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by

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Abstract

Using positions data for 18 commodity futures during 2001-2020, we examine systematic and idiosyncratic determinants of Amihud price impact and microstructure noise proxying for permanent and transitory components of commodity futures liquidity. Idiosyncratic factors have the largest economic impact: while excess hedging demand increases price impact and noise, active position taking (by market-makers) in excess of the hedging demand reduces noise. Systematic factors, including the lack of competition among liquidity providers, adversely impact liquidity, but this effect is mitigated if liquidity providers are well capitalized. Supplementary leverage ratio (SLR) makes holding inventory costlier and is associated with lower liquidity.

1. INTRODUCTION

What systematic, idiosyncratic, and regulatory factors drive liquidity in commodity futures? A holistic approach to answer this question is important because liquidity affects not only the ability of market participants to open and close their positions at reasonable costs, but also the real economy as operating firms' business decisions are impacted by large movements in commodity prices during illiquid market conditions.[1] Another intriguing aspect of liquidity in commodity futures is that it is influenced by the actions of a variety of market participants including commercial end-users, who use these markets for operational hedging (Giambona, Graham, Harvey, and Bodnar (2018)); and non-commercial market participants who provide liquidity by stepping in as counterparties for commercial participants (Manaster and Mann

[1] Gilje, Ready, Roussanov, and Taillard (2020) provide a stark example of this channel.

(1996), Goldstein and Hotchkiss (2020)). Regulators and policymakers are also interested in the smooth functioning of commodity markets, which is affected by the key determinants of commodity market liquidity.

This paper attempts to answer this headline question with an empirical model that relies on two complementary views on the determinants of liquidity: market participants' day-to-day management of their positions in relation to their targets, as well as systematic factors resulting from the industrial organization of the marketplace.[2] Commodity futures markets provide a unique setting for this comprehensive approach since not only market participants are naturally separated into liquidity providers (non-commerical traders) and hedgers (commercial traders), which allows us to distinguish the impact of active position taking of liquidity providers (over and above the positions resulting from serving as a market making counterparty) from the hedging demand of hedgers, but also the individual contract markets themselves have unique set of participants, which help us identify how the market power of market makers as well as the size and the breadth of participation of the top liquidity provider in a given market affect market liquidity.

To investigate the role of these complementary factors on determining commodity futures liquidity, we use propriety data on daily end-of-day positions of individual traders from 2001 to 2020 across 18 commodity futures markets covering four broad commodity groups (agriculture, energy, livestock, and metals) where individual traders self-identify themselves as market

[2] The first view is expressed in inventory control models where market liquidity is primarily determined by market makers' deviations from their inventory targets. See for example, models by Shen and Starr (2002) and O'Hara and Oldfield (1986) where large deviations from inventory is associated with decline in liquidity because of the various costs associated with maintaining inventory such as price fluctuations risk and capital requirements. The second view is examined in studies including Van Ness, Van Ness, Warr (2005), Mayhew (2002), Huang and Masulis (1999), Kaul and Sapp (2009).

makers (non-commercial traders) or hedgers (commercial traders).[3] The evidence shows that idiosyncratic factors are important for explaining changes in liquidity. Mainly, the hedging pressure coming from commercial traders is associated with a deterioration in liquidity, while the active position taking by the non-commercial traders improves it. We also show that the effect of systematic factors on liquidity, mainly the concentration of market makers and the top liquidity providers' size and breadth of participation, but with relatively more modest economic impact. These findings highlight that separating the permanent (Amihud price impact) and transitory (microstructure noise) components of market liquidity is important to understand the differential roles idiosyncratic and systematic factors play on liquidity. Overall, our empirical model provides the largest explanatory power for changes in liquidity in the metals futures markets, followed by energy and agriculture.

With respect to hedging pressure from commercial traders, proxied for by commercial traders' deviation of their end of day position from their long-term inventory target, we find that both permanent and transitory components of liquidity deteriorate when hedging demand increases. This result implies that the increase in the hedging demand is not completely met by the speculators taking the opposite side at the prevailing prices. It is important, however, to note that the commercial traders category in our data includes end-users, who use futures market to hedge their risk in product markets, as well as swap dealers, who use commodity futures to hedge their risk exposure in their financial portfolios. In regressions we where separate the commercial swap dealers and traditional commercial traders, we find evidence consistent with the view that while the hedging pressure from the commercial swap dealers has a detrimental impact on the

[3] In terms of analyzing liquidity of numerous commodity futures markets, our study is similar to Marshall, Nguyen, and Visaltanachoti (2012); however, the focus of our paper is different. We not only introduce a transitory component of liquidity through microstructure noise, we also make use of our daily trader-level data to investigate the effect of systemic and idiosyncratic components of liquidity.

transitory component of market liquidity, the hedging pressure from traditional commercial traders has a detrimental impact on the permanent component of liquidity. Interestingly, for contract markets grouped under energy (natural gas, oil, gasoline futures), the hedging pressure from commercial swap dealers results in deterioration of transitory market liquidity, whereas hedging pressure by commercial traders improves transitory market liquidity.[4]

With respect to non-commercial traders, who could either be acting as market makers providing liquidity to commercial traders or assume a speculative role and trade actively to build positions over and beyond what is required in their market making activity, our empirical evidence shows two distinct effects on permanent and transitory components of liquidity for their two separate roles. In the case of their role as speculative traders, while their active position taking improves liquidity by lowering the transitory price impact, with the largest economic effect observed in the metals category, active position taking results in deterioration in liquidity by increasing the permanent price impact specifically in copper and coffee contracts. In the case of their role as market makers, evidence shows that deviations of their positions from zero inventory levels lead to liquidity deterioration in the form of higher transitory price impact. This effect, which presents more in energy and the agricultural markets, is consistent with the view that maintaining a zero inventory is an important consideration for liquidity provision.

With respect to systematic factors, evidence shows that increased concentration of market makers is detrimental to liquidity, consistent with the view that the lack of competition allows liquidity providers to potentially charge higher prices for liquidity provision to traders

[4] This finding is consistent with the implications of the theoretical model developed by Goldstein and Yang (2022) which formulates the mechanism by which the financialization of commodity futures affects liquidity. Financialization is generally defined as the increased presence of index investors in the commodity futures markets which starts around 2006. See Brunetti et. al, 2016; Cheng et al, 2015; Tang and Xiong, 2012 for examples on the impact of financialization on commodity futures.

demanding liquidity. In contrast, the larger size and breadth of market participation of the top market maker (the trader with the largest inventory) in a given commodity market results in improved market liquidity, possibly reflecting the top traders' lower inventory risk. These results are supported for both permanent and transitory components of liquidity and are present across most of the commodity markets with the largest economic impact among metals and agriculture commodities.

Our contributions in this paper are two-fold. First, we contribute to the commodity futures pricing and microstructure literature (e.g., Fernandez-Perez, Fuertes, and Miffre (2017), Gorton, Hayashi, and Rouwenhorst (2013), and Liu, Tse, and Zheng (2021)) by developing measures based on trader level commodity futures positions to proxy for systematic and idiosyncratic determinants of liquidity and microstructure noise. Second, we contribute to the growing literature on commodity futures liquidity by testing models developed in the context of equity and fixed income markets on commodity futures markets.

The remainder of the paper is organized as follows. Section II develops our research questions and introduces the measures we use to proxy for liquidity as well as the measures we develop to proxy for systematic and idiosyncratic determinants of liquidity. Section III provides a general description of the data and the sample. Section IV presents our results for Amihud liquidity and Section V does the same for Microstructure noise. Section VI discusses our robustness analyses and Section VII concludes.

2. RESEARCH QUESTIONS AND MEASURES

In this section, we develop two new hypotheses dealing with idiosyncratic factors relating to the inventory management of commercial and non-commercial traders and systematic factors relating to the industrial organization of the commodity markets and the characteristics of the liquidity providers.

