Contagion and Spillovers across Futures Markets

Alex Ferko, Esen Onur and Tugkan Tuzun*

December 16, 2022

ABSTRACT

Following a shock to futures markets that result in significant price movement, we provide new evidence that the shocks propagate across futures markets. Using a new measure of interconnectedness between markets (i.e., the common market participants who hold positions in connected contracts), we show that such shocks would cause market participants to rebalance their futures portfolios. Due to the sizable margin calls, large traders can cause fire sales in other markets. These spillover adversely affects returns and liquidity in the non-shocked markets and are more prevalent when borrowing costs are relatively high. Using an exogenous margin shock from MF Global's collapse, we show that our results are unlikely to be driven by fundamentals.

JEL classification: G11, G14

Keywords:Interconnectedness, Contagion, Funding Liquidity, Futures Networks

*The research presented in this paper was co-authored by Alex Ferko and Esen Onur, both CFTC employees who wrote this paper in their official capacity, and Tugkan Tuzun, a Federal Reserve Board economist detailed to the CFTC who also wrote this paper in his official capacity. The analyses and conclusions expressed in this paper are those of the authors and do not reflect the views of Federal Reserve Board, Federal Reserve System, their respective staff, other members of the Office of CFTC Chief Economist, other Commission staff, or the Commission itself.

I. Introduction

Return co-movement is shown to be associated with institutional frictions and asset class effects (Barberis, Shleifer and Wurgler (2005); Basak and Pavlova (2013)) as well as commonality in mutual fund portfolio holdings (Anton and Polk 2014).[1] By virtue of belonging to many different portfolios, commonly held positions may display return co-movement following a shock through investor funding costs (Brunnermeier and Pedersen 2009). Following a market wide liquidity shock, investors may be forced to rebalance their portfolios and liquidate assets in fire sales (Shleifer and Vishny 2011) and this fire sale has the potential to spill over across portfolios.

In this paper we study how traders change their positions when faced with large price movements. Specifically, we consider how a *margin breach*, when the market value of a contract's daily move is greater than the margin required to be held by the clearing-house, forces traders to rebalance their portfolio in order to cover the margin call.[2] To better understand how a systemic rebalancing of portfolios can propagate shocks across markets, we propose a methodology to map the network structure of futures markets that measures market connectedness through shared portfolio positions. This approach allows us to link markets together even if they are not otherwise connected through fundamentals and study how liquidity shocks can spillover into commonly held positions. Using regulatory data on daily trader positions, we find that spillovers, measured through reduction in traders' holdings in non-shocked markets, are more likely to occur in markets where there are large, concentrated cross-holdings between two markets during periods with elevated funding costs.

[1]In Anton and Polk (2014), the mechanism driving co-movement is price pressure due to flows in and out of mutual funds. This mechanism is somewhat unique to mutual funds and may not be as relevant to other types of institutional traders such as hedge funds or prop traders.

[2]This rebalancing activity could be considered a type of fire sale when traders are forced to sell portfolio positions to meet their margin requirements.

Our paper uses fire sales as a mechanism which drives co-movement in prices[3] A market participant might choose to have exposure to two uncorrelated markets for diversification purposes, with the assumption that an idiosyncratic shock to the fundamentals of one market would not impact the price of the other. However, a large enough shock, defined by margin breaches, may force market participants to significantly reduce their exposure in markets that *did not* experience the shock in order to cover the associated margin calls.

While other papers on firesales have generally relied on quarterly mutual fund disclosures(Coval and Stafford (2007), Anton and Polk (2014), Edmans, Goldstein and Jiang (2012)), we take advantage of a regulatory dataset to that directly observes daily portfolio changes of individual traders in futures markets. This novel dataset allows us to observe the daily trading activities of individual traders and directly measure the same day response to shocks. We show that on average traders reduce their positions in the shocked market by 3.6% as of the day following the shock. More significantly, we find an even larger 8.4% reduction in the positions in the rest of their futures portfolio – in non-shocked markets, suggesting that traders rebalance their entire portfolio when faced with a major liquidity shock. Size is a mitigating factor with larger investors reducing their portfolios by a lesser amount. Utilizing an exogenous shock to trader's margin trading accounts due to the collapse of MF Global, we show that these non-discretionary portfolio position changes are unlikely due to information-induced rebalancing (Huang, Ringgenberg and Zhang (2022)), but rather reflect the funding constraints of leveraged trader portfolios (Brunnermeier and Pedersen (2009))

Our focus, U.S. futures markets, contains many contracts on a wide range of under-

[3] Institutional fire sales have been previously studied following adverse fund-flows (Coval and Stafford (2007) and Huang, Ringgenberg and Zhang (2022)) and bond rating downgrades (Ellul, Jotikasthira and Lundblad (2011)). Barbon et al. (2019) look at predatory trading against the institution experiencing the liquidity crisis. See Shleifer and Vishny (2011) for a review of this literature.

