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# Liquidity Provision under Stress: *Trading Frequency, Automation, and Anonymity*

**Vikas Raman, Michel A. Robe, and Pradeep K. Yadav***

* **Vikas Raman** is at the Warwick Business School, University of Warwick (United Kingdom). **Michel A. Robe (corresponding author)** is at the Kogod School of Business, American University (Washington, DC) and at the U.S. Commodity Futures Trading Commission (CFTC). **Pradeep K. Yadav** is at the Price College of Business, University of Oklahoma. Their email addresses are: vikas.raman@wbs.ac.uk, mrobe@american.edu, and pyadav@ou.edu. We thank the late Jim Moser, Sophie Moinas (our AEA discussant), Andrei Kirilenko, Albert Menkveld, Craig Pirrong, Kumar Venkataraman, Alexandre Batista, Praveen Kumar, Dmitriy Muravyev, Richard Haynes, David Reiffen, Kristian Rydqvist, Michel Van der Wel, and seminar participants at the CFTC, the U.S. Securities and Exchange Commission (SEC), the U.S. Treasury's Office of Financial Research (OFR), the State University of New York (Binghamton), the University of Colorado (Denver), the University of Oklahoma, George Washington University, the University of Sydney, the University of New South Wales, Warwick University, Université Paris-Dauphine, ESSEC Business School, and participants at Princeton University's *Workshop on Commodity Markets' Financialization and Regulation* and at the *2017 Meeting of the American Economic Association* (Chicago) for helpful comments. The research presented in this paper was co-authored by Michel Robe, a CFTC limited-term consultant who worked in his official capacity; Vikas Raman, a CFTC contractor who worked under CFTC OCE contract CFCE-10-CO-0237; and Pradeep Yadav, a CFTC contractor who worked under CFTC OCE contract CFOCE-13-0064. The Office of the Chief Economist and CFTC economists produce original research on a broad range of topics relevant to the CFTC's mandate to regulate commodity future markets, commodity options markets, and the expanded mandate to regulate the swaps markets pursuant to the Dodd-Frank Wall Street Reform and Consumer Protection Act. These papers are often presented at conferences, and many are later published in peer-reviewed or other scholarly outlets. The analyses and conclusions expressed in this paper are the authors' and do not reflect the views of other members of the Office of Chief Economist, other Commission staff, or the Commission itself. The authors are responsible for all errors, if any.

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### Abstract

We investigate high-frequency liquidity providers ("HFLPs") in periods of market stress. Using trader-level data from the world's largest commodity market in 2006—2009, we contrast HFLPs with: (a) the erstwhile Locals in the Pits, (b) electronically-trading human traders, and (c) moderate-frequency (but likely automated) liquidity providers. Compared to all other trader categories, HFLPs withdraw more (and provide less liquidity to customers) in information-rich periods but are not sensitive to customer-demand imbalances. Customers' trading costs with HFLPs go up when HFLPs withdraw, but do not exceed those with other liquidity providers. HFLPs' trading frequency seems key to their behavior under stress.



**Keywords:** Trading Frequency, Liquidity provision, Spreads, Volatility, Information, Crude oil futures

**JEL classification:** G10, G14, G18, Q40

## 1. Introduction

Following the development of electronic trading platforms and innovations in trading technology, an important new economic agent emerged and achieved a preeminent position in financial and commodity markets: the high-frequency liquidity provider ("HFLP")[1]. The HFLP is a high-frequency machine trader that acts voluntarily in a proprietary capacity, and exploits its competitive advantage in capturing information from the order flow in order to harvest bid-offer spread revenues through net liquidity supply (Biais, Declerck, and Moinas, 2016). HFLP profits are driven by trading financial instruments at ultra-high frequency, typically without human trade-by-trade interaction or premeditated directional bets, by participating on both sides of the order book, and by turning over inventory with extremely short horizons—thereby generating a relatively high amount of trading volume with minimal capital investment.

Liquidity in today's electronic order-matching markets is usually provided entirely voluntarily. "Market-makers" do not have an affirmative obligation to maintain liquid and orderly markets through continually posting buy and sell limit orders, or otherwise standing ready to trade against external customer order-flow: they are endogenous liquidity providers ("ELPs"), supplying liquidity only when it is optimal for them to do so. HFLPs are now the dominant subset of the ELP universe.[2] In U.S. futures markets in particular, HFLPs have displaced the erstwhile "Locals"— human traders who used to provide liquidity face-to-face in the trading pits. HFLPs now compete with other ELP-types, including electronically-trading human traders ("*e*-Locals"), and 'moderate-frequency' (but likely automated) traders ("MFLPs").

While several studies find that HFTs generally improve overall market liquidity *on average*, we know very little empirically about HFLP activity during periods of market "stress"—howsoever defined.[3] Several important questions remain answered. First, does HFLP participation and liquidity provision

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[1] HFLPs are the highest-frequency echelon of liquidity-providing high-frequency traders ("HFTs").

[2] For 2013-17, regulatory data show that automatons (including HFLPs) were the long or short party in 70 to 90 percent of trades in major U.S. financial and commodity futures markets (Haynes and Roberts, 2017).

[3] Menkveld (2016) reviews the HFT literature, including HFT liquidity provision. For commodities, see Raman, Robe, and Yadav (2017). Section 2 includes a fuller literature review relevant to this paper.

decrease during episodes of market stress? Second, does HFLP behavior in stressful periods differ materially from the behavior of other kinds of ELPs? Third, is trading frequency the defining feature underlying this HFLP behavior in periods of stress? Fourth, as theorized in recent models (e.g., Bongaerts and Van Achter, 2016), do HFLPs react differently to predominantly information-related stresses —such as episodes of *persistently* high return volatility or information asymmetry—as opposed to stresses that are predominantly order-flow-related—such as episodes of large imbalances between buys and sells of external exchange customers? These are the four questions we address. For large and persistent information-related shocks, the short answers are unequivocally: *yes*, *yes*, *yes*, and *yes*.

In addition to their implications regarding exchange customers' trading costs, which we also investigate empirically, these answers are of first-order importance to all stakeholders in financial markets—including policy makers and market regulators—for at least two reasons. First, given that HFLPs dominate liquidity provision in today's markets, our finding that HFLPs pull back due to information shocks has implications for the systemic risk of high episodic illiquidity during periods of market stress. Such HFLP-associated systemic risk has long been a concern for regulators,[4] and theory predicts that it should arise at the intersection of high-frequency trading speed technology and information asymmetries.[5] Second, even though pure-ELP U.S. markets have hitherto been relatively stable in practice, if customers fear possible HFLP pullbacks due to information-related stress, then such fears can still substantially reduce *ex-ante* allocative efficiency by distorting prices (Bessembinder, Hao, and Zheng, 2015).[6] The questions we

[4] In 2012, the U.K. Foresight Project on computer-based trading, following over 50 commissioned peer-reviewed papers by over 150 leading academics in over 20 countries, concluded (albeit without any direct empirical evidence) that HFTs could create "greater potential for *periodic* illiquidity" (emphasis added). In 2010, the then- SEC Chairman said to the Security Traders Association: "Given their volume and access, [HFT] firms have a tremendous capacity to affect the stability and integrity of the equity markets."

[5] See Bongaerts and Van Achter (2016). The models of Zigrand, Cliff, and Hendershott (2011) and Cespa and Vives (2016) further highlight negative feedback effects and the consequent risk of liquidity fragility.

[6] Bessembinder, Hao, and Zheng (2015) focus on distortions to initial public offerings valuations in the equity space. Analogous distortions should arise in the commodity space insofar as commodity price

address take on even greater significance in the case of the crude oil futures market we analyze in this paper, since crude oil futures prices drive prices in the underlying physical market—which is the most important commodity market in the world.

Our results are based on a trader-level investigation of a novel, comprehensive, non-public, account-level intraday dataset of trading activity—between January 2006 and June 2009—at the New York Mercantile Exchange's (NYMEX) West Texas Intermediate (WTI) light sweet crude oil futures market. The WTI futures market provides an ideal laboratory for our investigation. Firstly, it has always relied on wholly voluntary liquidity provision, with trading concentrated in a single venue. In contrast, equity markets have switched from imposing affirmative obligations on liquidity providers (e.g., the erstwhile specialists/dealers on NYSE/NASDAQ) to relying on voluntary liquidity providers. U.S. equity markets have also become heavily fragmented across competing venues operating under different rules (Menkveld, 2013; O'Hara, 2015). Both of these structural changes make it difficult to cleanly benchmark HFLPs' impact on liquidity provision in equity markets. Secondly, the WTI market was transformed by the onset of electronic trading on September 5th, 2006 and has since become dominated by HFLPs (Raman, Robe, and Yadav, 2017). In our sample period, we are therefore able to compare the impacts of various kinds of stress on liquidity provision in environments without HFLPs (i.e., prior to electronification) *versus* in settings where HFLPs compete with other ELPs: Locals trading without automation or anonymity, *e*-Locals trading anonymously but without automation, and MFLPs trading with anonymity and automation but at a lower frequency than HFLPs. Thirdly, in addition to the aftermath of Lehman Brothers' failure, the WTI market experienced during the Winter of 2009 an episode of extraordinarily severe stress that was exogenous to the trading activities of automated crude oil traders in general and HFLPs in particular: an unprecedented petroleum storage-capacity shortfall at the WTI futures delivery point in Cushing, Oklahoma. This entailed a major informational disadvantage for machines compared to human traders. As

volatility directly affects real investment decisions—see Elder and Serletis (2010), Kellog (2014), and Doshi, Kumar, and Yerramilli (2015).

such, this event and our 2008-2009 data afford a unique opportunity to compare HFLPs and other ELPs in terms of the willingness to provide liquidity in the presence of unexpectedly large and long-lasting information asymmetries regarding fundamental asset values.

Overall, we document that HFLPs are largely insensitive to order flow-related stresses in the form of unusually large and persistent (buy-sell) demand imbalances for exchange "customers" (i.e., external traders that are not exchange members and hence not financial intermediaries). This customer demand imbalance ("CDI") measure is not predictive of future returns, and thus CDIs reflect customer-driven demand surges or shortages that generate order-flow stresses but are otherwise uninformative, on average, for this market.[7] Following CDI shocks, our logistic regressions show only insignificant increases in the likelihood of HFLPs' pulling back from providing liquidity. Additional regression analyses show that the magnitude of any pullback is also insignificant. In sharp contrast, in stressful periods characterized by informational asymmetries and/or by unusually large and persistent volatility (which likely reflects information arrivals), we find that HFLP participation and liquidity provision drop very significantly—but we find no concomitant pullback by other ELP-types (Locals, *e*-Locals, or MFLPs). Customers' trading costs go up when HFLPs withdraw because customer-to-HFLP effective spreads increase and also because customers trade more with other ELPs—whose spreads are on average higher than HFLPs'.

Specifically, in 2006-2007, we investigate episodes of large and persistent intraday volatility. For such events, we show that the likelihood HFLPs provide less liquidity than usual to the overall market (*to customers*) increases by 83 (*53*) percent, while HFLPs' shares of the total (*customer*) trading volume and of liquidity provision overall (*to customers*) both fall by 15 (*20*) percent. During the Cushing crisis of 2008-

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[7] Our data allow us to identify actual customers of the exchange, unlike most datasets that do not distinguish between financial intermediaries trading on their own account and external traders using exchange services. Our CDI variable thus differs economically from the "order-imbalance" variable used in Chordia, Roll, and Subrahmanyam (2002) and many other papers, which is the overall buy-sell imbalance after including the trades of financial intermediaries. For equities, that overall order-imbalance has some return predictability, as does the PIN measure based on it (Easley, Hvidkjaer, and O'Hara, 2002).

2009, HFLP participation and liquidity provision are 4 to 5 percent lower than in normal times (notably, this drop is over and above the HFLP pullback attributable to the Lehman crisis); logit regressions, in the same vein, show statistically and economically highly significant increases in the likelihood of HFLP pullback.

Unlike HFLPs, we generally do not find such pullback patterns either for the erstwhile Locals in trading Pits or for the "*e*-Locals" and "MFLPs" in the electronic market. To wit, HFLPs are 25.1 *(11.6)* times more likely than *e*-Locals *(MFLPs)* to pull back from trading during the Cushing episode. Similarly, the odds of HFLPs' cutting back liquidity provision more than *e*-Locals or than MFLPs are much higher during the Cushing crisis (22.6 or 7.7 times greater, respectively).

We find that, in regular periods, HFLPs provide liquidity to customers at lower cost relative to other ELPs—similar to the evidence in equity markets (Menkveld, 2016). However, when HFLPs reduce their liquidity provision following intraday and long-lasting information shocks, customers end up trading relatively more with other liquidity providers—whose effective spreads are on average higher than HFLPs'—and effective customer-to-HFLP spreads themselves go up substantially —against baseline spreads, by 19 percent (after persistently-high intraday volatility) to 72 percent (in the Cushing crisis). As a result, the customer advantage of lower trading costs attributable to HFLPs in regular times vanishes in information-related stressful periods. Nevertheless, HFLP spreads in such periods do not exceed those of other ELPs.

Our empirical research design enables us to hold the separate effects of anonymity and/or automation invariant. First, insofar as HFLPs pull back much more than *both* Locals (trading face-to-face in the Pits) and *e*-Locals (trading anonymously on an electronic platform), it is unlikely that anonymity (Benveniste, Marcus, and Wilhelm, 1992) is what makes HFLP behavior special in high-volatility and other information-rich periods. Second, the similarities between the behaviors of *e*-Locals and MFLPs under stress (when contrasted with HFLPs' reactions) suggest that automation *per se* is not what makes HFLP behavior special. Instead, given the significant differences between HFLPs and MFLPs, HFLPs' reliance on high trading frequency appears key to understanding their response to stress.

The remainder of the paper is organized as follows. Section 2 places our contribution within the extant finance literature. Section 3 describes the data. Sections 4, 5, and 6 present our empirical results. Section 7 concludes the paper and offers possible venues for further research.

## 2. Contribution

Our first and most direct contribution is to the currently thin literature on HFLP behavior in stressful market conditions. Most empirical studies examining the impact of HFTs or HFLPs on market quality do so only under normal or average market conditions—but not separately during stressful periods.[8] Unlike the few extant studies that do look at the impact of market stress, our empirical setup and account-level data let us to examine HFLPs' trading behavior: (i) amid different kinds of market stress—e.g., elevated customer demand imbalances *vs*. high price volatility and other information events; (ii) in a non-fragmented market; (iii) through the prism of trader-level ELP activity rather than an "aggregate ELP"; (iv) and, crucially, we are able to compare, amid the very same events, HFLPs with other ELPs—including lower frequency automated machine traders (MFLPs), which allows us to isolate the impact of trading frequency on ELP liquidity provision.

In this literature, the two closest papers are: (a) Brogaard, Hendershott, and Riordan (2014), who conclude using 2008-2009 NASDAQ trade data that HFTs do not reduce their liquidity supply on high-volatility days—an inference that appears directly at odds with our findings; and (b) Brogaard *et al*. (2017), who argue that HFTs provide liquidity during extreme price movements in a given stock yet demand

[8] For example, Hendershott, Jones, and Menkveld (2011) find that the introduction of auto-quote on the NYSE improves liquidity and enhances the informativeness of quotes. Hendershott and Riordan (2013) find that high-frequency traders play a positive role in price efficiency through their marketable orders. Hasbrouck and Saar (2013) find that low-latency activity improves traditional market quality measures such as short-term volatility, spreads, and displayed depth in the limit order book. Carrion (2013, equities), Brogaard, Hendershott, and Riordan (2014, equities) and Raman, Robe, and Yadav (2017, commodities) also find that high-frequency traders generally provide liquidity and correct the mispricing of securities. See Jones (2013) and Menkveld (2016) for excellent literature reviews.

liquidity when several stocks concurrently experience extreme price movements.[9] Our findings are consistent with this last result insofar as crude oil price fluctuations are systematic in nature (reflecting macroeconomic rather than idiosyncratic shocks). Two facts arguably explain our differences with the other bottom line inferences. First, unlike those studies, our data identify each trader individually—so our results do not rely on "aggregate" HFT trading and, thus, can account for a significant heterogeneity amongst automated traders that we exploit. Indeed, we give novel evidence that HFLPs and MFLPs (some of which might be identified as HFTs in aggregated data) respond differently to market stress: while HFLPs cut their liquidity provision and raise its cost in periods of high volatility, MFLPs are generally unaffected. Second, those other two studies' datasets are "limited to trades occurring on NASDAQ. Although trades on NASDAQ make up 30—40% of all trading activity in [the] sample, there is a possibility that during extreme price movements HFTs provide liquidity on NASDAQ while taking it from the other markets" (Brogaard *et al.*, 2017 p.5). Unlike that fragmented U.S. equity market (Menkveld, 2013; O'Hara, 2015), the exchange on which we focus (NYMEX) was the sole U.S. market for WTI futures in our entire sample period—ruling out the possibility that HFLPs engage in cross-market arbitrage.[10]

Our second main contribution is to provide evidence on heterogeneity amongst ELPs. As noted in the above paragraph, we document substantial heterogeneity amongst automatons by identifying behavioral differences between two major kinds of machine traders (HFLPs *vs*. MFLPs). More broadly, we contribute to the growing literature on trader competition based on trading frequency (e.g., Bongaerts and Van Achter, 2016; Shkilko, 2017; Boco, Germain, and Rousseau, 2017). While Anand and Venkataraman (2016) find

[9] Albeit less relevant, there are some other studies on HFT responses to stress. Kirilenko *et al*. (2017) find that some HFTs withdrew in the flash crash of 2010. Jain, Jain, and McInish (2016) conclude that increased high-frequency quoting on the Tokyo Stock Exchange increases systemic risk, especially during tail events. Those papers focus on high-volatility events; Korajczyk and Murphy (2016) instead look at liquidity shocks on the TSX, where designated and voluntary liquidity providers coexist. They show that, "over the life of a large (institutional) trade, HFTs initially accommodate the order but switch to competing with the order."