2.1 Hypotheses development

First, we examine the impact of fluctuations in traders' inventory positions of non-commercial and commercial traders. While we rely on prior studies focusing on equity and bond markets in developing our hypothesis, we account for the special nature of the commodity markets, where trading could be motivated by either hedging, market making, or speculative purposes.[5] Specifically, in the case of commercial traders, when their hedging needs increase, their deviations from target inventory may create liquidity pressure, resulting in higher price impact.[6] In contrast, the inventory of non-commercial participants can have opposing effects on commodity liquidity depending on whether they are serving as market-making counterparties to commercial participants (see, e.g., Brunetti et al. (2016) and Ludwig (2019)), or actively building speculative positions themselves (see, e.g., Manaster and Mann (1996)). In the case of active position taking, where non-commercials actively trade to build positions above and beyond the hedging demand, their enhanced activity will result in greater liquidity. In the case of their role as market makers, their deviations from their target inventory will result in deterioration in liquidity reflecting the cost of inventory maintenance. We test the effects of these fluctuations in traders' inventory, which we simply refer as idiosyncratic factors, on liquidity with the following hypothesis:

[5] See, for example, Mildenstein and Schleef (1983), Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010), and Goldstein and Hotchkiss (2020) for the impact of inventories on the liquidity in equity and bond markets.
[6] See, for example, Cheng, Kirilenko, and Xiong (2015) and Kang, Rouwenhorst, Tang (2020).

H1: Excess hedging demand by commercial traders adversely affects liquidity and increases price impact. Active position taking by non-commercial traders improves liquidity and results in lower price impact. However, building up sizeable inventory by non-commercial traders for the purposes of market making results in higher price impact.

We further consider three additional extensions to this hypothesis to incorporate the specific nature of the commodity futures. First, we separate commercial swap dealers, who use commodity futures to hedge their financial portfolios, from the rest of the commercial traders who primarily trade to hedge their risk in the product markets.[7] Second, we test our hypothesis across four commodity sub-groups as well as individual commodities to better capture the unique properties of these markets including how they are affected by macro factors, or other systematic risks as well as the institutional differences of the trading in the contract market.[8] Third, we examine the effect of the Supplemental Leverage Ratio (SLR) requirement that took place during the sample period.[9] Specifically, we test whether the SLR, through increased capitalization requirement, adversely affects liquidity due to higher cost of carrying inventory.[10]

Our second hypothesis examines the effect of systematic factors, including competition among liquidity providers, as well as the size and the breadth of market participation by the top

[7] See Mixon and Onur (2020) for how swap dealers use futures markets to hedge their swaps book.

[8] For example, commodities in metals category are central bank reserves which affect their pricing in product markets (Smales and Lucey (2019)); commodities in energy category are shown to have price inelasticities (Hammoudeh, Nguyen, and Sousa (2015)); commodities in livestock and agriculture category are sensitive to extreme weather (Makaudze (2012) and due to their continuing reliance on pit trading (Gousgounis and Onur, 2018) they are thinly traded and have quality certification issues (Linhoff, Mußhoff, and Parlasca, 2023).

[9] U.S. G-SIBs (U.S. global systemically important BHCs) are required to maintain a supplementary leverage ratio of at least 5 percent and that IDI subsidiaries of U.S. G-SIBs have an SLR of at least 6 percent.. While the rule directly impacts the 8 US bank holding companies that are considered G-SIBS and indirectly affects its subsidiaries, we do not differentiate the traders whether they are affiliated with an entity that is subject to the requirement and instead focus on the effect of the rule as it became the accepted policy.

[10] Using a similar empirical design Haynes and McPhail (2021) show that the SLR has increased the cost of holding derivative positions that are disadvantaged with the way derivative exposures are calculated.

liquidityprovider in a given commodity market, on liquidity.[11] Specifically, we conjecture that the price impact of liquidity provision is higher in concentrated markets as top liquidity providers do not face stiff competition from other liquidity providers and are able to charge a higher price for liquidity provision. In addition, we conjecture that when the top liquidity provider in a given commodity also trades numerous other commodities, which we refer to as the breadth of participation, it will result in lower price impact due to lower inventory risk resulting from diversification.[12] If the top liquidity provider, however, is well capitalized, this can help mitigate the potential adverse selection risk and reduce its price impact. We formulate our hypothesis as follows:

H2a. Increased concentration among liquidity providers has an adverse effect on commodity liquidity. This effect, however, is mitigated if the top liquidity providers are well capitalized and have higher breadth of participation across commodity futures markets.

We test the effects of well capitalized top non-commercial traders by controlling for their breadth because, on the one hand, their participation in multiple commodity markets can spread their capital too thin, but on the other hand, can also bring them diversification benefits.

Commodity market systematic factors may also affect the correlation among liquidity of various types of commodities which is generally referred to as liquidity commonality.[13] On the one hand, commodity market participants, who use commodity futures for hedging purposes (commercial

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[11] For the impact of market maker concentration on liquidity in equity and equity options, see, for example, Mildenstein and Schleef (1983) and Van Ness, Van Ness, Warr (2005) and Mayhew (2002), respectively. In the case of foreign exchange markets, while Huang and Masulis (1999) find that bid-ask spreads decrease with an increase in competition, Kaul and Sapp (2009) show that greater concentration among large dealers makes market prices less noisy.

[12] It is plausible that the top liquidity provider may face increased adverse selection risk due to the division of attention with the excessive breadth of market participation which will result in an opposite effect on liquidity.

[13] In equity markets Chordia, Roll, and Subrahmanyam (2000) examine the common domestic component in liquidity changes; and Karolyi, Lee, and van Dijk (2012) identify global liquidity commonality.

traders), may have private information only in commodities that are relevant for their risk management programs. Consequently, the trading activities of commercial traders are unlikely to cause liquidity commonality. On the other hand, enhanced investor access to commodities as an asset class through commodity indices, which is generally referred to as financialization, may contribute to liquidity commonality in the broad commodity markets (Tang and Xiong (2012), Marshall, Nguyen, and Visaltanachoti (2013), Le Pen and Sévi (2018)), especially through activities of non-commercial financial participants. The following hypothesis summarizes our predictions:

H2b. There is a positive correlation between commodity market index liquidity (GSCI index ETF liquidity) and individual commodity market liquidity.

2.2 Measures to proxy for systematic factors

We construct three measures to proxy for systematic factors including market concentration, breadth of market participation, and capitalization of the non-commercial traders. Our first measure, Trader Concentration (*Conc*), is the Herfindahl-Hirschman concentration index of non-commercial market participants' share of open interest in a given commodity market, where we first scale the number of open interest positions held by each non-commercial trader *i* in commodity market *m* on trading day *t* ($OI_{i(NC),m,t}$) with the total open interest positions (contract volume) by all non-commercial (*NC*) traders ($\sum_{i=1}^{NC} OI_{i(NC),m,t}$) in market *m* :

$$\%OI_{i(NC),,m,t} = \frac{OI_{i(NC),m,t}}{\sum_{i=1}^{NC} OI_{i(NC),m,t}} \qquad (1)$$

And then aggregate the squared term of this ratio across all non-commercial traders.

$$Conc_{m,t} = \sum_{i=1}^{NC} \left(\%OI_{i(NC),m,t}\right)^2 \qquad (2)$$

A higher value for the concentration measure suggests that a fewer number of non-commercial traders account for a greater market share of the total non-commercial open interest position, indicating a less competitive trading environment.

Our second measure, *Breadth*, proxies for the breadth of market participation by the non-commercial traders. To construct this measure, we first identify the top trader in a given commodity market *m* on a given day *t* ($TopT_{m,t}$) and trace this trader across each of the remaining 17 commodity markets in our sample on the same day *t* and construct the indicator variable $I_A(TopT_{m,t})$. The Breadth measure for market *m* on day *t* is then the sum of this indicator variable across the 17 markets plus one:[14]

$$Breadth_{mt} = 1 + \sum_{i=1}^{17} I_A(TopT_{m,t}) \tag{3}$$

Our third measure, *Size*, is our proxy for the amount of capital available to top non-commercial trader for market making in a given commodity market. We constructure our proxy for *Size* by first aggregating the open interest positions of the top trader in market *m* on day *t* $\left(TopT_{m,t}\right)$ across all the 18 commodity markets in our sample and then scaling it by the count of markets where $TopT_{m,t}$ has a non-zero position.

$$SizeTopT_{m,t} = \frac{\sum_{N=1}^{18} OI(TopT_{mt})}{count(if\ OI_{TopT(NC),m,t} <> 0)} \tag{4}$$

A higher value for the size measure would imply that the top trader has a large amount of its capital available for market making across the commodity markets which may indicate better resources and monitoring ability to respond to commercial trader demand for hedging.

[14] For example, if the top trader in market *M* carries non-zero net open positions in only one of the remaining 17 other markets (regardless of its size) than the breadth measures will take the value of 2. In our descriptive statistics we present the breadth measure as a count measure, whereas in regression analysis we divide the count by 17, which is the maximum number of markets they could be in other than the one they are identified as the top trader.

