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Market Liquidity in Treasury Futures Market During March 2020

Eleni Gousgounis, Scott Mixon, Tugkan Tuzun, and Clara Vega*

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Abstract

We study the behavior of liquidity providers and liquidity consumers in the 10-year U.S. Treasury futures market during the height of the COVID-19 shock in March 2020, a period of market turmoil when demand for liquidity was high. In March 2020, PTFs reduced their volume of liquidity providing trades as a share of total trading volume. However, they still accounted for the lion share of total liquidity provision and their liquidity provision improved market liquidity. In contrast, dealers (banks and non-banks) increased their volume of liquidity providing trades as a share of total trading volume, but their activity did not have a large effect on overall liquidity. Among the traders that place liquidity consuming trades, asset managers had the largest impact on liquidity by increasing transaction costs. Despite a significant attention to the role of basis traders in the Treasury market disruption of March 2020, we do not find evidence for basis traders being important drivers of disruption in Treasury futures market.

JEL classification: G10, G13

Keywords:PTFs; Basis Traders; Treasury Futures

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1. Introduction

News about events that have large macroeconomic consequences, such as the onset of COVID-19 in March 2020, cause large asset price movements as investors incorporate information they receive into asset prices. Market participants not only incorporate relevant information into asset prices but their actions can also affect financial stress. For example, traders, who normally post limit orders, can potentially attenuate market stress by continuing to post limit orders and provide liquidity (Brogaard et al. 2018), or they can exacerbate market stress by exiting the market. On the other hand, traders, who normally execute trades against limit orders and trade in the same direction of price moves, can potentially exacerbate market stress by continuing to consume liquidity(Vissing-Jorgensen 2021), or they can execute "contrarian" trades, which could mitigate price movements (Colliard 2014).

We use confidential data on 10-year U.S. Treasury futures market to study the trading behavior of different market participants in the past decade with a focus on their behavior in March 2020.[1] The confidential data allows us to identify which side of each trade had a resting limit order and provided liquidity, and which side of the trade initiated the trade and consumed liquidity. In addition, it allows us to classify traders into different categories based on the traders' self-reporting to the U.S. Commodity Futures Trading Commission (CFTC) classification, their names, and trading behavior. Our analysis focuses on four large categories: bank dealers, non-bank dealers, hedge funds (leveraged money firms), other asset managers, and principal trading firms (PTFs). In addition, we identify basis traders that engage in arbitrage activity between Treasury cash and futures markets. Taken together, this confidential data allows for separately measuring

[1]We focus on 10-year U.S. Treasury futures, which trade on an electronic limit-order book market, for two reasons. First, the U.S. Treasury market plays an important role in the U.S. economy. Second, as documented by Vissing-Jorgensen (2021), among others, the 10-year U.S. Treasury bond experienced significant market turmoil in March 2020.

liquidity provision and liquidity consumption by each trader category defined as the volume of liquidity providing or consuming trades of that trader category as a share of total trading volume.

Using these measures of liquidity provision and liquidity consumption, we observe three important trends over the last ten years. First, we document a decline in liquidity provision by dealers which was offset by an increase in liquidity provision by PTFs, consistent with prior studies (e.g. Joint Staff Report 2015). PTFs do not hold large inventory of Treasury futures, suggesting that they have low balance sheet capacity to provide liquidity during stressful times when investors demand for futures contracts is unidirectional investors are either all buying or selling futures. In contrast, bank and non-bank broker dealers, which hold larger inventory of Treasury futures, may be able to manage unidirectional demand better. Second, we document an increase in the concentration of liquidity provision, also consistent with prior studies (Joint Staff Report 2015; Kirilenko et al. 2017).[2] The concentration in liquidity provision may cause market liquidity to be less resilient since a dominant liquidity provider exiting the market would have a large effect on market liquidity if others do not quickly step in. Third, while liquidity demand by hedge funds and other asset managers appears stable over time, starting in 2018 we observe an increase in their U.S. Treasury futures net short and net long positions, respectively. The increase in net positions suggests an increase in directional trading which can exacerbate price movements after a news shocks, especially when market participants engage in similar trading strategies. The increase in basis trading, for example, is commonly cited as a highly leveraged directional trading strategy that potentially deteriorated liquidity in March 2020 (Vissing-Jorgensen 2021).

Looking at the liquidity provision measure by trader categories, we also observe

[2]For the concentration of liquidity provision measure, we sum the square of traders's share of liquidity providing volume to compute the Herfindahl-Hirschman index.

that PTFs and bank dealers are the main liquidity providers, accounting for 70 and 15 percent of the volume of liquidity providing trades, respectively. While PTFs provide the lion share of liquidity, dealers hold relatively more inventory and may be better able to increase their liquidity provision during periods of market turmoil. Even though non-bank dealers face less balance sheet constrains because they are exempt from the Dodd-Frank Act regulation (see, for example Adrian et al. 2017), as a group, they provide a relatively small share of liquidity (less than five percent). It is important to note that PTFs and bank dealers are not always liquidity providers as they also post a large volume of liquidity consuming orders. In fact, PTFs consume the most liquidity, dealers are second, and asset managers and hedge funds follow.

Next, we estimate a vector autoregressive (VAR) model to investigate how the trading behavior of various liquidity providers and liquidity consumers may have affected market liquidity in March 2020. We find that PTFs reduced their provision of liquidity as a share of total trading volume and relative to their past liquidity provision. However, they still accounted for the lion share of liquidity provision and their liquidity provision, on average, improved liquidity in the market. In contrast, bank and non-bank broker dealers increased their liquidity provision, but their activity did not have a significant effect on overall market liquidity.

Turning to the liquidity consumption measure by trader categories, we observe that asset managers' trading activity had the biggest negative impact on liquidity. Their activity as a group increased transaction costs in March 2020. In contrast, the trading activity of hedge funds reduced transaction costs, but this reduction is modest compared to asset managers' effect. We also find that basis traders, which we classify based on their trading behavior (most of which originally self-report as asset managers and hedge funds (leveraged money firms) in the CFTC data), did not appear to have a large impact on liquidity in March 2020. Our results on basis traders complement the work of Mixon and Orlov (2024), who also study the trading behavior of basis traders in U.S. Treasury markets during the first quarter of 2020 and find that their gross cash market exposure increased while their futures positions contracted.

The organization of the paper is as follows. Section 2 describes the data we use and how we group different market participants. Section 3 provides summary statistics for our sample, develops the empirical models used and explains our results. Section 4 offers our concluding remarks.

2. Data and Methodology

2.1. Data

We use CFTC's Trade Capture Report (TCR) transaction data for 10-year Treasury Note futures contracts from February 15th, 2012, to March 31st, 2021. These contracts are traded electronically on Globex, the electronic platform of the Chicago Mercantile Exchange (CME). The data contains detailed transaction information, including the transaction time, price and quantity of every futures transaction. It also provides a variable indicating which side initiated the trade (buyer initiated, seller initiated). The database also includes the type (e.g. market, limit, stop-order) of the order from which each trade originated and an indicator for trading strategies (i.e. calendar spreads). We limit our attention to electronic outright trades (e.g., excluding calendar spreads) in the front month futures contracts and to transactions that originate from market or limit orders. Finally, the database has identifying information for the counterparties to each transaction; it provides their name and a corresponding account number. Each participant name can be linked to more than one account number. In our analysis, we aggregate transactions by name and track the trading behavior of those participants.

While the trading activity of participants identified by name account for the bulk of the trading volume, our sample also includes participants for which we have account information, but no participant name. In the classification scheme described in the following section, we group those participants in a group which we call "unidentified."