[10] Shkilko and Sokolov (2016) examine high-frequency cross-market arbitraging and its implication for market quality.

that ELPs as a whole withdraw at times of increased intraday information asymmetry, we show that an ELP's response to information shocks (whether intraday or for longer periods) depends on the frequency at which the ELP trades—which provides empirical support for Bongaerts and Van Achter (2016).

A third contribution is to distinguish exchange customers from financial intermediaries and to utilize a customer-based perspective in two important ways. Firstly, we take customer-focused approaches to ELP liquidity provision in addition to the usual approaches (based on the textbook definition that a trader "supplies liquidity" when s/he posts a standing limit order and "demands liquidity" when s/he "picks" an existing limit order through a market or marketable limit order). For each ELP category, we construct a nuanced measure of liquidity provision based on the extent to which external customer order flow that is demanding liquidity finds ELPs (in that category) as counterparties (with standing limit orders) to consummate their trades. In addition, we recognize that ELPs fulfill a useful role for the functioning of markets also when they just act as counterparties to external customers irrespective of whether these customers are trading through standing limit orders or market or marketable limit orders. This approach to liquidity provision, based on the functional role of consummating customer trades (as distinct from just passively posting standing limit orders), is a novel addition to the liquidity supply literature in the spirit of Menkveld (2015). Notably, we show that qualitatively similar results obtain using traditional and customer-focused measures of liquidity provision.

Secondly, continuing the customer-focus contribution, we construct a direct measure of customer order flow-related stress by capturing customer demand (buy-sell) imbalances or "CDIs". Our CDI measure is uninformative of future returns—unlike "order-imbalance" measures proposed in prior work using datasets that do not separate customers from financial intermediaries. As such, it allows us to show that "pure" external order-flow demand shocks do not cause HFLPs to pull back and do not bring about an increase in the effective spreads customers pay to HFLPs.

Finally, by studying HFLP behavior during turbulent conditions in the WTI crude oil market, our study also contributes to the literature on the financialization of commodities. Most papers on financialization examine overnight and longer-term trading strategies of commodity index traders and hedge funds, and their effects on the daily, weekly, or monthly distributions of commodity returns.[11] To date, not much attention has been devoted to the impact of the *intraday* activities of financial institutions, including algorithmic and high-frequency traders—even though increased intraday activity by such traders is a major aspect of the financialization of commodity markets. To our knowledge, there are but two exceptions—both utilizing the same trader-level regulatory WTI data as does the present paper. One of those studies is Bessembinder, Carrion, Tuttle, and Venkataraman (2016), providing evidence of improved crude oil futures market liquidity around commodity index trading in 2008-2009. The other paper is Raman, Robe, and Yadav (2017), documenting that the intraday financialization of the WTI market (taking the form of a massive growth in institutional financial trading of WTI futures following the NYMEX's electronification in 2006) has, *on average,* brought about major improvements in market liquidity and in intraday pricing efficiency. Our paper complements those two papers with an investigation focused on periods of market stress and on the specific issues relevant thereto. Our results indicate that, even though HFLPs pull back and the cost at which they provide liquidity to customers rises substantially amid information-related stress, the magnitude of the cost remains at a level that is similar to the costs at which liquidity is provided by other ELPs.

## 3. Data

The data we employ comprise all intraday transaction records for WTI light sweet crude oil futures and options-on-futures at the New York Mercantile Exchange (NYMEX) from January 3rd, 2006 to June 30th, 2009. The U.S. derivatives market regulator (the CFTC) provided these confidential data for the purpose of the present study.

[11] See for example Büyükşahin *et al*. (2011), Tang and Xiong (2012), Acharya, Lochstoer, and Ramadorai (2013), Büyükşahin and Robe (2014), Hamilton and Wu (2014), Singleton (2014), Henderson, Pearson, and Wang (2015), Sockin and Xiong (2015), and Başak and Pavlova (2016). Cheng and Xiong (2014) provide a general review of the financialization and Fattouh, Kilian, and Mahadeva (2013) for an overview focusing on crude oil markets.

The raw CFTC data include details such as the commodity traded and delivery month, the quantity, the price, the date, and the time of the transaction, and buyer and seller identity codes. These codes conceal the actual identities of the market participants while enabling the analysis of a trader's activity in different contracts over time. In any event, we aggregate the account-level data across dozens or more of accounts in any particular category in order to protect the confidentiality of individual traders' underlying position(s) and trade secrets or trading strategies.

Importantly, these data classify traders into one of four customer types via a Customer Type Indicator (CTI), which ranges from 1 to 4 as follows:

- CTI 1 traders are the individual members of the exchange, also known as "Locals";
- CTI 2 traders are the institutional members of the exchange;
- CTI 3 traders are exchange member traders trading on behalf of other member traders;
- CTI 4 are external "customers" of the exchange.

The era of electronic trading of WTI futures on the Globex platform starts September 5$^{th}$, 2006. Prior to that day, there was no electronic trading during Pit hours. In order to ensure proper comparisons between the *pre*- and *post*-electronic periods, we restrict the analysis of Globex (*Pit*) trading to the activity that takes place between the hours of 9am—2.30pm (*Pit business hours*).[12] Figure 1 shows the evolution of trading volume on different NYMEX platforms between January 2006 and December 2007. Electronic trading develops rapidly and volume on Globex already exceeds that in the Pits by mid-October 2006, i.e., less than six weeks after electronification.

[12] We exclude data for the last trading days of futures contracts. In our Globex sample, WTI futures trade around the clock except between 5:15pm-6pm. Even on the Globex platform, most of the WTI futures trades (~90%) in our sample take place between 9am-2.30pm. Until January 31$^{st}$, 2007, Pit trading used to take place between 10am and 2:30pm (EST); starting February 1$^{st}$, 2007, Pit hours were extended to 9am-2.30pm.

Our final samples use data from January 3rd, 2006 to March 31st, 2007 for the intraday analyses, and from April 1st, 2008 to June 30th, 2009 for the daily analyses.[13] We separate the intraday sample into two sub-periods, one before and the other after electronification: January to June 2006 *vs*. October 2006 to March 2007. Figure 2 displays the Hasbrouck (1995, 2002) information shares of the electronic and Pit WTI futures trading venues after electronification. The graph shows that much, but not all, of the price discovery takes place on Globex in the October 2006—March 2007 period.

### *3.1 Market Variables*

For our intraday analyses, we calculate all market variables (returns, volatility of returns, bid-ask spreads, customer demand imbalances) as volume-weighted averages. We first compute these market variables in 1-minute intervals for each contract maturity. We then compute volume-weighted average figures across all (84 or more) futures contract maturities. We compute absolute customer demand imbalances (denoted *AbsCDI* as the absolute value of Customer (or CTI-4) Buy Volumes *minus* Customer (or CTI-4) Sell Volumes) to indicate the magnitude of the liquidity demanded by customers of the exchange.

Table 1 provides descriptive statistics of the market variables in the time periods for which we use them (January to June 2006 in the Pits; October 2006 to March 2007 on Globex). It is clear from Table 1 that the volume of trading and the magnitude of absolute customer imbalances are not substantially different between the two intraday sub-samples immediately before and after electronification. This similarity allows for valid comparisons of intraday market participation and liquidity provision before and after the onset of electronic trading at the NYMEX.

### *3.2 Identifying HFLPs and MFLPs*

All of the trading in our *pre*-electronic sample happens in the Pits. There are, therefore, no HFLPs or MFLPs prior to September 5th, 2006. In our *post*-electronification sample, the 2006—2009 CFTC data do not separate machines from human traders. Similar to Kirilenko, Kyle, Samadi, and Tuzun (2017), whose

[13] We exclude the Friday immediately after Thanksgiving, days from the last business day before Christmas until the first business day after New Year, and days that coincide with the Martin Luther King holiday.

use the same CFTC transaction data that flag neither automatons nor HFTs, we deal with this absence by relying on trading frequency as part of the classification strategy.

We identify HFLPs and MFLPs in the electronic sample on a monthly rolling basis, using two criteria. First, our intention is for HFLPs and MFLPs to be both algorithmic traders. As noted in Section 3.3 below, we find no trader in the WTI Pits who trades more than 450 times a day.[14] Out of an abundance of caution, we guarantee that our MFLP and HFLP samples only contain machines by focusing on participants that trade more than twice as frequently as the most active human. We set the minimum requirement for inclusion in the MFLP *(HFLP)* group at an average of 3 to 6 *(6 or more)* trades per minute during trading hours for every day when the trader is active in at least one month prior to the month when the trader is being classified as an MFLP or an HFLP.[15] This level of trading frequency amounts to trading more than 990 *(2000)* times a day. Second, in order to focus on short-horizon liquidity providers rather than long-horizon position-takers, we require that (in that same prior month) each HFLP or MFLP's absolute average end-of-day position be tiny compared to its daily trading volume. In line with Kirilenko *et al*. (*ibidem*, Section II.A), who also use similar CFTC data, we set that cutoff at 5 percent.

Based on these criteria, we identify 16 HFLPs *(35 MFLPs)* for our intraday analyses in the six-month period from October 2006 to March 2007 and 87 HFLPs *(138 MFLPs)* for the daily analyses in the one-year period from July 2008 to June 2009. Notably, HFLPs make up less than one percent of all trading accounts but are involved in approximately 30 percent (Fall 2006) to 50 percent (2008-2009) of the overall trading volume in the world's most active commodity futures market. Consistent with our selection criteria, HFLPs in our samples carry little of their daily trading overnight: their Mean Closing Ratio (End-of-Day Inventory/Total Trading) is less than 0.01%.

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[14] This figure is consistent with a CFTC analysis (Fishe, Haynes, and Onur, 2016) based on more recent futures order-book data that do contain a "algorithmic trader" flag. That paper suggests that the fastest humans trade about 60 times an hour, amounting to 330 trades per day in the WTI futures market case.

[15] Using prior-month behavior for HFLP classification is meant to rule out possible endogeneity issues. For this reason, our analysis of HFLP liquidity provision starts in October, rather than in September, of 2006.

### *3.3 Identifying Locals and* e*-Locals*

As do Manaster and Mann (1996), we identify Locals as CTI-1 traders in the Pits. There are close to one thousand Locals in our pit sample (January 2006 till March 2007). As is the case for HFLPs, Locals' mean trade size is less than the average market trade size, and they tend to go home 'flat' (their *Mean Closing Ratio* is also less than 0.01%).

More than half of all CTI-1 traders in the pit sample trade less than 25 times a day, and no CTI-1 trader in our sample trades more than 450 times a day. On Globex (after electronification), we therefore define "*e*-Locals" as CTI-1 traders who likewise trade less than 450 times a day. This cutoff guarantees that there is a big difference in our sample between the trading frequency of human (Locals and *e*-Locals) *vs*. machine traders (whether MFLPs or HFLPs).

### *3.4 ELP Participation and Liquidity Provision*

We define four measures of ELP participation and liquidity provision for each ELP category—HFLP, MFLP or (*e*-)Local. We use these four measures to estimate the trading behavior of different ELP groups in the context of our research. Table 2 provides summary statistics of these measures of ELP activity in the periods on which we focus for our intraday (October 2006 to March 2007 in the Pits and on Globex) and daily (July 2008 to June 2009 on Globex) analyses.

Our first measure is the "*Share of Total Volume"* of the ELP group. This is defined as the proportion of the total trading volume in which those traders are involved on the buy- or sell-side of the transaction. For our intraday analyses (2006-2007), we calculate participation rates every minute as volume-weighted averages across all (84) futures contract maturities. For our 2008-2009 analyses, we aggregate figures daily.

As seen in Table 2, Locals participate in over four-fifths (80.6 percent) of all trading volume in the futures Pits (Panel A). This proportion is more than thrice the contemporaneous volume share of *e*-Locals on the electronic platform—24.8 percent, a figure that further shrinks by half in 2008-2009 (to one-eighth of all transactions). MFLPs and HFLPs together are involved in over 40 percent of the electronic trading volume on average in 2006-2007. This figure increases to over 75 percent in 2008-2009, with most of that increase attributable to HFLPs (whose volume share rises from 24.8 in 2006-2007 to a whopping 57.5 percent in 2008-2009).

Recognizing the potentially useful role that ELPs fulfil when they act as counterparties to external customers (irrespective of whether these customers are trading through standing limit orders or market or marketable limit orders), we compute, as our second measure of activity for each ELP category, the "*Share of Customer Volume"* or proportion of all trades by customers (i.e., traders classified as CTI-4 in CFTC data) in which a given type of ELP is the counterparty.

As seen in Panel A of Table 2, in the 2006-2007 Pits, Locals are the counterparty to 74 percent of customers' trading volume. In the fourth quarter of 2006 and the first quarter of 2007, *e*-Locals, HFLPs, and MFLPs participate in more than 24, 20, and 10 percent of external customers' electronic trading volume, respectively. Panel C shows that the HFLP share of the customer volume more than doubles (to 42.6 percent) by 2008-2009.

For our third measure, "*Share of Liquidity Provision*," we follow the typical approach used for this purpose in extant research. Namely, we estimate the proportion of total trading volume for which an ELP group is passively posting standing limit orders and thereby providing liquidity.

Table 2, Panel A, shows that Locals provided almost 50 percent of the total liquidity in the Pits. Given that they participated in 80.6 percent of the total trading volume, Locals provided liquidity in about 62 percent of all their trading. Similarly, Panel B shows that HFLPs, MFLPs, and *e*-Locals together made up over 37.5 percent (17.1, 7.4, and 12.8 percent respectively) of the total WTI futures liquidity on the Globex electronic platform in our 2006-2007 sample period.

Finally, our fourth measure is each ELP group's share of the aggregate "*Share of Liquidity Provision to Customers*,*"* measured as the proportion of the total customer trading volume in which a member of that ELP group is providing liquidity (i.e., the customer is the "aggressor" demanding liquidity by executing against a pre-existing standing limit order posted by a member of that ELP group). For example, as reported in Table 2, Panel A, Locals provided over 38 percent of all liquidity provided to customers. Given that Locals participated in about 74 percent of customer trading, they provided liquidity in about 51 percent of their trading with the customers.

It is worth noting that market microstructure researchers are typically not in a position to estimate the second and fourth measures above but the richness of our dataset enables us to do so. Our approach to liquidity provision based on the functional role of consummating customer trades (as distinct from just passively posting standing limit orders), is a novel addition to the literature.

### *3.5 Effective spreads*

For customers trading with different categories of ELPs (HFLPs, MFLPs, Locals, or *e*-Locals), we calculate an *Effective Spread* estimate as the difference between the one-minute average buy prices paid by customers to that ELP category and the sell prices received by customers from that same ELP category. For the 2008-2009 analyses, we aggregate these one-minute figures daily on a volume-weighted basis.

## 4. HFLP Participation and Liquidity Provision under Stress

Intuitively, one would expect market makers to be reluctant to trade and provide liquidity during crashes. To wit, floor traders on the New York Stock Exchange (NYSE) and NASDAQ dealers closed shop on "Black Monday" (October 19$^{th}$, 1987). HFLPs may particularly have an inherent disadvantage in dealing with fundamental information arrivals (Aït-Sahalia and Saglam, 2016). Insofar as their goal is to maximize their trading with minimal capital investment, HFLPs may be extremely sensitive to even minor deviations from "normal" market conditions. Put differently, it might not take a market-wide crash for HFLPs to pull back: relatively smaller intraday perturbations also have the potential to instigate an HFLP withdrawal.

To test this conjecture, we carry out intraday (2006-2007, Section 4.1) and daily (2008-2009, Section 4.2) analyses of how HFLP behavior is affected by different market conditions. Section 4.1 examines HFLP trading and liquidity provision when intraday market conditions deviate from their sample mean by more than two standard deviations for at least 60 minutes. Section 4.2 investigates HFLP behavior in response to a major, multi-week change in the informational environment. In all cases, we consider participation (the proportion of trades in which HFLPs are involved on at least one side of the transaction) and liquidity provision (the proportion of trades in which the HFLP is passive)—overall and when trading with customers.

### *4.1 HFLP Activity in Unusual Intraday Market Conditions: Order-Flow and Volatility Shocks*

#### *4.1.1 Univariate analysis*

This sub-Section provides the results of univariate intraday analyses of HFLP behavior in normal market conditions *vs*. during periods of market stress. The latter are defined in terms of either high return volatility or high absolute customer demand imbalances (*AbsCDI*), with "high" is defined in terms of being two standard deviations away from the mean for the past 60 minutes. When *Volatility* (*AbsCDI*) is greater than two standard deviations, it means that the average of the one-minute volatility returns (one-minute *AbsCDI*) over the past one hour has been abnormally high. All variables are standardized by quarter prior to running T-tests.[16] In all cases, the univariate analyses omit the first 30 minutes of the trading day.