2.3 Measures to proxy for idiosyncratic factors

We construct three measures to proxy for idiosyncratic factors all based on individual traders' deviations from their target inventory levels to capture the effect of excess hedging demand by commercial traders as well as active position taking and market making by non-commercial traders. Specifically, while commercial traders may need to maintain a certain level of exposure at a given time for hedging purposes, non-commercial traders may find it optimal to respond to commercial traders hedging demand and not carry inventory from one trading day to the other. Furthermore, non-commercial traders may also engage in active position taking where their positions may go over and beyond responding to the hedging demand by commercial traders.

Our inventory deviation proxy for a given commodity market *m* on day *t* for each trader category *k* is constructed as:

$$InvDev_{k,m,t} = \frac{\sum_{i \in C,NC} \left| OI_{i,,m,t} - OI^{*}_{i,m,t} \right|}{OI_{m,t}} \qquad (5)$$

where $OI_{i,m,t}$ and $OI^{*}_{i,m,t}$ are, respectively, open interest and target inventory at day *t* for trader i in market m.[15] The individual trader i belongs to the one of two trader category *k* either as a commercial trader or a non-commercial trader. Accordingly, the inventory deviation proxy aggregates the deviation of trader i's inventory from its own target inventory, over all the traders in the same trader category resulting in two inventory deviation measures, one for commercial traders and the other for non-commercial traders. The construct for target inventory we use in

[15] We aggregate futures and delta adjusted options exposure of the trader across all expirations to compute OI, to capture their aggregate risk. Options positions are important in estimating inventory deviations because traders will pay attention to the aggregate risk in their combined futures and options positions.

Equation (5) varies depending on the specific idiosyncratic factor we construct as we explain below.

In the case of commercial traders, who generally use derivatives markets for risk management purposes, we conjecture that their long-run inventory levels are likely to be the best approximation for their target inventory. Specifically, we proxy for the target inventory as the median value of end of day open positions within the last 90 trading days and refer to as $InvDevMed_C$. Note that, the commercial trader classification we rely on includes swap dealers who trade in futures markets to hedge their portfolio risks unlike the rest of commercial traders. Consequently, we construct the inventory deviation for commercial traders separately for commercial swap-dealers ($InvDevMed_{C,SD}$) and non-dealers ($InvDevMed_{C,ND}$).

In the case of non-commercial traders acting as market makers, who respond to commercial traders' hedging demand and provide liquidity, we conjecture that their target level of inventory is not holding any inventory at hand due to its cost. Specifically, in Equation (5) we set the target inventory $OI^*_{i,m,t}$ to zero and we refer to this proxy as $InvDevZero_{NC}$.

In the case of non-commercial traders engaging in active position taking where their positions go over and beyond responding to the hedging demand by commercial traders we use a two-step procedure to construct a proxy for the inventory management of non-commercials which we call as *Active Position Taking* (*APT*). In the first step, we estimate the following regression:

$$InvDevZero_{NC,t} = Intercept + \beta 1 \, InvDevZero_{C,t} + Residual_t \qquad (6)$$

where $InvDevZero_{NC,t}$ and $InvDevZero_{C,t}$ are the inventory deviation of, respectively, non-commercial traders and commercial traders from a target of zero inventory.[16] In the second step, we construct the active position taking measure, $APT_{NC,t}$, as the absolute value of the residuals in Equation (6) which is, by construction, orthogonal to hedging demand by commercial traders.

2.4 Measures to proxy for commodity liquidity

We use two liquidity measures to capture the permanent and transitory components of commodity futures liquidity. Permanent price changes are reflected in our first measure - the Amihud (2002) price impact of total trading volume, which is important for commercial traders or longer term speculators as it reflects changes in fundamental or intrinsic values.[17] Our second measure, the microstructure noise, captures transitory price pressures reflected in the intra-day high and low prices, which may subsequently reverse within the day but are extremely important to frequent intra-day traders. Both permanent and transitory price impact measures are inverse measures of liquidity, i.e., higher numbers indicate illiquidity whereas lower numbers imply more liquid markets.

Following Marshall, Nguyen, and Visaltanachoti (2012), we define Amihud price impact as the absolute percentage price change associated with per unit of trading volume for commodity market m measured in number of contracts:

$$\text{Amihud } PI_{m,t} = |r_{m,t}|/volume_{m,t} \tag{7}$$

[16] In Internet Appendix Table A, the coefficient estimate for the $InvDevZero_C$ variable is -0.89 suggesting that to a large extent non-commercial traders provide market making services to the commercial traders by acting as their counterparty.
[17] Settlement prices in futures are calculated as the volume-weighted average of transaction prices during the settlement period at the end of the trading day.

where $r_{m,t} = (P_{m,t} - P_{m,t-1})/P_{m,t}$ is the return on day *t* computed as the difference between settlement prices of commodity *m* on day *t* and *t-1*, respectively, divided by the settlement price on day *t-1*. $Volume_{m,t}$ is the number of contracts traded on day *t* in commodity *m*.

Theoretically motivated by Goettler, Parlour, and Rajan (2009) and empirically inspired by Jain, McInish, and Miller (2019), we define our microstructure noise measure as the difference between intra-day high price (H) and intra-day low price (L) subtracted by the absolute value of closing (C) minus opening price (O).[18] We scale microstructure noise by the closing price of commodity *m* to allow comparison across commodity contracts.

$$\text{Microstructure Noise}_{m,t} = \{(H_{m,t} - L_{m,t}) \text{ minus } \mathrm{abs}(C_{m,t} - O_{m,t})\}/C_{m,t} \qquad (8)$$

The decline in the liquidity of a contract, which is reflected in an increase in the microstructure noise, causes transaction prices to be temporarily far away from the fundamental value because of buying or selling pressure.[19] In contrast, a liquid contract can easily absorb buying and selling demand without deviating too much from fundamental value resulting in a smaller intra-day devation between high and low prices for a liquid commodity. Some days, however, have a lot of information release which changes fundamental price itself from open to close, which is why we need to subtract the difference between the closing and the opening prices as it reflects the change in prices not related to microstructure noise (but related to news. Finally, as noted above, we normalize our measure across commodities by dividing the expression with that commodity's closing price. This step makes our measure unitless and comparable across commodities.

[18] We use CFTC's non-public data for intra-day transaction prices to construc the microstructure noise measure where we take the opening price to be the price of the first transaction of the day, and the closing price that of the last transaction. We also use the exchange's definition of what constitutes a trading day. For example, the first trading day of the week for the NYMEX WTI crude oil contract starts at 5:00pm CT on Sunday and ends at 4:00pm CT on Monday.

3. DATA

3.1 Data Sources

Over a sample period from April 2001 through November 2020, we use individual traders' daily positions in futures and options on futures for 18 commodity futures markets in four broad categories: agriculture (cocoa, coffee, corn, cotton, soybean, sugar, Kansas wheat HRW, and Chicago wheat SRW), livestock (feeder cattle, lean hogs, and live cattle), metals (copper, gold, and silver), and energy (heating oil, crude oil, gasoline, and natural gas).[20] Our data source is the U.S. CFTC's Large Trader Reporting System (LTRS) and are composed of end-of-day long and short positions of futures and delta-adjusted options for each large trader.[21] This data also includes information on daily prices, open interest, and volume information for each contract in our sample. We use the prices and volume from lead month contracts to compute our Amihud price impact measure for each contract on a given day. [22] We pick the lead month of a commodity to be that contract's expiration with the highest amount of open interest and roll our lead month when the highest amount of open interest moves from one expiration to another. A second source of proprietary data we rely on to construct our Microstructure Noise measure is called Trade Capture Report (TCR) data which includes the intraday prices on all the transactions in the 18 commodity markets we analyze, and are available October 2009 onward.

[20] The commodity markets we analyze are constituents of the GSCI commodity index. The internet Appendix B presents the relative weights of these markets in the GSCI index. The weights of the 18 contracts included in our study add up to about 69% of the index as contracts that are predominantly traded in non-US exchanges are excluded.

[21] See Robe and Roberts (2019), Dewally, Ederington and Fernando (2013) and Brunetti and Reiffen (2014), and our Internet Appendix for additional data details.

[22] We construct the Working's T variable that we use in our robustness analysis using the Commitments of Traders (COT) data, which is the publicly available version of the regulatory LTRS made available by the CFTC. COT data can be accessed at https://www.cftc.gov/MarketReports/CommitmentsofTraders/index.htm.