2.2. Classification of Trader Types and General Trends

The first step in our analysis is to classify traders into different categories. We classify traders using the self-classification of these market participants in the Integrated Surveillance System (ISS) of the CFTC and the accounts legal name identifier into four large categories: bank dealer, non-bank dealer, leveraged money (hedge fund), asset manager and PTFs. To these four categories, we add four smaller ones to make sure we include all participants: individual, foreign central banks, other, and unidentified. The "individual" category is for accounts with the legal name identifier of an individual; the "foreign central bank" category is for accounts that are either self-classified in the ISS data as "central banks" or the participants' name is that of a foreign central bank; the "other" category includes accounts with an identifiable legal name but whose activity is small, those of sovereign wealth funds, mutual funds, etc; the "unidentified" category is for accounts anonymous to us. We track the general trends in all groups' trading behavior over time and we subsequently focus on how they may have affected liquidity during March 2020.

For our analysis during March 2020, we also identify traders whose trading behavior is consistent with that of a basis trader and we reclassify them as basis traders. Specifically, we identify firms that specialize in relative-value trading strategies or the basis trade based on their trading behavior. To this end, we estimate daily basis trade profits using Barth and Kahn (2021)'s methodology and correlate profits with the daily position change of each market participant separately estimated using transaction data. If the correlation of a market participant's daily position change with basis trade profits is higher than 15 percent and in the right direction, i.e. shorting futures contract when the profit opportunities are high. Using this definition we find that on average, basis traders' aggressive orders account for less than 5 percent of total aggressive orders and most of the basis traders are self-classified in the ISS data as either leveraged money or asset managers, but there are other types that also appear to engage in relative value trading strategies. In our study of the March 2020 liquidity crisis, we force the categories to be mutually exclusive by separating basis traders out of groups such as leveraged money and asset managers. Hence, leveraged money and asset manager categories exclude basis traders.

2.2.1. Liquidity Provision Dynamics over Time

Similar to previous studies, e.g. Chaboud et al. (2014), we compute the monthly share of liquidity provision by a particular participant during our sample as $100 \times \frac{PassiveVolume_i}{\sum_{i=1}^{N} PassiveVolume_i}$, where $PassiveVolume_i$ is the number of contracts traded by participant i when the participant posted a passive order or had a standing order in the limit order book that resulted into a transaction.[3] N is the number of total participants. In Figure 1 Panel A, we show that the share of liquidity provision by PTFs has increased over time. PTFs, as a group, accounted for about 40 percent of all passive orders, and in 2021 they account for about 72 percent. In contrast, the share of liquidity provision by dealers (bank and non-bank together) has decreased over time. In 2012, dealers accounted for about 20 percent, and in 2021 they account for about 10 percent. The figure

[3]Every trade by definition comprises an aggressive and a passive side. The passive order is the standing order to buy or sell an instrument in the limit order book, while the aggressive order is that which is executed when matched against a standing passive order. Liquidity providers by definition post standing orders in the limit order book. However, they also use aggressive orders to manage their inventory.

also shows that asset managers and leveraged money come third in providing liquidity. Finally, individual participants, as well as "other" and "unidentified" categories provide liquidity, but none of them (as separate groups) provide more liquidity than dealers and PTFs. Foreign central banks, which account for a small percentage of the trading volume are not included in the graphs for privacy and confidentiality reasons. In Figure 1 Panel B dealers are separated into bank and non-bank dealers. Also, the share of passive orders for asset managers and leveraged money is presented separately. Bank dealers provide more liquidity than non-bank dealers, while leveraged money provide more liquidity compared to asset managers.

2.2.2. Concentration in Liquidity Provision over Time

Joint Staff Report (2015), Kirilenko et al. (2017), among others, document a liquidity provision shift from dealers to PTFs, and an increase in the concentration of liquidity provision. In Figure 2, we confirm their findings in the 10-year Treasury futures market and show that concentration has increased over time. We use the Herfindahl-Hirschman (HH) index on the share of passive orders as a measure of concentration. In 2012, the index was below 1500, but in 2016 the index increased and is now above the 1500 threshold, which is generally considered as the threshold for an industry to go from "unconcentrated" to "moderately concentrated." The HH index was close to 2000 (an index of 2500 is considered a highly concentrated industry) prior to February 2020, when the market experienced extreme illiquidity amid price volatility and high liquidity demand, and the concentration of liquidity provision may have exacerbated movements in March 2020.

2.2.3. Liquidity Demand Dynamics over Time

Similar to our computation of liquidity provision and to previous studies, e.g. Chaboud et al. (2014), we compute the monthly share of liquidity demand by a particular participant i during our sample as $100 \times \frac{AggressiveVolume_i}{\sum_{i=1}^{N} AggressiveVolume_i}$, where $AggressiveVolume_i$ is the number of contracts traded by participant i when the participant posted an aggressive order that is executed against a standing passive order. In Panel A Figure 3 we show that the share of liquidity demand by PTFs and dealers is the largest, followed by asset managers and leveraged money. Panel B of 3 shows that bank dealers are consuming more liquidity than non-bank dealers, while asset managers and leveraged money appear comparable post 2015.

The high share of liquidity demand by PTFs and Dealers is consistent with the view that liquidity providers are also the biggest liquidity demanders because they use "aggressive" orders to manage their inventory. However, liquidity providers (PTFs and Dealers) tend to have net positions close to zero so that their liquidity demand may not have as big of an impact on liquidity as other traders whose net positions are large. To investigate this possibility, we show in Figure 4 the cumulative net position of all firms. This graph illustrates that asset Managers, "other," dealers and leveraged money have the largest changes in cumulative positions, and thus they are likely the ones that exert the most pressure on liquidity and prices.

3. Effect of Different Types of Traders on Liquidity, and Volatility during March 2020

We study the link between the various groups' trading behavior, liquidity and volatility during March 2020. This is a challenging task, since liquidity, volatility and trading volume are endogenous and non-negative variables. Engle (2002) discusses key difficulties of the standard, widely used linear Gaussian framework in modeling non-negative variables, especially the challenge of ensuring non-negativity of the conditional mean and in describing closely their empirical dynamics. To address these difficulties, we model the behavior of the natural logarithm of liquidity, volatility and trading activity using a vector autoregressive model and note that our conclusions are similar when we estimate a multiplicative error model as suggested by Engle (2002) and used by Nguyen et al. (2020) to describe the volatility-liquidity dynamics in the US Treasury futures market. Specifically, we estimate the following system during March 2020:

$$\begin{aligned}
Illiquidity_t &= \sum_{i=1}^{N} a_i Illiquidity_{t-i} + \sum_{i=0}^{N} b_i Volatility_{t-i} + \sum_{i=0}^{N} c_i Volume^j_{t-i} + \epsilon^{il}_t, \\
Volatility_t &= \sum_{i=1}^{N} d_i Illiquidity_{t-i} + \sum_{i=1}^{N} f_i Volatility_{t-i} + \sum_{i=1}^{N} g_i Volume^j_{t-i} + \epsilon^{vol}_t, \\
Volume^j_t &= \sum_{i=1}^{N} h_i Illiquidity_{t-i} + \sum_{i=1}^{N} k_i Volatility_{t-i} + \sum_{i=1}^{N} l_i Volume^j_{t-i} + \epsilon^{vol^j}_t,
\end{aligned} \tag{1}$$

where $Illiquidity_t$ is the natural logarithm of the bid-ask spread at time t, $Volatility$ is the natural logarithm of the absolute value of the return at time t, and $Volume^j_t$ is the natural logarithm of the passive or aggressive volume of market participant type j at time t. We add "1" to the absolute value of the return and volume because we estimate the VAR using transaction time (similar to Hasbrouck (1991)'s VAR estimation) and at this frequency returns and volume are often zero.[4] Our measure of illiquidity is the bid-ask spread, a standard measure of illiquidity in the literature. However, we note that

[4] Hasbrouck (1991)'s favors a transaction-by-transaction VAR estimation instead of a 1-minute or lower frequency because to estimate impulse response functions we need to assume a particular order. The order of causality is easier to justify in a transaction-by-transaction VAR estimation than in a lower frequency VAR estimation.

bid-ask spreads over our sample period were often constrained by the minimum tick size (e.g., in March 2020, 94% of bid-ask spread observations are "stuck" at one tick).