Table 3 provides strong and statistically significant conclusions. On the one hand, when return *Volatility* is persistently high, HFLPs reduce their participation substantially. They also service significantly fewer customer trades, their overall liquidity provision in terms of posting standing limit orders falls significantly, and their liquidity provision to customers also falls significantly. On the other hand, when *AbsCDI* is persistently high, the HFLP univariate results are in the same (negative) direction but are economically and statistically weaker. That is, the extent of participation and the liquidity provision by HFLPs are affected, both in general and specifically to customers, but to a much lesser extent than amid high-volatility episodes. This finding is consistent with the intuition that abnormally high *customer* demand imbalances are pure order-flow shocks that do not contain much information regarding future returns.

#### *4.1.2 Multivariate analyses: Methodology*

This sub-Section revisits our univariate results (Section 4.1.1) by carrying out Newey-West (OLS) and logit regressions of HFLP participation and liquidity provision on the extreme events already discussed (persistently high intraday return volatility or persistently high absolute customer demand imbalances), on

[16] HFLPs are involved in between a quarter and a third of all trades in the last quarter of 2006, and in approximately one half of all trades starting in January 2007. For this reason, we standardize variables separately for each quarter.

1-minute lagged values of the market condition variables (standardized returns, volatility of returns, and absolute customer demand imbalances), and on dummy variables that capture exogenous changes in the liquidity or information environment.

We control for the 30 minutes right after the beginning ("*Open*") or right before the end ("*Close*") of the main business hours, and we use day-of-the-week dummies. We account for key market-moving announcements—for WTI crude oil futures, they are the Energy Information Administration's (EIA) weekly report on petroleum inventories, which are released at either 10:30 AM on Wednesdays (most weeks) or 11AM on Thursdays (some weeks). We use dummy variables for windows before (30 minutes, "*EIA Pre-Event*"), during (5 minutes, "*EIA Event*"), and after (30 minutes, "*EIA Post-Event*") each announcement. Finally, we control for days when the commodity index traders ("CITs") that follow the GSCI indexing methodology roll over their near-dated positions (between the 5$^{th}$ and 9$^{th}$ business days of the month). Singleton (2014) and Sockin and Xiong (2015) argue that, in theory, commodity futures trading volumes during GSCI rolls could reveal (or could be perceived to contain) new information about fundamental market conditions. Accordingly, we include two dummy variables: one (denoted "*First GSCI Roll*") for the first day of the GSCI roll (i.e., when the information would first percolate) and another (denoted "*GSCI Days 2 to 5*") for the next four days (when changes to the environment would mostly stem from the need to accommodate unusually large customer demand imbalances).

### *4.1.3 Multivariate analyses: Magnitude of HFLP pull-back*

Overall, the OLS results (Table 4, Panel A) confirm that HFLPs significantly reduce their participation (columns 1 to 4) and contribution to liquidity provision (columns 5 to 8) during periods of persistently high volatility of returns, and that HFLPs are less sensitive to persistent order-flow shocks (as captured by persistently high absolute customer demand imbalances). To wit, the "*Volatility-High*" regression coefficients in all of our models are negative and statistically highly significant, whereas the "*AbsCDI-High*" regression coefficients are much smaller in magnitude and are statistically significant only in the case of overall participation (what is more, HFLP trading with—and HFLP liquidity provision to—customers are either insignificantly or barely significantly affected by extreme *AbsCDI*). HFLPs' pullback during episodes of high volatility is not just statistically but also economically significant: the HFLP share of the total trading volume and of overall liquidity provision both fall by over 15 percent, and the drops are even bigger (20 percent) in the case of trades with exchange customers.

#### *4.1.4 Multivariate analyses: Likelihood of HFLP pull-back*

It is well known that OLS can be problematic when dependent variables are range bound—as are the proportion variables analyzed so far. Hence, we also use logit regressions to examine HFLP behavior in extreme market conditions. The dependent variables in all logit regressions are binary; we set each of ours equal to 1 in any minute when the actual proportion is less than its quarterly median, and 0 otherwise.

Table 4, Panel B summarizes the results of our logit analyses by presenting regressions coefficients and odds ratios for each logit analysis. Similar to the results in Panel A, we see that HFLP trading activity is statistically and economically significantly very sensitive to periods of high volatility. The magnitude of the coefficients is quite large. Furthermore, the odds ratios are very substantial. The ratio associated with the first proportion variable we analyze, "*HFLP Share of Total Volume*", is 1.765; that is, HFLPs are 76.5% more likely to pull back (compared to their median participation rate) during high-volatility periods than they are at other times of the trading day. Similarly, the odds ratio for the *HFLP Shares of Customer Trading*, of *Liquidity Provision*, and of *Liquidity Provision to Customers* are 1.837, 1.832, and 1.532 respectively.

In other words, HFLPs are almost twice as likely to pull back from intermediating trades and providing liquidity during volatile periods. This finding strongly supports the results of our Newey-West (OLS) regressions. As well, consistent with the OLS results, the effect of *AbsCDI-High* is again weak and even statistically insignificant for three of the four dependent variables.

### ***4.2 HFLP Reaction to Long-lasting Informational Asymmetries***

A natural question is whether our main finding in Section 4.1—the significant decrease in HFLP participation and liquidity provision rates in periods of information arrival, as captured by elevated intraday return volatility—is echoed by HFLPs' responses to a major, multi-week change in the informational environment. In Section 4.2.1, we argue that the Winter 2009 storage glut crisis in Cushing, OK, constitutes an ideal such episode. In Sections 4.2.2 to 4.2.4, we exploit this multi-week episode of physical-market stress to show that HFLPs indeed do pull back in situations where they have a major, long-lasting informational disadvantage.

### *4.2.1 The Cushing storage crisis*

The NYMEX's WTI light sweet oil futures are commodity-settled. The contract delivery point is Cushing, a small Oklahoma town that is a major cog in the U.S. oil infrastructure. Pipelines running through the municipality connect the main landlocked North-American oil fields to the Gulf of Mexico and points beyond, while Cushing's storage tanks have the capacity to hold tens of millions of barrels of crude oil.

Due to a massive growth in North-American crude oil production brought about by the shale fracking revolution and due to infrastructure bottlenecks hindering the shipment of crude from Cushing to the Gulf of Mexico, exceptionally large amounts of oil were stored in Cushing by late Fall 2008 and Winter 2009 (Borenstein and Kellogg, 2014). As a result, a shortage of storage capacity developed. These conditions brought about "a change in price dynamics for WTI crude" and a partial decoupling of the WTI benchmark from other crude oil benchmarks (Büyükşahin, Lee, Moser, and Robe, 2013). Crucially for our purposes, these price dynamics changes were due solely to local inventory conditions—and, as a result, they affected WTI only and not "seaborne crudes like Brent (that could) easily be transported to meet worldwide demand (or, given weak energy demand, could be stockpiled cheaply on floating storage)" (Büyükşahin *et al*., 2013 p.132).

The 2008-2009 Cushing crisis involved large levels of informational asymmetries regarding physical oil market fundamentals in general and the state of petroleum inventories in particular. Intuitively, HFLPs should be less adept than humans at processing this type of environment. That is, the crisis gave human traders an informational advantage over machines, in that adapting trading strategies to uncertainty regarding changing inventory conditions at required Cushing-specific knowledge—only part of which became known to the public, through EIA reports on U.S. national and regional inventories, and only at discrete (weekly) intervals.

#### 4.2.2 HFLP Trading and Liquidity Provision during the Cushing crisis: Methodology

The Cushing crisis is clearly exogenous to the trading activities of automated traders in general and HFLPs in particular. We therefore exploit it to carry out a regression analysis of HFLP liquidity provision under extreme informational stress. To this end, we analyze one year of daily data covering the period from July 1st, 2008 to June 30th, 2009.

We start our analysis by dividing the 2008-2009 period into three intervals, depicted in Figure 3. We define a *Cushing_Crisis* dummy that takes the value 1 from December 17th, 2008 to February 17th, 2009 and 0 otherwise. The cutoffs are based on extreme crude oil inventory levels during that period, with the slope of the term structure of WTI futures prices exceeding its 2002-2012 mean by more than two standard deviations (Robe and Wallen, 2016). Because the Cushing crisis came on the heels of the global market upheavals brought about by the demise of Lehman Brothers, we control for possible changes in the crude oil futures trading environment caused by Lehman's failure. To that effect, we use a *Lehman_Crisis* dummy variable that takes the value 1 from September 15th, 2008 (the day Lehman Brothers filed for bankruptcy protection) to January 15th, 2009—and 0 otherwise. We select the end date based on the level of the TED spread, which exceeded its 2002-2012 mean by more than two standard deviations during that four-month period.

#### 4.2.3 HFLP Behavior during the Cushing Crisis: Magnitude of the Pull-back

The results of our daily OLS regressions are summarized in Panel A of Table 5. For both the HFLP rates of participation and liquidity provision (whether overall or with customers), the sign of the *Cushing_Crisis* dummy is negative in all models: clearly, high-frequency liquidity providers pull back during the crisis. During the Lehman crisis, HFLP results are statistically significant (at the 5 percent level) only for liquidity provision—not for participation. In contrast, HFLP trading and liquidity provision both fall substantially, by 4-5 percent, in the case of the Cushing crisis. The magnitude of HFLPs' pullback is economically even more significant when the quantum of pull back is compared to the standard deviations of the participation and liquidity provision variables during the 2008-2009 sample period. The drop in

HFLP share of trading volume is about 0.55 standard deviations; the same for participation with customers, liquidity provision and liquidity provision to customers are 0.61, 0.53 and 0.45 respectively.[17] Insofar as HFLPs are worse at handling fundamental (as opposed to order flow-based) information, these results support the notion that HFLPs pull back in situations where they have an informational disadvantage.

#### *4.2.4 HFLP Behavior during the Cushing Crisis: Likelihood of Pull-back*

As we did in our intraday analyses (Section 4.1.4), we also examine HFLP trading behavior during the Cushing crisis using logit regressions. The results, presented in Panel B of Table 5, are in line with those presented in Panel A—but the effect of the Cushing crisis, as evidenced by the odds ratios, appears even more pronounced here. In terms of their share of the total trading volume, HFLPs are 5 times more likely to pull back (i.e., to collectively account for a share of the trading volume below its sample median) during the Cushing episode than at other times in our 2008-2009 sample. Their withdrawal is even more dramatic in the case liquidity provision, with HFLPs being 7 times more likely to pull back their liquidity provision during the *Cushing* episode than on other days in our 2008-2009 sample. The odds ratios for participation and liquidity provision with customers show similar patterns.

As a robustness check, we replace the *Cushing_Crisis* and *Lehman_Crisis* dummy variables by the continuous variables whose extreme values we used to identify either crisis episode. Panel B shows that the effect of the standardized value of the slope of the WTI futures term structure (net of interest costs, and denoted *Cost_of_Carry_Std*) is also significant. Precisely, a one-standard deviation increase in the intensity of oil inventory issues (as captured by the net cost of carry) increases by 35.7% the odds of HFLPs' pulling

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[17] As an alternative empirical approach, we replace the Lehman and Cushing crisis dummies by two continuous variables designed to capture each crisis episode: respectively, the VIX for the Lehman Brothers crisis, and the absolute value of the WTI futures term structure slope (denoted *Slope*) to capture the Cushing crisis. Using these alternative specifications, we obtain qualitatively similar results (which we therefore do not report) as with the dummy regressions: HFLP participation and liquidity provision are statistically significantly depressed by storage-related informational asymmetries in the physical space (captured by the *Slope* variable) but much less so by the economy-wide stress that characterized the Lehman episode (captured by the *VIX*).

back from trading. The corresponding odds for refraining from trading with customers, providing liquidity in general, and providing liquidity to customers in particular, are 28.1%, 34.6% and 38.6% respectively. In other words, after controlling for other pertinent variables (including the market changes wrought by the Lehman bankruptcy), HFLP intermediation and liquidity provision fall markedly during periods of heightened information asymmetry, proxied here by the Cushing crisis.

## 5. Benchmarking HFLPs' Behavior under Stress: Locals, *e*-Locals, MFLPs

The analyses of Section 4 indicate that HFLPs tend to withdraw and to provide less liquidity in episodes of market stress, most notably when they are at an informational disadvantage (high return *Volatility*, Cushing crisis). Insofar as Section 4 constitutes the first empirical analysis of *purely* voluntary liquidity provision in periods of market stress, one might be tempted to conclude that these patterns are representative of all voluntary market-makers' behavior during stressful periods. This Section shows how and why HFLPs differ from others.

It provides the first empirical test, with precisely-controlled benchmarks, of how HFLPs' contribution to liquidity supply during times of market stress differs from that of other voluntary liquidity providers: Locals in the trading Pits, and *e*-Locals and MFLPs on the Globex electronic platform. Section 5.1 carries out these analyses intraday, in 2006-2007. Section 5.2 does so using daily data around the 2008-2009 Cushing oil storage crisis.

### *5.1 Intraday analyses*

We start by comparing the impact of stress on the participation and liquidity provision rates of HFLPs *vs*. Locals in the Pits or *vs*. *e*-Locals or MFLPs on Globex during the same period of time (October 2006 to March 2007).

#### *5.1.1 Locals in the Pits*

Similar to what we did for HFLPs on Globex (Section 4.1.2), we carry out multivariate analyses of Locals in the futures Pits for the same sample period (October 2006 to March 2007) as well as prior to the electronification of the crude oil market (January to June 2006). The results are qualitatively similar for both periods, so for brevity we focus on the post-electronification results.[18]

We run OLS (Newey-West) and logit regressions of Locals' trading activity and liquidity provision on extreme events (persistently high intraday volatility or absolute customer demand imbalances), on 1-minute lagged values of the market-condition variables (standardized returns, volatility of returns, and absolute customer demand imbalances), and on a set of dummy variables that capture exogenous changes in the liquidity or information environment.

Table 6 summarizes the results. First, the OLS regressions (Panel A) show that, in sharp contrast to HFLPs, Locals neither pull back from the market nor reduce their provision of liquidity (overall and to customers) in periods of persistently high volatility. Except for one specification, Locals' contributions to trading volume and liquidity provision appear to be (statistically speaking) quite insensitive to persistently high absolute customer demand imbalances, as well. Second, logit regression results (Panel B) are qualitatively quite similar to the results of the OLS analyses. The likelihood that Locals' shares of the trading volume and liquidity provision falls below the sample median is not statistically significantly higher during periods of unusually high return volatility. We do find that Locals pull back when faced with abnormally high absolute customer demand imbalances; notably, however, the Locals' pull back due to high customer demand imbalances is neither as large nor as consistent as HFLPs' is during periods of high volatility.

### *5.1.2* e-*Locals and MFLPs in the electronic market*

A natural question is whether the differences observed between HFLPs and Locals are due to anonymity, or to some other HFLP-specific characteristic. Table 7 helps answer this question by reporting the results of OLS (Newey-West, Panel A) and logit (Panel B) regressions that directly compare HFLPs with two other groups of traders competing with them on the electronic platform: *e*-Locals and MFLPs. For the sharpest possible comparison, all regressions in Table 7 look at how the *differences* between HFLPs'

[18] Summary tables of the January-June 2006 regressions analyses are available upon request.

and each liquidity-providing group's (*e*-Locals or MFLPs) rates of participation and liquidity provision are impacted by stressful events.

Similar to Locals in the Pits (Table 6), Panel A of Table 7 shows that HFLPs withdraw from the market more than do *e*-Locals (and, interestingly, than do MFLPs) both right after information shocks, as captured by persistently high return volatility, and (to some extent) amid order-flow shocks, as reflected in persistently large customer demand imbalances.[19] While the differences between HFLPs and other kinds of ELPs are large in the case of volatility shocks, in the case of order-flow shocks we find only statistically insignificant differences for liquidity provision.

The difference in the unconditional averages of HFLP and *e*-Local shares of the total trading volume is 3.94%. For HFLPs *vs*. MFLPs, the difference is 15.99%. To put things in perspective, during periods of persistently high volatility, this finding implies that the difference between HFLPs' and *e*-Locals' respective volume shares further widens by almost 100% of its average value and that, during the same high-volatility episodes, the difference between HFLPs' and MFLPs' respective volume shares widens by almost 20% of its sample-period average. The corresponding increases for HFLPs' *vs*. e-Locals' or MFLPs' respective shares of total liquidity provision are 55% and 19% of their sample averages. Clearly, the effects of persistently high return volatility are economically much more significant for HFLPs than for other liquidity providers.

Panel B of Table 7 summarizes logit regressions that examine how differently from other voluntary intermediaries HFLPs behave in periods of market stress. Similar to the analyses in Panel B of Tables 4 and 6, the dependent variables in all logit regressions are binary: we set them equal to 1 when the corresponding differences in proportions are lower than their quarterly medians. Panel B of Table 7 focuses on the odds ratios. The results clearly show that the HFLPs are more sensitive to periods of persistently high return volatility than are *e*-Locals or MFLPs. For example, HFLPs are 81% more likely to pull back more than MFLPs (in term of share of trading volume) during periods of high volatility than at other times during the

[19] Indeed, e-Locals *increase* both their overall participation and liquidity provision (though the increase is statistically insignificant in their interactions with customers). Tables summarizing these results are available upon request.

trading day. The same number for *e*-Locals is 56%. Similarly, the odds of HFLPs' reducing liquidity provision more than *e*-Locals or MFLPs are substantially higher during periods of high volatility: the ratios are 1.575 and 1.846, respectively. The results pertaining to HFLPs' shares of customer volume and of liquidity provision to customers also indicate that, immediately after high-volatility episodes, HFLPs are more likely to pull back more than *e*-Locals or MFLPs. In contrast, as discussed previously, the results are weak and inconsistent during periods of high customer demand imbalance. Overall, the conclusion remains that HFLPs are much more sensitive to volatility shocks than to order-flow shocks.