We also make use of two non-CFTC data sources in our analysis. We use Chicago Board Options Exchange's CBOE Volatility Index, VIX, to measure overall market volatility and price and trading volume data on the iShares S&P GSCI Commodity-Indexed Trust (GSG) to capture the market-wide price impact variable. Both data are sourced from Bloomberg.

3.2 Descriptive Statistics

In this section, we present simple descriptive statistics on variables used in our analysis. Panel A in Table 1 shows these descriptive statistics for the dependent variables and key explanatory variables for all of the 18 commodity contract markets together during the sample period (April 2001 – November 2020). The interpretation of the descriptive statistics are provided in the Internet Appendix.

[Insert Table I here]

Panels B presents the correlation matrix between the Amihud price impact for the market index GSCI based ETF GSG (MPI) and the Amihud price impact (PI) of individual commodity markets in our sample. The positive correlation coefficients in the MPI column is consistent with Hypothesis 2b on effects of the common market wide liquidity factor on individual contract liquidity. The presence of a common effect is also reflected in the fact that all the cross-correlation coefficients across individual commodity markets are also positive. Although most correlations are about 0.3, some of them are higher (especially for energy contracts) and some of them are closer to zero. To directly control for this heterogeneity across the commodity markets, we include commodity fixed effects throughout our analysis.

4. EMPIRICAL DETERMINANTS OF COMMODITY FUTURES LIQUIDITY

We estimate our baseline regression model where we regress permanent liquidity proxy (Amihud Price Impact (PI)) on the idiosyncratic and systematic factors that uniquely determine commodity futures liquidity with the following equation:

$$PI_{m,t} = \alpha + \theta' Idiosyncratic\ factors_{m,t-1} + \gamma'\ Systematic\ factors_{m,t} + \delta'\ Controls_t + e \qquad (9)$$

The set of proxies we consider for the idiosyncratic factors include commercial traders' inventory deviation from their target inventories for swap dealers (*InvDevMedSD*) and non-swap dealers (*InvDevMedND*) , and active position taking by non-commercial traders (*APT_NC*). Our consideration of idiosyncratic factors also includes an indicator variable for the regulatory shock (*SLR*) and its interaction with the non-commerical traders' inventory deviation from a zero inventory target (*InvDevZeroNC*). The set of proxies we consider for systematic factors are constructed to capture for a given commodity market, the concentration of non-commerical traders (*Conc*), the breadth of participation for the top liquidity provider (*Breadth*) and the size of top liquidity provider (*SizeTop*). The regression model also includes a proxy for overall market liquidity (*MPI*). Finally, the model includes market wide controls such as volatility (*VIX*) and total number of futures contracts (*Volume*)[23], time trend, quarter fixed effects, and contract market fixed effects.[24] Table 2 presents the results estimated on the aggregate sample (Panel A), as well as commodity market groups (Panel B) and individual commodity markets (Panel C).

[Insert Table 2 here]

[23] We are using lagged value of Volume.
[24] We include quarterly fixed effects to control for the seasonality of the commodity markets.

Overall, we find that the idiosyncratic factors, namely the hedging pressure from the non-swap-dealer commercial traders' inventory deviations (*InvDevMedND)*, is associated with the largest amount of liquidity deterioration. Specifically, a one standard deviation increase in *InvDevMedND* results in 0.14 standard deviation increase in the predicted value of PI.[25] An increase in the hedging pressure from the swap dealer commercial traders also results in deterioration in liquidity but the economic significance is to a lesser extent. Increased active position taking by liquidity providers (*APT_NC*) results in improved liquidity while the regulatory shock, which increased the cost of carrying inventory for market makers, results in even larger deterioration when market makers carry large inventories (*SLR_InvDevZeroNC*). Among the systematic factors, *SizeTop*, which proxies for the amount of capital available for market making by the top non-commercial trader is associated with the largest amount of liquidity improvement (a one standard deviation increase in *SizeTop* results in -0.06 standard deviation decline in predicted value of *PI*). An increase the concentration of market makers (*Conc*) in a given contract market is associated with a decline in liquidity where a one standard deviation increase in *Conc* results in a 0.03 standard deviation increase in *PI*. We are not able to isolate a statistically significant impact of the breadth of market participation by the top liquidity provider (*Breadth*) to on liquidity.

The control variables have expected relationship with market liquidity. For example, the increase in marketwide price impact (*MPI*) and volatility (*VIX*) results in an increase in commodity level price impact, whereas an increase in the amount of lagged trading volume (*Volume*) is associated

[25] We refer to this change as the *beta* of the coefficient, which we report in our regression tables and they allow us to put our estimated coefficients into perspective.

with an improvement in liquidity or a decrease in price impact. The negative coefficient of the trend variable also confirms an improvement in liquidity throughout our sample.[26]

4.1 Commodity futures market groups

Each commodity market can have various differences such as storage costs, seasonality, delivery details or even just the composition of traders in each market. To capture the importance of these nuances, we analyze determinants of liquidity by the four main commodity groupings, namely livestock (live cattle, feeder cattle, and lean hog), energy (natural gas, WTI, RBOB gasoline and heating oil), metals (silver, gold, and copper) and agriculture (corn, cocoa, coffee, cotton, soybeans, sugar, hard red wheat and soft red wheat).

In Panel B, we present the regression results estimated across these four commodity market groups. Overall, we find that our empirical model have the best fit in the Metals (R^2 of 45%), followed by Agriculture (R^2 of 37%) and Energy (R^2 of 35%) commodity groups. With respect to the various factors explaining the commodity liquidity, the results for each commodity group is largely consistent with the results we get with the aggregate sample. For example, the hedging pressure from non-swap dealer commercial traders (*InvDevMedND*) presents the largest detrimental negative impact on liquidity compared to other factors across these three commodity grouping. In Metals and Agriculture, the impact of hedging pressure on liquidity is even larger than Volume, which is considered to have a major influence on liquidity. The *SLR* variable also seems to have consistency across commodity groupings, statistically significant in three out of

[26] Timeseries graphs of our liquidity variables in the Internet Appendix F confirm the existence of a time trend in the Amihud liquidity measure, however there does not seem to be such trend in our other two liquidity measures, namely Microstructure Noise and Residual Amihud.

four groupings. Our control variable coefficients are also quite persistent and significant across all the four groupings.

Comparing the pooled regressions of each commodity group, we note that liquidity in metals seems to have the strongest association with our determinants, presenting the highest adjusted R^2, with only swap dealer inventory deviation, *InvDevMedSD*, and SLR inventory deviation from zero interactive term, *SLR_InvDevZeroNC*, not having any statistical significance. Agriculture is the commodity grouping that has the second highest explanatory power with our determinant variables, followed by energy and livestock.

4.2 Individual commodity futures markets

While grouping the individual commodity futures markets with respect to their economic functions allows us to isolate the relevance and economic significance of individual liquidity factors among markets with similar roles in real economy, one could argue that the liquidity factors could still have different roles on the individual commodity futures markets. For example, while commodity futures for wheat, corn, and crude oil are in separate commodity groups, they are similar with respect to the steep storage costs, compared to commodity futures for gold and silver which are much cheaper to store. Furthermore, some commodity futures contracts, such as lean hog, are financially settled, so may be further insulated from any aspect of storage costs. To better isolate how these differences manifest themselves in the way idiosyncratic and systematic factors affect liquidity, we estimate PI regressions for each commodity market separately. The results are presented in Panel C, which only presents the betas and statistically significant values are bolded.

Overall, our empirical model examining the role of idiosyncratic and systematic factors in determining liquidity has the highest R^2s for copper (49%), gasoline (41%), and heating oil

(40%) futures. The fit of the model for the rest of 15 commodity futures all but one have double digit R^2swith exception of lean hogs which is 5%. For almost all of the individual commodity futures grouped under metals, energy, and agriculture, we find that hedging pressure by commercial traders have the largest impact on liquidity where the dominant pressure for some markets is coming from non-swap dealers (feeder cattle, lean hogs, copper, crude oil, natural gas, and wheat) and in others it is coming from swap dealers (heating oil, and most of markets in agriculture except wheat). For example, a one standard deviation increase in *InvDevMedND* , our proxy for the inventory deviation of non-swap dealers from their targets, results in 0.21 (0.18) standard deviation increase in the predicted value of PI in natural gas (copper and wheat hrw) futures. Hedging pressure for commercial traders that are not swap dealers also result in deterioration in liquidity. For example, a one standard deviation increase in *InvDevMedSD* , our proxy for the inventory deviation of swap dealers from their targets, results in 0.2 standard deviation increase in the predicted value of PI in cotton futures.