lying commodities from coffee, cotton, and livestock to euro-dollars, equity indices, and crypto-currencies. These markets cover many different fundamental sources of risk and span across varying asset classes. An important feature of these markets is their use of leverage and margining mechanisms. Unlike equity markets where investors can hold onto losing positions, futures traders, due to being leverged positions, are required by brokers to provide additional capital in the form of variation margin on an ongoing basis to hold onto positions after adverse price movements. These characteristics, combined with Commodity Futures Trading Commission (CFTC) regulatory data on trader portfolio holdings, makes futures markets a unique setting in which to examine how shocks may be transmitted through common portfolio holdings. This regulatory data allows us to follow owners of futures contracts, through common IDs, across exchanges and in markets within exchanges. Specifically, we make use of end-of-day position data from 2004 to 2022 collected by the CFTC to measure the impact of large price movements on traders' portfolios, and to measure the connections between markets through individual traders portfolios. By measuring connectedness with end-of-day position data, we are able to show how portfolio rebalancing at the daily level is a driver of return co-movement within commonly held positions.

When many traders hold large concentrated positions in the same pair of markets, after a shock in one market the portfolio fire-sale activity of individual investors may have observable adverse effects on the second non-shocked market. Braverman and Andreea (2014) and Greenwood, Landier and Thesmar (2015) model how contagion can spread across otherwise uncorrelated assets due to being jointly held in the same portfolio [4] In this paper, we propose a measure based on the prior work of Elliott, Golub and Jackson

[4]Researchers have examined financial networks in a variety of other settings including broker-client connections Maggio et al. (2019), Babus and Kondor (2018) and prime-broker credit networks(Kruttli, Monin and Watugala (2019)). Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) study the stability of financial networks for different sizes of shocks.

(2014) to capture this interconnectedness between financial markets based upon common trader portfolio holdings. Our measure identifies market pairs with significant overlap in the positions of individual traders and allows us to gauge the potential exposure markets have to shocks in other markets through the portfolio holdings channel[5]. Market pairs with a high degree of overlap in traders have greater exposure to investor firesales and are more likely to experience spillover effects following a shock. We find that for uncorrelated markets, market pairs with large common trader connections, a negative price shock to a given market decreases returns and adversely affects liquidity when funding costs are high. We also find symmetry in this effect between traders who held long positions in the shocked market(negative shocks), and traders that are short(positive shocks).

Throughout our analysis, we find that the funding liquidity constraint is an important mechanism in explaining market spillovers (Brunnermeier and Pedersen (2009)). When faced with large losses, traders may choose to either raise capital to meet margin requirements, or rebalance their portfolio and liquidate positions in a fire-sale. In periods of low cost capital, we provide evidence that firesales and spillovers in affected markets following portfolio shocks are less prominent.Kahraman and Tookes (2019) build on this same idea of funding constraints and find co-movement in prices of stocks that are connected through common brokers. Our findings highlight the importance of traders holding market pairs in common portfolios in explaining co-movement of positions following liquidity shocks.

While margin calls are normally driven by changes in the market fundamentals such as abnormal volatility, the 2011 bankruptcy of MF Global provides us with an alternative, natural experiment setting to study customer fire sales in response to an exogenous liquidity shock. In the case of the MF Global bankruptcy, customer positions were

[5] Diebold, Liu and Yilmaz (2017) also examine networks within futures contracts. Our focus is on trader portfolio positions, while their paper measures connections using contract returns.

quickly transferred to other brokerages following the bankruptcy announcement, but only a portion of customer collateral was transferred with the remaining collateral being held at MF Global pending the completion of the bankruptcy reorganization. MF Global customers were faced with a large exogenous liquidity shock, and we find evidence of widespread fire sales amongst MF Global customers with traders in aggregate reducing their portfolio size by 20.65% in the week following the position transfer with traders who had the largest exposures to MF Global reducing their portfolios by the greatest amount. Furthermore, we use our regulatory position data to identify the positions exited by MF Global customers to test for spillover effects and find that the portfolio of markets sold during the fire sale period of November 7 to November 9, 2011 underperformed their daily benchmarks by more than 2% each day.

The rest of the paper is as follows. Section II introduces the data set used in our study. Section III presents our trader-level analysis, and in section IV we introduce our market connection measure and provide evidence on across market contagion of shocks. In section V we use the collapse of MF Global to provide evidence of cross-market shocks, and in section VI we offer our concluding remarks.

II. Data

We make use of two different sources of regulatory data in our main analysis. The data is submitted to the Commodity Futures Trading Commission by the Futures Commission Merchants (FCMs) and central clearinghouses (CCPs) and is composed of end-of-day positions of traders as well as the amount of margin required by the CCPs. We supplement these two data sets with market statistics, reported by exchanges, as well as VIX data from Bloomberg and Ted Spread data from FRED.

A. Positions

For our data on trader positions, we use end of day position data for large traders. This is a regulatory data collected by the Commodity Futures Trading Commission (CFTC) and forms the basis for the Commitment of Traders (COT) report[6].

Per CFTC rules, only those traders that are classified as *large traders* are required to report their end-of-day positions of the CFTC.[7] Our primary sample consists of end-of-day position data for large traders from July 2004-April 2022. This data includes identifiers for each trader, the futures contracts each trader is holding, as well as the FCM each trader used to acquire their positions.