### *5.2 HFLP, MFLP, Local, and e-Local behaviors during the Cushing crisis*

Similar to our analysis of intraday volatility and order-flow shocks, we compare HFLPs' behavior with that of humans (Locals and *e*-Locals) and moderately frequent machine liquidity providers (MFLPs). One possible concern is that, by 2008, most of the trading activity in the futures Pits had died out. However, much of the option trading activity at the time still took place in the Pits. We therefore use, as benchmarks for HFLP behavior, futures trading by hundreds of *e*-Locals and MFLPs on Globex (Table 8) as well as options trading by hundreds of Locals in the Pits (Table 9). Panels A in Tables 8 and 9 show that, controlling for the Lehman bankruptcy, GSCI roll days, time fixed effects and other pertinent controls, the coefficient associated with the *Cushing_Crisis* dummy variable is consistently negative and statistically significant. Clearly, HFLPs pull back significantly more than do Locals, *e*-Locals, or MFLPs during the Cushing crisis.

The economic significance of the result is best indicated through the logits results presented in Panel B of Tables 8 (*e*-Locals, MFLPs) and 9 (option Locals). Similar to the previous logit regressions, the dependent variables are binary and assume a value of 1 when the differences in corresponding proportions are less than their sample median. Once again, the results show that HFLPs are more likely to pull back than any other category of voluntary market makers—Locals, *e*-Locals, or MFLPs. The difference with HFLPs is greatest in the case of *e*-Locals or MFLPs. As seen in Panel B of Table 8, the magnitude of the odds ratios associated with the *Cushing* episode dummy variable are quite large. HFLPs are 25.11 times more likely to pull back more than *e*-Locals (in term of share of trading volume) during the *Cushing* episode than at other times in our 2008-2009 sample period; the same number for MFLPs is 11.6. Similarly, the odds of HFLPs reducing liquidity provision more than *e*-Locals or than MFLPs are substantially higher during the *Cushing* episode: 22.55 or 7.73 times greater, respectively. The results pertaining to HFLPs' share of customer volume and liquidity provision to customers also show HFLPs significantly more likely to pull back than *e*-Locals or MFLPs during periods of increased information asymmetry.

Similar to the analysis of HFLP trading during periods of high volatility, our results are consistent with the hypothesis that the frequency of trading, rather than anonymity of counterparties or trader automation *per se*, is most germane to explaining how voluntary intermediaries respond to abnormally high levels of information asymmetry.

### *5.3 Discussion*

Together, Tables 4 to 9 show that HFLPs are more sensitive to high information arrival rates (proxied by elevated return volatilities) and intense informational asymmetries (e.g., during the Cushing crisis) than are other voluntary intermediaries (Locals, *e*-Locals, or MFLPs). They also enable us to understand *why* HFLPs behave differently from those other voluntary market makers.

First, we might think that the reason why HFLPs behave differently from Locals stems from the nature of trading in the Pits. One, face-to-face human interactions in the Pits might provide more intelligence than what is available through anonymous trading in the electronic market, making Locals better-informed about price and liquidity schedules and allowing them to not have to pull back amid high volatility. Two, the lack of anonymity in the Pits might entail reputational costs for market makers who desert customers when needed the most, e.g., amid high volatility (Benveniste *et al*., 1992). The fact that we find little difference between the behaviors of Locals (who trading face-to-face in the Pits) and *e*-Locals (who do so anonymously on the electronic platform), however, suggests that the anonymity of counterparties on Globex is not the primary reason for HFLPs' behavior special in high-volatility periods.

Unlike HFLPs, of course, *e*-Locals are human. Thus, a subset of our *e*-Local sample could also be trading in the Pits. In order to rule out the possibility that the difference between *e*-Local and HFLP trading patterns is driven by information gleaned through human interaction the trading Pits, we revisit the behavior of Locals whose activities "overlap" electronic and human spaces by limiting the analysis only to CTI-1s who are active concurrently in the Pits and on Globex between October 2006 and March 2007. More than half of all Locals in our Pit sample fall in that category. In unreported results, for this subset of Locals, we again find (similar to our results for all Locals) no impact of high return volatility on either participation or liquidity provision, and only an impact on participation in the case of high absolute CDIs.

Finally, we note that HFLPs significantly reduce their market participation and liquidity provisions during high-volatility periods while MFLPs (who trade less frequently but are also automated traders) do not. This finding suggests that automation *per se* is not the reason for HFLPs' special behavior, either. Rather, because our trader classification scheme ensures that HFLPs' reliance on trading frequency is (by construction) their only difference with MFLPs, our results suggest that the key to understanding HFLPs' unique response to stress is their trading frequency. In that sense, our findings regarding HFLPs' aggregate trading and liquidity provision under stress are in line with the theoretical predictions of Aït-Sahalia and Saglam (2016) that, since high-frequency traders (HFTs) have no competitive advantage regarding fundamental information and rely on high-frequency trading speed technology to capture tiny spreads, liquidity-providing HFTs (i.e., HFLPs) will be at an informational disadvantage during high return-volatility episodes—and, hence, are likely to pull back more than are other voluntary market makers.

## 6. Spreads

Sections 4 and 5 analyze the impact of information and order-flow shocks on the extent to which various kinds of voluntary market makers participate in trading and liquidity provision. Liquidity providers facing stress, however, can react not only by changing the volume of liquidity provided but also by changing its price. Also, the two need not change always in the same direction. The finding that HFLPs decrease their participation and liquidity provision during stressful periods need not imply that they would also increase the price of liquidity provision. Hence, in this section, we turn to the impact of different kinds of market stress on the price of liquidity.

Generally, studies examining the price of liquidity estimate its coast for the overall market. Our data, however, enables a more precise estimate. Since we can identify the counterparties in every trade, we calculate effective spreads paid by customers in general, and the effective spreads paid by customers when trading with HFLPs, MFLPs, and *e*-Locals separately. This allows us to not only compare and contrast how different voluntary market makers change their price of liquidity provision in stressful conditions but also enables us to accurately identify the source of the observed change in the aggregate cost of liquidity.

Similar to our modeling approach for participation rates, we start with intraday analyses of the stress impacts stemming from one-hour elevated return volatility or customer demand imbalances (Table 10, Section 6.1) and daily analyses of the effects of large exogenous increases in information asymmetry represented by the Cushing crises (Table 11, Section 6.2).

Table 10 presents the results of intraday regressions, from October 2006 to March 2007. It shows that the hypothesis holds overall (columns 1 and 2), and it also teases out the source of that increase. While Customer-to-HFLP spreads increase by a statistically and economically significant 19 percent due to persistently-high volatility episodes, neither Customer-to-MFLP nor Customer-to-*e*-Local spreads are (statistically speaking) impacted by high volatility. We also find that customer overall spreads also increase by approximately 15%. In other words, as HFLPs withdraw, they also increase their effective spread (and customers' costs go up)—but this is not all: a second source of increased trading costs for customers is because, due to high-volatility periods, customers end up trading more with other liquidity providers (whose spreads are on average higher than HFLPs'). Interestingly, customers' effective spreads do not increase significantly due to persistently high customer demand imbalances.

Table 11 rounds out our investigation by summarizing daily analyses of the impact of the Winter 2009 Cushing crisis on customers' effective spreads. Table 11 shows that those spreads rose during that major fundamental-information event, with the impact of the information-rich Cushing crisis on spreads (captured by the Cushing dummy coefficient of regression) being about as large as that of the Lehman crisis. The increase is massive, amounting to about two-thirds of baseline costs in the case of customer-to-HFLP spreads. Like the results for HFLP participation rates in Section 5 (Table 7), Table 11 shows the Cushing crisis to be more impactful on HFLP spreads than on *e*-Local or MFLP spreads.

In robustness checks, we replace the Cushing crisis dummy by a continuous variable that capture the episode: the absolute value of the WTI futures term structure slope (denoted *Slope*). Using these alternative specifications, Table 11 shows that we get similar results as with the dummy-variables approach— the spread differences are statistically significantly boosted by the *Slope* (the variable that captures storage-related informational asymmetries in the physical space). A one-standard deviation increase in the volatility of the net cost-of-carry increases the price of liquidity provided by the HFLPs by 15 basis points or about 9% of its base value.

Overall, our results show that the HFLPs respond to abnormally high information asymmetry by significantly withdrawing their liquidity provision and by markedly increasing their price of liquidity provision. The fact that HFLP-provided liquidity is more sensitive to information asymmetry than is the liquidity provided by lower frequency and/or manual ELPs further indicates that frequency-of-trading is key to understanding voluntary liquidity provision in stressful conditions.

## 7. Concluding Remarks

Liquidity in today's electronic financial markets is typically provided wholly by endogenous liquidity providers ("ELPs") who do so entirely *voluntarily* with no affirmative obligations to maintain liquid and orderly markets. Automated high frequency liquidity providers ("HFLPs") dominate this ELP universe. In this context, regulators and policy makers have expressed concerns about the significant risks of periodic episodic illiquidity in these markets in periods of market turbulence. Extant theoretical models also predict withdrawal of high-frequency traders from liquidity provision in periods of high information flows or asymmetries, and they show that fears of such pullbacks under information-related stress could substantially reduce *ex-ante* allocative efficiency by distorting prices. In this environment, we investigate empirically the impact of information-related and order flow-related stresses on the reliability and cost of transactional liquidity services.

Numerous empirical studies find a large beneficial impact of high-frequency trading on various measures of market liquidity. Most of those papers, however, focus on normal days: very few empirical studies look at the impact of market stress on HFLP behavior. Unlike the few that do, we are able to (a) show that HFLPs react differently to diverse types of market stress; (b) document what is unique or different about HFLP behavior under stress *vs*. the behaviors of other ELPs; (c) incorporate the crucial effects of heterogeneity across different categories of ELPs and specifically different types of automated ELPs—

thereby providing novel evidence on the crucial role of trading frequency.

In order to benchmark the behavior of HFLPs against the behaviors of other ELPs in similar circumstances both before and after electronification and the concomitant arrival of HFLPs, we use a comprehensive and uniquely detailed, account-level transaction dataset provided by the U.S. crude oil futures market regulator for 2006—2009. Those futures traded on a single exchange during that period, and liquidity provision in that market has always been wholly voluntary—avoiding potential limitations on inferences linked to market fragmentation and/or liquidity provision mandates. Further, the crude oil futures market provides two major exogenous events for econometric analyses—electronification of the market in September 2006, and an oil storage crisis in Cushing, Oklahoma, during the winter of 2009. As such, this market provides an ideal laboratory for our investigation.

We find strong evidence that, relative both to Locals trading face-to-face in the futures and options Pits and to *e*-Locals or moderate-frequency machine liquidity providers (MFLPs) transacting futures contracts contemporaneously on the electronic platform, HFLPs reduce their participation and liquidity provision much more in periods of high and persistent volatility (a proxy for informationally-rich environments). The difference between HFLPs and either Locals, *e*-Locals, or MFLPs is not significant in the case of responses to direct order flow-related stresses (taking the form of exceptional customer demand imbalances). Analyses of changes in the participation and liquidity provision rates of different kinds of ELPs during the two-month Cushing crisis in 2008–2009 provide further support for the claim that HFLPs do not withdraw just due to volatility but, especially, pull back in situations where they face informational disadvantages. Our findings are consistent with the notion that HFLPs withdraw when the risks arising from fundamental volatility exceed the benefits that they can reap from using their high trading-frequency advantage to tease out information in the order flow.

While HFLPs pull back in response to volatility and/or information-asymmetry shocks, other types of ELPs respond differently—indeed, lower trading-frequency ELPs tend to step in and to provide liquidity at precisely such times. Customers' trading costs do go up when HFLPs withdraw, because customer-to-HFLP effective spreads increase, and because customers trade more with other ELPs—whose effective spreads are on average higher than HFLPs'. Overall, in environments where HFLPs' high trading frequency does not provide them with an advantage, customers lose the benefit of lower spreads that HFLPs generally bring to the market.

Overall, our results have significant policy implications for exchanges, policy-makers, and regulators. While they show that regulatory concerns about the risks of periodic episodic illiquidity (in periods of market stress) arising from the increasing dominance of HFLPs may be well-founded, they also point to the need for nuanced policy responses. Firstly, HFLP-associated episodic illiquidity risk is confined to information-related market stresses; HFLPs cope very well with relatively uninformative buy-sell demand imbalances of external market users. And secondly, while it is true that the cost at which HFLPs provide liquidity to customers rises substantially amid information-related stresses, it is also true that the increased cost still does not exceed the (generally much higher) costs at which liquidity is provided by other ELPs. From the sole perspective of customer trading costs, this clearly points to caution in imposing any measures that constrain the high-frequency trading speed technology advantages of HFLPs. Still, there could also be other important perspectives in this context. In particular, over and above effective spread increases, if customers worry about possible HFLP pullbacks due to information-related stress, then such fears might still substantially impact *ex-ante* allocative efficiency through price distortions. We leave examinations of these policy trade-offs, and empirical work on associated topics, for further research.

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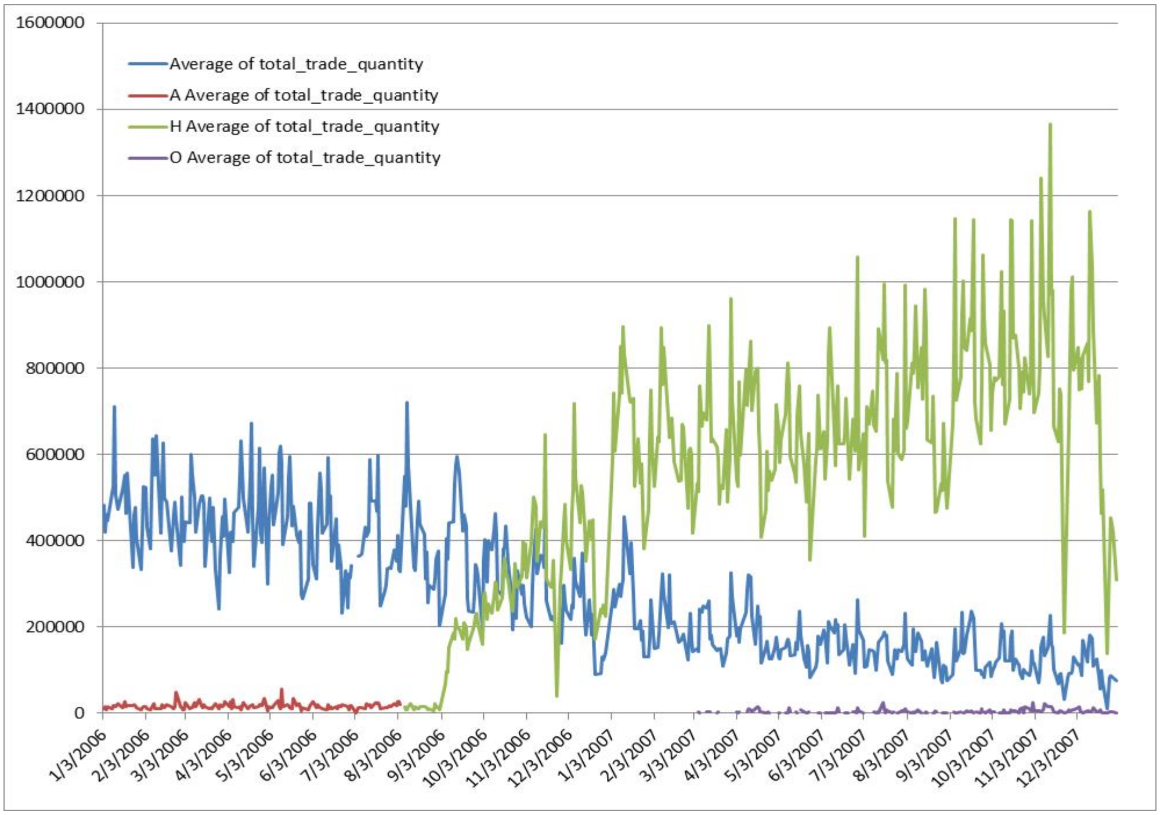
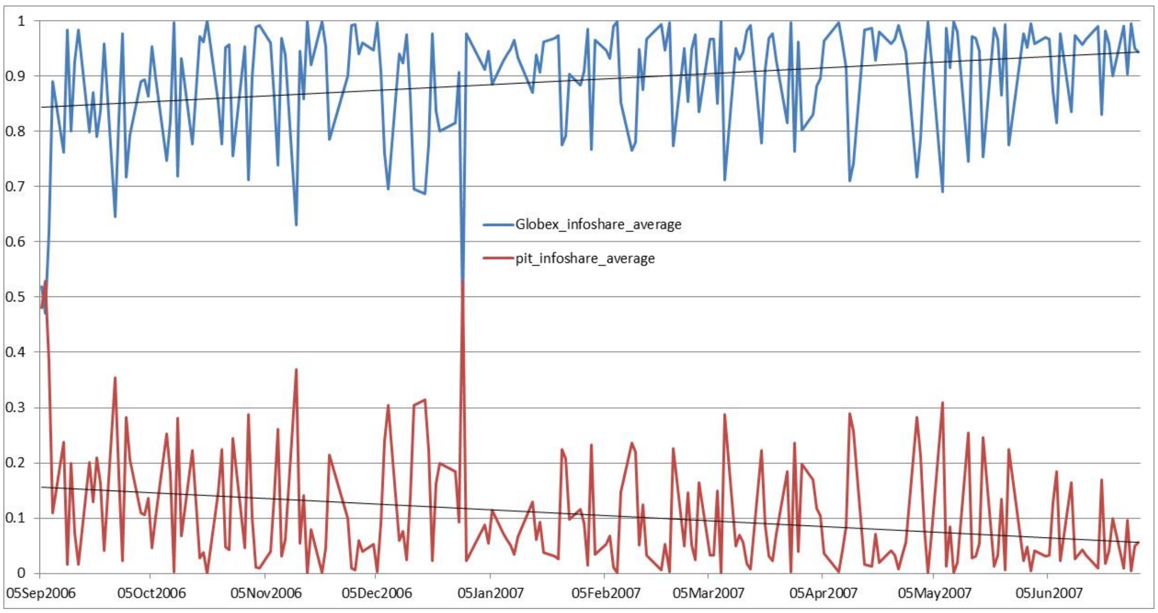
**Figure 1: Globex *vs*. Pit Trading Volumes, January 2006 to December 2007**