Among systematic factors, concentration of liquidity providers (*Conc*) have the strongest detrimental impact on liquidity for individual commodity futures across almost all markets except the ones in metals group. For example, a one standard deviation increase in *Conc* results in 0.41 standard deviation increase in the predicted value of PI in natural gas (0.26 in gasoline and 0.22 in crude oil) futures. Our second proxy for systematic factors, the breadth of market participation for the top liquidity provider generally results in improved liquidity particularly among metals where a one standard deviation increase in *Breadth* results in 0.7 (0.06) standard deviation decline in the predicted value of PI in copper and gold (silver) futures.

These findings showcase the need to consider the special nature of each commodity when analyzing the determinants of commodity market liquidity over and beyond using commodity market fixed effects and are supportive of the similar assertion in Manaster and Mann's (1996).

5. MICROSTRUCTURE NOISE

While the Amihud Price Impact measure is one of the most widely used liquidity measures, in principal it contains information from long lasting price movements that are reflective of changes in fundamental information, instead of capturing price movements that are more transient in nature. We consider an alternative measure of liquidity, namely microstructure noise, to focus on capturing information that come purely from various trading frictions including bid-ask spreads, triggering of various circuit breakers, and transitory market impact of block trades, and thereby removing the price impact associated with the changes in the fundamental information that is reflected in the prices.

Our empirical strategy is similar to the model we have estimated using the Amihud Price Impact measure that is summarized in Equation (9). Specifically, we regress our proxy for transitory price impact (*MS noise*) on our proxies for the idiosyncratic and systematic factors. Our results are presented in Table 3.

[Insert Table 3 here]

Similar to our findings using PI as the liquidity proxy, we find that our model has the best explanatory power for commodities in Metals and Energy groups and that the idiosyncratic factors have the largest economic impact on transitory liquidity (*MS Noise*). For example, a one standard deviation increase in the hedging pressure emanating from the commercial non-swap dealers (*InvDevMedND*) results in 0.14 (0.08) standard deviation decline in the predicted value of *MS Noise* in metals (agriculture) futures commodities group. The economic significance of hedging pressure emanating from the commercial swap dealers (*InvDevMedSD*) is more dominant when we estimate our model on the entire sample where a one standard deviation increase in *InvDevMedSD* results in 0.10 standard deviation decline in the predicted value of *MS Noise*, possibly reflecting the strong presence of this factor in the Energy commodities group. Our finding on *InvDevMedSD* is consistent with the results reported in Mixon and Onur (2020), who show that swap dealers tend to use the futures market to hedge their swaps books and their more-than-normal hedging need may be price insensitive, causing an increase in the transitory portion of the liquidity.

In contrast to the findings with PI, however, our empirical model results in better fit for commodities in Livestock and worse fit commodities in Agriculture when estimated using microstructure noise as a liquidity proxy. Furthermore, unlike our results on PI, we find that the economic significance of the effect of active position taking by market makers results in improved transitory liquidity. For example, a one standard deviation increase in *Apt_NC* results in 0.06 (0.04) standard deviation decline in the predicted value of *MS Noise* for commodities futures grouped Metals (aggregate sample) consistent with the idea that market makers stand ready to buy low and sell high to other more aggressive market participants. Another contrasting finding, while mostly driven by commodity futures in Energy and Agriculture group, is the detrimental impact of inventory holdings by market makers on transitory liquidity. A one standard deviation increase in *InvDevZeroNC* results in 0.12 (0.07) standard deviation increase in the predicted value of *MS Noise* for commodities futures grouped under Energy (Agriculture). Furthermore, we find that the regulatory change that increased the cost of holding inventories (proxied for by *SLR*) by majority of the market makers further increases this cost. For example, in our aggregate sample, a one standard deviation increase in *InvDevZeroNC* results in an additional 0.10 standard deviation increase predicted value of *MS Noise*.

The impact of systematic factors on microstructure noise is similar to our previous results with the Amihud Price Impact. Specifically, we find that while a larger capitalization (*SizeTop*) and enhanced breadth of market participation of the top liquidity provider (*Breadth*) results in improved liquidity, increased concentration of the market makers (*Conc*) leads to its deterioration. Economic significance of these factors are most salient in the Metals group where a one standard deviation increase in *Conc* results in a 0.10 standard deviation increase predicted value of *MS Noise* whereas a similar calculation leads to a 0.06 and 0.04 decline in *MS Noise* for *Breadth* and *SizeTop*. The detrimental impact of market maker concentration is also noteworthy for commodity futures grouped under Livestock where a one standard deviation increase in *Conc* results in a 0.12 standard deviation increase predicted value of *MS Noise.*

Our findings on the impact of control variables is also similar to those we find in our Amihud price impact analysis where marketwide noise (*MPI noise*) and *VIX* are associated with worsened liquidity. But unlike our results with Amihud price impact, where higher *Volume* is associated with lower permanent price impact, we find that higher Volume is associated with higher microstructure noise which might reflect the mechanical relationship between *PI* and *Volume*.

6. ROBUSTNESS ANALYSES

In this section we present robustness analysis on two levels. First, we use alternative proxies in our analysis; one for our PI liquidity measure and another one for our active position taking measure. Second, we adjust our regression specification to show that our results are not driven by any potential spurious correlation.

While we mainly use PI and MS Noise as our liquidity measures, we also test our hypothesis with *unexpected* liquidity (Amihud (2002); Asem (2009)). To construct this measure, which we call *Residual Price Impact* (*RPI*), we first regress Amihud Price Impact on *MPI* and *VIX,* factors to isolate the expected portion of the permanent liquidity as shown in the Internet Appendix Table C, and then we capture the residuals from this regression. In the second stage, we regress *RPI* using the regression model summarized in Equation (9) without *MPI* and *VIX*. Our results are presented in Table 4.

[Insert Table 4 here]

Consistent with our goal of isolating the impact of idiosyncratic factors on liquidity, we find that hedging pressure has a substantial detrimental economic impact on *RPI*. For example, a one standard deviation increase in commercial non-swap dealers' deviation from their target inventories (*InvDevMedND*) results in 0.45 standard deviation decline in the predicted value of *RPI*. Similar to our findings using *PI* and *MS Noise* as liquidity proxies, our model estimated using RPI shows that higher capitalization by top liquidity results in provided liquidity. The results for *Breadth* and *AptNC* are less robust; either statistically insignificant or their signs fluctuating across different commodity futures groups. For the less than robust evidence on systematic factors we are not entirely surprised since unexpected portion of permanent liquidity changes are not likely to be determined by systematic factors. Next, we address the potential mechanical relation between PI and Volume by removing Volume from our list of regressors. The results for this regression model is presented in the Internet Appendix Table D. The direction and significance of all results remain largely unchanged relative to the Amihud total price impact reported in Table 2 Panel (A), suggesting that the results in our baseline regression model are free from potential endogeneity problem resulting from the spurious correlation between PI and Volume.

Finally, we test the robustness of our results with respect to our proxy for active position taking by non-commercials by replacing it with a measure used in prior literature, namely, Working's T. In Büyükşahin and Harris (2011), Working's T is used to proxy for "excess" hedging and/or speculation, which is based on Working (1931, 1960). Working's T can be calculated using publicly available Commitment of Traders data published weekly by CFTC. Our results are reported in the Internet Appendix Table E. We find that Working's T results in improved transitory liquidity (proxied for by *MS Noise*) but it is not statistically significant for the regression models that use PI and RPI as the dependent variable. The coefficient estimates for the rest of our right hand side variables are consistent with our results reported in prior tables.

7. CONCLUSIONS

The empirical analysis we provide in this paper reveals strong and consistent evidence that the trading behavior of market makers and hedgers in relation to their target inventory, as well as the industrial organization of the individual commodity markets, explain a large portion of the variation in the transitory as well as permanent price impact components of the liquidity in commodity futures markets. The following three conclusions are the main takeaways.

First, we conclude that traders' management of their daily inventory positions, which we categorize as idiosyncratic factors, have important implications for commodity futures liquidity. This conclusion is based on two complementary findings. On the one hand, we find that the inventory adjustment of hedgers in response to their hedging demand increases both permanent (Amihud price impact) as well as transitory (microstructure noise) components of liquidity costs.

