during the COVID-19 crisis. This table presents regression results for the following specification: $y_{ijt} = \alpha_i + \alpha_s + \beta_1 \times \text{Crisis}_t + \beta_2 \times \text{Intervention}_t + \varepsilon_{ijt}$. The dependent variables are our measures of transactions costs for risky-principal and agency trades. Crisis_t and Intervention_t are dummies which take the value of 1 if day t falls into the Crisis and Intervention sub-periods defined above. There are three trade size categories: less than \$100,000, between \$100,000 and \$1 million, and larger than \$1 million. Clustered standard errors at the day and bond levels are shown in parentheses.

	Dependent variable:			
	Risky-principal		Agency	
	All	US Only	All	US Only
	(1)	(2)	(3)	(4)
Crisis	106.57***	105.63***	10.43***	12.03***
	(14.17)	(14.93)	(1.83)	(2.16)
Intervention	51.28***	52.09***	9.39***	10.16***
	(5.62)	(5.92)	(0.74)	(1.03)
Bond FE	Yes	Yes	Yes	Yes
Trade size category FE	Yes	Yes	Yes	Yes
Observations	769,809	581,217	245,670	147,042
Adjusted R^2	0.17	0.18	0.26	0.27
Note:				*p<0.1; **p<0.05; ***p<0.01

trades, they would underestimate the erosion in liquidity as the composition of trades shifted from faster, more expensive risky-principal trades to less costly, but slower agency trades.

To study the substitution from risky-principal to agency trades more carefully, we consider a regression with the following specification:

$$\text{Agency}_{ijt} = \alpha_i + \alpha_s + \beta_1 \times \text{Crisis}_t + \beta_2 \times \text{Intervention}_t + \varepsilon_{ijt}, \tag{3}$$

where Agency_{ijt} is an indicator variable that takes the value one if trade j for bond i on day t is an agency trade and zero otherwise. The variables on the right-hand side of specification (3) are the same as in (2). Under this specification, the coefficients β_1 and β_2 measure the change in the probability of an agency trade during the crisis and intervention periods, respectively, relative to the pre-crisis period. For robustness, we present results using linear probability (OLS), logit, and probit models.

Table 2 presents the results. As shown in column (1), during the crisis period of March 5–23, the probability of an agency trade for a given bond, on average, rose by approximately 3.8 percentage points relative to the pre-crisis period. After the Fed interventions on March 23, this

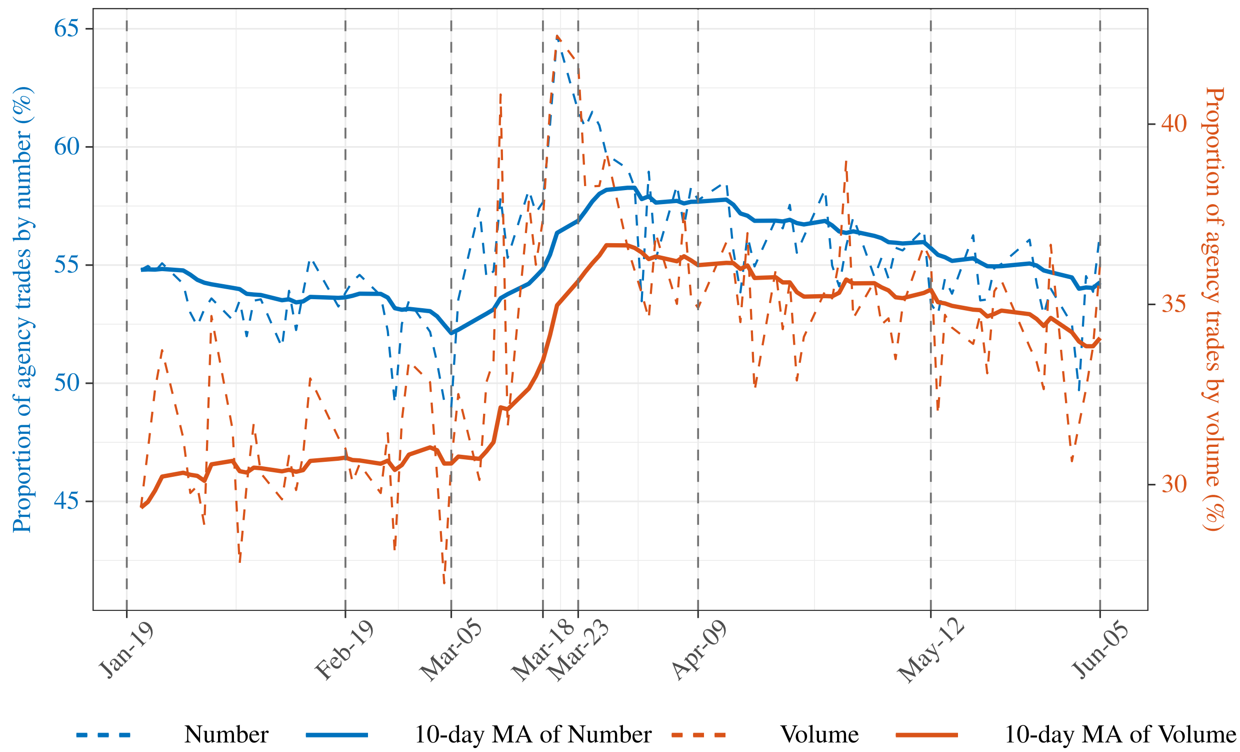

Figure 4. Proportion of agency trades, all bonds.

probability decreased slightly from the crisis period (by 70 bps) to 3.1 percentage points higher than the pre-crisis period. For the sake of completeness, we report marginal effects calculated at the sample means for logit and probit models in columns (2) and (3); the results are very similar to the linear probability model (OLS) in column (1).[20]

4.4 Dealers' inventory accumulation

To summarize our results thus far, at the height of massive selling pressure in mid-March, the price of trading immediately through risky-principal trades increased substantially and, in response, customers substituted towards slower, less costly agency trades. In light of these observations, one might naturally wonder: who was providing liquidity in the corporate bond market? Were dealers "leaning against the wind" and absorbing some of the inventory during the selloff? Or was the shift to agency trades sufficiently large that other customers were ultimately providing liquidity?

To answer this question, we construct a measure of the (cumulative) value of bonds that were

[20]For the interested reader, we also report results from a linear probability model that distinguishes between eligible and ineligible bonds for the SMCCF in Appendix D. We find that the shift towards agency trades was more pronounced among bonds that were eligible for the Fed's purchasing program.

Table 2. Probability of an agency trade for all bonds. This table presents regression results for the following specification from: $\text{Agency}_{ijt} = \alpha_i + \alpha_s + \beta_1 \times \text{Crisis}_t + \beta_2 \times \text{Intervention}_t + \varepsilon_{ijt}$. The dependent variable, Agency_{ijt}, is an indicator variable that takes the value 1 if trade j for bond i on day t is an agency trade and 0 otherwise. Columns (1), (2), and (3) report result for the linear probability (OLS), logit, and probit models, respectively. We report marginals effects calculated at the sample means for logit and probit models in columns (2) and (3). Crisis_t and Intervention_t are dummies which take the value of 1 if day t falls into Crisis and Intervention sub-periods defined above. There are three trade size categories: less than \$100,000, between \$100,000 and \$1 million, and larger than \$1 million. In logit and probit specifications, the pseudo-R^2 is defined as $1 - L_1/L_0$, where L_0 is the log likelihood for the constant-only model and L_1 is the log likelihood for the full model with constant and predictors. The sample starts on January 3 and ends on June 5, 2020. Clustered standard errors at the day and bond levels are shown in parentheses.

	Dependent variable:		
	Probability of agency trade		
	OLS	Logit	Probit
	(1)	(2)	(3)
Crisis	0.038***	0.037***	0.037***
	(0.010)	(0.010)	(0.009)
Intervention	0.031***	0.030***	0.030***
	(0.004)	(0.004)	(0.004)
Bond FE	Yes	Yes	Yes
Trade size category FE	Yes	Yes	Yes
Observations	7,052,589	7,052,589	7,052,589
Adjusted R^2	0.113		
Pseudo R^2		0.085	0.085
Note:			*p<0.1; **p<0.05; ***p<0.01

absorbed over time by the dealer sector. In particular, using the daily Market Sentiment data from FINRA, we subtract the value of bonds that dealers sell to customers from the value of bonds that they buy from customers each day, and then calculate the cumulative sum of the net changes.[21] Figure 5 plots the cumulative net change in inventory held in the dealer sector, both in levels (left axis) and as a fraction of pre-crisis outstanding supply (right axis), starting on February 19, 2020.

Several aspects of Figure 5 are striking. First, during the most tumultuous period of trading, the dealer sector absorbed, on net, *no* additional inventory despite the considerable selling pressure from customers. In fact, dealers actually *reduced* inventory holdings and became net sellers. Hence, during this period, it was indeed other customers that were supplying liquidity to the market. Second, dealers' reluctance to absorb inventory appears to have changed substantially

[21]The Market Sentiment data is available through FINRA TRACE Market Aggregate Information. We use this data, as opposed to the standard or End-of-Day TRACE data, because it is not top-coded and hence allows for a more accurate assessment of the inflow and outflow of bonds in the dealer sector.

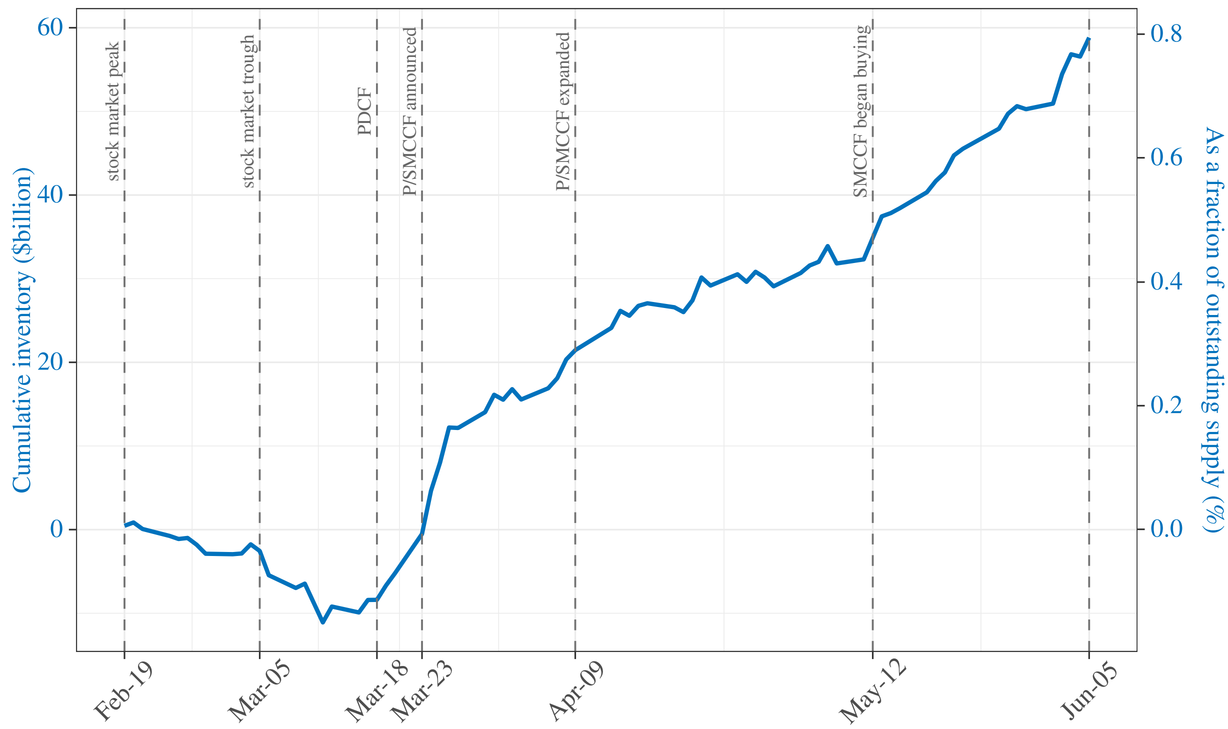

Figure 5. Cumulative inventory change (USD billions) in the dealer sector and as a fraction of total supply (%), according to FINRA market sentiment tables.