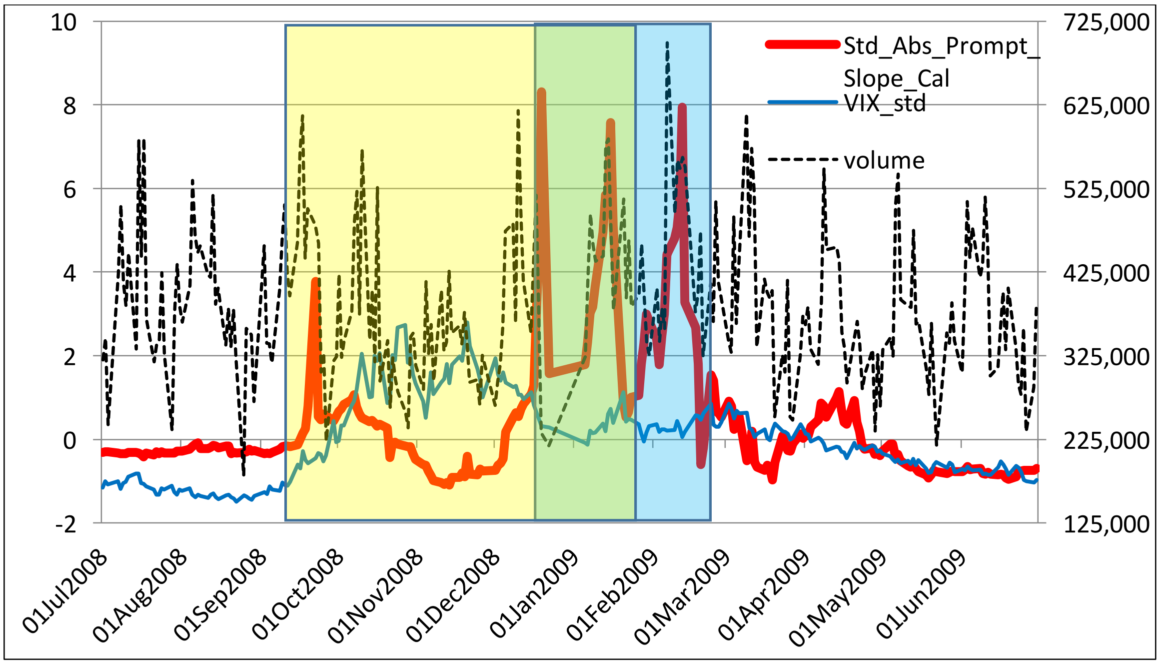

**Notes**: Figure 1 plots total trading volumes by platform for the NYMEX WTI sweet crude oil futures (all maturities). In green is Globex (H). In blue are the Pits. Electronic trades outside of business hours are depicted, until September 1st, 2006, in red (January to July 2006) or in green (August 2006). Sample period: January 3rd, 2006 to December 31st, 2007.

**Figure 2: Globex *vs*. Pit Information Shares, September 2006 to June 2007**




**Notes**: Figure 2 plots the Hasbrouck (1995, 2002) information shares of the electronic and Pit platforms, estimated through a vector error correction model (VECM) for the bivariate NYMEX floor and electronic (Globex) WTI futures price innovations. Sample period: September 5th, 2006 to June 30th, 2007. *Source*: CFTC and authors' computations.

**Figure 3: Visual Depiction of the Lehman and Cushing Crises, 2008-2009**




**Notes**: Figure 3 plots the nearby net cost of carry for WTI light sweet crude oil (in red), the VIX (in blue), and WTI futures trading volume on the NYMEX electronic platform from July 1st, 2008 to June 30th, 2009. Elevated values of the net crude oil cost of carry capture extreme petroleum inventory conditions at the WTI futures delivery point in Cushing, Oklahoma. We compute the net cost-of-carry by taking the absolute value of the nearby WTI light sweet crude oil futures prices' term structure slope, subtracting the same-maturity LIBOR interest rate, and then standardizing the resulting variable over the 2000-2012 period (*Source:* Bloomberg and authors' computations). The blue-shade area indicates the period between December 17th, 2008 and February 17th, 2009, when that variable was more than two standard deviations away from its long-term mean due to a glut of crude oil in Cushing. The VIX is similarly standardized prior to plotting (*Source:* Bloomberg and authors' computations). The area shaded in yellow indicates the period when Lehman Brothers' demise led to unusually high values of the VIX, between September 16th, 2008 and January 19th, 2009. The dashed line plots our measure of the WTI futures trading volume between 9AM and 2:30PM during that period; trades at settlement, cabinet trades, exchanges for physical, option conversions, and other such transactions are not included (*Source:* CFTC and authors' computations).

**Table 1: Sample Description—Market Variables (2006-2007)**

**Note**: Table 1 presents summary statistics on market variables for several data periods in the WTI crude oil futures market. *Abs CDI* (Absolute Customer Demand Imbalance) is the absolute value of the difference between CTI-4 (Customers) Buy and Sell trading volume. *Returns, Volatility, Volume*, and *Abs CDI* are calculated at 1-minute intervals and are volume-weighted averages across all futures contract maturities.

**Panel A: January to June 2006—Pits**

| | **Mean** | **Median** | **Std. Dev.** | **P10** | **P90** |
|---|---|---|---|---|---|
| *Volume* | 818 | 633 | 836 | 169 | 1598 |
| *Return* | 0.00% | 0.00% | 0.20% | -0.20% | 0.20% |
| *Volatility* | 0.18% | 0.13% | 0.17% | 0.03% | 0.39% |
| *Abs CDI* | 42.15 | 21.34 | 81.86 | 2.39 | 96.79 |

**Panel B: October 2006 to March 2007—Globex**

| | **Mean** | **Median** | **Std. Dev.** | **P10** | **P90** |
|---|---|---|---|---|---|
| *Volume* | 749 | 543 | 749 | 114 | 1598 |
| *Return* | 0.00% | 0.00% | 0.08% | -0.09% | 0.09% |
| *Volatility* | 0.06% | 0.05% | 0.05% | 0.01% | 0.12% |
| *Abs CDI* | 38.67 | 21.01 | 59.98 | 2.55 | 89.81 |

**Table 2: Sample Description—Trader Activity**

**Note**: Table 2 presents summary statistics on voluntary liquidity provider (Locals, *e*-Locals, HFLPs, MFLPs) activity for several data periods in the WTI crude oil futures market. *HFLPs* (*MFLPs*) are traders who trade more than 2,000 *(between 990 and 2000)* times a day and carry less than 5% of their daily trading volume overnight. *Locals* are traders who are categorized under CTI (Customer Type Indicator) 1 category in CFTC data and trade in the Pits. The term "*e-Locals*" refers to traders who are categorized under CTI-1 category and trade on the electronic platform (Globex). *Customers* are traders who are categorized under CTI-4 category. All variables are calculated over 1-minute intervals during business hours, as volume weighted averages across all futures contract maturities. *HFLP Share of Total Volume* is the proportion of the futures trading volume in which HFLP participation are on the long and/or short side of a transaction. *HFLP Share of Customer Volume* is the proportion of the customer volume where *HFLPs* trade against *Customers*. *HFLP Share of Liquidity Provision* is the proportion of trading volume where *HFLPs* trade passively. *HFLP Share of Liquidity Provision to Customers* is the proportion of customer volume where *HFLPs* provide liquidity to *Customers*. Locals', *e*-Locals' and MFLPs' variables are constructed analogously.

**Panel A: October, 2006 to March, 2007—Pits**

| | Mean | Median | Std. Dev. |
|---|---|---|---|
| *Local Share of Total Volume* | 80.59% | 99.30% | 29.03% |
| *Local Share of Customer Volume* | 74.07% | 98.04% | 34.14% |
| *Local Share of Liquidity Provision* | 49.85% | 50.00% | 30.57% |
| *Local Share of Liquidity Provision to Customers* | 38.80% | 36.76% | 33.20% |

**Panel B: October, 2006 to March, 2007—Globex electronic platform**

| | Mean | Median | Std. Dev. |
|---|---|---|---|
| *HFLP Share of Total Volume* | 28.71% | 27.25% | 13.86% |
| *HFLP Share of Customer Volume* | 20.19% | 17.40% | 13.14% |
| *HFLP Share of Liquidity Provision* | 17.17% | 15.83% | 9.44% |
| *HFLP Share of Liquidity Provision to Customers* | 11.45% | 9.39% | 9.00% |
| | | | |
| *MFLP Share of Total Volume* | 12.72% | 10.61% | 9.06% |
| *MFLP Share of Customer Volume* | 10.27% | 7.79% | 8.98% |
| *MFLP Share of Liquidity Provision* | 7.41% | 5.99% | 5.73% |
| *MFLP Share of Liquidity Provision to Customers* | 4.85% | 3.13% | 5.27% |
| | | | |
| *e-Local Share of Total Volume* | 24.77% | 21.90% | 16.89% |
| *e-Local Share of Customer Volume* | 15.49% | 11.28% | 15.07% |
| *e-Local Share of Liquidity Provision* | 12.86% | 10.31% | 11.00% |
| *e-Local Share of Liquidity Provision to Customers* | 7.48% | 4.63% | 9.16% |

**Panel C: July 2008 to June 2009—Globex electronic platform**

| | **Mean** | **Median** | **Std. Dev.** |
|---|---|---|---|
| *HFLP Share of Total Volume* | 57.55% | 57.83% | 3.60% |
| *HFLP Share of Customer Volume* | 42.60% | 42.96% | 3.34% |
| *HFLP Share of Liquidity Provision* | 35.93% | 36.02% | 2.54% |
| *HFLP Share of Liquidity Provision to Customers* | 22.53% | 22.57% | 1.81% |
| | | | |
| *MFLP Share of Total Volume* | 19.46% | 19.65% | 3.22% |
| *MFLP Share of Customer Volume* | 11.70% | 11.77% | 2.13% |
| *MFLP Share of Liquidity Provision* | 10.43% | 10.52% | 1.81% |
| *MFLP Share of Liquidity Provision to Customers* | 6.03% | 6.02% | 1.09% |
| | | | |
| *e-Local Share of Total Volume* | 12.80% | 12.85% | 2.06% |
| *e-Local Share of Customer Volume* | 7.67% | 7.75% | 1.29% |
| *e-Local Share of Liquidity Provision* | 6.53% | 6.54% | 1.03% |
| *e-Local Share of Liquidity Provision to Customers* | 3.83% | 3.87% | 0.63% |

**Table 3: HFLP Trading and Liquidity Provision by Market Conditions—Univariate Analysis (2006-2007)**

**Note**: Table 3 presents univariate intraday analyses of trading activity and liquidity provision by high-frequency liquidity providers (*HFLPs*) between October 2006 to March 2007. It compares regular periods with periods of market stress, i.e., when market conditions (absolute customer demand imbalances, denoted *Abs CDI*, in the top sub-panel; return volatility, denoted *Volatility,* in the bottom one) are abnormally high (greater than 2 standard deviations from the mean) for prolonged periods of time (60 minutes). For example, *Volatility-High* is when 1-minute *Volatility* (and/or *AbsCDI*) over the past one hour has been greater than twice its standard deviation over the sample period. *HFLPs* are traders who trade more than 2,000 times a day and carry less than 5% of their daily trading volume overnight. *Customers* are traders who are classified under the CTI (Customer Type Indicator) 4 category in the dataset. All variables are standardized by quarter (either Fall 2006 or Winter 2007). Data for the t-tests exclude the first 30 minutes of the main electronic business hours. Two-tailed *p-values* are also reported.

| | N | Volume | HFLP Share of Total Volume | HFLP Share of Customer Volume | HFLP Share of Liquidity Provision | HFLP Share of Liquidity Provision to Customers |
|---|---|---|---|---|---|---|
| *AbsCDI—Regular* | 32,846 | -0.008 | 0.005 | 0.004 | 0.003 | 0.002 |
| *AbsCDI—High* | 1,610 | 0.166 | -0.103 | -0.075 | -0.062 | -0.041 |
| *Difference* | | 0.174 | -0.108 | -0.078 | -0.065 | -0.043 |
| *p-value* | | <.0001 | <.0001 | 0.002 | 0.011 | 0.092 |
| | | | | | | |
| *Volatility—Regular* | 33,356 | -0.005 | 0.011 | 0.009 | 0.010 | 0.008 |
| *Volatility—High* | 1,100 | 0.139 | -0.329 | -0.287 | -0.300 | -0.228 |
| *Difference* | | 0.143 | -0.340 | -0.297 | -0.310 | -0.236 |
| *p-value* | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |

**Table 4: HFLP Trading Activity and Market Conditions—Q4 2006 to Q1 2007**

**Note**: Table 4 presents an analysis of high-frequency liquidity providers" (*HFLPs*) trading during periods of market stress. *HFLPs* are defined as traders who make more than 2,000 trades a day and carry less than 5% of their daily trading volume overnight. The analysis is conducted on WTI crude oil futures trading on the Globex platform in the time period from October 2006 through March 2007. *Dummy_Q1_2007* is a dummy variable equal to 1 during the first quarter of 2007 and 0 otherwise. *Volatility* is the 1-minute volatility of returns. *AbsCDI* is the absolute value of customer (traders classified as CTI 4 traders in the CFTC database) demand imbalance over a 1-minute interval. *Volatility-High* (*AbsCDI-High*) is a dummy variable set equal to 1 when the 1-minute *Volatility* (*AbsCDI*) over the past hour has been greater than twice its standard deviation over the sample period, and 0 otherwise. *Open* (*Close*) is a dummy variable equal 1 during the first (last) 30 minutes of trading, and 0 otherwise. *EIA Pre-Event* is a dummy variable equal to 1 during the 30 minutes before a weekly EIA announcement, and 0 otherwise. *EIA Event* is a dummy variable equal to 1 during the 5 minutes after a weekly EIA announcement, and 0 otherwise. *EIA Post-Event* is a dummy variable equal to 1 between 5 and 35 minutes after a weekly EIA announcement, and 0 otherwise. *First GSCI Roll* is a dummy variable equal to 1 on the day of a GSCI roll, and 0 otherwise. *GSCI_Roll_Days2to5* is a dummy variable equal to 1 between the 2$^{nd}$ and 5$^{th}$ day after a GSCI roll, and 0 otherwise. *Day of the Week* are dummy variables for the first 4 days of the week. *HFLP Share of Total Volume* is the proportion of trading volume with HFLP participation. *HFLP Share of Customer Volume* is the proportion of Customer volume where *HFLPs* trade against *Customers*. *HFLP Share of Liquidity Provision* is the proportion of trading volume where *HFLPs* trade passively. *HFLP Share of Liquidity Provision to Customers* is the proportion of Customer volume where *HFLPs* provide liquidity to *Customers*. ***Panel A*** reports the results of OLS regressions of the proportion variables indicated in the column heading. *Lags* indicate the number of lags of the dependent variable included in the regression. Two-tailed *p-values* are also reported, and are obtained using Newey-West standard errors with 5 lags. ***Panel B*** reports results of logit regressions, where the binary dependent variable is 1 when the corresponding proportion variable (indicated in the column heading) is less than its (quarterly) median value. Regression coefficients and odds ratios are presented with two-tailed *p-values* and $\chi^2$ tests of likelihood ratios.