We choose to truncate the VAR at $N = 4$ based on Schwarz's Bayesian information criteria. We estimate VAR equation (1) using data from March 2020, a month of market turmoil especially in the U.S. Treasury market (see: Vissing-Jorgensen 2021; He et al. 2022). Note that running this VAR during a market turmoil period may not be representative of usual trading conditions in Treasury markets. We aim to explore the behavior of market participants during a market stress period.

We analyze the impulse response of the bid-ask spreads, volatility and the passive trading volume, as a proxy for liquidity provision trading activity, of three types of traders separately: PTFs, bank dealers and non-bank dealers. To estimate the impulse response function, we use a Cholesky decomposition and assume the following order: bid-ask spreads, volatility and passive trading volume. Granger-causality tests cannot help us with the ordering because there is dual causality (volume, volatility and illiquidity granger cause each other). Our ordering assumes that market participants first observe liquidity and volatility, and then decide whether to provide liquidity or not. Below we discuss how the ordering affects the results.

Ordering choice of variables in the impulse response function has implications for the results as PTF passive trading volume is contemporaneously correlated with bid-ask spreads. If we change the ordering to have PTF participation first and then bid-ask spreads, instead of the ordering in Figure 5 the conclusion would be that PTFs liquidity provision increases bid-ask spreads the first period and subsequently their participation decreases bid-ask spreads. This interpretation is at odds with economic theory which predicts that an increase in liquidity provision should improve liquidity, we therefore favor the ordering that assumes that market participants first observe liquidity and volatility conditions, and then decide whether to provide liquidity.

Figure 5 shows the impulse response functions of bid-ask spreads and passive trading volume (liquidity providing trading activity) of traders that account for the largest share of passive trading: PTFs, bank dealers, non-bank dealer. Results suggest that the passive trading volume of PTFs only has an effect on bid-ask spreads. Panel A shows that a one standard deviation shock to PTF liquidity provision reduces bid-ask spreads by 0.005 standard deviations. Panel B shows that one standard deviation shock to bid-ask spreads increases PTF participation by 0.15 standard deviation in the first period and PTFs subsequently decrease their participation, suggesting that PTFs provide liquidity when bid-ask spreads are high and it is profitable to provide liquidity. Once they participate in the market, bid-ask spreads come down, and they subsequently decrease their participation. In contrast to PTFs, passive trading volume of bank and non-bank dealers had no statistically significant impact on bid-ask spreads while their passive trading volume declined slightly in response to higher bid-ask spreads.

Figure 6 shows the impulse response functions of volatility and passive trading volume of PTFs, bank dealers and non-bank dealers. As shown in Panel B and F, when volatility increases, liquidity provision by PTFs and non-bank dealers decreases, consistent with the idea that liquidity provision declines with higher volatility (for example, see: Nagel 2012). In contrast, liquidity provision by bank dealers appears to increase with higher volatility. This might be a direct consequence of lower liquidity provision by other traders. A one standard deviation increase in liquidity provision by PTFs decreases volatility significantly while a one standard deviation increase in liquidity provision by non-bank dealers also decreases volatility, but to a lesser extend.

Next, we study the liquidity demand of traders. We run the VAR equation system (1) with aggressive trading volume by trader groups: PTFs, bank dealers, non-bank dealers, asset managers, leveraged money, and basis traders. We force the categories to be mutually exclusive by separating basis traders out of groups such as leveraged money and asset managers. Similar to our estimation of impulse response functions from the VAR that uses passive trading volume, we use a Cholesky decomposition and assume the following order: bid-ask spreads, volatility and aggressive trading volume. Our ordering assumes that market participants first observe liquidity and volatility, and then decide whether to consume liquidity or not. Figure 7 displays the impulse response functions of bid-ask spreads and aggressive trading volume of PTFs, bank dealers, and non-bank dealers. As shown in Panels B and F, when bid-ask spreads increase, aggressive volume of PTFs and non-bank dealers decreases, suggesting that they do not want to pay higher transaction costs. In contrast, aggressive trading volume of bank dealers increase in response to higher illiquidity. Even more surprising is the behavior of bid-ask spreads in response to aggressive trading of PTFs and bank dealers. As shown in Panels A and C, when PTFs and bank-dealers aggressively trade, bid-ask spreads come down. These results may suggest that aggressive trading behavior of PTFs and bank-dealers may have some forecasting power for improvements in liquidity during market stress periods. While this finding might be surprising in normal times, during stressful times, aggressive trading by liquidity providers is likely correlated with market conditions that can prompt an intervention by the central bank. In fact, the Federal Reserve took numerous actions in March 2020 to calm the markets and provide liquidity in various markets including U.S. Treasury markets.[5]

Figure 8 displays the impulse response functions of bid-ask spreads and aggressive trading volume of asset managers (AM), leveraged money (LM), and basis traders. Panels A and C suggest that an increase in liquidity demand by asset managers widens bid-ask spreads while the liquidity demand of leveraged money shrinks bid-ask spreads, but a lesser degree. Panel E suggests that liquidity demand of basis traders had no impact on bid-ask spreads in March 2020. In other words, despite a significant attention

[5] For a complete list of the Federal Reserve actions, please see Clarida et al. (2021).

to the basis traders in Treasury markets (see: Barth et al. 2021; Banegas et al. 2021; Kruttli et al. 2023), we do not find evidence for basis traders being important drivers of liquidity disruption in Treasury futures markets in March 2020.

Figure 9 displays the impulse response function of volatility and aggressive trading volume of PTFs, bank dealers and non-bank dealers. In line with the impulse response function of illiquidity and aggressive trading of these traders, volatility decreases with the aggressive trading of PTFs, bank dealers and non-bank dealers during market stress. Again, this might be due to the correlation between the aggressive volume of liquidity providers and deteriorating market conditions, which prompted the market intervention by the Federal Reserve in March 2020.

Figure 10 displays the impulse response functions of volatility and aggressive trading volume of asset managers (AM), leveraged money (LM), and basis traders. Aggressive trading by asset managers, leveraged money and basis traders decreases volatility during the market stress of March 2020. This finding also may suggest a correlation between the aggressive volume of these traders and deteriorating market conditions, which prompted the market intervention by the Federal Reserve in March 2020.

4. Concluding Remarks

We study the liquidity provision and liquidity demand behavior of different trader categories in the 10-year U.S. Treasury futures market. Over time, there has been an increase in the concentration of liquidity provision and a change in the composition of firms who provide liquidity. The share of liquidity provision by PTFs has increased over time while the share of liquidity provision by dealers (bank and non-bank together) has decreased over time. PTFs also consume large amounts of liquidity. As a group, PTFs consume the most liquidity, asset managers second, and leveraged money are the third group.

In March 2020, asset managers' aggressive orders had the biggest impact on liquidity. Their activity as a group increased transaction costs. The effect of the liquidity demand of leveraged money was negative, but the magnitude was lower than the asset managers' impact. In contrast, basis traders aggressive orders did not appear to have a big impact on liquidity.

References

Adrian, Tobias, Nina Boyarchenko, and Or Shachar, 2017, Dealer balance sheets and bond liquidity provision, *Journal of Monetary Economics* 89, 92–109.

Banegas, Ayelen, Phillip J Monin, and Lubomir Petrasek, 2021, Sizing hedge funds' treasury market activities and holdings, FEDS Notes, Federal Reserve Board of Governors.

Barth, Daniel, and Jay Kahn, 2021, Basis trades and treasury market illiquidity, Working paper, Office of Financial Research.

Barth, Daniel, R Jay Kahn, et al., 2021, Hedge funds and the treasury cash-futures disconnect, *OFR WP* 21–01.

Brogaard, Jonathan, Allen Carrion, Thibaut Moyaert, Ryan Riordan, Andriy Shkilko, and Konstantin Sokolov, 2018, High frequency trading and extreme price movements, *Journal of Financial Economics* 128, 253–265.