around the dates corresponding to the Fed's announcement of the Primary Dealer Credit Facility (March 18) and the Primary and Secondary Market Corporate Credit Facilities (March 23). Lastly, dealers continued to accumulate inventory through April and May. Indeed, from March 18, the data indicates that dealers absorbed more than $50 billion in corporate debt, or roughly doubled their inventory holdings relative to pre-pandemic levels.[22]

4.5 Effects of the Fed's intervention

The results above suggest that the Fed's interventions—in particular, the March 23 announcement of the SMCCF—had a significant effect on dealers' willingness to absorb inventory onto their balance sheets, and hence on market liquidity. In this section, we exploit the eligibility requirements specified in the SMCCF to test this hypothesis more formally.

According to the original term sheet, a bond is eligible to be purchased through the SMCCF if it has an investment-grade rating on March 23, 2020; if it has a time-to-maturity of five years or less; and if its issuer is domiciled in the US.[23] However, the Fed has a considerable degree of

[22]From Table L.130 of the Flow of Funds, at the end of 2019Q4, security brokers and dealers held $54 billion in corporate and foreign bonds on the asset side of their balance sheets.

[23]The original March 23rd term sheet can be found here. Initially, there was an additional eligibility criterion for

discretion to determine whether a foreign issuer is domiciled in the US. Indeed, in the Feds SMCCF transaction-level disclosures, we found many cases in which the holding firm of the security is a non-US entity.[24] Given this lack of clarity, we chose to focus on US firms exclusively, and classify a bond as eligible based on credit rating and time-to-maturity alone.[25]

To start, we repeat the regression specified in (2) with two modifications. First, we separate the sample of bonds into those that were eligible for purchase through the SMCCF and those that were not. Second, we separate the intervention period into two sub-periods. The first sub-period, which we call the "SMCCF," covers from March 23-April 8, 2020. During this period, it appeared that only investment-grade bonds would be eligible for purchase. The second sub-period, which we call the "SMCCF expansion," starts on April 9, when the Fed announced that it was increasing the size of the program and expanding the set of eligible bonds to include high-yield debt.

Table 3 reports the results. Interestingly, the initial decline in trading costs was entirely driven by bonds that were eligible for the SMCCF: the price of risky-principal trades for ineligible bonds was unchanged during the initial expansion, relative to the crisis period, while the price of agency trades for ineligible bonds actually increased during this time period. After the program was expanded on April 9, in both scope and size, the price of all bonds declined significantly.

To further explore the causal effect of the SMCCF on bond market liquidity during the crisis, we consider a difference-in-differences regression over a sub-sample of our data from March 6 to April 9, 2020. These dates are chosen to exclude the pre-crisis period, when spreads were very low, and the post-expansion period, when the set of bonds available for purchase through the SMCCF was widened to include high-yield bonds. In particular, we use the specification

$$y_{ijt} = \alpha_s + \alpha_k + \beta_1 \times \text{SMCCF}_t \times \text{Eligible}_t + \beta_2 \times \text{SMCCF}_t + \beta_3 \times \text{Eligible}_t + \gamma \times X_{i,t} + \varepsilon_{ijt}, \quad (4)$$

where, as before, y_{ijt} represents our measures of transactions costs; Eligible_t takes the value of 1 if the bond in trade j has an investment-grade rating and time-to-maturity of five years or less on March 23, 2020; SMCCF_t takes the value of 1 if the trade occurs between March 23 and April 9, 2020; and α_s controls for size fixed effects.

Unlike specification (2), we do not include bond fixed effects in the baseline specification (4), but instead control for industry fixed effects (α_k) and bond-specific characteristics such as bond age, amount outstanding, and time-to-maturity ($X_{i,t}$). However, for robustness, we also include results allowing for bond fixed effects, as well as credit rating fixed effects. To ensure that treatment

the SMCCF on March 23: eligible issuers excluded firms that were expected to receive direct financial assistance from the then-pending CARES act. This criterion (and others) were later added to the SMCCF term sheet on April 9. See Appendix C for more details.

[24]SMCCF transaction-level disclosures are available here. We provide additional details of this issue, including examples, in Appendix B.

[25]Recall from Table 1 that transaction costs for US firms behaved very similarly to all bonds in our sample.

Table 3. Trading costs across eligible and ineligible bonds during the initial and expanded interventions. This table presents regression results for the following specification: $y_{ijt} = \alpha_i + \alpha_s + \beta_1 \times \text{Crisis}_t + \beta_2 \times \text{SMCCF}_t + \beta_3 \times \text{SMCCF Expansion}_t + \varepsilon_{ijt}$. The dependent variables are measures of transactions costs for risky-principal and agency trades. Crisis_t is a dummy which takes the value of 1 if day t falls into the Crisis sub-periods defined above. SMCCF and SMCCF Expansion_t are dummies that take the value of 1 if the trading day t is between March 23 and April 9, and after April 9, 2020, respectively. The SMCCF eligibility criteria were expanded to include fallen angels on April 9, 2020. There are three trade size categories: less than \$100,000, between \$100,000 and \$1 million, and larger than \$1 million. A bond is considered eligible if it has an investment-grade rating and time-to-maturity of five years or less on March 23, 2020. The sample begins on January 3 and ends on June 5, 2020, when the SMCCF expanded eligibility criterion to fallen angels. Only US firms are included in the regressions. Clustered standard errors at the day and bond levels are shown in parentheses.

	Dependent variable:					
	Risky-principal			Agency		
	All	Eligible	Ineligible	All	Eligible	Ineligible
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis	105.64***	111.67***	102.16***	11.92***	16.32***	9.64***
	(14.96)	(15.62)	(15.65)	(2.16)	(3.52)	(1.80)
SMCCF	88.96***	62.14***	104.30***	14.35***	11.78***	15.98***
	(8.38)	(8.68)	(9.42)	(1.15)	(1.26)	(1.49)
SMCCF Expansion	31.15***	15.35***	40.16***	7.20***	4.56***	9.08***
	(3.14)	(3.08)	(4.28)	(1.01)	(0.98)	(1.44)
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Trade size category FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	580,698	200,761	379,937	146,864	50,192	96,672
Adjusted R^2	0.18	0.19	0.18	0.27	0.21	0.27

Note: *p<0.1; **p<0.05; ***p<0.01

and control groups do not overlap, we remove from our sample all trades in bonds that were downgraded from IG to HY. Finally, we drop all foreign bonds and focus only on bonds issued by US firms.

Table 4 contains our results. As is standard in difference-in-differences regressions, β_1 is the primary coefficient of interest. The first key takeaway is that the SMCCF had a significant effect on the cost of risky-principal trades for eligible bonds, relative to ineligible bonds (which were essentially unaffected during this period). The quantitative magnitude of this effect is approximately 50 bps, and is robust to a variety of alternative specifications. For example, in column (2) we include a credit rating fixed effect, which absorbs some of the effects of eligibility related to the ratings restriction, leaving (roughly speaking) the effects of eligibility based on time-to-maturity.

In columns (3) and (4), we allow for bond-specific fixed effects, which increase the explanatory power of the regressions (i.e., the R^2) but do not significantly change the estimates of β_1.

The second noteworthy result is that, for risky-principal trades, β_2 is not statistically different from zero under any of our specifications. Hence, it appears that the *announcement* of the initial SMCCF did not have significant spillover effects on the cost of risky-principal trades for ineligible bonds. However, this does not rule out the potential for spillover effects from the actual *purchase* of eligible bonds, which began on May 12, 2020. In particular, by purchasing bonds and relaxing dealers' balance sheet constraints, the SMCCF could potentially increase dealers' willingness to purchase any bond. If this is true, then some of the post-expansion decline in the costs of risky-principle trades for ineligible bonds (reported in Table 3) could be attributed to spillover effects from the Fed's bond purchases.

Columns (5)–(8) indicate that the announcement of the SMCCF on March 23 also reduced the cost of agency trades for eligible bonds.[26] One possible explanation is that, by establishing itself as a buyer of last resort, the Federal Reserve reduced the risk to private investors from purchasing eligible corporate bonds. According to this logic, it is possible that the announcement of the SMCCF made it easier for dealers to locate customer-buyers, hence reducing the spreads they charged on agency trades for eligible bonds. Note that this mechanism could also explain why the cost of agency trades for ineligible bonds went up in the immediate aftermath of the SMCCF announcement, if budget-constrained customers substituted from ineligible to eligible bonds, it would become more difficult for dealers to locate consumer-buyers for ineligible bonds, driving spreads up.

In Appendix D, we provide several additional robustness checks for the results discussed above. In particular, in Tables 8 and 9, we show that the impact of the SMCCF on the trading cost of eligible bonds is even more pronounced if we limit our sample to those bonds that are just above and below the eligibility thresholds for and credit rating, respectively. In addition, in Tables 10–12, we show that small and large trades are responsible for the entire liquidity improvement documented in Table 4: small trades (with par volume of \$100,000 or less) become much more liquid after the SMCCF announcements, while large trades (with volume larger than \$1 million) also exhibit a significant decline in trading costs. Odd-lot trades (with volume between \$100,000 and \$1 million), however, are essentially unaffected by the Fed's intervention. This complements the evidence of Feldhütter (2012), who showed that trades are affected differently by market turmoil depending on their size.

[26] Note that, looking at the overall effect $(\beta_1 + \beta_2 + \beta_3)$, column (6) indicates that, after controlling for credit rating, the cost of agency trades for eligible bonds decreased after SMCCF announcement.

Table 4. The Effects of Fed Intervention: difference-in-differences. This table presents regression results for the following difference-in-differences specification from equation (4): $y_{ijt} = \alpha_s + \alpha_k + \beta_1 \times \text{SMCCF}_t \times \text{Eligible}_t + \beta_2 \times \text{SMCCF}_t + \beta_3 \times \text{Eligible}_t + \gamma \times X_{i,t} + \varepsilon_{ijt}$. The dependent variables are measures of transactions costs for risky-principal and agency trades. SMCCF_t is a dummy that takes the value of 1 if day t falls between March 23 and April 9, and 0 otherwise. Eligible_t takes the value of 1 if the bond has an investment-grade rating and time-to-maturity of five years or less on March 23, 2020. X_{it} controls for log(Amt outstanding), log(Age), and log(Time-to-maturity): logs of bond's amount outstanding, years since bond issuance, and years to maturity, respectively. There are three trade size categories: less than \$100,000, between \$100,000 and \$1 million, and larger than \$1 million. The sample begins on March 6 and ends on April 9, 2020. Only US firms are included and bonds that change credit grade are excluded. Clustered standard errors at the day and bond levels are shown in parentheses.