**Panel A: OLS Regressions**

| *Parameter* | **HFLP Share of Total Volume** | | **HFLP Share of Customer Volume** | | **HFLP Share of Liquidity Provision** | | **HFLP Share of Liquidity Provision to Customers** | |
|---|---|---|---|---|---|---|---|---|
| *Intercept* | 19.45% | 11.72% | 13.27% | 9.34% | 12.29% | 8.03% | 8.34% | 6.52% |
| | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| ***Volatility—High*** | -4.30% | -2.84% | -3.68% | -2.67% | -2.72% | -1.86% | -2.02% | -1.56% |
| | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| ***AbsCDI—High*** | -0.84% | -0.76% | -0.53% | -0.50% | -0.25% | -0.31% | -0.19% | -0.18% |
| | 0.024 | 0.011 | 0.108 | 0.078 | 0.293 | 0.12 | 0.371 | 0.361 |
| *Volatility* | | -0.03% | | -0.03% | | 0.01% | | 0.05% |
| | | 0.775 | | 0.804 | | 0.958 | | 0.629 |
| *AbsCDI* | | 0.04% | | -0.12% | | 0.01% | | -0.11% |
| | | 0.544 | | 0.045 | | 0.756 | | 0.003 |
| *Return* | | -0.09% | | -0.06% | | -0.09% | | -0.04% |
| | | 0.161 | | 0.297 | | 0.063 | | 0.323 |
| *Open* | | -0.95% | | -0.34% | | -0.43% | | 0.17% |
| | | 0.002 | | 0.241 | | 0.049 | | 0.443 |
| *Close* | | -1.19% | | -1.19% | | -0.79% | | -0.75% |
| | | <.0001 | | <.0001 | | <.0001 | | <.0001 |
| *EIA Pre-Event* | | -1.33% | | -0.84% | | -1.03% | | -0.57% |
| | | 0.001 | | 0.032 | | 0 | | 0.035 |
| *EIA Event* | | 1.12% | | 0.66% | | 0.16% | | -0.18% |
| | | 0.199 | | 0.455 | | 0.774 | | 0.736 |
| *EIA Post-Event* | | 0.05% | | -0.19% | | -0.11% | | -0.29% |
| | | 0.871 | | 0.51 | | 0.587 | | 0.125 |
| *First GSCI Roll* | | -0.11% | | 0.28% | | -0.16% | | 0.13% |
| | | 0.725 | | 0.364 | | 0.459 | | 0.523 |
| *GSCI_Roll_Days2to5* | | 0.21% | | 0.29% | | 0.17% | | 0.15% |
| | | 0.202 | | 0.071 | | 0.142 | | 0.182 |
| *Dummy_Q1_2007* | 19.01% | 11.05% | 14.19% | 9.54% | 10.03% | 6.32% | 6.41% | 4.81% |
| | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| *Day of the Week* | | Yes | | Yes | | Yes | | Yes |
| *Lags* | | 3 | | 3 | | 3 | | 3 |
| *N* | 37,997 | 37,997 | 37,997 | 37,997 | 37,997 | 37,997 | 37,997 | 37,997 |
| *Adj RSq* | 32.05% | 38.17% | 22.71% | 26.56% | 22.03% | 27.31% | 11.36% | 13.80% |

**Panel B: Logit Regressions**

| *Parameter* | HFLP Share of Total Volume | | HFLP Share of Customer Volume | | HFLP Share of Liquidity Provision | | HFLP Share of Liquidity Provision to Customers | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | Odds Ratio | Coefficient | Odds Ratio | Coefficient | Odds Ratio | Coefficient | Odds Ratio |
| *Intercept* | 0.492 | | 0.610 | | 0.318 | | 0.317 | |
| | <.001 | | <.001 | | 0.007 | | 0.006 | |
| ***Volatility—High*** | 0.284 | 1.765 | 0.304 | 1.837 | 0.303 | 1.832 | 0.213 | 1.532 |
| | <.001 | | <.001 | | <.001 | | <.001 | |
| ***AbsCDI—High*** | 0.047 | 1.099 | -0.002 | 0.996 | -0.003 | 0.995 | -0.019 | 0.962 |
| | 0.070 | | 0.942 | | 0.916 | | 0.459 | |
| *Volatility* | 0.047 | 1.048 | 0.048 | 1.049 | 0.030 | 1.031 | 0.016 | 1.016 |
| | <.001 | | <.001 | | 0.006 | | 0.144 | |
| *AbsCDI* | -0.011 | 0.989 | -0.009 | 0.991 | -0.006 | 0.994 | -0.010 | 0.990 |
| | 0.289 | | 0.412 | | 0.573 | | 0.334 | |
| *Return* | 0.013 | 1.013 | 0.015 | 1.015 | 0.007 | 1.007 | 0.012 | 1.013 |
| | 0.217 | | 0.142 | | 0.508 | | 0.229 | |
| *Open* | 0.152 | 1.354 | 0.134 | 1.308 | 0.123 | 1.278 | 0.122 | 1.277 |
| | <.001 | | <.001 | | <.001 | | <.001 | |
| *Close* | 0.107 | 1.239 | 0.077 | 1.166 | 0.077 | 1.167 | 0.049 | 1.103 |
| | <.001 | | <.001 | | <.001 | | 0.007 | |
| *EIA Pre-Event* | 0.196 | 1.479 | 0.190 | 1.462 | 0.134 | 1.307 | 0.135 | 1.311 |
| | <.001 | | <.001 | | <.001 | | <.001 | |
| *EIA Event* | -0.218 | 0.647 | -0.036 | 0.931 | -0.212 | 0.655 | -0.100 | 0.819 |
| | 0.023 | | 0.699 | | 0.026 | | 0.286 | |
| *EIA Post-Event* | -0.053 | 0.900 | -0.044 | 0.916 | -0.063 | 0.882 | -0.053 | 0.900 |
| | 0.052 | | 0.105 | | 0.022 | | 0.053 | |
| *First GSCI Roll* | 0.036 | 1.074 | 0.041 | 1.085 | -0.009 | 0.982 | 0.007 | 1.013 |
| | 0.128 | | 0.084 | | 0.703 | | 0.777 | |
| *GSCI_Roll_Days2to5* | -0.014 | 0.972 | -0.024 | 0.953 | -0.026 | 0.950 | -0.018 | 0.965 |
| | 0.264 | | 0.062 | | 0.045 | | 0.166 | |
| *Day of the Week* | Yes | | Yes | | Yes | | Yes | |
| *N* | 37,997 | | 37,997 | | 37,997 | | 37,997 | |
| $\chi^2$ (*p-Value)* | <0.001 | | <0.001 | | <0.001 | | <0.001 | |

**Table 5: HFLPs' Trading Activity during the Cushing Crisis—Q3, 2008 to Q2, 2009**

**Note**: Table 5 presents an analysis of high-frequency liquidity providers (*HFLPs*) trading during the oil storage crisis of Winter 2009. *HFLPs* are traders who make more than 2,000 trades a day and carry less than 5% of their daily trading volume overnight. The analysis is conducted using daily data on WTI crude oil futures trading on Globex over the time-period July 1st, 2008 to June 30th, 2009. *Lehman_Crisis* is a dummy variable that equals 1 from September 15, 2008 to January 15, 2009, and 0 otherwise. Storage issues in Cushing, OK, are captured by *Cushing_Crisis,* a dummy variable set equal to 1 from December 17, 2008 to February 17, 2009, and 0 otherwise. *EIA_Inventory* is a dummy variable equal to 1 during EIA announcement days, and 0 otherwise. *Lead_Inventory* is a dummy variable equal to 1 during the days prior to the EIA announcements, and 0 otherwise*. First GSCI Roll* is a dummy variable equal to 1 on the day of a GSCI roll, and 0 otherwise. *GSCI_Roll_Days2to5* is a dummy variable equal to 1 between the 2nd and 5th day after a GSCI roll, and 0 otherwise. *Day of the Week* are a set of dummy variable for the first four days of the week. *Lags* indicate the number of lags of the dependent variable included in the regression. *HFLP Share of Total Volume* is the proportion of trading volume with HFLP participation. *HFLP Share of Customer Volume* is the proportion of Customer volume where *HFLPs* trade against *Customers*. *HFLP Share of Liquidity Provision* is the proportion of trading volume where *HFLPs* trade passively. *HFLP Share of Liquidity Provision to Customers* is the proportion of Customer volume where *HFLPs* provide liquidity to *Customers.* ***Panel A*** reports the results of OLS regressions of the proportion variables indicated in the column heading. *Lags* indicate the number of lags of the dependent variable included in the regression. Two-tailed *p-values* are also reported, and are obtained using Newey-West standard errors with 5 lags. ***Panel B*** reports results of logit regressions, where the binary dependent variable is 1 when the corresponding proportion variable (indicated in the column heading) is less than its (quarterly) median value. Odds ratios are presented with two-tailed *p-values* and $\chi^2$ tests of likelihood ratios. *Source:* CFTC, EIA, and authors' computations.

**Panel A: OLS Regressions**

| *Parameter* | **HFLP Share of Total Volume** | | **HFLP Share of Customer Volume** | | **HFLP Share of Liquidity Provision** | | **HFLP Share of Liquidity Provision to Customers** | |
|---|---|---|---|---|---|---|---|---|
| *Intercept* | 33.86% | 32.41% | 28.87% | 26.58% | 23.21% | 21.43% | 15.56% | 14.39% |
| | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 |
| ***Cushing_Crisis*** | -1.36% | | -1.50% | | -0.95% | | -0.58% | |
| | 0.032 | | 0.010 | | 0.042 | | 0.073 | |
| *Lehman_Crisis* | -0.34% | | -0.70% | | -0.65% | | -0.43% | |
| | 0.468 | | 0.129 | | 0.064 | | 0.078 | |
| *VIX_std* | | -0.21% | | -0.28% | | -0.24% | | -0.14% |
| | | 0.352 | | 0.187 | | 0.126 | | 0.181 |
| ***Cost_of_Carry_Std*** | | -0.20% | | -0.20% | | -0.13% | | -0.07% |
| | | 0.101 | | 0.124 | | 0.126 | | 0.130 |
| *EIA_Inventory* | 0.05% | 0.02% | -0.23% | -0.25% | 0.03% | 0.04% | -0.41% | -0.40% |
| | 0.949 | 0.985 | 0.761 | 0.744 | 0.963 | 0.945 | 0.407 | 0.415 |
| *Lead_Inventory* | -0.23% | -0.16% | -0.36% | -0.23% | -0.21% | -0.07% | -0.24% | -0.15% |
| | 0.790 | 0.858 | 0.636 | 0.771 | 0.744 | 0.915 | 0.596 | 0.747 |
| *First_GSCI_Roll* | -3.04% | -3.05% | -3.49% | -3.55% | -2.17% | -2.21% | -1.88% | -1.92% |
| | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 |
| *GSCI_Roll_Days2to4* | -2.45% | -2.33% | -2.46% | -2.31% | -1.72% | -1.62% | -1.28% | -1.22% |
| | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 |
| *Day of the Week* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Lags* | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| *N* | 240 | 240 | 240 | 240 | 240 | 240 | 240 | 240 |
| *Adj RSq* | 31.07% | 30.49% | 30.93% | 29.50% | 29.84% | 29.84% | 26.92% | 25.61% |

**Panel B: Logit Regressions (Odds Ratios)**

| | **HFLP Share of Total Volume** | | **HFLP Share of Customer Volume** | | **HFLP Share of Liquidity Provision** | | **HFLP Share of Liquidity Provision to Customers** | |
|---|---|---|---|---|---|---|---|---|
| ***Cushing_Crisis*** | 5.032 | | 4.893 | | 7.611 | | 5.861 | |
| | 0.001 | | 0.001 | | <.001 | | <.001 | |
| *Lehman_Crisis* | 1.441 | | 1.788 | | 1.985 | | 1.826 | |
| | 0.242 | | 0.066 | | 0.034 | | 0.061 | |
| *VIX_std* | | 1.173 | | 1.312 | | 1.255 | | 1.004 |
| | | 0.263 | | 0.062 | | 0.121 | | 0.981 |
| ***Cost_of_Carry_Std*** | | 1.357 | | 1.281 | | 1.346 | | 1.386 |
| | | 0.010 | | 0.030 | | 0.015 | | 0.008 |
| *EIA_Inventory* | 1.552 | 1.692 | 0.870 | 0.928 | 0.845 | 0.906 | 1.964 | 2.050 |
| | 0.595 | 0.517 | 0.874 | 0.931 | 0.850 | 0.908 | 0.426 | 0.377 |
| *Lead_Inventory* | 0.918 | 0.923 | 0.470 | 0.465 | 0.661 | 0.649 | 1.556 | 1.493 |
| | 0.924 | 0.927 | 0.424 | 0.416 | 0.658 | 0.635 | 0.631 | 0.649 |
| *First_GSCI_Roll* | 24.048 | 22.828 | 11.981 | 10.995 | 21.250 | 18.382 | 9.996 | 9.105 |
| | 0.004 | 0.005 | 0.004 | 0.005 | 0.006 | 0.008 | 0.007 | 0.009 |
| *GSCI_Roll_Days2to5* | 8.317 | 7.435 | 10.811 | 9.441 | 10.372 | 8.467 | 13.919 | 12.130 |
| | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 |
| *Day of the Week* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 244 | 244 | 244 | 244 | 244 | 244 | 244 | 244 |
| $\chi 2$ (*p-Value*) | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |

**Table 6: Locals' Trading Activity and Market Conditions—Q4 2006 to Q1 2007**

**Note**: Table 6 presents an analysis of trading by "Locals" during periods of market stress. *Locals* are defined as Pit traders who are categorized under CTI (Customer Type Indicator) 1 category. The analysis is conducted on WTI crude oil futures trading in the Pits over the period September 2006 to March 2007. *Dummy_Q1_2007* is a dummy variable equal to 1 during the first quarter of 2007 and 0 otherwise. *Volatility* is the 1-minute volatility of returns. *AbsCDI* is the absolute value of customer (traders classified as CTI-4 traders in the CFTC database) demand imbalances over a 1-minute interval. *Volatility-High* (*AbsCDI-High*) is a dummy variable set equal to 1 when the 1-minute *Volatility* (*AbsCDI*) over the past hour has been greater than twice its standard deviation over the sample period, and 0 otherwise. *Open* (*Close*) is a dummy variable equal 1 during the first (last) 30 minutes of trading, and 0 otherwise. *EIA Pre-Event* is a dummy variable equal to 1 during the 30 minutes before a weekly EIA announcement, and 0 otherwise. *EIA Event* is a dummy variable equal to 1 during the 5 minutes after a weekly EIA announcement, and 0 otherwise. *EIA Post-Event* is a dummy variable equal to 1 between 5 and 35 minutes after a weekly EIA announcement, and 0 otherwise. *First GSCI Roll* is a dummy variable equal to 1 on the day of a GSCI roll, and 0 otherwise. *GSCI_Roll_Days2to5* is a dummy variable equal to 1 between the 2nd and 5th day after a GSCI roll, and 0 otherwise. *Day of the Week* are dummy variables for the first 4 days of the week. *Lags* indicate the number of lags of the dependent variable included in the regression. *Local Share of Total Volume* is the proportion of trading volume with *Local* participation. *Local Share of Customer Volume* is the proportion of Customer volume where *Locals* trade against *Customers*. *Local Share of Liquidity Provision* is the proportion of trading volume where *Locals* trade passively. *Local Share of Liquidity Provision to Customers* is the proportion of customer trading volume for which Locals are the passive traders. ***Panel A*** reports the results of OLS regressions of the proportion variables indicated in the column heading. *Lags* indicate the number of lags of the dependent variable included in the regression. Two-tailed *p-values* are also reported, and are obtained using Newey-West standard errors with 5 lags. ***Panel B*** reports results of logit regressions, where the binary dependent variable is 1 when the corresponding proportion variable (indicated in the column heading) is less than its (quarterly) median value. Regression coefficients and odds ratios are presented with two-tailed *p-values* and $\chi^2$ tests of likelihood ratios.

**Panel A: OLS Regressions**

| *Parameter* | **Locals' Share of Total Volume** | | **Locals' Share of Customer Volume** | | **Locals' Share of Liquidity Provision** | | **Locals' Share of Liquidity Provision to Customers** | |
|---|---|---|---|---|---|---|---|---|
| *Intercept* | 80.58% | 71.08% | 74.38% | 66.32% | 50.20% | 44.82% | 39.20% | 36.23% |
| | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| ***Volatility—High*** | 0.45% | -0.95% | 1.07% | -0.76% | 1.20% | -0.01% | 1.73% | 0.55% |
| | 0.598 | 0.262 | 0.323 | 0.505 | 0.150 | 0.987 | 0.079 | 0.610 |
| ***AbsCDI—High*** | 0.71% | -0.70% | 1.79% | 0.29% | -1.21% | -2.13% | 0.10% | -0.85% |
| | 0.434 | 0.428 | 0.115 | 0.814 | 0.202 | 0.022 | 0.924 | 0.459 |
| *Volatility* | | -0.10% | | 0.09% | | -0.27% | | 0.00% |
| | | 0.538 | | 0.691 | | 0.100 | | 0.999 |
| *AbsCDI* | | -0.37% | | -0.51% | | -0.43% | | -0.30% |
| | | 0.067 | | 0.047 | | 0.016 | | 0.114 |
| *Return* | | 0.07% | | -0.04% | | 0.07% | | 0.01% |
| | | 0.653 | | 0.875 | | 0.660 | | 0.975 |
| *Open* | | -4.14% | | -4.21% | | -4.64% | | -2.08% |
| | | <.0001 | | <.0001 | | <.0001 | | 0.003 |
| *Close* | | -5.89% | | -6.52% | | -4.20% | | -3.08% |
| | | <.0001 | | <.0001 | | <.0001 | | <.0001 |
| *EIA Pre-Event* | | -1.85% | | -0.03% | | -2.07% | | -1.02% |
| | | 0.079 | | 0.986 | | 0.049 | | 0.428 |
| *EIA Event* | | 3.25% | | 6.34% | | -0.73% | | 1.95% |
| | | 0.110 | | 0.016 | | 0.753 | | 0.493 |
| *EIA Post-Event* | | 1.68% | | 2.48% | | 1.83% | | 1.49% |
| | | 0.020 | | 0.011 | | 0.017 | | 0.125 |
| *First GSCI Roll* | | 0.38% | | -0.21% | | -0.08% | | -1.66% |
| | | 0.603 | | 0.850 | | 0.916 | | 0.082 |
| *GSCI_Roll_Days2to5* | | -0.18% | | -0.96% | | -0.73% | | -1.28% |
| | | 0.647 | | 0.093 | | 0.080 | | 0.016 |
| *Dummy_Q1_2007* | -0.06% | -0.33% | -0.82% | -1.20% | -0.65% | -0.62% | -0.93% | -0.55% |
| | 0.867 | 0.306 | 0.060 | 0.011 | 0.069 | 0.070 | 0.022 | 0.225 |
| *Day of the Week* | | Yes | | Yes | | Yes | | Yes |
| *Lags* | | 3 Lags | | 3 Lags | | 3 Lags | | 3 Lags |
| *N* | 32519 | 32519 | 32519 | 32519 | 32519 | 32519 | 32519 | 32519 |
| *Adj RSq* | -0.01% | 1.40% | 0.01% | 1.40% | 0.01% | 1.11% | 0.02% | 0.57% |