Chaboud, Alain P., Benjamin Chiquoine, Erik Hjalmarsson, and Clara Vega, 2014, Rise of the machines: Algorithmic trading in the foreign exchange market, *Journal of Finance* 69, 2045–2084.

Clarida, Richard, Burcu Duygan-Bump, and Chiara Scotti, 2021, The covid-19 crisis and the federal reserve's policy response, Finance and economics discussion series no. 035, Federal Reserve Board of Governors.

Colliard, Jean-Edouard, 2014, Catching falling knives: Speculating on liquidity shocks, *Management Science* 63, 2573–2591.

Engle, Robert, 2002, New frontiers for arch models, *Journal of Applied Econometrics* 17, 425–446.

Hasbrouck, Joel, 1991, Measuring the information content of stock trades, *Journal of Finance* 46, 179–207.

He, Zhiguo, Stefan Nagel, and Zhaogang Song, 2022, Treasury inconvenience yields during the covid-19 crisis, *Journal of Financial Economics* 143, 57–79.

Joint Staff Report, 2015, The U.S. Treasury Market on October 15, 2014, Joint report of the staffs of the SEC, CFTC, Treasury, NY Fed, and Federal Reserve Board.

Kirilenko, Andrei, Albert S. Kyle, Mehrdad Samadi, and Tugkan Tuzun, 2017, The flash crash: High-frequency trading in an electronic market, *Journal of Finance* 72, 967–998.

Kruttli, Mathias S, Phillip Monin, Lubomir Petrasek, and Sumudu W Watugala, 2023, Ltcm redux? hedge fund treasury trading and funding fragility, *Available at SSRN 3817978* .

Mixon, Scott, and Alexei Orlov, 2024, Observations on the treasury cash-futures basis trades, Staff Reports, CFTC and OCE.

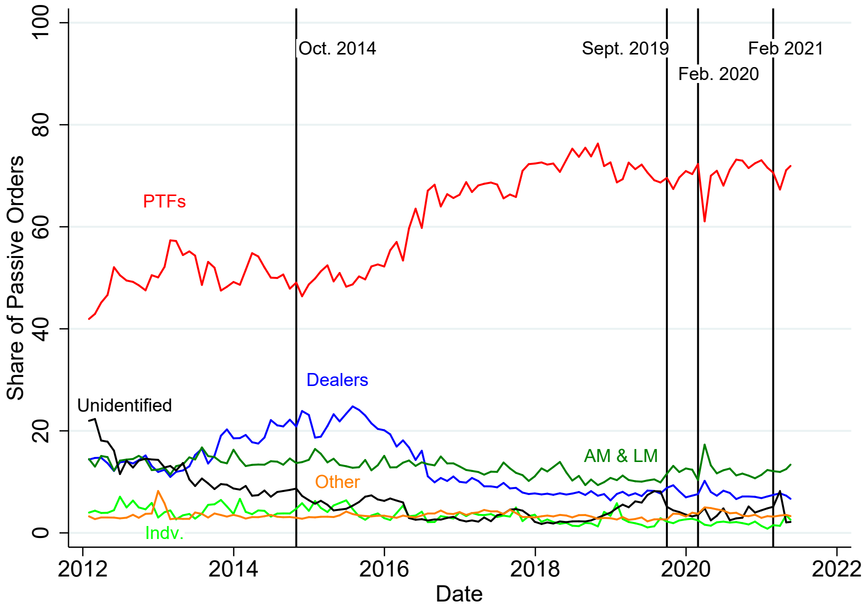
Nagel, Stefan, 2012, Evaporating liquidity, *The Review of Financial Studies* 25, 2005–2039.

Nguyen, Giang, Robert Engle, Michael Fleming, and Eric Ghysels, 2020, Liquidity and volatility in the U.S. Treasury market, *Journal of Econometrics* 217, 207–229.

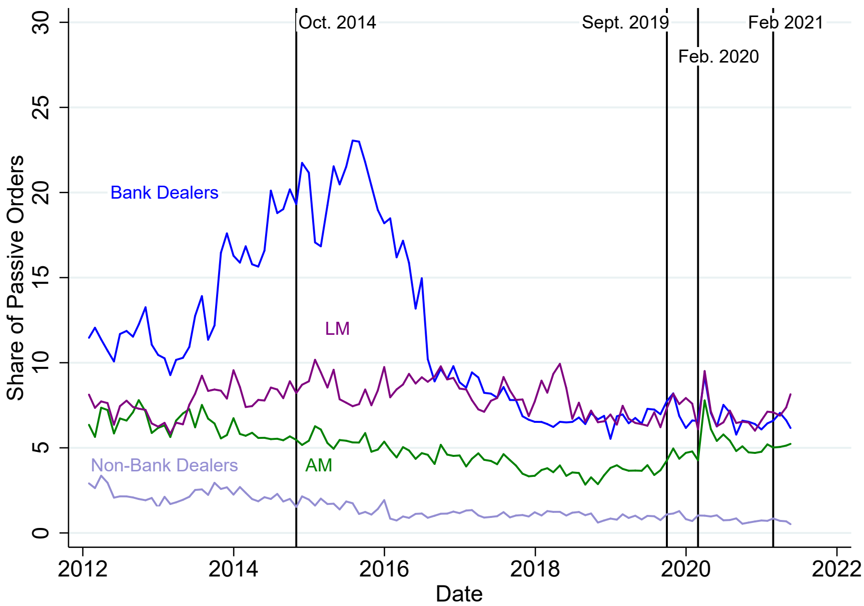
Vissing-Jorgensen, Annette, 2021, The treasury market in spring 2020 and the response of the federal reserve, *Journal of Monetary Economics* 124, 19–47.

Figure 1: Liquidity Provision: Share of Passive Trade

Panel A: All Firms



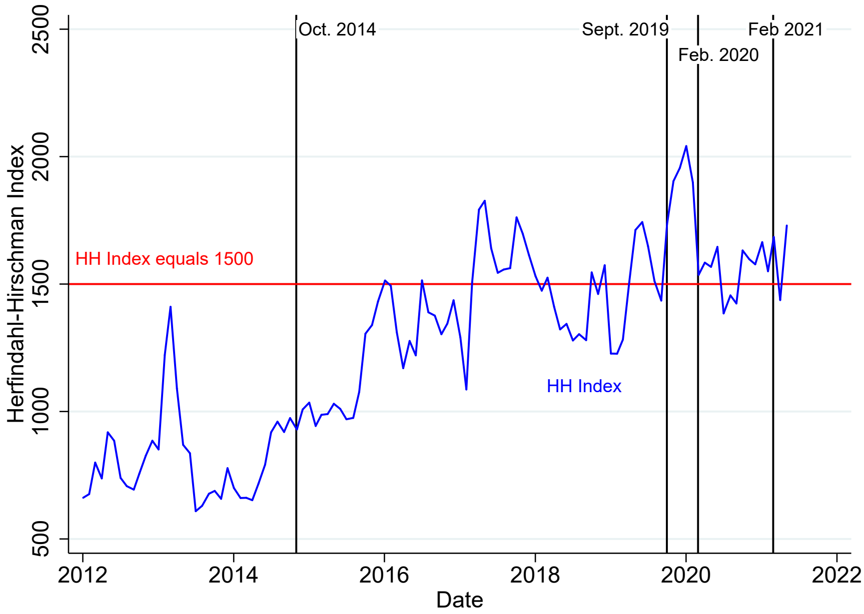
Panel B: More Detailed Breakdown



The figure displays the share of passive trades by trader groups. Panel A shows the share of passive trades done by all firms in our sample. AM&LM group includes both asset managers and leveraged money firms as defined in the CFTC Large Trader Report. Panel B shows the share of passive trades done by a more detailed breakdown. Dealers are broken down into bank dealers and non-bank dealers. AM&LM group is broken down into leveraged money (LM) and asset managers (AM).