Complementary to this finding, results show that market markers' response to inventory deviations over and above the hedging demand, i.e., active position taking, improves transitory liquidity while their response to deviations from zero inventory levels improves long term liquidity. While the conclusion on hedgers is surprising (Kang et al., 2020), the results on market makers to a large extent support the models where market makers not only fulfill their role as passive liquidity providers (by supporting the permanent component of liquidity) but also act as profit seeking traders (by supporting the transitory component of the liquidity).

Second, despite strong evidence on the detrimental role of hedging demand on liquidity, the heterogeneity among the commercial traders (swap dealers and non-swap dealers) and their differential effects on liquidity is worth noting. Evidence supports the view that hedging demand by non-swap dealers, traders that trade futures to hedge their risk exposure in product markets, are more relevant for permanent price-impact component of liquidity, whereas the hedging demand by swap-dealers, traders who use the futures market to hedge their positions in the swaps markets, are more relevant for the transitory component of the liquidity. Moreover, commodity futures markets under the energy category present a curious anomaly; the hedging demand by non-swap dealers improves the transitory component of the liquidity. While our tests are not a direct examination of the financialization of the futures market, these results support the view that the increased activity in the swaps markets (energy contracts have the largest swap market activity according to Mixon, Onur, and Riggs (2018)) potentially results in increased activity in the corresponding futures markets.

Third, we conclude that the industrial organization of the individual commodity markets, which we categorize as systematic factors, is an important component of commodity futures liquidity. This conclusion is supported by the evidence that the concentration of market makers, as well as the size and the breadth of futures activity of the top liquidity provider in a given commodity, has strong implications for liquidity.

Overall, our goal of fitting an empirical model to explain the liquidity of 18 commodity futures with very diverse characteristics, as well as different composition of various trader types, is accomplished with reasonable success with the best fit for commodities observed in the metals group. Besides metals, the contract markets in agriculture and energy also present a good fit, especially in the context of idiosyncratic factors, which includes hedging pressure by hedgers as well as active position taking and liquidity provision by market makers. In the case of contract markets grouped under livestock, most of the variation in liquidity is explained by the time and market fixed effects and other macro variables including VIX and volume. These varying degrees of success in individual contract markets are not surprising, especially in the context of livestock as these contract markets are thinly traded, continued to rely on pit trading until 2015 relative to electronic trading, and have higher sensitivity to climate and extreme weather events, all of which are beyond the scope of our paper. We hope that the evidence presented in this paper will encourage a more holistic approach to modeling and empirically testing liquidity.

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Table 1. Descriptive Statistics

Panel A presents descriptive statistics for the variables used in our analysis for the 18 commodity contract markets between April 2001 –November 2020. Amihud Price Impact (PI) is the defined for each commodity contract as $|r_t|$/ Volume$_t$ where r_t is the difference between settlement prices on day t and t-1, divided by the settlement price on day t-1. Microstructure noise (MN) is the difference between intra-day high price and intra-day low price subtracted by the absolute value of closing minus opening price, divided by the closing price. Residual Amihud Price Impact is the residual from regressing Amihud price impact on market-wide illiquidity (MarketPI) and VIX. Volume is expressed in million contracts for PI calculation. MarketPI and MarketMN are defined analogously for PI and MN based on commodity index exchange traded fund with ticker symbol GSG. Conc refers to the Herfindahl-Hirschman concentration index of non-commercial traders' share of open interest in the given commodity. Breadth is the number of different commodities in which the top trader for a given commodity has open interest, divided by 17. SizeTopT is the value of the given commodity's top non-commercial trader's open interest proportional to the open interest for all non-commercial traders in the given commodity market averaged across the same trader's positions in all commodities. APT_{NC} is the non-commercial active position taking constructed as the residual from regressing non-commercial inventory deviation on commercial inventory deviation. $InvDevMed_{ND}$, $InvDevMed_{SD}$, $InvDevMed_{NC}$ refer to inventory deviations from median level of the prior 90-day inventory for, respectively, commercial non-swap dealers, commercial swap dealers and non-commercial market participants. SLR is an indicator variable that takes the value 1 for years 2018 and after and zero otherwise. $InvDevZero_C$ ($InvDevZero_{NC}$) refers to inventory deviations from a target inventory of zero for commercial (non-commercial) market participants. VIX is the volatility index. Working's T is the measures the extent to which non-commercial participants' speculation is in excess relative to the level of commercial participants' hedging open positions.

Panel A. Sample Statistics

	MEAN	STD	N
Amihud Price Impact (PI)	0.61	1.11	64411
Microstructure noise (MN) (*x100*)	1.15	1.06	44599
Residual Amihud Price Impact	0.004	1.09	64411
GSG Marketwide Amihud Price Impact (MarketPI)	0.05	0.07	64411
GSG Marketwide Microstructure Noise (MarketMN) (*x100*)	0.79	0.67	64411
Trader Concentration (Conc)	0.04	0.03	64411
Top Trader's Breadth of Participation (Breadth)	0.64	0.34	64411
Top Trader's Size (SizeTopT)	0.05	0.03	64411
Non-commercial active position taking (APT_{NC})	0.02	0.02	64411
Non-Swap Dealer Inventory deviation from median ($InvDevMed_{ND}$) (*x100)*	0.09	0.09	64411
Swap Dealer Inventory deviation from median ($InvDevMed_{SD}$)	0.15	0.10	64411
Non-commercial Inventory deviation from median ($InvDevMed_{NC}$)	0.43	0.20	64411
Supplemental Leverage Ratio (SLR)	0.41	0.49	64411
Non-commercial Inventory deviation from zero ($InvDevZero_{NC}$)	0.08	0.06	64411
Commercial Inventory deviation from zero ($InvDevZero_{C}$)	0.07	0.19	64411
VIX Volatility Index (VIX)	0.02	0.01	64411
Trading volume in number of contracts in millions (Volume)	10.50	1.19	64411
Working's T	1.17	0.14	64411

Panel B: Correlation coefficients for Commodity Contracts' Amihud Price Impact (PI)

	MPI	(1) FEEDERCATTLE	(2) LEANHOGS	(3) LIVECATTLE	(4) COPPER	(5) GOLD	(6) SILVER	(7) CRUDEOIL	(8) GASOLINE	(9) HEATINGOIL	(10) NATURALGAS	(11) COCOA	(12) COFFEEC	(13) CORN	(14) COTTON	(15) SOYBEANS	(16) SUGAR	(17) WHEATHRW	(18) WHEATSRW
		Livestock			Metals			Energy				Agriculture							
MPI	1																		
(1)	0.11	1																	
(2)	0.04	0.28	1																
(3)	0.08	0.54	0.36	1															
(4)	0.33	0.24	0.13	0.20	1														
(5)	0.27	0.24	0.27	0.27	0.41	1													
(6)	0.24	0.25	0.16	0.22	0.48	0.58	1												
(7)	0.34	0.24	0.26	0.30	0.31	0.38	0.32	1											
(8)	0.39	0.02	0.01	0.02	0.13	0.15	0.09	0.18	1										
(9)	0.41	0.27	0.24	0.30	0.38	0.37	0.34	0.72	0.22	1									
(10)	0.22	0.21	0.16	0.19	0.32	0.32	0.30	0.30	0.21	0.37	1								
(11)	0.12	0.29	0.30	0.31	0.30	0.35	0.31	0.33	0.10	0.36	0.30	1							
(12)	0.07	0.23	0.27	0.24	0.18	0.28	0.21	0.29	0.08	0.26	0.22	0.34	1						
(13)	0.17	0.22	0.22	0.23	0.31	0.28	0.30	0.27	0.09	0.29	0.22	0.28	0.21	1					
(14)	0.05	0.22	0.26	0.23	0.25	0.28	0.24	0.29	0.03	0.28	0.20	0.34	0.29	0.26	1				
(15)	0.19	0.25	0.23	0.25	0.33	0.30	0.31	0.30	0.11	0.33	0.25	0.32	0.28	0.49	0.31	1			
(16)	0.15	0.26	0.38	0.31	0.22	0.36	0.26	0.34	0.18	0.32	0.25	0.42	0.36	0.27	0.35	0.30	1		
(17)	0.16	0.20	0.12	0.14	0.30	0.21	0.24	0.23	0.05	0.25	0.16	0.25	0.19	0.38	0.18	0.34	0.18	1	
(18)	0.15	0.26	0.27	0.25	0.30	0.30	0.29	0.31	0.07	0.33	0.25	0.39	0.27	0.46	0.27	0.42	0.32	0.65	1

Table 2. Regressions of Amihud Price Impact

The table presents regressions of Amihud price impact PI on systematic factors (Conc, Breadth, and SizeTopT), idiosyncratic factors (APT, InvDevMedND, and InvDevMedSD), and regulatory shock factors (SLR, SLR*InvDevZeroNC, and InvDevZeroNC) as well as control variables including MPI, VIX, Volume, and Trend. Panel A presents the estimates for models with each factor individually (columns 1-3) in addition to the full model (column 4). Panel B presents regression results estimated for each of the commodity market group subsample: Livestock, Metals, Energy, and Agriculture. Panel C presents regressions estimated individually for each commodity market. The regression sample covers years 2006-2020 for 18 contract markets. Regressions models include contract market, quarter fixed effects, and a time trend. In Panels A and B, statistical significance (t-stats) and the beta values for each estimate are shown in the columns adjacent to the estimates and ***, **, * denote significance at 1%, 5%, and 10%, respectively. In Panel C, only betas are presented and statistically significant values are bolded.