	Dependent variable:							
	Risky-principal				Agency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SMCCF × Eligible	-57.70^{***}	-41.72^{***}	-47.24^{***}	-41.45^{***}	-10.25^{***}	-12.85^{***}	-9.59^{**}	-9.85^{***}
	(11.80)	(12.27)	(10.21)	(10.34)	(2.99)	(3.11)	(3.44)	(3.47)
SMCCF	-1.89	-21.75	-14.30	-20.03	6.33^{***}	8.10^{***}	4.56^{**}	4.72^{**}
	(14.58)	(14.64)	(14.65)	(14.43)	(2.00)	(2.11)	(1.97)	(2.02)
Eligible	2.86	-14.81			0.37	9.93^{***}		
	(14.24)	(11.36)			(3.15)	(3.69)		
log(Amt outstanding)	-30.33^{***}	-31.88^{***}			-3.62^{***}	-1.87^{***}		
	(7.25)	(9.19)			(0.64)	(0.65)		
log(Time-to-maturity)	15.40^{***}	16.77^{***}			4.00^{***}	5.53^{***}		
	(4.96)	(4.99)			(0.85)	(1.26)		
log(Age)	27.61^{***}	28.84^{***}			4.93^{***}	5.24^{***}		
	(7.54)	(6.40)			(1.10)	(1.14)		
Trade size category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Bond FE	No	No	Yes	Yes	No	No	Yes	Yes
Credit rating FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	158,647	146,143	158,649	146,143	47,628	45,324	47,630	45,324
Adjusted R^2	0.04	0.05	0.20	0.20	0.08	0.10	0.25	0.26
Note:								*p<0.1; **p<0.05; ***p<0.01

5 Consumer surplus and dealer profits

The analysis above provides a detailed account of liquidity conditions in the corporate bond market during the COVID-19 crisis. However, our analysis thus far—and, to the best of our knowledge, other related studies—have little to say about the effects of these recent events on consumers' surplus and dealers' profits. Absent such analysis, it's impossible to even consider whether such interventions were warranted, whether they were too big or small, and which parties ultimately benefited. In this section, we attempt to shed light on these important questions by combining our empirical estimates of prices and trading volume (for risky-principal and agency trades) with simple calculations derived from our theoretical framework.

Again, the distinction between risky-principal and agency trades is important. On the consumer side, we find that the large drop in consumer surplus during the panic of mid-March was largely due to increased transaction costs but, as the crisis evolved and consumers shifted towards low-quality agency trades, we find that transaction costs only explain about half of the loss in consumer surplus. On the dealer side, our estimates confirm existing news and earning reports that profits from market-making spiked during the height of the selling pressure, reflecting the large increase in bid-ask spreads. However, while spreads and volume remained elevated through the recovery, our estimates suggest that profits returned to pre-crisis levels, as dealers' cost of providing more intermediation services remained elevated as well. Finally, we consider the possibility that (at least some of) the deterioration in trading conditions was due to a supply shock, i.e., an increase in dealers' cost of intermediating. We find that, by attributing the rise in trading costs to supply shocks, the model infers a smaller spike in profits in mid-March, but elevated profits through the recovery.

5.1 Consumer surplus

We adopt the convention that one unit of transaction services is being provided for each dollar of transaction. This means that the proportional trading costs we measured can be interpreted as prices per unit of transaction services. With this in mind, we use our theoretical framework from Section 3 to write the consumer surplus per dollar unit of transaction as

$$s_t = u(x_t) - p_t \cdot x_t,$$

where $x_t = (x_{lt}, x_{ht})$ and $p_t = (p_{lt}, p_{ht})$. Then, under appropriate regularity conditions, the Envelope Theorem implies that the instantaneous change in surplus is given by

$$ds_t = -dp_t \cdot x_t. \tag{5}$$

Interpreting p_{lt} and p_{ht} as the cost of agency and risky-principal trades, respectively, and $x_{ht} = 1 - x_{lt}$ as the proportion of aggregate trading volume (in dollar amounts) executed as risky-principal trades, the solid red line in Figure 6 plots the change in consumer surplus per dollar unit of transaction,

$$s_t - s_0 = \int_0^t ds_u,$$

by adding up the instantaneous changes measured according to (5), from a January 1st time-zero baseline,[27] up to time t, as a function of t.[28] One sees that the consumer surplus per dollar of transaction declined by about 150 bps during the crisis, then recovered slowly and partially.

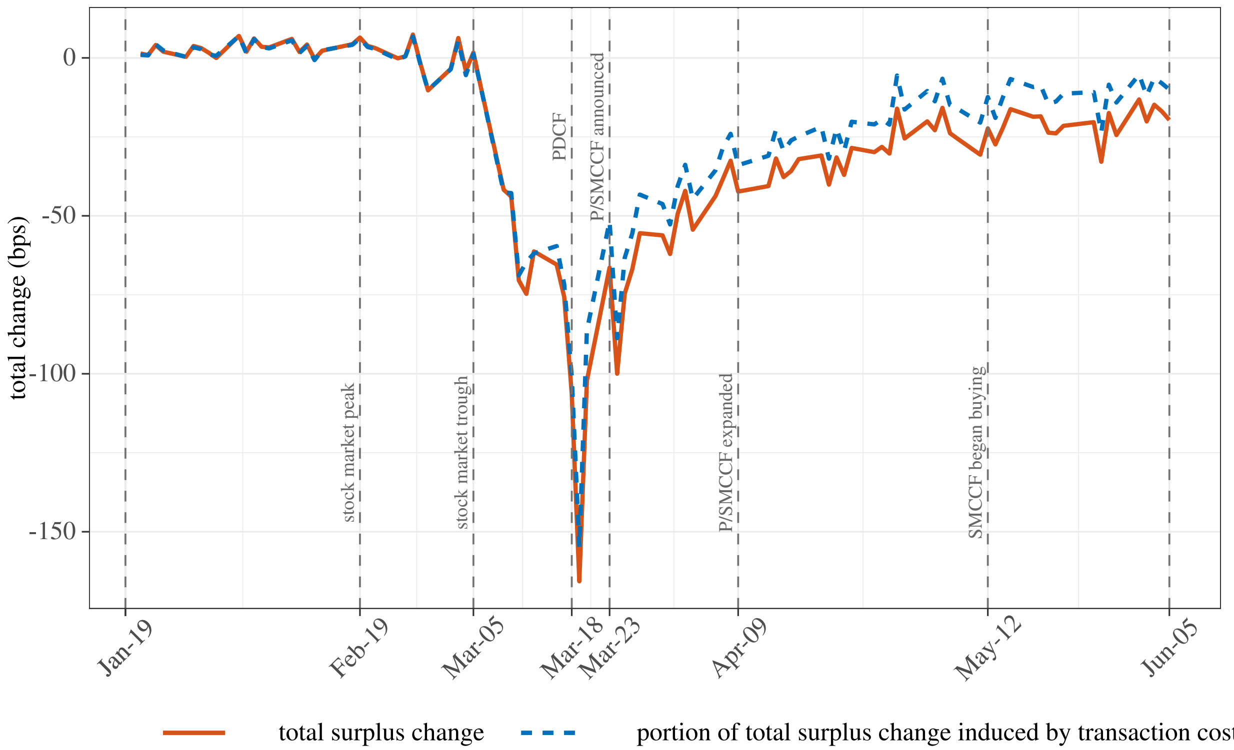

Figure 6. Change in daily consumer surplus and portion of change in due to increasing transaction costs.

While the solid red line in Figure 6 appears like the mirror image of the transaction costs plotted in Figure 2, it is both conceptually and quantitatively different from a calculation of the average transaction cost. More specifically, letting the average transaction cost be $a_t = p_t \cdot x_t$, the

[27] Given the relatively stable conditions before the pandemic, the quantitative results are robust to changing the baseline to other dates in January.

[28] Of course, in discrete time, the Envelope Theorem does not apply exactly. Instead, the first few steps of the proof of the Envelope Theorem deliver an upper and a lower bound for the day-to-day change in surplus, $-(p_t - p_{t-1}) \cdot x_{t-1} \leq s_t - s_{t-1} \leq -(p_t - p_{t-1}) \cdot x_t$. The figure reports the upper bound. Since the change is negative, this is a conservative estimate. In any case, for this calculation, there is no much difference between the two bounds.

instantaneous change in average transaction cost can be written

$$da_t = dp_t \cdot x_t + p_t \cdot dx_t = -ds_t + (p_{ht} - p_{lt})\, dx_{ht},$$

where we make use of the maintained assumption that $dx_{ht} = -dx_{lt}$. One sees that if $p_{ht} > p_{lt} > 0$ and if $dx_{ht} < 0$, as we observed during the crisis, the effects of an increase in average transaction costs alone underestimate the decrease in consumer surplus. This is because the change in average transaction cost does not capture the utility loss associated with customers substituting from high-quality risky-principal trades to lower-quality agency trades. To illustrate this point, the blue dashed line in Figure 6 plots the (negative of the) total change in average transaction costs. This represents the change in surplus that is induced by the change in transaction costs alone. As expected, the blue curve lies above the red curve. The difference is minimal at the beginning of the time period under consideration, but it widens around the end of March by about 10 bps. This decomposition illustrates that the change in transaction costs alone fails to capture the total decline in consumer surplus, especially after the crisis peaks: during this period, while transaction costs have recovered, the proportion of agency trades remain elevated, and transaction costs only explain about half of the loss in consumer surplus.

5.2 Dealer profits

Within the context of our theoretical framework, dealers' profits are

$$\Pi_t = p_t \cdot X_t - C(X_t),$$

where $X_t = N_t x_t$ is the total dollar value of low- and high-quality transaction services. Again, using the Envelope Theorem, we obtain the instantaneous change in profits:

$$d\Pi_t = dp_t \cdot X_t = -N_t\, ds_t.$$

In words, the instantaneous change in profits is equal to the negative of the instantaneous change in consumer surplus, per dollar of transaction, multiplied by the total dollar value of transactions. The plain red line in Figure 7 plots the total change in daily profits, $\Pi_t - \Pi_0 = \int_0^u d\Pi_u$, relative to a January 1st time-zero baseline.[29]

One can see that daily profits were large during the most tumultuous trading days, but have since returned to normal. This is perhaps puzzling in light of the observation that average transaction costs remain elevated. The reason for the difference is that transaction costs represent

[29]We calculate the day-to-day changes in profit using the formula $(p_t - p_{t-1}) \cdot X_t$. As noted above, in discrete time, this should be viewed as an upper bound for the true total change in profits $\Pi_t - \Pi_{t-1}$.