Figure 2: Liquidity Provision: Concentration Measures

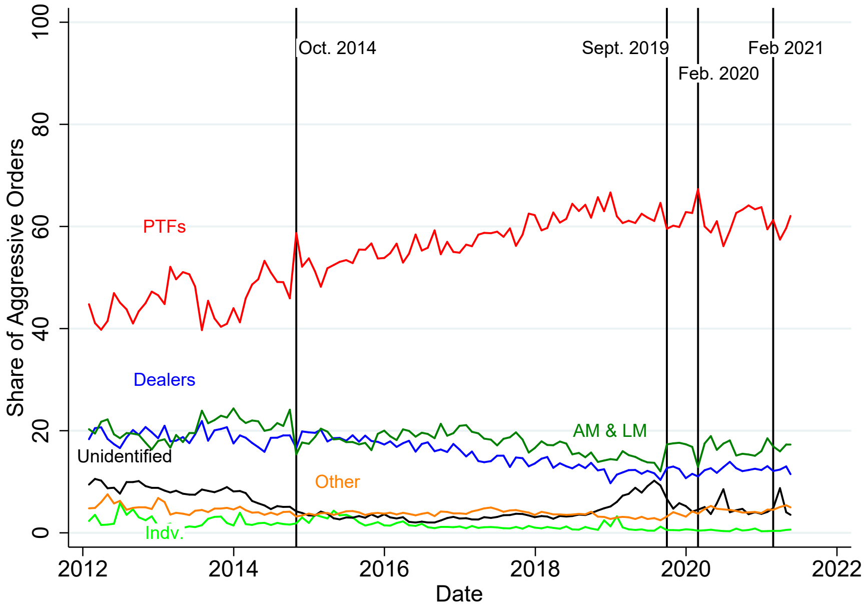
Herfindahl-Hirschman Index



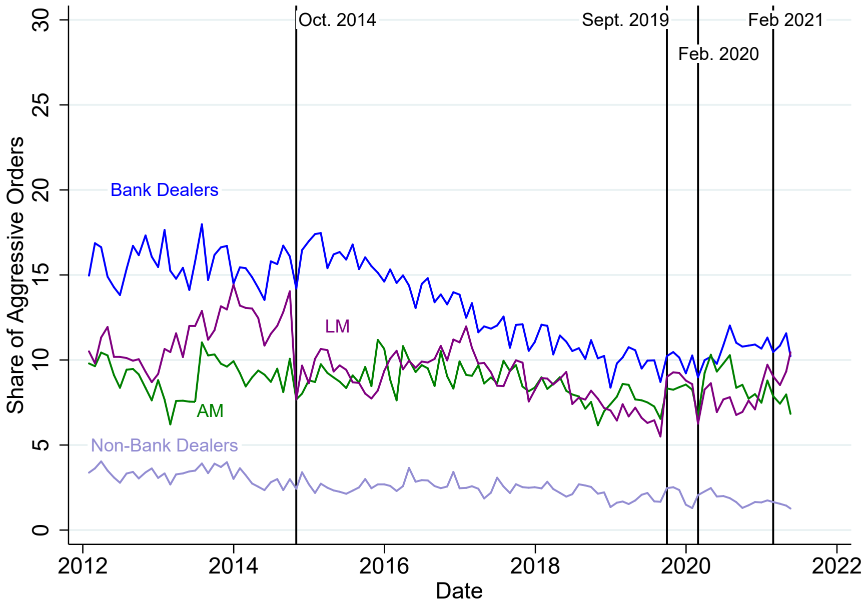
This figure shows the Herfindahl-Hirschman Index (blue line) estimated using the share of passive trade orders done by all PTFs and dealers. The red horizontal line indicates a 1500 HH index. An industry with an HH index between 1500 and 2500 is considered a moderately concentrated industry, while an industry with an HH index equal to or higher than 2500 is considered to be a highly concentrated industry.

Figure 3: Liquidity Demand

Panel A: All Firms

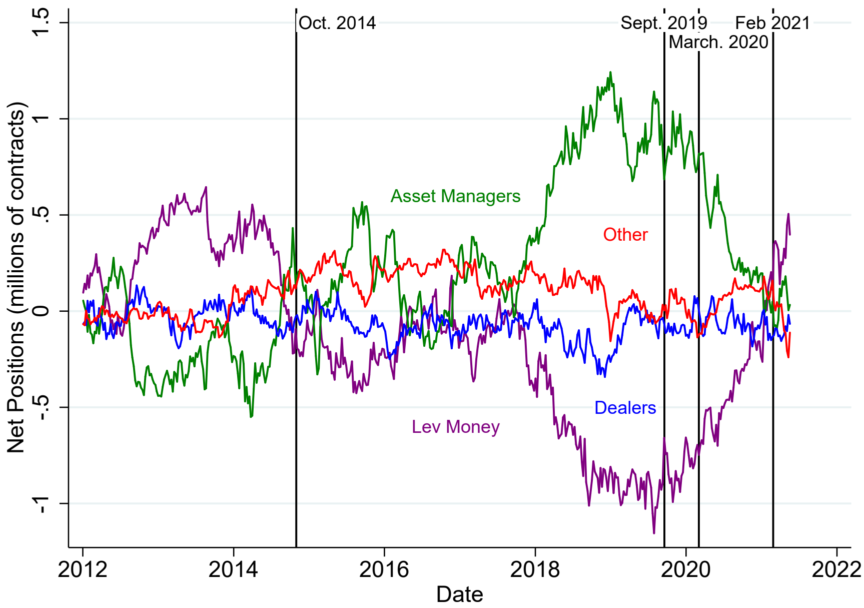


Panel B: More Detailed Breakdown



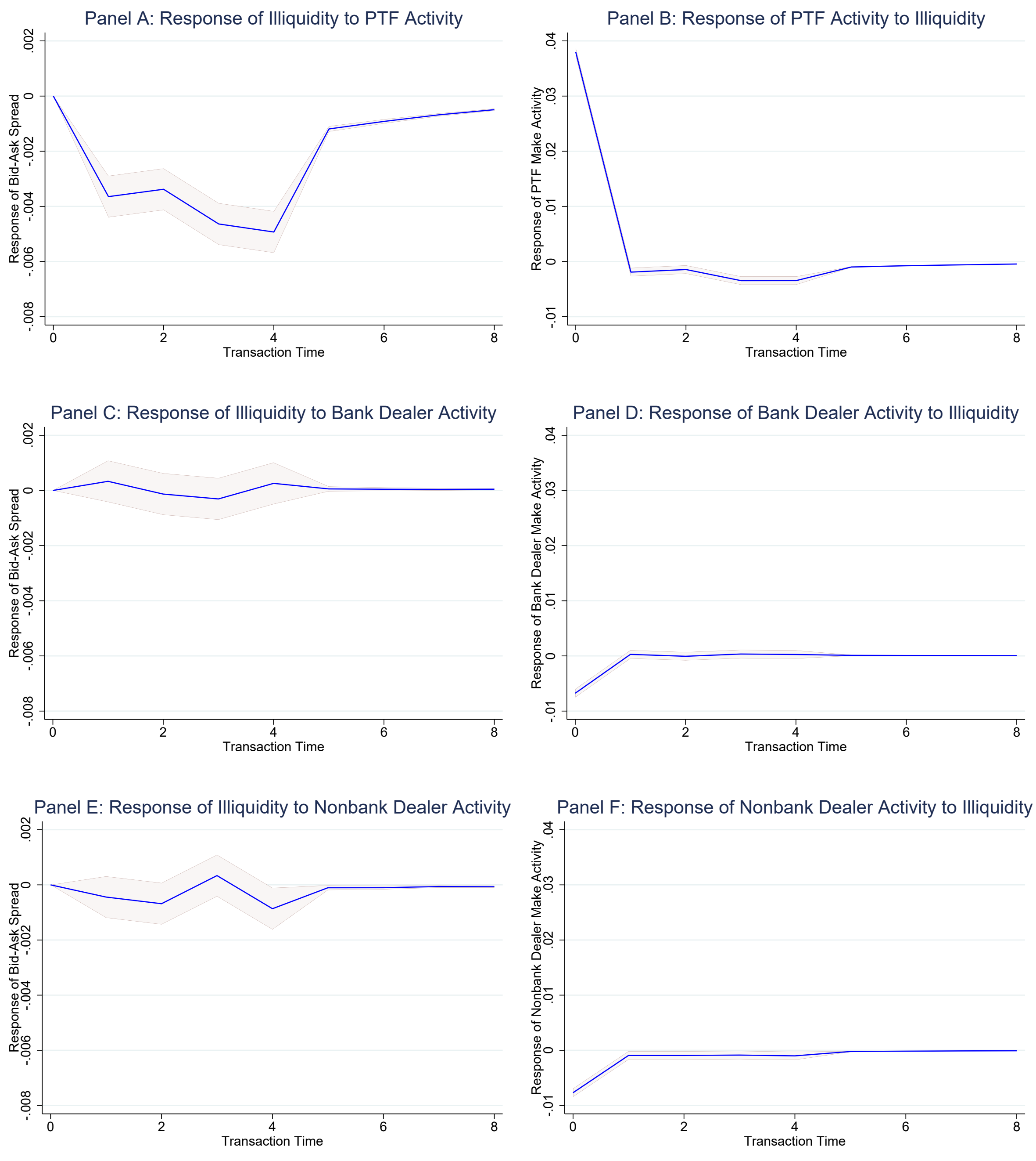
The figure displays the share of aggressive trades by trader types. Panel A shows the share of aggressive trades done by all firms in our sample. AM&LM group includes both asset managers and leveraged money firms as defined in the CFTC Large Trader Report. Panel B shows the share of passive trades done by a more detailed breakdown. Dealers are broken down into bank dealers and non-bank dealers. AM&LM group is broken down into leveraged money (LM) and asset managers (AM).