**Panel B: Logit Regressions**

| *Parameter* | **Locals' Share of Total Volume** | | **Locals' Share of Customer Volume** | | **Locals' Share of Liquidity Provision** | | **Locals' Share of Liquidity Provision to Customers** | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | Odds Ratio | Coefficient | Odds Ratio | Coefficient | Odds Ratio | Coefficient | Odds Ratio |
| *Intercept* | 2.056 | | 0.270 | | 1.626 | | -0.163 | |
| | <.001 | | 0.025 | | <.001 | | 0.176 | |
| ***Volatility—High*** | -0.027 | 0.948 | 0.036 | 1.074 | -0.042 | 0.920 | -0.060 | 0.887 |
| | 0.440 | | 0.236 | | 0.234 | | 0.047 | |
| ***AbsCDI—High*** | 0.186 | 1.451 | 0.079 | 1.172 | 0.169 | 1.402 | 0.015 | 1.031 |
| | <.001 | | 0.009 | | <.001 | | 0.617 | |
| *Volatility* | 0.044 | 1.045 | -0.005 | 0.995 | 0.031 | 1.031 | -0.064 | 0.938 |
| | 0.004 | | 0.691 | | 0.045 | | <.001 | |
| *AbsCDI* | 0.046 | 1.047 | 0.040 | 1.040 | 0.011 | 1.011 | 0.022 | 1.022 |
| | 0.016 | | 0.004 | | 0.497 | | 0.094 | |
| *Return* | -0.007 | 0.993 | -0.011 | 0.989 | -0.008 | 0.992 | -0.003 | 0.997 |
| | 0.620 | | 0.328 | | 0.580 | | 0.787 | |
| *Open* | 0.157 | 1.369 | 0.139 | 1.319 | 0.084 | 1.183 | -0.013 | 0.974 |
| | <.001 | | <.001 | | <.001 | | 0.506 | |
| *Close* | 0.299 | 1.818 | 0.142 | 1.329 | 0.220 | 1.551 | 0.009 | 1.017 |
| | <.001 | | <.001 | | <.001 | | 0.646 | |
| *EIA Pre-Event* | 0.378 | 2.131 | 0.057 | 1.121 | 0.281 | 1.755 | -0.018 | 0.964 |
| | <.001 | | 0.113 | | <.001 | | 0.608 | |
| *EIA Event* | 0.303 | 1.832 | 0.023 | 1.047 | 0.052 | 1.109 | -0.172 | 0.710 |
| | 0.017 | | 0.806 | | 0.647 | | 0.068 | |
| *EIA Post-Event* | 0.043 | 1.091 | -0.105 | 0.811 | -0.012 | 0.977 | -0.145 | 0.748 |
| | 0.171 | | 0.000 | | 0.719 | | <.001 | |
| *First GSCI Roll* | -0.020 | 0.960 | -0.007 | 0.987 | -0.024 | 0.954 | 0.055 | 1.116 |
| | 0.503 | | 0.801 | | 0.444 | | 0.037 | |
| *GSCI_Roll_Days2to5* | 0.043 | 1.090 | 0.031 | 1.065 | 0.027 | 1.055 | -0.017 | 0.967 |
| | 0.012 | | 0.028 | | 0.124 | | 0.243 | |
| *Day of the Week* | Yes | | Yes | | Yes | | Yes | |
| *N* | | | | | | | | |
| $\chi^2$ (*p-Value*) | <0.001 | | <0.001 | | <0.001 | | <0.001 | |

**Table 7: HFLPs *vs*. MFLPs or *e*-Locals and Market Conditions—Q4, 2006 to Q1, 2007**

**Note**: Table 7 presents an analysis of difference between high-frequency liquidity providers" (*HFLPs*), moderate-frequency liquidity providers" (MFLPs), and "*e*-Locals" trading on Globex during periods of market stress. *HFLPs* (*MFLPs*) are defined as traders who make more than 2,000 *(between 990 and 2000 trades a day)* trades a day and carry less than 5% of their daily trading volume overnight. *E-Locals* are defined as traders who trade at most 450 times a day on Globex and are categorized under the CTI (Customer Type Indicator) 1 category. The analysis is conducted on WTI crude oil futures trading on Globex over the time-period from October 2006 to March 2007. *Dummy_Q1_2007* is a dummy variable equal to 1 during the first quarter of 2007 and 0 otherwise. *Volatility* is the 1-minute volatility of returns. *AbsCDI* is the absolute value of customer (traders classified as CTI 4 traders in the CFTC database) trade imbalance over a 1-minute interval. *Volatility-High* (*AbsCDI-High*) is a dummy variable set equal to 1 when the 1-minute *Volatility* (*AbsCDI*) over the past hour has been greater than twice its standard deviation over the sample period, and 0 otherwise. *Open* (*Close*) is a dummy variable equal 1 during the first (last) 30 minutes of trading, and 0 otherwise. *EIA Pre-Event* is a dummy variable equal to 1 during the 30 minutes before a weekly EIA announcement, and 0 otherwise. *EIA Event* is a dummy variable equal to 1 during the 5 minutes after a weekly EIA announcement, and 0 otherwise. *EIA Post-Event* is a dummy variable equal to 1 between 5 and 35 minutes after a weekly EIA announcement, and 0 otherwise. *First GSCI Roll* is a dummy variable equal to 1 on the day of a GSCI roll, and 0 otherwise. *GSCI_Roll_Days2to5* is a dummy variable equal to 1 between the $2^{nd}$ and $5^{th}$ day after a GSCI roll, and 0 otherwise. *Day of the Week* are dummy variables for the first 4 days of the week. *Lags* indicate the number of lags of the dependent variable included in the regression. *HFLP Share of Total Volume* is the proportion of trading volume with HFLP participation. *HFLP Share of Customer Volume* is the proportion of Customer volume where *HFLPs* trade against *Customers*. *HFLP Share of Liquidity Provision* is the proportion of trading volume where *HFLPs* trade passively. *HFLP Share of Liquidity Provision to Customers* is the proportion of Customer volume where *HFLPs* provide liquidity to *Customers.* Similarly-defined variables are computed for *e*-Locals and MFLPs. ***Panel A*** reports the results of OLS regressions of the proportion variables indicated in the column heading. *Lags* indicate the number of lags of the dependent variable included in the regression. Two-tailed *p-values* are also reported, and are obtained using Newey-West standard errors with 5 lags. ***Panel B*** reports results of logit regressions, where the binary dependent variable is 1 when the corresponding proportion variable (indicated in the column heading) is less than its (quarterly) median value. Odds ratios are presented with two-tailed *p-values* and $\chi^2$ tests of likelihood ratios.

**Panel A: OLS Regressions**

| *Parameter* | **Share of Total Volume** | | **Share of Total Customer Volume** | | **Share of Liquidity Provision** | | **Share of Liquidity Provision to Customers** | |
|---|---|---|---|---|---|---|---|---|
| | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - *e*Locals | HFLPs - MFLPs |
| *Intercept* | -3.33% | 4.61% | -1.54% | 3.31% | -0.13% | 3.81% | 0.71% | 3.24% |
| | <.001 | <.001 | <.001 | <.001 | 0.552 | <.001 | <.001 | <.001 |
| ***Volatility—High*** | -3.79% | -3.10% | -3.35% | -2.76% | -2.36% | -1.84% | -1.76% | -1.47% |
| | <.001 | <.001 | <.001 | <.001 | <.0001 | <.001 | <.001 | <.001 |
| ***AbsCDI—High*** | -1.44% | -0.91% | -1.16% | -0.49% | -0.51% | -0.16% | -0.35% | -0.01% |
| | 0.006 | 0.018 | 0.026 | 0.185 | 0.148 | 0.485 | 0.252 | 0.964 |
| *Volatility* | -0.07% | -0.12% | -0.12% | -0.18% | -0.15% | -0.17% | -0.09% | -0.17% |
| | 0.571 | 0.259 | 0.322 | 0.089 | 0.086 | 0.019 | 0.263 | 0.025 |
| *AbsCDI* | 0.10% | 0.04% | -0.06% | -0.04% | 0.10% | -0.01% | -0.09% | -0.08% |
| | 0.267 | 0.574 | 0.557 | 0.538 | 0.110 | 0.864 | 0.147 | 0.065 |
| *Return* | -0.13% | -0.08% | -0.10% | -0.06% | -0.10% | -0.05% | -0.06% | -0.01% |
| | 0.189 | 0.290 | 0.297 | 0.390 | 0.156 | 0.291 | 0.349 | 0.908 |
| *Open* | 3.62% | -0.50% | 2.56% | -0.27% | 2.33% | -0.38% | 1.93% | -0.13% |
| | <.001 | 0.213 | <.001 | 0.491 | <.0001 | 0.179 | <.001 | 0.636 |
| *Close* | -0.61% | 0.79% | -1.02% | 0.66% | -0.30% | 0.59% | -0.58% | 0.26% |
| | 0.086 | 0.002 | 0.003 | 0.006 | 0.206 | <.001 | 0.006 | 0.089 |
| *EIA Pre-Event* | -0.24% | -0.45% | -0.43% | -0.04% | -0.61% | -0.64% | -0.49% | -0.55% |
| | 0.729 | 0.370 | 0.534 | 0.943 | 0.186 | 0.052 | 0.238 | 0.097 |
| *EIA Event* | 3.31% | 1.29% | 3.40% | 0.55% | 1.52% | 0.13% | 0.91% | -0.61% |
| | 0.016 | 0.294 | 0.006 | 0.670 | 0.084 | 0.884 | 0.204 | 0.473 |
| *EIA Post-Event* | 0.14% | -0.67% | -0.30% | -0.73% | -0.17% | -0.45% | -0.49% | -0.34% |
| | 0.789 | 0.085 | 0.541 | 0.054 | 0.614 | 0.074 | 0.101 | 0.139 |
| *First GSCI Roll* | -0.05% | -1.21% | -0.14% | -0.63% | -0.32% | -0.90% | -0.15% | -0.33% |
| | 0.925 | 0.004 | 0.800 | 0.111 | 0.378 | 0.001 | 0.637 | 0.183 |
| *GSCI_Roll_Days2to5* | 0.16% | 0.43% | -0.06% | 0.57% | 0.17% | 0.35% | 0.02% | 0.31% |
| | 0.584 | 0.044 | 0.841 | 0.005 | 0.364 | 0.013 | 0.897 | 0.025 |
| *Dummy_Q1_2007* | 11.12% | 9.44% | 9.64% | 7.81% | 6.17% | 5.17% | 4.73% | 4.28% |
| | <.001 | <.001 | <.001 | <.001 | <.0001 | <.001 | <.001 | <.001 |
| *Day of the Week* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Lags* | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| N | 37995 | 37582 | 37995 | 37477 | 37995 | 37582 | 37456 | 37477 |
| Adj RSq | 18.26% | 29.61% | 11.71% | 17.99% | 11.61% | 20.25% | 6.61% | 10.23% |

**Panel B: Logit Regressions (Odds Ratios)**

| *Parameter* | **Share of Total Volume** | | **Share of Total Customer Volume** | | **Share of Liquidity Provision** | | **Share of Liquidity Provision to Customers** | |
|---|---|---|---|---|---|---|---|---|
| | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - *e*Locals | HFLPs - MFLPs |
| ***Volatility—High*** | 1.560 | 1.818 | 1.575 | 1.846 | 1.590 | 1.730 | 1.503 | 1.585 |
| | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 |
| ***AbsCDI—High*** | 1.176 | 1.169 | 1.073 | 0.937 | 1.131 | 1.024 | 1.094 | 0.950 |
| | 0.002 | 0.003 | 0.175 | 0.208 | 0.018 | 0.649 | 0.082 | 0.322 |
| *Volatility* | 1.043 | 1.043 | 1.032 | 1.051 | 1.035 | 1.021 | 1.033 | 1.020 |
| | <.001 | <.001 | 0.005 | <.001 | 0.002 | 0.059 | 0.003 | 0.063 |
| *AbsCDI* | 0.998 | 1.003 | 0.983 | 1.001 | 1.020 | 0.999 | 0.990 | 0.989 |
| | 0.825 | 0.775 | 0.110 | 0.948 | 0.068 | 0.923 | 0.353 | 0.302 |
| *Return* | 1.008 | 1.006 | 1.016 | 1.004 | 1.017 | 0.998 | 1.017 | 0.999 |
| | 0.451 | 0.543 | 0.116 | 0.677 | 0.105 | 0.837 | 0.109 | 0.910 |
| *Open* | 0.581 | 1.215 | 0.797 | 1.230 | 0.858 | 1.206 | 0.989 | 1.235 |
| | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | 0.774 | <.001 |
| *Close* | 1.132 | 0.827 | 1.141 | 0.812 | 1.154 | 0.835 | 1.127 | 0.872 |
| | 0.001 | <.001 | <.001 | <.001 | <.001 | <.001 | 0.001 | <.001 |
| *EIA Pre-Event* | 0.999 | 1.204 | 1.114 | 1.329 | 1.049 | 1.177 | 1.151 | 1.256 |
| | 0.989 | 0.001 | 0.043 | <.001 | 0.369 | 0.002 | 0.008 | <.001 |
| *EIA Event* | 0.540 | 0.648 | 0.773 | 0.840 | 0.663 | 0.766 | 0.834 | 1.098 |
| | 0.001 | 0.022 | 0.169 | 0.351 | 0.029 | 0.153 | 0.329 | 0.613 |
| *EIA Post-Event* | 1.059 | 1.127 | 1.106 | 1.118 | 1.019 | 1.143 | 1.058 | 0.999 |
| | 0.290 | 0.028 | 0.064 | 0.040 | 0.724 | 0.014 | 0.299 | 0.986 |
| *First GSCI Roll* | 1.043 | 1.242 | 1.053 | 1.276 | 0.967 | 1.108 | 0.991 | 1.109 |
| | 0.365 | <.001 | 0.267 | <.001 | 0.476 | 0.029 | 0.846 | 0.028 |
| *GSCI_Roll_Days2to4* | 0.994 | 0.934 | 0.987 | 0.921 | 1.008 | 0.945 | 0.968 | 0.950 |
| | 0.827 | 0.008 | 0.597 | 0.001 | 0.747 | 0.027 | 0.203 | 0.044 |
| *Day of the Week* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 37995 | 37582 | 37995 | 37582 | 37995 | 37582 | 37995 | 37582 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $\chi2$ (*p-Value)* | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |

**Table 8: HFLPs *vs*. MFLPs or *e*-Locals or Locals Trading Activity during the Financial Crisis—Q3, 2008 to Q2, 2009**

**Note**: Table 8 presents an analysis of difference between high-frequency liquidity providers" (*HFLPs*), moderate-frequency machine liquidity providers (MFLPs), and "*e*-Locals" trading during the financial crisis of 2008-09. *HFLPs* (MFLPs) are traders who trade more than 2000 trades a day (between 990 and 2000 trades a day) and carry less than 5% of their daily trading volume overnight. *E-Locals* are defined as traders who trade at most 450 times a day and are categorized under CTI (Customer Type Indicator) 1 category in the Globex (electronic) market. "Locals" are traders in the options-on-futures pits who are categorized as CTI (Customer Type Indicator) 1 traders. The analysis is conducted on WTI light sweet crude oil futures (on the Globex platform) and options-on-futures (Pits Locals) over the time-period July, 2008 to June, 2009. *Lehman_Crisis* is a dummy variable that equals 1 from September 15, 2008 to January 15, 2009, and 0 otherwise. Storage issues in Cushing, OK are captured by *Cushing_Crisis,* a dummy variable set equal to 1 from December 17, 2008 to February 17, 2009, and 0 otherwise. *EIA_Inventory* is a dummy variable equal to 1 during EIA announcement days, and 0 otherwise. *Lead_Inventory* is a dummy variable equal to 1 during the days prior to the EIA announcements, and 0 otherwise*.* *First GSCI Roll* is a dummy variable equal to 1 on the day of a GSCI roll, and 0 otherwise. *GSCI_Roll_Days2to5* is a dummy variable equal to 1 between the $2^{nd}$ and $5^{th}$ day after a GSCI roll, and 0 otherwise. *Day of the Week* are a set of dummy variable for the first four days of the week. *Lags* indicate the number of lags of the dependent variable included in the regression. *HFLP Share of Total Volume* is the proportion of trading volume with HFLP participation. *HFLP Share of Customer Volume* is the proportion of Customer volume where *HFLPs* trade against *Customers*. *HFLP Share of Liquidity Provision* is the proportion of trading volume where *HFLPs* trade passively. *HFLP Share of Liquidity Provision to Customers* is the proportion of Customer volume where *HFLPs* provide liquidity to *Customers.* Similarly-defined variables are computed for Locals, *e*-Locals and MFLPs. ***Panel A*** reports the results of OLS regressions of the proportion variables indicated in the column heading. *Lags* indicate the number of lags of the dependent variable included in the regression. Two-tailed *p-values* are also reported, and are obtained using Newey-West standard errors with 5 lags. ***Panel B*** reports results of logit regressions, where the binary dependent variable is 1 when the corresponding proportion variable (indicated in the column heading) is less than its (quarterly) median value. Odds ratios are presented with two-tailed *p-values* and $\chi^2$ tests of likelihood ratios. Source: CFTC, EIA, and authors' computations.