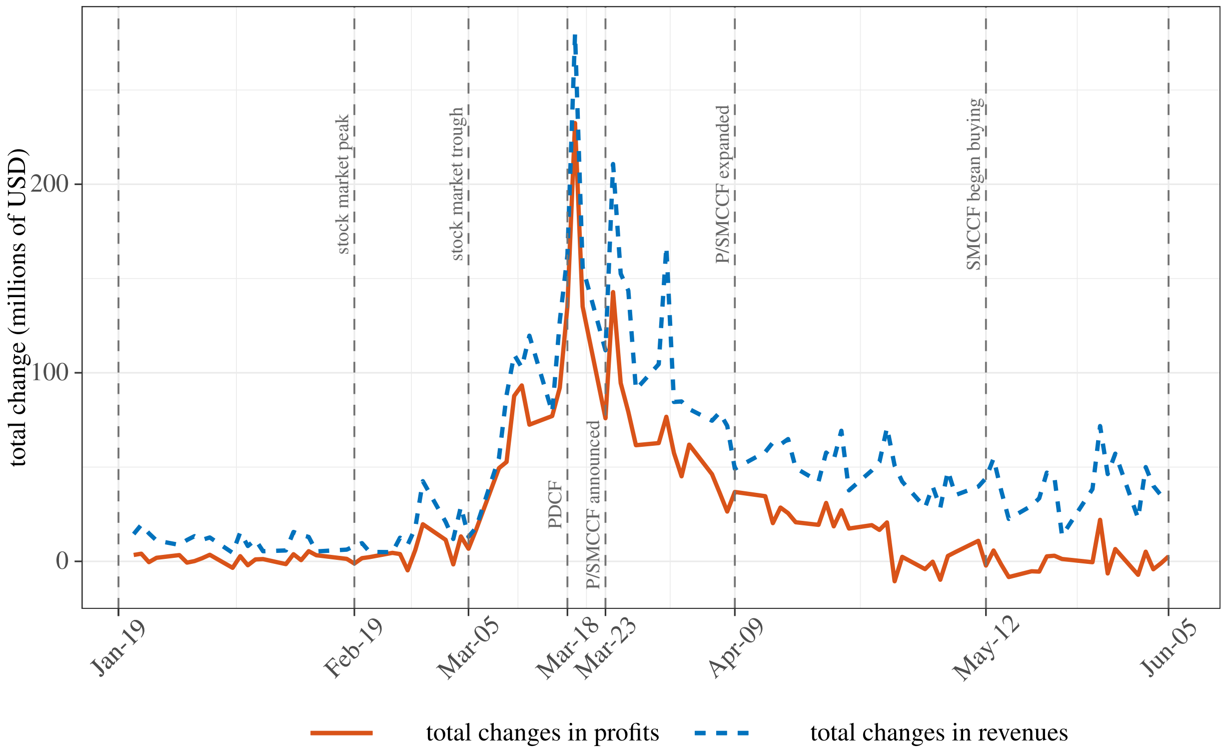

Figure 7. Change in daily dealer profits vs. revenue, relative to a January 1st baseline.

revenues, while profits account for the dealers' cost, $C(X)$. Namely, since the change in total revenues is

$$dR_t = d(N_t\, a_t) = dN_t\, a_t + N_t\, da_t = dN_t\, a_t + d\Pi_t + N_t(p_{ht} - p_{lt})\, dx_{ht},$$

we can rearrange the terms to express profits as

$$d\Pi_t = dR_t - dN_t\, a_t - N_t(p_{ht} - p_{lt})\, dx_{ht}. \tag{6}$$

The formula reveals that the change in profits differ from the change in revenues for two reasons, captured by the second and third terms in equation (6). Namely the second term,

$$-dN_t\, a_t = -dN_t\left[x_l C_l(X_l, X_h) + x_h C_h(X_l, X_h)\right],$$

implies that the change in profits will be lower than the corresponding change in revenue when trading volume goes up, or $dN_t > 0$. This is because dealers' marginal cost is increasing: holding the composition of low- and high-quality transaction services the same, dealers find it more costly to provide these services as trading volume increases. The third term,

$$-N_t(p_{ht} - p_{lt})\, dx_{ht} = -C_l(X_{lt}, X_{ht})\, N_t dx_{lt} - C_h(X_{lt}, X_{ht})\, N_t dx_{ht},$$

implies that the change in profit tends to be larger than the corresponding change in revenue when customers substitute towards low-quality transaction services, or $dx_{ht} = -dx_{lt} < 0$. This is because a shift towards low-quality services reduces the dealers' total costs.

The blue dashed line in Figure 7 plots the total change in daily revenue, $R_t - R_0$, relative to a January 1st time-zero baseline. Profits increased considerably in March, consistent with reports that some broker-dealers have generated large market-making revenues. For example, the earning reports of Goldman Sachs indicates that quarterly market-making revenues in March 2020 were 35 percent larger than in March 2019. The figure also reveals that, while revenues were still somewhat elevated in May, profits had returned to the baseline. In Appendix D, we plot the second and third components of (6) separately to establish that the (negative) effect of the second term dominates the (positive) effect of the third term since the interventions of March 23. Hence, while dealers appeared to have earned significant extra profits at the height of the crisis, our data suggests that since early May the increased cost of providing transaction services have neutralized the added revenue from elevated prices.[30]

5.3 Supply vs. demand shock

Finally, let us stress an important caveat in our profit calculation: it assumes that the cost function, $C(X)$, remained stable over the time period. If it did not remain stable, e.g., because of supply shocks, then the calculation of profits would be impacted.[31] For example, one could imagine that, due to risk aversion and high volatility, the marginal cost of providing intermediation services went up, holding everything else constant. Under this scenario, our calculation of profits would fail to capture the true risk-adjusted cost of providing intermediation services.[32]

[30] One may be concerned that, on some days, the change in profits exceeds the change in revenues. This is feasible because the series do not measure levels but *changes* in profits and extra revenues, relative to a January 1st baseline. Hence, it is theoretically possible that profits on a particular day increase by more than revenue. For example, if trading volume fell ($dN_t < 0$) and $dx_h \simeq 0$, changes in profit can be larger than corresponding changes in revenue because the cost of providing intermediation services falls.

[31] Another caveat is that it assumes price-taking. Perhaps the rise in the bid-ask spread could be attributed to an increase in concentration during turbulent times, e.g., because only a few dealers are willing and able to use balance-sheet capacity. Unfortunately, because our data does not include dealer identifiers, we are not able to address this hypothesis.

[32] In recent work, Goldberg and Nozawa (2020) propose a methodology for measuring the relative contribution of shocks to supply vs. demand, and apply this methodology to the corporate bond market after the implementation of post-2008 regulations. Hence, one could potentially extend their estimates to the COVID-19 time period and, in conjunction with our framework, construct estimates of dealer profits. However, this is beyond the scope of the current paper.

To illustrate this point formally and quantitatively, suppose that the cost function is:

$$C(X_l, X_h) = \Psi(X_l, \gamma X_h)$$

for some increasing and convex function Ψ, where $\gamma > 1$ is a cost shifter for risky-principal trades. The Envelope Theorem then implies that the instantaneous change in profits is

$$d\Pi_t = dp_t \cdot X_t - p_{ht} X_{ht} \frac{d\gamma_t}{\gamma_t},$$

where we used that $p_h = C_h = \gamma \Psi_h$. The second term, which is new, accounts for shifts in the cost of providing risky-principal trades.

To gain insight into the size of this adjustment, notice that

$$\frac{p_h}{p_l} = \frac{C_h}{C_l} = \gamma \frac{\Psi_h}{\Psi_l}. \tag{7}$$

The ratio C_h/C_l has the interpretation of a marginal rate of substitution (MRS) between agency and risky-principal trades, i.e., it is the number of extra agency trades a dealer can supply if she reduces the number of risky-principal trades by one unit, keeping the total cost constant. Figure 8 shows that, during the crisis, the marginal rate of substitution increased dramatically. According to the MRS equation, (7), this could have happened for two reasons. First, holding the cost shifter, γ, constant, the increase in the demand for transaction services, N, could have led to an increase in the marginal rate of substitution. Second, holding the demand side fixed, the increase in the MRS could have been generated by an increase in the cost shifter.[33]

The relative importance of both effects matters a great deal for the calculation of profits. Assuming that changes in Ψ_h/Ψ_l and γ always have the same sign, equation (7) implies that changes in γ are bounded by changes in the MRS. To get a quantitative sense of the relationship between dealers' profits and the source of the shock (supply or demand), suppose that

$$\gamma = (p_h/p_l)^z.$$

This assumption states that, at any time, the log changes in the cost shifter are equal to a fraction z of the log changes in MRS. In the $z = 0$ case, there are no change in the cost shifter: this corresponds to our benchmark model with no role for supply shocks. Correspondingly, the $z = 1$

[33]Notice that we could also introduce a cost shifter for agency trade, in which case the increase in MRS could indicate that agency trades have become much cheaper to provide, in absolute terms. We view this scenario as less plausible in light of the commonly held view that balance sheet costs mostly apply to risky-principal trades.

case corresponds to the case in which all changes in the MRS are accounted for by supply shocks. Naturally, $z \in (0, 1)$ corresponds to intermediate cases, where both shocks are active.

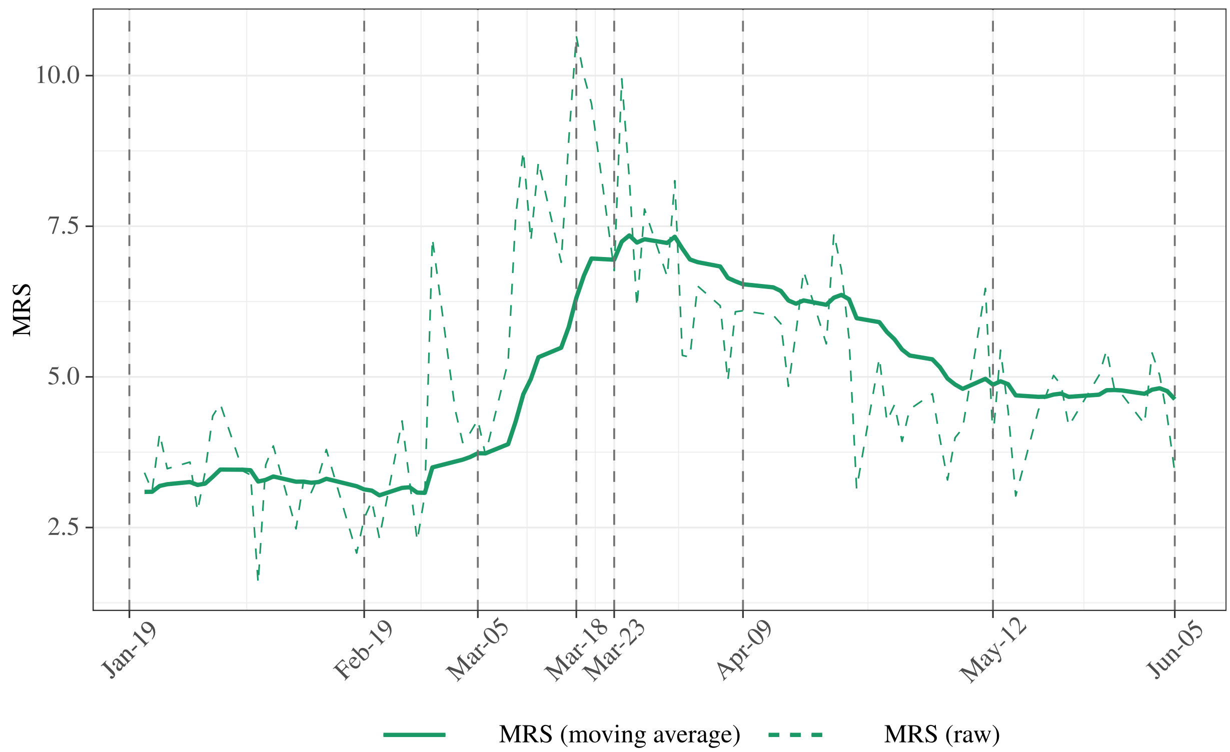

Figure 8. The marginal rate of substitution.