Figure 4: Liquidity Demand: Net Positions



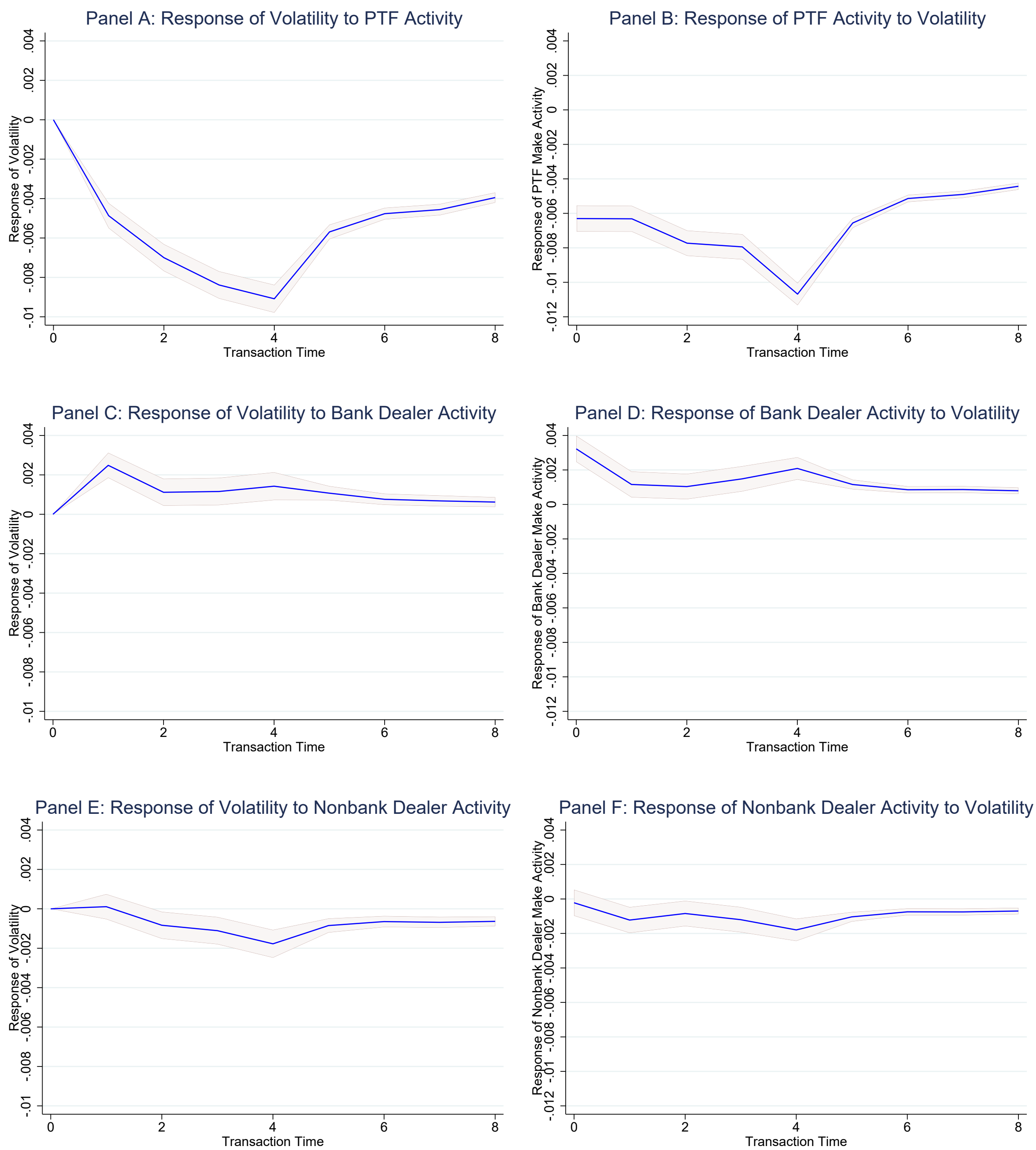
Notes: The figure shows net positions according to the CFTC Large Trader Report classifications: Asset managers (green), leveraged money (purple), dealers (blue) and other.