Panel A	(1) Systematic			(2) Idiosyncratic			(3) SLR			(4) all		
	coeff	t	beta	Coeff	t	beta	coeff	t	beta	coeff	t	beta
Conc	1.32**	2.32	0.04							1.18**	2.26	0.03
Breadth	-0.01	-0.19	-0.00							0.01	0.46	0.00
SizeTop	-1.93***	-3.87	-0.06							-2.00***	-3.83	-0.06
APT_NC				-0.91***	-2.96	-0.02				-0.61	-1.53	-0.01
InvDevMedND				176.73***	3.10	0.14				182.80***	3.16	0.14
InvDevMedSD				0.20	1.58	0.02				0.27**	2.19	0.03
SLR							0.09*	1.90	0.04	0.16***	3.05	0.07
InvDevZeroNC							-0.44***	-2.83	-0.02	-0.46	-1.66	-0.02
SLR_InvDevZeroNC							0.89***	4.62	0.04	0.63***	2.68	0.03
MPI	0.63***	4.96	0.04	0.62***	4.89	0.04	0.48***	3.96	0.03	0.49***	4.28	0.03
VIX	15.66***	6.39	0.14	14.44***	6.31	0.13	15.50***	8.27	0.14	15.05***	6.35	0.13
Volume	-0.40***	-9.01	-0.42	-0.37***	-8.77	-0.40	-0.40***	-9.50	-0.43	-0.38***	-8.50	-0.40
Trend	-0.00***	-4.76	-0.05	-0.00***	-4.09	-0.04	-0.01***	-6.26	-0.11	-0.01***	-6.88	-0.13
Constant	4.51***	9.80		4.10***	9.52		4.67***	11.28		4.37***	9.37	
Observations	64,431			65,401			65,421			64,411		
R-squared	0.37			0.37			0.37			0.37		
Y FE	N			N			N			N		
Quarter FE	Y			Y			Y			Y		

CM FE	Y	Y	Y	Y

Panel B	(1) Livestock			(2) Metals			(3) Energy			(4) Agriculture		
	coeff	t	beta	coeff	t	beta	coeff	t	beta	coeff	t	beta
Conc	2.11	-0.30	0.01	1.74*	-1.69	0.07	0.53	-0.43	0.04	3.26***	-4.39	0.09
Breadth	0.13	-1.11	0.02	-0.17***	-4.92	-0.08	-0.04	-1.12	-0.03	0.04	-1.08	0.02
SizeTop	2.47	-1.52	0.02	-1.89***	-4.45	-0.1	-0.87	-0.89	-0.08	-2.37**	-2.14	-0.07
APT_NC	-1.33	-1.19	-0.02	2.05***	-3.96	0.05	-0.58	-1.64	-0.03	0.39	-0.83	0.01
InvDevMedND	90.5	-1.32	0.07	1,109.28***	-6.64	0.43	524.79***	-4.12	0.38	462.28***	-5.02	0.25
InvDevMedSD	0.16	-0.19	0	0.21	-1.47	0.03	0.11	-1.37	0.03	0.60**	-2.02	0.04
SLR	0.51***	-3.52	0.13	0.22***	-3.95	0.16	0.27***	-4.48	0.25	-0.02	-0.43	-0.01
InvDevZeroNC	0.65	-0.71	0.02	-1.90***	-4.44	-0.12	-0.06	-0.45	-0.01	-2.37***	-6.00	-0.09
SLR_InvDevZeroNC	-0.1	-0.11	0	0.25	-0.76	0.02	-0.41**	-2.02	-0.05	1.46***	-3.27	0.07
MPI	0.14	-0.42	0.01	0.80***	-4.91	0.09	1.20***	-8.4	0.17	0.17	-1.44	0.01
VIX	32.26***	-5.92	0.16	11.14***	-4.49	0.16	7.05***	-2.9	0.13	9.26***	-3.84	0.10
Volume	-0.72***	-5.07	-0.34	-0.22***	-10.09	-0.31	-0.30***	-4.75	-0.53	-0.29***	-5.74	-0.33
Trend	-0.01***	-2.82	-0.11	-0.01**	-2.57	-0.15	0	-1.60	-0.07	-0.01***	-4.29	-0.10
Constant	7.23***	-5.61		2.54***	-8.76		2.99***	-4.58		3.34***	-6.16	
Observations	10,740			10,728			14,320			28,623		
R-squared	0.30			0.45			0.35			0.37		
Y FE	N			N			N			N		
Quarter FE	Y			Y			Y			Y		
CM FE	Y			Y			Y			Y		

Panel C	(1) FEEDER CATTLE	(2) LEANHOGS	(3) LIVECATTLE	(4) COPPER	(5) GOLD	(6) SILVER	(7) CRUDEOIL	(8) GASOLINE	(9) HEATINGOIL	(10) NATURALGAS	(11) COCOA	(12) COFFEEC	(13) CORN	(14) COTTON	(15) SOYBEANS	(16) SUGAR	(17) WHEATHRW	(18) WHEATSRW
	Livestock			Metals			Energy				Agriculture							
Conc	**-0.06**	**0.10**	**0.07**	0.05	0.09	0.02	**0.22**	**0.26**	-0.04	**0.41**	**0.19**	**0.05**	**0.15**	**0.19**	**0.21**	0.03	0.00	0.02
Breadth	**0.07**	-0.02	-0.02	**-0.07**	**-0.07**	**-0.06**	-0.01	-0.00	0.01	**-0.09**	**0.07**	**-0.05**	**-0.07**	-0.05	0.01	**0.12**	-0.05	**-0.08**
SizeTop	-0.00	**-0.07**	-0.00	-0.03	-0.11	-0.07	**-0.11**	0.03	0.05	**-0.50**	0.00	0.01	-0.01	0.06	-0.01	-0.03	0.03	**0.06**
APT_NC	0.02	**-0.06**	-0.01	**0.03**	0.01	0.03	0.00	0.00	0.02	**-0.06**	0.03	**0.11**	**-0.05**	0.04	-0.01	-0.02	**-0.06**	**-0.03**
InvDev - MedND	**0.11**	**0.07**	0.03	**0.18**	**0.09**	**0.05**	**0.12**	0.06	**0.06**	**0.21**	-0.01	0.04	0.01	-0.02	**0.05**	**0.07**	**0.18**	**0.11**
InvDev - MedSD	0.03	-0.03	0.03	0.05	**0.07**	**0.07**	**0.06**	**0.07**	**0.11**	0.00	0.03	**0.07**	**0.10**	**0.24**	**0.12**	**0.10**	0.04	**0.07**
SLR	**0.24**	**0.24**	**0.29**	**0.25**	**0.13**	**0.13**	**0.12**	**0.06**	**0.19**	**0.19**	0.10	**-0.28**	-0.05	0.06	0.04	**0.19**	**0.10**	0.06
InvDev -ZeroNC	**-0.05**	0.05	**-0.10**	-0.04	-0.05	-0.01	0.00	-0.03	-0.03	0.02	**-0.13**	**-0.22**	0.04	**-0.11**	-0.01	**-0.09**	0.04	**-0.08**
SLR_InvDev - ZeroNC	-0.00	-0.01	0.00	-0.04	-0.00	0.01	0.12	**0.06**	0.04	**-0.06**	0.03	0.03	0.02	0.02	-0.05	-0.04	-0.01	0.08
MPI	0.01	0.02	0.02	**0.13**	**0.13**	**0.09**	**0.30**	**0.22**	**0.32**	**0.05**	-0.02	**0.02**	**0.06**	-0.02	**0.08**	0.08	**0.06**	0.03
VIX	**0.27**	**0.14**	**0.26**	**0.20**	**0.12**	**0.22**	**0.22**	**0.21**	**0.29**	0.01	**0.20**	**0.07**	0.05	**0.17**	**0.04**	**0.12**	**0.15**	**0.09**
Volume	**-0.23**	-0.01	-0.01	**-0.24**	**-0.31**	**-0.32**	**-0.34**	**-0.27**	**-0.22**	**-0.42**	-0.02	0.03	**-0.13**	**-0.15**	**-0.09**	0.04	**-0.36**	**-0.07**
Trend	**-0.30**	**-0.12**	**-0.19**	**-0.25**	**-0.20**	**-0.21**	0.02	**0.16**	**-0.12**	-0.05	**-0.32**	0.03	**-0.13**	**-0.19**	**-0.20**	**-0.37**	-0.07	**-0.32**
Observations	3,580	3,580	3,580	3,576	3,576	3,576	3,580	3,580	3,580	3,580	3,577	3,577	3,578	3,578	3,578	3,577	3,580	3,578
R-squared	0.18	0.05	0.11	0.49	0.31	0.34	0.37	0.41	0.40	0.38	0.28	0.14	0.22	0.26	0.23	0.15	0.34	0.24
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 3: Regressions of Microstructure Noise