Figure 9 reveals that shocks to the cost of providing risky-principal transaction services can have significant quantitative effects on the profit calculations. There are two reasons for this result. First, as expected, when the MRS increased at the end of March, the model with $z \approx 1$ infers a large upward shift in dealers' costs of providing risky-principal trades, $d\gamma/\gamma > 0$ and so it adjusts profits downward. Second, and perhaps more surprisingly, when the MRS decreased after the Fed's intervention, the model infers the opposite—that the cost shifted down—so that profits are adjusted upward. Of course, it's possible that the relative contribution of supply and demand shocks is time-varying so that, for example, cost shifters played an important role at the height of the crisis but have since abated.

6 Conclusion

Since the introduction of stricter banking regulations after the 2008 financial crisis, academics and policymakers alike have wondered whether dealers would (or could) absorb a surge in selling pressure and maintain a liquid market if participants experienced a large, negative shock. Given

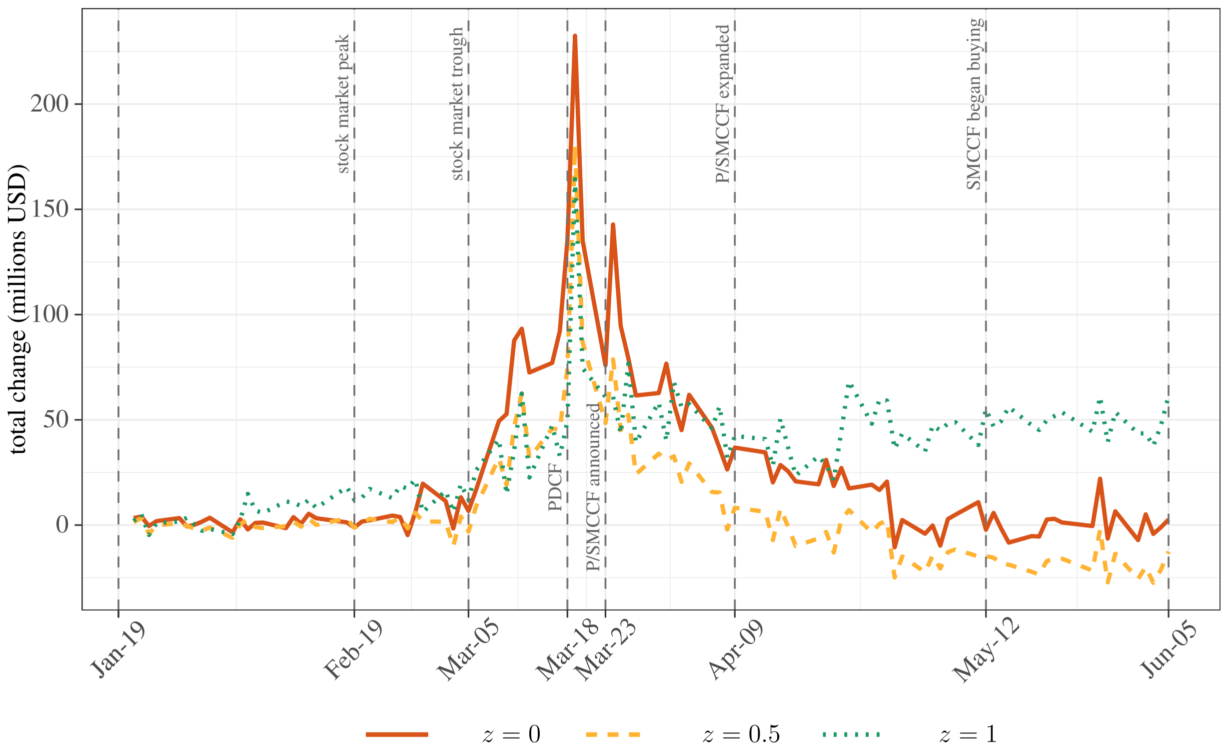

Figure 9. Changes in daily profits relative to a January 1st baseline (millions USD, per day).

the exogenous nature of the COVID-19 pandemic, the events of March 2020 provide a unique opportunity to study liquidity provision during a crisis, and the effects of the historic response by the Federal Reserve. We find that, to provide a comprehensive assessment of trading conditions, it is important to consider both the cost and the quality (or speed) of transaction services.

We document that, at the height of the crisis, corporate bond dealers appeared unwilling to use their own balance sheets to "lean against the wind": the price of risky-principal trades surged, and trading shifted towards slower, agency trades. In fact, during the most tumultuous trading days, the dealer sector absorbed no net inventory. However, these trends reversed after the Federal Reserve announced corporate credit facilities designed to purchase corporate debt. In the immediate aftermath of these announcements, we establish that liquidity conditions improved significantly for bonds that were eligible to be purchased, but not for ineligible bonds, suggesting that Fed interventions improved trading conditions.

Importantly, we go beyond documenting a collection of new facts from this important market during the pandemic-induced crisis and recovery. In particular, we employ a reduced-form model that allows us to interpret our results and, crucially, to derive estimates of the impact of these shocks on what policymakers ultimately care about: the well-being of market participants. We find that consumers' surplus and dealers' profits behave qualitatively similar to our estimates of trading costs, but capturing the true *quantitative* effects of the crisis and subsequent interventions requires accounting for the deterioration in the quality of trades, too.

While the analysis here provides a detailed look into trading conditions during this extraordinary episode, much work remains to be done. For example, one would like to further understand the microfoundations of customers' demand for risky-principal and agency trades and, perhaps even more importantly, the costs associated with dealers supplying these two types of transaction services. Doing so would be particularly helpful in identifying the precise constraints behind dealers' unwillingness to absorb inventory, along with the exact channel through which the Fed's interventions relaxed these constraints. We leave this challenge, along with other potential extensions, for future work.

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Appendix

A Proof of Proposition 1

Assuming interior solutions, the first-order condition of the customers' problem writes:

$$u_h(x_l, x_h) - u_l(x_l, x_h) = p_h - p_l.$$

Likewise, the first-order condition for the dealers' problem writes:

$$p_l = C_l(X_l, X_h) \text{ and } p_h = C_h(X_l, X_h).$$

Together the equilibrium conditions $N\,x_l = X_l$ and $N\,x_h = X_h$, we obtain that p_l, p_h, and x_h solve the following system of equations

$$p_h - p_l = u_h(1 - x_h, x_h) - u_l(1 - x_h, x_h) \tag{8}$$

$$p_l = C_l(N(1 - x_h), Nx_h) \tag{9}$$

$$p_h = C_h(N(1 - x_h), Nx_h).$$

Combining the three equations lead an implicit function for x_h:

$$u_h(1 - x_h, x_h) - u_l(1 - x_h, x_h) = C_h(N(1 - x_h), Nx_h) - C_l(N(1 - x_h), Nx_h). \tag{10}$$

Since the functions $x \mapsto u(1 - x, x)$ is concave, and the function $x \mapsto C(N(1 - x), Nx)$ is convex, it follows that the left-hand side of the equation is decreasing in x, while the right-hand side is increasing in x. The condition stated in the Proposition implies that, locally, the right-hand side is increasing in N. Therefore, the solution x_h to this equation is, locally, decreasing in N. See Figure 1. It then follows from equation (8) that $p_h - p_l$ is increasing as well.

The only result that remained to be shown is that p_l is, locally, increasing in N. To do so, we totally differentiate equation (9) with respect to N:

$$\frac{dp_l}{dN} = C_{ll} \times \left(1 - x_h - N\frac{dx_h}{dN}\right) + C_{lh} \times \left(x_h + N\frac{dx_h}{dN}\right),$$

where we use double subscript for second derivatives, and we omit the arguments of C_{ll} and C_{lh} to simplify notations. Let

$$\varepsilon \equiv \frac{N}{x_h}\frac{dx_h}{dN},$$

denote the elasticity of high-quality transaction services, x_h, with respect to total transaction demand, N. Plugging back, we obtain:

$$\frac{dp_l}{dN} = C_{ll} \times (1 - x_h(1+\varepsilon)) + C_{lh} \times x_h \left(1+\varepsilon\right).$$

Next, applying the Implicit Function Theorem to equation (10), we obtain the following explicit expression for the elasticity ε:

$$\varepsilon = \frac{N}{x_h}\frac{(1-x_h)\left(C_{lh}-C_{ll}\right) + x_h\left(C_{hh}-C_{lh}\right)}{\partial^2 u - N\left(C_{hh} - 2C_{lh} + C_{ll}\right)}.$$

where $\partial^2 u \equiv u_{ll} - 2u_{lh} + u_{hh} \leq 0$ by concavity. Plugging back into the equation for dp_l/dN, we obtain after some algebra that:

$$\frac{dp_l}{dN} \geq 0 \Leftrightarrow N\left(C_{ll}C_{hh} - C_{lh}^2\right) \geq \partial^2 u\left((1-x_h)C_{ll} + x_h C_{lh}\right).$$

The left-hand side, $N\left(C_{ll}C_{hh} - C_{lh}^2\right)$ is positive because C is convex.

As for the right-hand side, recall our maintained assumption that, holding (x_l, x_h) fixed, $C_l(Nx_l, Nx_h)$ is increasing. Taking derivatives, and replacing x_l by $1-x_h$, this means that $(1-x_h)C_{ll} + x_h C_{lh} \geq 0$. Keeping in mind that $\partial^2 u \leq 0$, we obtain that the right-hand side is negative, concluding the proof.

B Data and definitions

B.1 Data description

We use data from the Trade Reporting Compliance Engine (TRACE), made available by the Financial Industry Regulation Authority (FINRA). The raw TRACE data provides detailed information on all secondary market transactions self-reported by FINRA member dealers. These include bonds CUSIP, trade execution time and date, transaction price ($100 = par), the volume traded (in dollars of par), a buy/sell indicator, and flags for dealer-to-customer and inter-dealer trades. To construct our sample, we combine two versions of TRACE: the standard version (2020Q1), and the End-Of-Day version (2020Q2).

We first filter the report data following the procedure laid out in Dick-Nielsen (2014). We merge the resulting data set with the TRACE master file, which contains bond grade information, and with the Mergent Fixed Income Securities Database (FISD) to obtain bond fundamental characteristics. Following the bulk of the academic literature, we exclude bonds with optional characteristics, such as variable coupon, convertible, exchangeable, and puttable, as well as, asset-backed securities, and private placed instruments. Table 5 provides summary statistics for our sample.