Figure 5: Impact of Liquidity Provision by Different Trader Types on Illiquidity



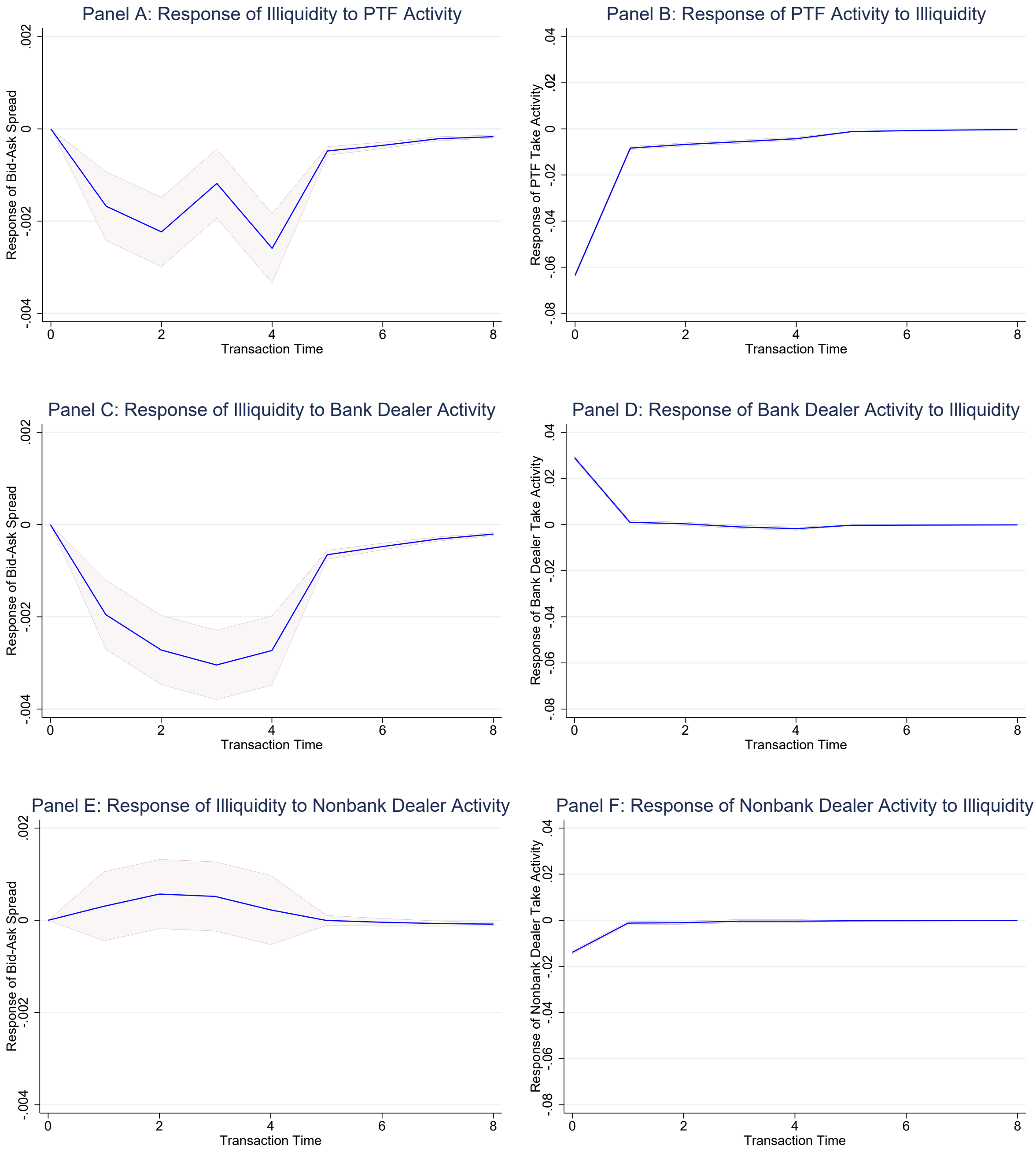
The figure shows impulse response functions based on the VAR estimation described in section 3. Panels A, C and E show the response of bid-ask spreads to a one standard deviation shock to PTF, bank dealer and non-bank dealer liquidity provision, respectively. Panels B, D and F show the response of PTF, bank dealer and non-bank dealer liquidity provision to a one standard deviation shock to bid-ask spreads, respectively.

Figure 6: Impact of Liquidity Provision by Different Trader Types on Volatility



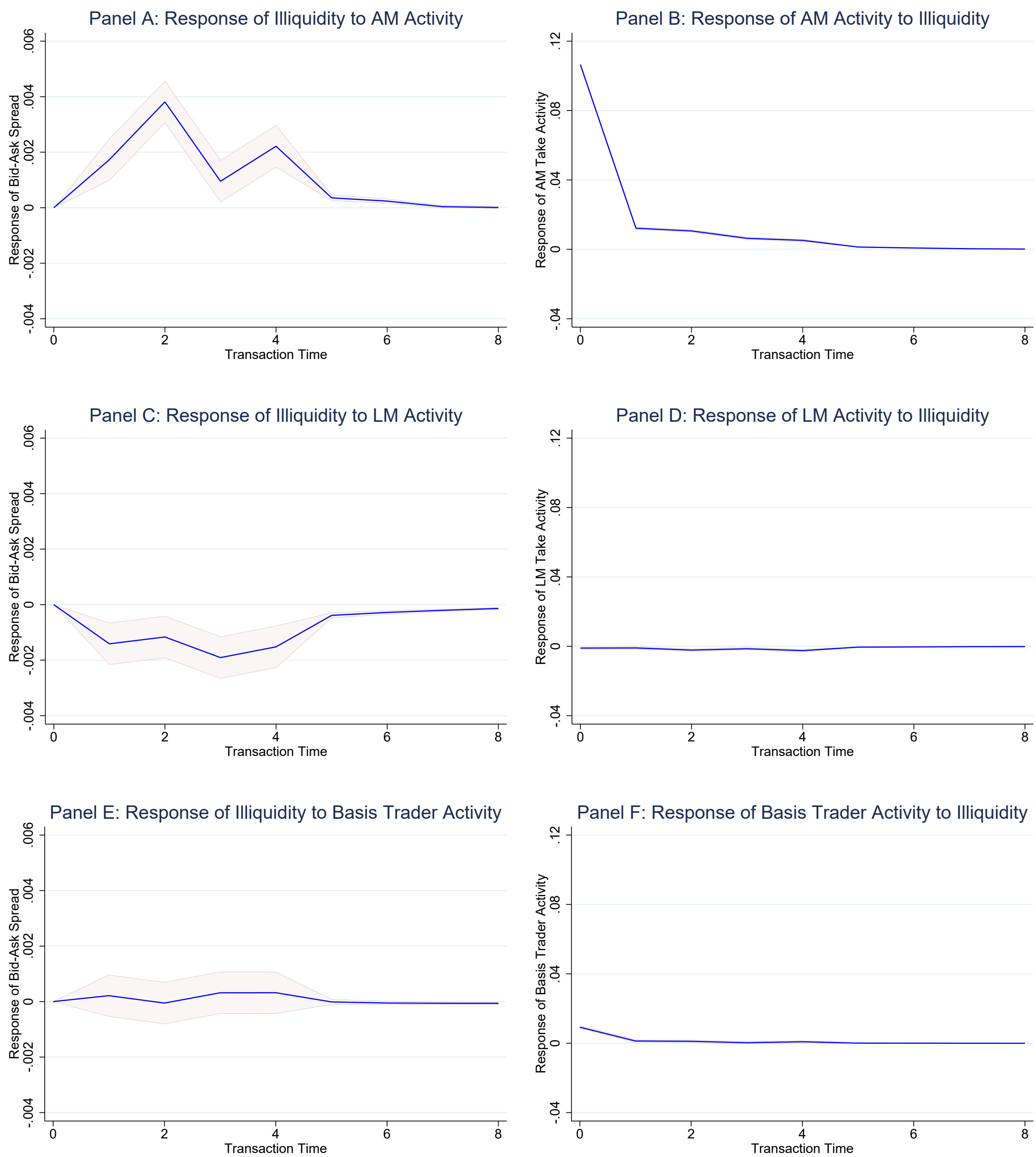
The figure shows impulse response functions based on the VAR estimation described in section 3. Panels A, C and E show the response of volatility to a one standard deviation shock to PTF, bank dealer and non-bank dealer liquidity provision, respectively. Panels B, D and F show the response of PTF, bank dealer and non-bank dealer liquidity provision to a one standard deviation shock to volatility, respectively.