The table presents regressions of Microstructure noise on systematic factors (Conc, Breadth, and SizeTopT), idiosyncratic factors (APT, InvDevMedND, and InvDevMedSD), and regulatory shock factors (SLR, SLR*InvDevZeroNC, and InvDevZeroNC) as well as control variables including MPI, VIX, and Volume. In addition to the all 18 contract markets (column 1), regression model is estimated for each of the commodity market group subsample: Livestock, Metals, Energy, and Agriculture (columns 2-). The regression sample covers years 2006-2020 for 18 contract markets. Regressions models include contract market, quarter fixed effects, and year fixed effects. Statistical significance (t-stats) and the beta values for each estimate are shown in the columns adjacent to the estimates and ***, **, * denote significance at 1%, 5%, and 10%, respectively.

VARIABLES	(1) All			(2) Livestock			(3) Metals			(4) Energy			(5) Agriculture		
	coeff	t	beta	coeff	t	beta	coeff	t	beta	coeff	t	beta	Coeff	t	beta
Conc	0.02*	1.73	0.03	0.09**	2.69	0.12	0.04***	3.88	0.10	-0.02*	-1.78	-0.03	-0.01	-0.83	-0.01
Breadth	-0.00	-0.21	-0.00	-0.00	-0.51	-0.01	-0.00***	-3.53	-0.06	0.00	1.68	0.05	0.00	0.10	0.00
SizeTop	-0.03**	-2.52	-0.05	-0.02*	-1.88	-0.05	-0.02*	-1.69	-0.04	0.01	1.26	0.03	-0.01	-1.20	-0.01
APT_NC	-0.02***	-3.78	-0.04	-0.01	-1.37	-0.03	-0.03***	-4.03	-0.06	-0.02*	-1.85	-0.03	-0.01**	-2.33	-0.02
InvDevMedND	-0.05	-0.24	-0.00	-0.03	-0.13	-0.01	5.88***	3.18	0.14	-2.02*	-1.70	-0.05	2.17***	3.12	0.08
InvDevMedSD	0.01***	4.03	0.10	0.00	1.33	0.03	0.01***	3.04	0.06	0.01***	3.53	0.08	0.01***	3.94	0.04
SLR	-0.00	-1.57	-0.07	0.00	1.55	0.17	-0.00**	-2.09	-0.15	0.01***	3.39	0.29	-0.00***	-3.35	-0.20
InvDevZeroNC	0.01*	1.75	0.03	-0.00	-0.86	-0.02	0.01	1.59	0.08	0.03***	3.84	0.12	0.02***	3.84	0.07
SLR_InvDevZeroNC	0.02**	2.21	0.10	0.01**	2.56	0.09	0.01	0.64	0.04	-0.00	-0.36	-0.02	-0.02**	-2.43	-0.07
MPI_noise	0.28***	5.12	0.13	0.14***	4.42	0.10	0.12***	3.51	0.07	0.83***	3.86	0.31	0.09***	4.36	0.04
VIX	0.18***	4.99	0.13	0.12**	2.33	0.13	0.24***	5.59	0.22	0.40***	5.46	0.22	0.07*	1.93	0.05
Volume	0.00***	12.29	0.40	0.00***	7.51	0.53	0.00***	9.52	0.43	0.00***	7.04	0.23	0.00***	12.33	0.28
Constant	-0.03***	-7.91		-0.04***	-5.47		-0.04***	-7.24		-0.05***	-5.21		-0.02***	-7.05	
Observations	44,599			7,997			8,025			10,698			17,879		
R-squared	0.17			0.23			0.30			0.32			0.07		
Year FE	Y			Y			Y			Y			Y		
Quarter FE	Y			Y			Y			Y			Y		
CM FE	Y			Y			Y			Y			Y		

Table 4: Regressions of Residual Amihud

The table presents regressions of Residual Amihud Price Impact on systematic factors (Conc, Breadth, and SizeTopT), idiosyncratic factors (APT, InvDevMedND, and InvDevMedSD), and regulatory shock factors (SLR, SLR*InvDevZeroNC, and InvDevZeroNC) as well as control variables including MPI, VIX, and Volume. In addition to the all 18 contract markets (column 1), regression model is estimated for each of the commodity market group subsample: Livestock, Metals, Energy, and Agriculture (columns 2-). The regression sample covers years 2006-2020 for 18 contract markets. Regressions models include contract market, quarter fixed effects, and year fixed effects. Statistical significance (t-stats) and the beta values for each estimate are shown in the columns adjacent to the estimates and ***, **, * denote significance at 1%, 5%, and 10%, respectively..

VARIABLES	(1) all			(2) Livestock			(3) Metals			(4) Energy			(5) Agriculture		
	coeff	t	beta	Coeff	t	beta	coeff	t	beta	coeff	t	beta	coeff	t	beta
Conc	0.64	1.23	0.02	3.05	0.41	0.02	1.89*	1.94	0.08	-0.75	-0.65	-0.06	2.06**	2.40	0.06
Breadth	0.03	0.97	0.01	0.14	1.10	0.02	-0.12***	-3.32	-0.06	-0.05	-1.65	-0.03	0.06*	1.74	0.02
SizeTop	-2.08***	-3.74	-0.07	2.66	1.53	0.03	-1.97***	-3.81	-0.12	-0.18	-0.25	-0.02	-2.72**	-2.10	-0.08
APT_NC	-0.54	-1.46	-0.01	-1.64	-1.42	-0.03	1.94***	3.68	0.05	-0.36	-1.05	-0.02	0.51	1.20	0.01
InvDevMedND	189.22***	3.39	0.15	99.21	1.48	0.07	1,078.38***	5.90	0.45	469.74***	3.90	0.35	440.19***	4.72	0.25
InvDevMedSD	0.07	0.42	0.01	0.09	0.09	0.00	-0.00	-0.02	-0.00	0.01	0.20	0.00	0.06	0.14	0.00
SLR	-0.41***	-6.98	-0.19	0.10	0.35	0.03	-0.53***	-3.91	-0.40	-0.51***	-3.81	-0.50	-0.41***	-5.95	-0.23
InvDevZeroNC	-0.43	-1.58	-0.02	1.01	1.01	0.03	-1.76***	-4.14	-0.12	-0.06	-0.53	-0.01	-2.34***	-6.72	-0.09
SLR_InvDevZero NC	0.55**	2.31	0.03	0.02	0.03	0.00	-0.01	-0.02	-0.00	-0.59***	-2.68	-0.08	1.35***	3.02	0.06
Volume	-0.37***	-8.31	-0.41	-0.71***	-4.71	-0.35	-0.21***	-9.44	-0.31	-0.27***	-4.74	-0.50	-0.29***	-5.61	-0.33
Constant	3.97***	8.33		6.93***	4.95		2.28***	11.22		2.81***	5.89		2.82***	4.99	
Observations	64,411			10,740			10,728			14,320			28,623		
R-squared	0.35			0.28			0.38			0.29			0.33		
Year FE	Y			Y			Y			Y			Y		
Quarter FE	Y			Y			Y			Y			Y		
CM FE	Y			Y			Y			Y			Y		