Table 5. Summary statistics. This table provides mean, standard deviation, median, 5th and 95th percentiles of the average daily number of trades and volume by counterparty type, proportion of agency trades, proportion of trades on IG bonds, proportion of trades on the bonds eligible for SMCCF, and daily average trading cost for risky-principal (CH) and agency trades (MIRC) for eligible and ineligible bonds respectively. "num" refers to number of trades, and the "vol" refers to volume of trades in par value. A bond is considered eligible for the SMCCF if it has an investment-grade rating and time-to-maturity of 5 years or less on the March 23 2020. Source: TRACE and FISD.

	Mean	Std.dev	Q05	Q50	Q95
daily num. interdealer	22,401	3,825	18,335	22,073	28,371
daily num. customer	32,729	54,69	26,183	32,587	40,506
daily num. customer-bought	16,989	30,26	12,860	17,376	21,515
daily num. customer-sold	15,740	31,55	11,914	15,336	20,292
daily vol. interdealer ($ billion)	3.35	0.58	2.44	3.43	4.16
daily vol. customer ($ billion)	7.60	1.48	5.39	7.66	9.93
daily vol. customer-bought ($ billion)	3.88	0.71	2.85	3.93	4.96
daily vol. customer-sold ($ billion)	3.72	0.85	2.43	3.76	5.08
prop. agency (num)	0.54	0.03	0.50	0.54	0.60
prop. agency (vol)	0.33	0.05	0.28	0.33	0.38
prop. IG (num)	0.74	0.03	0.70	0.74	0.79
prop. IG (vol)	0.83	0.03	0.79	0.83	0.87
prop. eligible (num)	0.33	0.05	0.30	0.33	0.42
prop. eligible (vol)	0.27	0.04	0.23	0.27	0.35
daily avg. CH (bps)	57.29	42.07	21.21	44.96	131.97
daily avg. CH for eligible bonds (bps)	32.25	31.66	9.77	21.86	102.01
daily avg. CH for ineligible bonds (bps)	68.17	49.73	25.00	53.46	157.26
daily avg. MIRC (bps)	11.29	3.91	6.98	10.39	18.80
daily avg. MIRC of eligible bonds (bps)	5.88	3.20	2.92	4.62	12.91
daily avg. MIRC of ineligible bonds (bps)	13.08	4.77	7.77	11.92	21.90

In our empirical specifications, we exclude newly-issued securities (with age less than 90 days), as on-the-run bonds tend to trade differently than off-the-run securities. Since our sample only contains about 130 days, the age and time-to-maturity of a particular bond will vary little over time. Thus, we do not include the standard cross-sectional controls related to the bond's age or time-to-maturity. Furthermore, since we exclude newly-issued bonds, over time, the age (maturity) of any bond will increase (decrease) by one day each day. Thus, the average age (maturity) of our bonds will increase (decrease) monotonically over time, meaning these controls will also correlate with the time trends we are documenting.

We also distinguish between bonds that are eligible for the SMCCF and ineligible bonds. In Appendix C, we present a detailed description of eligibility criteria for the SMCCF. We define a bond as eligible if it has investment-grade rating and time-to-maturity of five years or less on March 23, 2020, when the SMCCF was first announced. The eligibility criteria also state that the firm must be a US-domiciled corporation. Specifically, the Fed restricts its purchases to bonds where

> The issuer is a business that is created or organized in the United States or under the laws of the United States with significant operations in and a majority of its employees based in the United States.

This criterion leaves the Fed with a considerable degree of discretion. For instance, if a foreign-domiciled corporation uses a US subsidiary to issue dollar-dominated debt, our firm-level data identify the firm as non-US. We would then classify its bonds as foreign, making them ineligible for the SMCCF. However, under the Fed's definition of a US issuer, the bonds may be eligible for purchase. Using the Fed's SMCCF transaction-level disclosures, we find that in many cases, the holding firm of the security is a non-US entity.[34] One such example is British American Tobacco (BAT), a firm listed on the London Stock Exchange and domiciled in the UK. Our firm-level data correctly identifies this firm as foreign; however, its bonds were purchased by the Fed.[35] These bonds were issued by a US wholly-owned subsidiary of BAT, BAT Capital Corporation. Since this subsidiary is guaranteed and wholly-owned by BAT, it is very challenging to correctly classify these bonds as US-domiciled. We, therefore, do not use US vs. non-US as an SMCCF eligibility criterion in our regressions discussed below and focus only on US firms.

Moreover, we do not have access to the latest credit rating data for all bonds in our sample. For the sub-sample of bonds where the credit rating is available, we include a credit rating fixed effect to control for potentially time-invariant nature of bond credit ratings.

B.2 Dates highlighted in the figures

We choose the following dates to highlight in the figures with vertical, dashed lines:

January 19: beginning of the series, chosen to start the sample period one month before the stock market peak.

February 19 stock market peak.

March 5: beginning of extended fall in equity prices and rise in corporate credit spreads.

[34] SMCCF transaction-specific disclosures are provided by the Federal Reserve, available here.

[35] On July 10, 2020, the Fed reported that BAT's bonds were purchased as part of the SMCCF (CUSIP 05526DAZ8).

March 18: first day of trading after announcement of Primary Dealer Credit Facility (announced evening of March 17).

March 23: announcement of Primary and Secondary Market Corporate Credit Facilities.

April 9: expansion of PMCCF and SMCCF (in both size and scope).

May 12: the SMCCF began purchasing eligible ETFs.

B.3 Identifying agency trades

We define agency trades as two trades in a given bond with the same trade size that take place within 15 minutes of each other. For each bond, we divide its trading sample into three groups: customer-sell-to-dealer (C2D), dealer-sell-to-customer (D2C), and interdealer (D2D) trades. Our identification of agency trades includes the following steps:

1. We match each trade X in group C2D with a trade Y in group D2C that has the same trade size and happens within 15 minutes of X. If there are several trades in D2C satisfying these conditions, we choose the trade that takes place closest in time to X. The identified pair of agency trades is then (X, Y). After this step, we denote the collection of unmatched trades in C2D as u-C2D and that in D2C as u-D2C.

2. We match each trade in u-C2D with a trade in group D2D by the same algorithm. We then obtain a collection of unmatched trades in D2D, denoted by u-D2D.

3. We match each trade in u-D2D with one in u-D2C following the same algorithm.

4. We repeat steps 1–3 using all remaining unmatched trades in the three groups while relaxing the matching criteria. In each agency trade pair, we require the second trade to happen within 15 minutes of the first trade, but it can have a smaller trade size than the first one. By doing so, we consider the situation in which dealers split the trade volumes when they behave as matchmakers.

5. Finally, within all the remaining unmatched trades after steps 1–4, we identify trades with field `remuneration == "C"` in TRACE (commission is included in the price) as agency trades, because, by FINRA's definition, broker-dealers receive commissions only when they intermediate agency trades.

C Corporate credit facilities

The Primary Market Corporate Credit Facility (PMCCF) and the secondary Market Corporate Credit Facility (SMCCF) were established in March 2020 by the Federal Reserve to support liquidity conditions in the corporate bond market during the economic disruption caused by the COVID-19 pandemic. The PMCCF provides a funding backstop for corporate debt issuance to eligible issuers, and the SMCCF purchases individual corporate bonds of eligible issuers (see below) and ETFs in the secondary market. The combined size of the PMCCF and SMCCF will be up to $750 billion. The SMCCF began purchasing eligible ETFs and individual corporate bonds on May 12 and June 16, 2020, respectively. The PMCCF became operational on June 29, 2020.

The New York Fed lends, on a recourse basis, to a special purpose vehicle (SPV) through which the two facilities operate. The Treasury makes a $75 billion equity investment in the SPV, $50 billion toward the PMCCF, and $25 billion toward the SMCCF. Depending on bonds' credit ratings at the time of the acquisition, the PMCCF and SMCCF leverage up Treasury's equity position at different levels (10 to 1, 7 to 1, or 3 to 1) when purchasing them from eligible issuers. For more details, see FAQs for PMCCF and SMCCF from the New York Fed, available here.

C.1 Bond eligibility criteria for the SMCCF

Eligible individual corporate bonds: The SMCCF may purchase individual corporate bonds that, at the time of purchase: (i) were issued by an eligible issuer (mentioned below); (ii) have a remaining maturity of five years or less; and (iii) were sold to the Facility by an eligible seller.

Eligible issuers for individual corporate bonds: As specified in the SMCCF term sheet as of July 28, 2020, to qualify as an eligible issuer of an eligible individual corporate bond, the issuer must satisfy the following conditions:[36]

1. The issuer is a business that is created or organized in the United States or under the laws of the United States with significant operations in and a majority of its employees based in the United States.

2. The issuer was rated at least BBB−/Baa3 as of March 22, 2020, by a major nationally recognized statistical rating organization ("NRSRO"). If rated by multiple major NRSROs, the issuer must be rated at least BBB−/Baa3 by two or more NRSROs as of March 22, 2020.

   (a) An issuer that was rated at least BBB−/Baa3 as of March 22, 2020, but was subsequently downgraded, must be rated at least BB−/Ba3 as of the date on which the

[36] Source: Term sheet for the SMCCF, available here.

Facility makes a purchase. If rated by multiple major NRSROs, such an issuer must be rated at least BB−/Ba3 by two or more NRSROs at the time the Facility makes a purchase.

(b) In every case, issuer ratings are subject to review by the Federal Reserve.

3. The issuer is not an insured depository institution, depository institution holding company, or subsidiary of a depository institution holding company, as such terms are defined in the Dodd-Frank Act.

4. The issuer has not received specific support pursuant to the CARES Act or any subsequent federal legislation.

5. The issuer must satisfy the conflicts of interest requirements of section 4019 of the CARES Act.

D Additional empirical results

D.1 Transaction costs: impact of credit rating

We do not have access to the latest credit rating data for all bonds in our sample, just the binary IG/HY classification provided by TRACE. For the sub-sample of bonds where the credit rating is available, we include a credit rating fixed effect in specification (2) and run the following regressions

$$y_{ijt} = \alpha_i + \alpha_s + \alpha_r + \beta_1 \times \text{Crisis}_t + \beta_2 \times \text{Intervention}_t + \varepsilon_{ijt},$$

where α_r represents credit rating fixed effects to control for potentially time-invariant nature of bond credit ratings. In Table 6, we repeat the results in Table 1 for the sub-sample of bonds for which we have credit rating data. We see that the results are very similar to the ones from Table 1.

D.2 The fraction of agency trades

In Table 7, we repeat the OLS regression in column (1) of Table 2 but focusing only on bonds issued by US firms. In columns (2) and (3) we repeat the regression in column (1) restricting the sample to eligible and ineligible bonds, respectively. As before, a bond is considered eligible if it has an IG credit rating and remaining time-to-maturity of five years or less.