Figure 7: Impact of Liquidity Demand by Different Trader Types on Illiquidity I



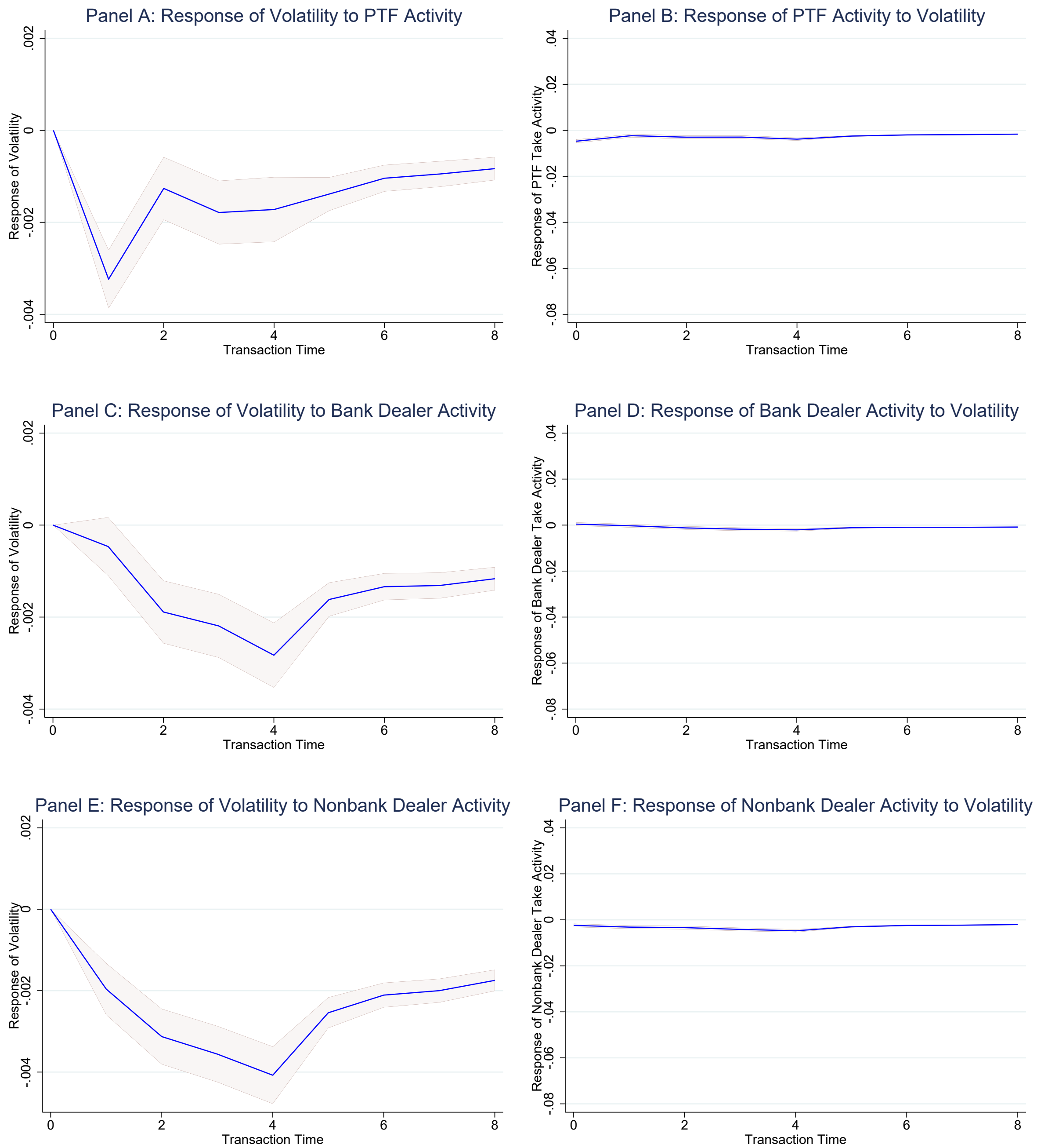
The figure shows impulse response functions based on the VAR estimation described in section 3. Panels A, C and E show the response of bid-ask spreads to a one standard deviation shock to PTF, bank dealer and non-bank dealer liquidity demand, respectively. Panels B, D and F show the response of PTF, bank dealer and non-bank dealer liquidity demand to a one standard deviation shock to bid-ask spreads, respectively.

Figure 8: Impact of Liquidity Demand by Different Trader Types on Illiquidity II



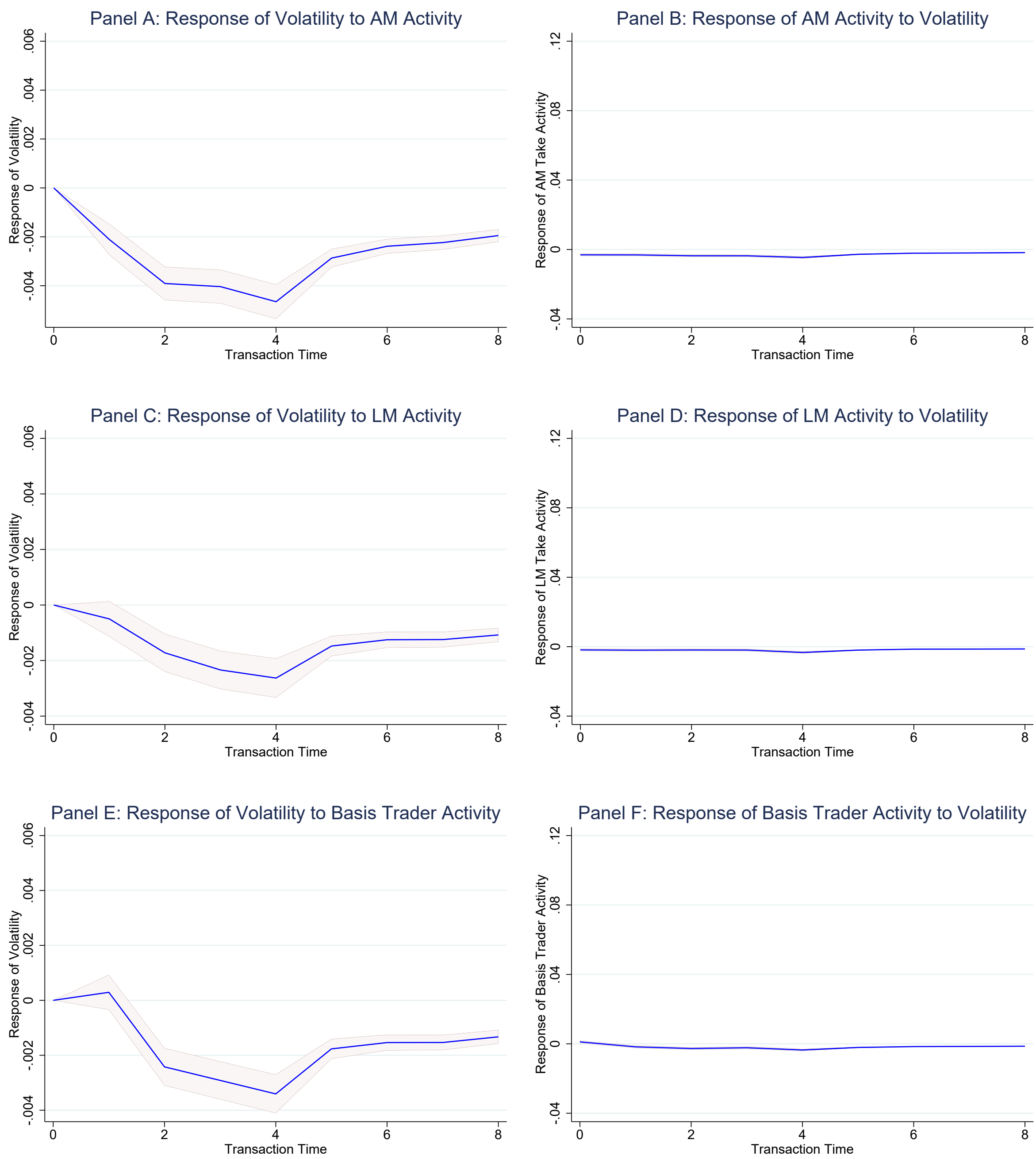
The figure shows impulse response functions based on the VAR estimation described in section 3. Panels A, C and E show the response of bid-ask spread to a one standard deviation shock to asset managers, leveraged money and basis traders' liquidity demand, respectively. Panels B, D and F show the response of asset managers, leveraged money and basis traders' liquidity demand to a one standard deviation shock to bid-ask spreads, respectively.

Figure 9: Impact of Liquidity Demand by Different Trader Types on Volatility I



The figure show impulse response functions based on the VAR estimation described in section 3. Panels A, C and E show the response of volatility to a one standard deviation shock to PTF, bank dealer and non-bank dealer liquidity demand, respectively. Panels B, D and F show the response of PTF, bank dealer and non-bank dealer liquidity demand to a one standard deviation shock to volatility, respectively.

Figure 10: Impact of Liquidity Demand by Different Trader Types on Volatility II



The figure shows impulse response functions based on the VAR estimation described in section 3. Panels A, C and E show the response of volatility to a one standard deviation shock to asset managers, leveraged money and basis traders' liquidity demand, respectively. Panels B, D and F show the response of asset managers, leveraged money and basis traders' liquidity demand to a one standard deviation shock to volatility, respectively.