**Panel A: OLS Regressions**

| *Parameter* | Share of Volume | | | Share of Customer Volume | | | Share of Liquidity Provision | | | Share of Liquidity Provision to Customers | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - Locals | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - Locals | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - Locals | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - Locals |
| *Intercept* | 18.66% | 16.23% | -12.58% | 20.26% | 16.93% | -16.41% | 16.67% | 14.05% | -8.41% | 12.68% | 11.33% | -13.02% |
| | <.001 | <.001 | <.0001 | <.001 | <.001 | <.0001 | <.001 | <.001 | <.0001 | <.001 | <.001 | <.0001 |
| ***Cushing_Crisis*** | -1.63% | -1.73% | -2.25% | -1.84% | -1.77% | -2.37% | -1.25% | -1.37% | -1.74% | -0.88% | -0.99% | -1.42% |
| | 0.018 | 0.040 | 0.036 | 0.004 | 0.012 | 0.052 | 0.013 | 0.020 | 0.076 | 0.016 | 0.015 | 0.301 |
| *Lehman_Crisis* | -0.47% | -0.04% | 1.67% | -0.74% | -0.27% | 2.00% | -0.78% | -0.37% | 2.48% | -0.53% | -0.24% | 3.15% |
| | 0.327 | 0.946 | 0.093 | 0.126 | 0.597 | 0.109 | 0.034 | 0.345 | 0.006 | 0.050 | 0.384 | 0.005 |
| *EIA_Inventory* | 0.82% | 0.68% | 2.79% | -0.20% | 0.22% | 4.28% | 0.52% | 0.41% | 2.31% | -0.26% | -0.08% | 3.53% |
| | 0.334 | 0.560 | 0.287 | 0.815 | 0.815 | 0.222 | 0.384 | 0.604 | 0.448 | 0.616 | 0.896 | 0.316 |
| *Lead_Inventory* | -0.73% | -0.57% | 1.65% | -0.99% | -0.58% | 2.86% | -0.53% | -0.29% | 2.19% | -0.55% | -0.34% | 0.75% |
| | 0.458 | 0.671 | 0.482 | 0.250 | 0.592 | 0.342 | 0.453 | 0.753 | 0.491 | 0.249 | 0.541 | 0.839 |
| *First_GSCI_Roll* | -2.74% | -2.95% | -5.02% | -3.31% | -3.30% | -6.06% | -2.07% | -2.04% | -3.67% | -1.79% | -1.66% | -2.43% |
| | <.001 | <.001 | 0.007 | <.001 | <.001 | 0.010 | <.001 | <.001 | 0.056 | <.001 | <.001 | 0.276 |
| *GSCI_Roll_Days2to5* | -1.47% | -2.52% | -4.29% | -1.93% | -2.58% | -5.16% | -1.25% | -1.84% | -2.72% | -1.11% | -1.55% | -3.30% |
| | 0.009 | 0.001 | <.0001 | <.001 | <.001 | <.0001 | 0.001 | <.001 | 0.006 | <.001 | <.001 | 0.004 |
| *Day of the Week* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Lags* | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| N | 240 | 240 | 240 | 240 | 240 | 240 | 240 | 240 | 240 | 240 | 240 | 240 |
| Adj RSq | 42.21% | 39.92% | 24.75% | 33.37% | 33.46% | 23.78% | 34.88% | 31.85% | 9.62% | 26.80% | 25.25% | 7.60% |

**Panel B: Logit Regressions (Odds Ratios)**

| *Parameter* | **Share of Volume** | | | **Share of Customer Volume** | | | **Share of Liquidity Provision** | | | **Share of Liquidity Provision to Customers** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - Locals | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - Locals | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - Locals | HFLPs - *e*Locals | HFLPs - MFLPs | HFLPs - Locals |
| ***Cushing_Crisis*** | 25.111 | 11.625 | 2.692 | 15.675 | 6.790 | 2.085 | 22.551 | 7.729 | 2.388 | 8.204 | 5.466 | 1.471 |
| | <.001 | <.001 | 0.025 | <.001 | <.001 | 0.078 | <.001 | <.001 | 0.046 | <.001 | <.001 | 0.344 |
| *Lehman_Crisis* | 1.388 | 0.925 | 0.574 | 3.390 | 1.361 | 0.392 | 2.378 | 1.415 | 0.651 | 2.641 | 1.455 | 0.413 |
| | 0.299 | 0.799 | 0.072 | <.001 | 0.306 | 0.002 | 0.008 | 0.261 | 0.155 | 0.003 | 0.220 | 0.003 |
| *EIA_Inventory* | 0.675 | 2.183 | 0.812 | 1.344 | 1.531 | 0.440 | 0.612 | 1.430 | 0.636 | 1.603 | 1.099 | 0.516 |
| | 0.658 | 0.347 | 0.797 | 0.744 | 0.602 | 0.318 | 0.592 | 0.665 | 0.568 | 0.577 | 0.907 | 0.396 |
| *Lead_Inventory* | 0.924 | 2.029 | 1.635 | 2.681 | 0.968 | 0.211 | 0.973 | 2.901 | 0.580 | 2.748 | 2.008 | 0.570 |
| | 0.932 | 0.417 | 0.583 | 0.306 | 0.971 | 0.087 | 0.977 | 0.232 | 0.518 | 0.268 | 0.422 | 0.501 |
| *First_GSCI_Roll* | 3.396 | 1.588 | 3.228 | 23.897 | 1.618 | 2.518 | 12.747 | 3.239 | 2.212 | 27.028 | 3.183 | 0.776 |
| | 0.087 | 0.499 | 0.092 | 0.001 | 0.476 | 0.183 | 0.004 | 0.095 | 0.247 | 0.003 | 0.098 | 0.705 |
| *GSCI_Roll_Days2to5* | 6.938 | 5.066 | 4.824 | 10.568 | 5.292 | 2.154 | 7.627 | 7.051 | 3.052 | 7.045 | 6.496 | 1.848 |
| | <.001 | <.001 | 0.000 | <.001 | <.001 | 0.054 | <.001 | <.001 | 0.007 | <.001 | <.001 | 0.117 |
| *Day of the Week* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 245 | 245 | 245 | 245 | 245 | 245 | 245 | 245 | 245 | 245 | 245 | 245 |
| $\chi 2$ (*p-Value)* | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | 0.88% | <0.001 | <0.001 | 0.02% | <0.001 | <0.001 | 4.68% |

**Table 9: Effective Customer Spreads and Market Conditions—Q4, 2006 to Q1, 2007**

**Note**: Table 9 presents an analysis of the impact of market stress on the effective spreads paid by customers in general or while trading with different kinds of voluntary liquidity providers specifically (e.g., *Customer-to-HFLP Spreads)*. *Customers* are traders classified as CTI-4 traders in the CFTC database. HFLPs (*MFLPs*) are traders who trade more than 2000 trades a day (*between 990 and 2000 trades a day*) and carry less than 5% of their daily trading volume overnight. *E-Locals* are traders who trade at most 450 times a day and are categorized under CTI (Customer Type Indicator) 1 category in the Globex (electronic) market. The analysis is conducted on WTI crude oil futures trading on the Globex platform over the time-period October 2006 to March 2007. *Dummy_Q1_2007* is a dummy variable equal to 1 during the first quarter of 2007 and 0 otherwise. *Volatility* is the 1-minute volatility of returns. *AbsCDI* is the absolute value of customer (traders classified as CTI 4 traders in the CFTC database) trade imbalance over a 1-minute interval. *Volatility-High* (*AbsCDI-High*) is a dummy variable equal to 1 when the 1-minute *Volatility* (*AbsCDI*) over the past hour has been greater than twice its standard deviation over the sample period, and 0 otherwise. *Open* (*Close*) is a dummy variable equal 1 during the first (last) 30 minutes of trading, and 0 otherwise. *EIA Pre-Event* is a dummy variable equal to 1 during the 30 minutes before a weekly EIA announcement, and 0 otherwise. *EIA Event* is a dummy variable equal to 1 during the 5 minutes after a weekly EIA announcement, and 0 otherwise. *EIA Post-Event* is a dummy variable equal to 1 between 5 and 35 minutes after a weekly EIA announcement, and 0 otherwise. *First_GSCI_Roll* is a dummy variable equal to 1 on the 1$^{st}$ day of the monthly GSCI roll, and 0 otherwise. *GSCI_Roll_Days2to5* is a dummy variable equal to 1 between the 2$^{nd}$ and 5$^{th}$ day after a GSCI roll, and 0 otherwise. *Day of the Week* are dummy variables for the first four days of the week. *Lags* indicate the number of lags of the dependent variable included in the regression. *Spreads* variables are calculated every minute using the percentage differences between the estimated mid-quote and customer buy or sell prices for each futures maturity, and then volume-weighted across all contract maturities. *Customer-to-HFLP Spreads* are *Spreads* for customer trades with HFLPs as their counterparties. *Customer-to-MFLP Spreads* and *Customer-to-e-Local Spreads* are calculated analogously. Two-tailed p-values, obtained using Newey-West standard errors with 5 lags, are also reported.

| *Parameter* | **Customer Spreads** | | **Customer-to-HFLP Spreads** | | **Customer-to-MFLP Spreads** | | **Customer-to-eLocal Spreads** | |
|---|---|---|---|---|---|---|---|---|
| *Intercept* | 1.840 | 1.640 | 1.050 | 0.990 | 1.190 | 1.180 | 2.370 | 2.100 |
| | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| ***Volatility—High*** | 0.360 | 0.260 | 0.130 | 0.180 | 0.096 | 0.100 | 0.240 | 0.022 |
| | 0.008 | 0.070 | 0.033 | 0.008 | 0.325 | 0.331 | 0.195 | 0.911 |
| ***Abs CDI—High*** | 0.090 | 0.075 | -0.100 | -0.045 | -0.063 | -0.069 | -0.063 | -0.082 |
| | 0.298 | 0.337 | 0.034 | 0.457 | 0.385 | 0.378 | 0.630 | 0.519 |
| *Volatility* | | 0.078 | | 0.034 | | 0.051 | | 0.190 |
| | | 0.002 | | 0.010 | | 0.015 | | 0.002 |
| *Abs CDI* | | 0.007 | | 0.024 | | 0.015 | | 0.046 |
| | | 0.652 | | 0.031 | | 0.420 | | 0.146 |
| *Return* | | 0.012 | | -0.007 | | -0.032 | | 0.024 |
| | | 0.419 | | 0.589 | | 0.078 | | 0.453 |
| *Open* | | 0.160 | | -0.012 | | -0.015 | | -0.500 |
| | | 0.191 | | 0.915 | | 0.855 | | 0.047 |
| *Close* | | 0.130 | | 0.018 | | 0.170 | | 0.340 |
| | | 0.012 | | 0.612 | | 0.021 | | 0.006 |
| *EIA Pre-Event* | | -0.096 | | 0.300 | | -0.032 | | -0.300 |
| | | 0.261 | | 0.001 | | 0.705 | | 0.183 |
| *EIA Event* | | 0.055 | | 0.360 | | 0.620 | | 0.210 |
| | | 0.811 | | 0.190 | | 0.166 | | 0.701 |
| *EIA Post-Event* | | -0.025 | | -0.200 | | -0.026 | | 0.160 |
| | | 0.779 | | 0.013 | | 0.749 | | 0.359 |
| *First GSCI Roll* | | 0.089 | | -0.031 | | -0.061 | | 0.350 |
| | | 0.205 | | 0.585 | | 0.501 | | 0.044 |
| *GSCI_Roll_Days2to4* | | 0.032 | | 0.009 | | 0.030 | | -0.027 |
| | | 0.484 | | 0.759 | | 0.572 | | 0.742 |
| *Dummy_Q1_2007* | 0.240 | 0.200 | 0.410 | 0.380 | 0.640 | 0.610 | 0.096 | 0.170 |
| | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | 0.125 | 0.008 |
| *Day of the Week* | | Yes | | Yes | | Yes | | Yes |
| *Lags* | | 2 Lags | | 2 Lags | | 2 Lags | | 2 Lags |
| *N* | 37422 | 36646 | 35958 | 33552 | 32805 | 26990 | 32360 | 27024 |
| *Adj RSq* | 0.14% | 0.80% | 0.67% | 1.46% | 1.03% | 1.21% | 0.01% | 0.51% |

**Table 10: Effective Customer Spreads during the Cushing Crisis—Q3, 2008 to Q2, 2009**

**Note**: Table 10 presents a daily analysis of the impact of market stress (specifically, the oil-storage crisis of Winter 2009) on the effective spreads paid by customers while trading WTI crude oil futures with various kinds of voluntary liquidity providers on the Globex platform. The sample includes daily data from July 1st, 2008 and June 30th, 2009. *Customers* are traders classified as CTI-4 traders in the CFTC database. HFLPs (*MFLPs*) are traders who trade more than 2000 (*between 990 and 2000*) times a day and carry less than 5% of their daily trading volume overnight. *E-Locals* are defined as traders who trade at most 450 times a day and are categorized under CTI (Customer Type Indicator) 1 category in the Globex (electronic) market. *Lehman_Crisis* is a dummy variable that equals 1 from September 15th, 2008 to January 15th, 2009, and 0 otherwise. Storage issues in Cushing, OK are captured by *Cushing_Crisis,* a dummy variable set equal to 1 from December 17, 2008 to February 17, 2009 and 0 otherwise. *EIA_Inventory* is a dummy variable equal to 1 during EIA announcement days, and 0 otherwise. *Lead_Inventory* is a dummy variable equal to 1 during the days prior to the EIA announcements, and 0 otherwise. *First GSCI Roll* is a dummy variable equal to 1 on the day of a GSCI roll, and 0 otherwise. *GSCI_Roll_Days2to5* is a dummy variable equal to 1 between the 2nd and 5th days after a GSCI roll, and 0 otherwise. *VIX_std* is the standardized value of the VIX, i.e., the S&P 500 stock index (option implied) volatility index. *Cost_of_Carry_Std* is the standardized value of the absolute near-dated cost-of-carry for WTI crude oil, measured as the percentage difference between the near-month and first-deferred crude oil WTI futures prices net of LIBOR. *Day_after_holiday* is a dummy variable equal to one on days after public holidays, and 0 otherwise. *Spreads* variables refer to effective spreads, calculated every minute using the percentage differences between the estimated mid-quote and customer buy or sell prices for each futures maturity, and then volume-weighted across all maturities on each trading day. *Customer-to-HFLP Spreads* are *Spreads* for customer trades with HFLPs as their counterparties. *Customer-to-MFLP Spreads* and *Customer-to-e-Local Spreads* are calculated analogously. Two-tailed p-values, obtained using Newey-West standard errors with 5 lags, are also reported. *Source:* CFTC, EIA, and authors' computations.

| *Parameter* | **Customer Spreads** | | **Customer-to-HFLP Spreads** | | **Customer-to-MFLP Spreads** | | **Customer-to-*e*Local Spreads** | |
|---|---|---|---|---|---|---|---|---|
| *Intercept* | 1.67 | 2.16 | 1.31 | 1.73 | 2.35 | 3.09 | 1.82 | 2.57 |
| | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 |
| ***Cushing_Crisis*** | 0.83 | | 0.95 | | 1.11 | | 0.55 | |
| | 0.007 | | 0.002 | | 0.097 | | 0.017 | |
| *Lehman_Crisis* | 0.92 | | 0.82 | | 0.91 | | 0.67 | |
| | <.001 | | <.001 | | <.001 | | <.001 | |
| *VIX_std* | | 0.53 | | 0.46 | | 0.73 | | 0.54 |
| | | <.001 | | <.001 | | <.001 | | <.001 |
| *Cost_of_Carry_Std* | | 0.11 | | 0.15 | | 0.16 | | 0.07 |
| | | 0.023 | | 0.002 | | 0.103 | | 0.063 |
| *EIA_Inventory* | -0.20 | -0.20 | -0.30 | -0.30 | -0.60 | -0.40 | -0.09 | 0.01 |
| | 0.634 | 0.693 | 0.466 | 0.518 | 0.469 | 0.570 | 0.827 | 0.979 |
| *Lead_Inventory* | -1.40 | -1.50 | -1.60 | -1.60 | -1.90 | -1.80 | -1.50 | -1.40 |
| | 0.139 | 0.123 | 0.102 | 0.094 | 0.265 | 0.286 | 0.071 | 0.066 |
| *First_GSCI_Roll* | -0.10 | -0.09 | -0.10 | -0.10 | -0.07 | -0.05 | -0.30 | -0.30 |
| | 0.442 | 0.535 | 0.412 | 0.481 | 0.822 | 0.847 | 0.225 | 0.180 |
| *GSCI_Roll_Days2to5* | -0.40 | -0.40 | -0.30 | -0.30 | -0.50 | -0.60 | -0.40 | -0.40 |
| | 0.030 | 0.013 | 0.096 | 0.044 | 0.060 | 0.025 | 0.025 | 0.003 |
| *Day_after_holiday* | 5.07 | 4.97 | 5.28 | 5.23 | 6.41 | 6.48 | 3.15 | 3.09 |
| | 0.010 | 0.013 | 0.008 | 0.011 | 0.110 | 0.117 | 0.024 | 0.025 |
| *Day of the Week* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Lags* | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| *N* | 244 | 244 | 244 | 244 | 244 | 244 | 244 | 244 |
| *Adj RSq* | 53.97% | 55.12% | 57.40% | 57.74% | 30.11% | 33.62% | 45.40% | 49.88% |