Results in column (1), for US bonds, are very similar to what shown in column (1) of Table 7 for all bonds. From columns (2) and (3), we observe that the shift towards agency trades was much more pronounced among bonds that were eligible for the Fed's purchasing program. The

Table 6. Robustness: Trading costs during the COVID-19 crisis adding credit rating FEs. This table presents regression results for the following specification: $y_{ijt} = \alpha_i + \alpha_s + \alpha_r + \beta_1 \times \text{Crisis}_t + \beta_2 \times \text{Intervention}_t + \varepsilon_{ijt}$. The dependent variables are our measures of transactions costs for risky-principal and agency trades. Crisis_t and Intervention_t are dummies which take the value of 1 if day t falls into the Crisis and Intervention sub-periods defined above. α_r represents credit rating fixed effects. There are three trade size categories: less than \$100,000, between \$100,000 and \$1 million, and larger than \$1 million. The sample starts on January 3 and ends on June 5, 2020. Clustered standard errors at the day and bond levels are shown in parentheses.

	Dependent variable:			
	Risky-principal		Agency	
	All	US Only	All	US Only
	(1)	(2)	(3)	(4)
Crisis	107.78***	105.67***	10.74***	11.63***
	(14.35)	(15.14)	(2.06)	(2.28)
Intervention	46.92***	48.32***	9.27***	9.85***
	(5.30)	(5.28)	(0.87)	(1.02)
Bond FE	Yes	Yes	Yes	Yes
Trade size category FE	Yes	Yes	Yes	Yes
Credit Rating FE	Yes	Yes	Yes	Yes
Observations	659,605	545,436	188,121	140,184
Adjusted R^2	0.18	0.18	0.26	0.27
Note:				*p<0.1; **p<0.05; ***p<0.01

probability of an agency trade for a given eligible bond, on average, rose by approximately seven percentage points relative to the pre-crisis period. After the Fed interventions on March 23, this probability decreased from the crisis period (by 200 bps) to five percentage points higher than the pre-crisis period. For ineligible bonds, in contrast, the probability of an agency trade rose by only 1.9 percentage points relative to the pre-crisis period and remained relatively unchanged after the Fed intervention.

D.3 Impact of Fed announcements

In this subsection, we present several robustness checks for the difference-in-differences (DID) results in Section 4.5.

Table 7. Robustness: Probability of an agency trade for US bonds (OLS only). This table presents regression results for the following specification from: $\text{Agency}_{ijt} = \alpha_i + \alpha_s + \beta_1 \times \text{Crisis}_t + \beta_2 \times \text{Intervention}_t + \varepsilon_{ijt}$. The dependent variable, Agency_{ijt}, is an indicator variable that takes the value 1 if trade j for bond i on day t is an agency trade and 0 otherwise. Only US firms are included in the regression. Crisis_t and Intervention_t are dummies which take the value of 1 if day t falls into Crisis and Intervention sub-periods defined above. There are three trade size categories: less than \$100,000, between \$100,000 and \$1 million, and larger than \$1 million. A bond is considered eligible if it has an investment-grade rating and time-to-maturity of 5 years or less on the March 23 2020. The sample starts on January 3 and ends on June 5, 2020. Clustered standard errors at the day and bond levels are shown in parentheses.

	Dependent variable:		
	Probability of agency trade		
	All	Eligible	Ineligible
	(1)	(2)	(3)
Crisis	0.038***	0.070***	0.019**
	(0.010)	(0.015)	(0.008)
Intervention	0.030***	0.050***	0.018***
	(0.004)	(0.005)	(0.004)
Bond FE	Yes	Yes	Yes
Trade size category FE	Yes	Yes	Yes
Observations	5,383,618	2,114,474	3,269,144
Adjusted R^2	0.109	0.078	0.126
Note:			*p<0.1; **p<0.05; ***p<0.01

Bonds close to the eligibility threshold for rating and maturity

First, in Table 8, we repeat the regressions in Table 4 but focusing only on bonds just above and below the SMCCF eligibility threshold for time-to-maturity (TTM): bonds with four to six years left to maturity.

Next, in Table 9, we repeat the regressions in Table 8 but adding the extra restriction that the bonds should be close to the IG-HY threshold. In particular, we only include bonds that in addition to having TTM of four, five and six years, are also rated at the bottom tier of investment-grade (BBB+/Baa1, BBB/Baa2, and BBB−/Baa3) or the top tier of high-yield (BB+/Ba1, BB/Ba2, and BB−/Ba3).

Table 8. DID robustness: only include bonds with 4 to 6 years left to maturity. This table presents regression results for the following DID specification from equation (4): $y_{ijt} = \alpha_s + \alpha_k + \beta_1 \times \text{SMCCF}_t \times \text{Eligible}_t + \beta_2 \times \text{SMCCF}_t + \beta_3 \times \text{Eligible}_t + \gamma \times X_{i,t} + \varepsilon_{ijt}$. The dependent variables are measures of transactions costs for risky-principal and agency trades. SMCCF_t is a dummy that takes the value of 1 if day t falls between March 23 and April 9, and 0 otherwise. Eligible_t takes the value of 1 if the bond has an investment-grade rating and time-to-maturity of 5 years or less on the March 23 2020. X_{it} controls for log(Amt outstanding), log(Age), and log(Time-to-maturity): logs of bond's amount outstanding, years since bond issuance, and years to maturity, respectively. There are three trade size categories: less than \$100,000, between \$100,000 and \$1 million, and larger than \$1 million. The sample begins on March 6 and ends on April 9, 2020. Only US firms, bonds with 4, 5, or 6 years left to maturity on the intervention date are included. Bonds that change credit grade are excluded. Clustered standard errors at the day and bond levels are shown in parentheses.

	Dependent variable:							
	Risky-principal				Agency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SMCCF × Eligible	-93.26^{**}	-76.08^{***}	-61.24^{***}	-61.42^{***}	-7.45^{*}	-9.13^{**}	-3.38	-3.79
	(39.33)	(27.87)	(17.83)	(17.89)	(4.36)	(4.22)	(4.14)	(4.09)
SMCCF	13.88	-0.46	-9.05	-9.14	2.82	5.15^{**}	1.46	1.75
	(35.04)	(25.14)	(16.58)	(16.64)	(2.37)	(2.47)	(2.14)	(2.14)
Eligible	54.22	12.27			-0.77	11.87^{**}		
	(50.71)	(33.55)			(4.42)	(5.46)		
log(Amount outstanding)	-3.86	-23.05^{**}			-4.06^{***}	-1.64		
	(16.73)	(10.71)			(1.03)	(1.07)		
log(Time-to-maturity)	-66.38	-102.01			8.79	30.42^{*}		
	(134.08)	(90.03)			(17.08)	(17.69)		
log(Age)	28.46^{*}	31.43^{**}			0.99	2.55^{*}		
	(15.69)	(12.45)			(1.95)	(1.45)		
Trade size category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Bond FE	No	No	Yes	Yes	No	No	Yes	Yes
Credit rating FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	30,743	30,430	30,744	30,430	9,182	9,004	9,183	9,004
Adjusted R^2	0.03	0.07	0.20	0.20	0.11	0.14	0.29	0.30

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 9. DID robustness: only include bonds with 4 to 6 years left to maturity and rating close to the IG/HY threshold. This table presents regression results for the following DID specification from equation (4): $y_{ijt} = \alpha_s + \alpha_k + \beta_1 \times \text{SMCCF}_t \times \text{Eligible}_t + \beta_2 \times \text{SMCCF}_t + \beta_3 \times \text{Eligible}_t + \gamma \times X_{i,t} + \varepsilon_{ijt}$. The dependent variables are measures of transactions costs for risky-principal and agency trades. SMCCF_t is a dummy that takes the value of 1 if day t falls between March 23 and April 9, and 0 otherwise. Eligible_t takes the value of 1 if the bond has an investment-grade rating and time-to-maturity of 5 years or less on the March 23 2020. X_{it} controls for log(Amt outstanding), log(Age), and log(Time-to-maturity): logs of bond's amount outstanding, years since bond issuance, and years to maturity, respectively. There are three trade size categories: less than \$100,000, between \$100,000 and \$1 million, and larger than \$1 million. The sample begins on March 6 and ends on April 9, 2020. Only US firms, bonds with 4, 5, or 6 years left to maturity that are rated at the bottom tier of IG (BBB+/Baa1, BBB/Baa2, and BBB−/Baa3) or the top tier of HY (BB+/Ba1, BB/Ba2, and BB−/Ba3) are included. Bonds that change credit grade are excluded. Clustered standard errors at the day and bond levels are shown in parentheses.

	Dependent variable:							
	Risky-principal				Agency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SMCCF × Eligible	-94.92^{**}	-86.46^{**}	-73.52^{**}	-73.52^{**}	-2.82	-5.38	-0.16	-0.16
	(45.73)	(43.93)	(30.56)	(30.56)	(3.58)	(3.80)	(3.90)	(3.90)
SMCCF	46.47	37.41	16.30	16.30	2.54	5.14^{**}	2.41	2.41
	(29.20)	(24.24)	(17.65)	(17.65)	(1.89)	(2.04)	(2.34)	(2.34)
Eligible	63.68	46.64			-1.18	7.74		
	(46.38)	(52.37)			(4.19)	(7.49)		
log(Amount outstanding)	-9.03	-18.19			-3.94^{***}	-2.58^{*}		
	(21.30)	(16.18)			(1.47)	(1.45)		
log(Time-to-maturity)	-160.39	-129.63			40.68	45.95		
	(150.14)	(130.02)			(30.85)	(30.34)		
log(Age)	36.44	30.68^{*}			-3.29	-1.56		
	(22.44)	(18.18)			(3.10)	(2.31)		
Trade size category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Bond FE	No	No	Yes	Yes	No	No	Yes	Yes
Credit rating FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	14,124	14,124	14,124	14,124	4,595	4,595	4,595	4,595
Adjusted R^2	0.04	0.05	0.16	0.16	0.12	0.13	0.28	0.28
Note:								*p<0.1; **p<0.05; ***p<0.01

Trade costs for different trade size bins

Here we run the regressions in (4) but with the trades of a particular size category in a different regression. In Tables 10-12, we show that small and large trades are responsible for the entire liquidity improvement documented in Table 4: small trades (with par volume of \$100,000 or less) become much more liquid after the Fed's CCF announcements followed by large trades (with volume larger than \$1 million). Liquidity of odd-lot trades (with volume between \$100,000 and \$1 million) seem to be unaffected by the Fed's intervention. Curiously we fail to find an affect for Odd-lot trades. There is some empirical evidence, e.g., Feldhütter (2012), suggesting that trades with different sizes are affected differently by market turmoil.

Table 10. DID robustness: only include trades with par volume $<$ \$100,000, i.e., micro trades. This table presents regression results for US firms for the following DID specification from equation (4): $y_{ijt} = \alpha_s + \alpha_k + \beta_1 \times \text{SMCCF}_t \times \text{Eligible}_t + \beta_2 \times \text{SMCCF}_t + \beta_3 \times \text{Eligible}_t + \gamma \times X_{i,t} + \varepsilon_{ijt}$. The dependent variables are measures of transactions costs for risky-principal and agency trades. SMCCF_t is a dummy that takes the value of 1 if day t falls between March 23 and April 9, and 0 otherwise. Eligible_t takes the value of 1 if the bond has an investment-grade rating and time-to-maturity of 5 years or less on the March 23 2020. X_{it} controls for log(Amt outstanding), log(Age), and log(Time-to-maturity): logs of bond's amount outstanding, years since bond issuance, and years to maturity, respectively. The sample begins on March 6 and ends on April 9, 2020. Only trades that are less than \$100,000 in par volume, i.e., micro trades, are included. Bonds that change credit grade are excluded. Clustered standard errors at the day and bond levels are shown in parentheses.

	Dependent variable:							
	Risky-principal				Agency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SMCCF $\times$ Eligible	-77.67^{***}	-54.42^{***}	-58.51^{***}	-45.93^{***}	-16.21^{***}	-19.37^{***}	-14.86^{***}	-15.66^{***}
	(19.69)	(18.51)	(12.66)	(12.56)	(4.45)	(4.53)	(5.24)	(5.27)
SMCCF	3.05	-28.30	-18.24	-30.64	9.45^{***}	11.48^{***}	6.63^{***}	7.26^{***}
	(24.08)	(23.12)	(20.75)	(21.29)	(3.06)	(2.97)	(2.28)	(2.36)
Eligible	0.94	-22.17			6.48	15.67^{***}		
	(23.80)	(18.37)			(4.66)	(4.64)		
log(Amt outstanding)	-38.79^{***}	-32.77^{**}			-4.24^{***}	-2.03^{**}		
	(11.74)	(13.90)			(0.79)	(0.79)		
log(Time-to-maturity)	11.54^{*}	7.93			4.26^{***}	5.98^{***}		
	(6.90)	(7.99)			(1.08)	(1.58)		
log(Age)	39.02^{***}	37.74^{***}			7.44^{***}	8.23^{***}		
	(13.24)	(11.15)			(1.85)	(1.84)		
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Bond FE	No	No	Yes	Yes	No	No	Yes	Yes
Credit rating FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	92,300	82,694	92,301	82,694	28,556	27,182	28,556	27,182
Adjusted R^2	0.05	0.08	0.35	0.37	0.05	0.08	0.26	0.27
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 11. DID robustness: only include trades with \$100,000 $\leq$ par volume $<$ \$1 million, i.e., odd-lot trades. This table presents regression results for US firms for the following DID specification from equation (4): $y_{ijt} = \alpha_s + \alpha_k + \beta_1 \times \text{SMCCF}_t \times \text{Eligible}_t + \beta_2 \times \text{SMCCF}_t + \beta_3 \times \text{Eligible}_t + \gamma \times X_{i,t} + \varepsilon_{ijt}$. The dependent variables are measures of transactions costs for risky-principal and agency trades. SMCCF_t is a dummy that takes the value of 1 if day t falls between March 23 and April 9, and 0 otherwise. Eligible_t takes the value of 1 if the bond has an investment-grade rating and time-to-maturity of 5 years or less on the March 23 2020. X_{it} controls for log(Amt outstanding), log(Age), and log(Time-to-maturity): logs of bond's amount outstanding, years since bond issuance, and years to maturity, respectively. The sample begins on March 6 and ends on April 9, 2020. Only trades that are greater than \$100,000 and less than \$1 million in par volume, i.e., odd-lot trades, are included. Bonds that change credit grade are excluded. Clustered standard errors at the day and bond levels are shown in parentheses.

	Dependent variable:							
	Risky-principal				Agency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SMCCF × Eligible	−11.67	−8.28	−6.37	−5.44	−1.21	−1.66	−1.84	−1.01
	(12.57)	(13.87)	(13.85)	(14.15)	(2.50)	(2.35)	(2.56)	(2.34)
SMCCF	−27.03*	−31.91*	−36.84**	−37.76**	2.42	2.82*	2.58	1.74
	(15.14)	(16.45)	(15.07)	(15.25)	(1.78)	(1.51)	(2.00)	(1.82)
Eligible	−0.33	−4.16			0.23	2.10		
	(12.17)	(13.48)			(1.99)	(1.81)		
log(Amt outstanding)	−18.54***	−25.29***			−2.97***	−2.40**		
	(4.34)	(3.84)			(0.99)	(1.02)		
log(Time-to-maturity)	26.48***	33.45***			3.86***	3.00***		
	(2.85)	(3.26)			(0.60)	(0.54)		
log(Age)	15.49***	17.94***			3.02***	2.43***		
	(3.10)	(3.08)			(0.58)	(0.76)		
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Bond FE	No	No	Yes	Yes	No	No	Yes	Yes
Credit rating FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	36,406	34,457	36,407	34,457	10,089	9,775	10,089	9,775
Adjusted R^2	0.03	0.03	0.07	0.07	0.04	0.03	0.20	0.22

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12. DID robustness: only include trades with par volume $\geq$ \$1 million, i.e., large trades. This table presents regression results for US firms for the following DID specification from equation (4): $y_{ijt} = \alpha_s + \alpha_k + \beta_1 \times \text{SMCCF}_t \times \text{Eligible}_t + \beta_2 \times \text{SMCCF}_t + \beta_3 \times \text{Eligible}_t + \gamma \times X_{i,t} + \varepsilon_{ijt}$. The dependent variables are measures of transactions costs for risky-principal and agency trades. SMCCF_t is a dummy that takes the value of 1 if day t falls between March 23 and April 9, and 0 otherwise. Eligible_t takes the value of 1 if the bond has an investment-grade rating and time-to-maturity of 5 years or less on the March 23 2020. X_{it} controls for log(Amt outstanding), log(Age), and log(Time-to-maturity): logs of bond's amount outstanding, years since bond issuance, and years to maturity, respectively. The sample begins on March 6 and ends on April 9, 2020. Only trades that are greater than or equal to \$1 million in par volume, i.e. large trades, are included. Bonds that change credit grade are excluded. Clustered standard errors at the day and bond levels are shown in parentheses.

	Dependent variable:							
	Risky-principal				Agency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SMCCF × Eligible	-24.22^{***}	-22.17^{**}	-29.02^{***}	-30.56^{***}	-6.45^{***}	-7.96^{***}	-1.81	-2.08
	(9.08)	(8.78)	(8.94)	(8.90)	(2.49)	(2.85)	(3.19)	(3.19)
SMCCF	6.70	4.25	5.12	6.66	4.43	5.76^{*}	-0.83	-0.63
	(9.27)	(10.06)	(9.91)	(9.96)	(2.82)	(3.03)	(3.16)	(3.18)
Eligible	-0.16	-9.19			-19.98^{***}	-7.83^{***}		
	(7.51)	(10.00)			(1.57)	(2.75)		
log(Amt outstanding)	-19.14^{***}	-26.76^{***}			-1.10	0.31		
	(2.67)	(3.17)			(0.98)	(0.94)		
log(Time-to-maturity)	19.55^{***}	22.15^{***}			2.49^{***}	4.99^{***}		
	(2.33)	(2.99)			(0.76)	(0.90)		
log(Age)	14.35^{***}	15.53^{***}			0.42	0.81		
	(2.43)	(2.99)			(1.28)	(1.28)		
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Bond FE	No	No	Yes	Yes	No	No	Yes	Yes
Credit rating FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	29,941	28,992	29,941	28,992	8,983	8,367	8,985	8,367
Adjusted R^2	0.02	0.02	0.02	0.02	0.13	0.18	0.28	0.28
Note:								*p<0.1; **p<0.05; ***p<0.01

D.4 A decomposition of the change in profits

As established in the text, the instantaneous changes in profit can be written. The first term is the instantaneous change in revenue, while the second and the third term capture instantaneous changes in costs.

$$d\Pi_t = dR_t - dN_t\, a_t - N_t(p_{ht} - p_{lt})\, dx_{ht}.$$

The plain blue line in Figure 10 shows the total change in the second term, $\int_0^t dN_u a_u$, and the dashed red line shows the total change in the third term, $\int_0^t N_u\, (p_{hu} - p_{lu})\, dx_{hu}$, from a January 1st time-zero baseline, up to time t, for all t. The blue curve shows the extra cost, relative to baseline, of handling a larger volume. This extra cost rose sharply during the crisis, but remains quite elevated, reflecting the fact that trading volume remains elevated. The dashed red curve represents the extra cost associated with substitution between different types of orders. This clearly mitigated the increase in handling costs associated to the rise in volume, but only to a small extent.

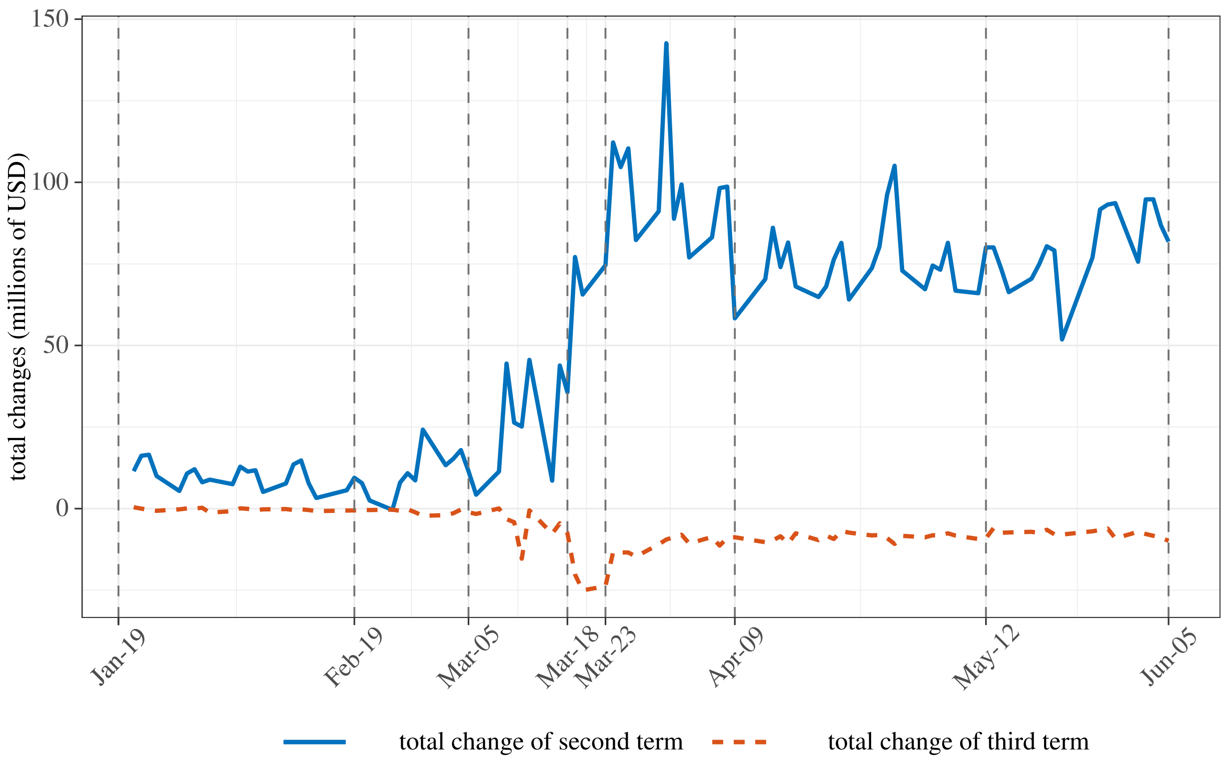

Figure 10. This figure plots the (negative of) the second and third terms in equation (6).