We use this end-of-day position data to calculate the notional value of customer portfolios. In order to be able to aggregate contracts in different markets to form futures portfolios, we aggregate all positions on a notional basis. Where for customer i and market m:

$$Notional\_Value_{i,m,t} = \frac{minimum\_tick\_value_m}{minimum\_tick_m} * currency\_conversion\_factor* \\ settlement\_price_{m,t} * abs(long\_contracts_{i,m,t} - short\_contracts_{i,m,t}) \quad (1)$$

The starting sample is formed as the set of traders who held reportable positions in any of the sample markets in the July 2004- April 2022 period. On each day, notional portfolios for traders are calculated along with the daily change in portfolio size. The following variables are calculated for trader i with respect to market m: notional portfolio size, $Port_{i,t}$; net exposure to market m, $Exposure_{i,m,t}$; percentage change in notional portfolio, $\Delta Port\_pct_{i,t-1,t+1}$; change in portfolio weight of market m in trader

[6]For a detailed description of the COT reports, go to CFTC's COT description.

[7]See https://www.cftc.gov/IndustryOversight/MarketSurveillance/LargeTraderReportingProgram/index.htm

i's portfolio, $\Delta port\_weight_{i,m,t-1,t+1}$; percentage change in portfolio size for positions that are not market m, where for positions p: $\Delta port\_pct_{p \neq m,i,t-1,t+1}$.

In order to determine the impact of margin breaches on traders, we specifically focus our analysis on non-commercial traders. Non-commercial traders are different than commercial hedgers; they trade in the futures market mainly for profit maximization purposes while the latter trade to hedge their exposure to the underlier such as a corn farmer hedging due to the corn in the field. As a result, we expect margin breaches to lead to portfolio rebalancing by non-commercial traders rather than commercial ones. Along these lines, we also exclude traders with highly concentrated positions since a shock to their concentrated position is not likely to create too much portfolio rebalancing. Hence, we remove traders who have more than 25% of their futures portfolio in a shocked market. We remove smaller traders from our sample and keep those with a portfolio value of $10 million and above. We also drop events where fewer than 10 large traders are exposed to the event. Finally, the variables are winsorized at the .5% level.

B. Margin Breaches

For each purchased futures contract, the exchange requires a certain amount of funds to be kept immediately accessible in the case of large, adverse price movements; this is referred to as maintenance margin. In order to define large daily price movements, we use this margin information and a measure generally calculated by exchanges in their internal risk models, *margin breaches*. A margin breach in a given contract is when the change in the notional value of all the outstanding contracts surpasses the total amount of margin required to be held for all the existing contracts. We use margin data reported by the exchanges to define margin breaches, so for each contract c and day t we calculate:

$$Margin\_Breach\_Level_{c,t} = \frac{\Delta Price_{c,t,t-1} * Contract\_Units_c}{Maintenance\_Margin_{c,t-1}} \tag{2}$$

When breach level is greater than 1, the daily price movement in a contract is greater than the maintenance margin level on that contract. This means in most cases traders will have to raise additional margin or exit their positions. For the purposes of the analysis below, a breach event is defined as events where the breach level in a contract is greater than

We constructed a sample of breach events over a 20 year time horizon. Our sample consists of 92 markets that are in the top 10% of notional size and volume with at least 6 years of daily observations and maintenance margins greater than $100 USD. This sample has a total of 3,556 breaches. Figure 1 shows the distribution of the breach measure over the sample period. By construction, breach events are a relatively rare event with few daily price movements greater than the maintenance margin level. As seen in figure 2, a typical month in the sample has fewer than 7 days with breach events with spikes during periods of market stress such as the 2008 financial crisis, March 2020 Covid-19 stress, and the recent 2022 war in Ukraine.

On days where there are multiple markets with a breach event, only the market with the largest notional dollar value change is kept in the sample. This assumption makes sure that on days with major events impacting numerous markets, such as the COVID 19 shock of March 2020, we are not labeling correlated market moves as contagion. Finally, for purposes of computational efficiency, we limit our sample to days with a maximum breach greater than

Figure 1: Daily Breach Level distribution for sample markets
Distribution of breach levels during our sample. We define breach events to be higher than 1.0 or lower than -1.0, which are in the right and left tails of the figure.

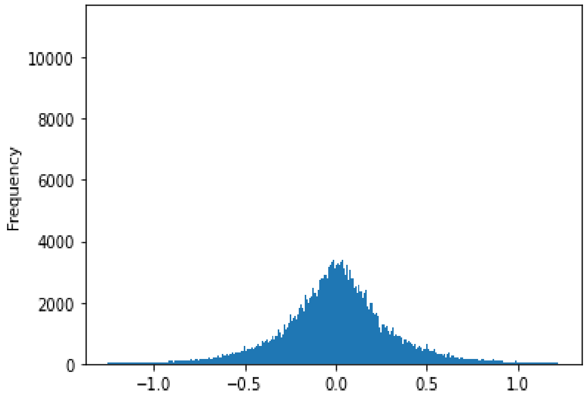
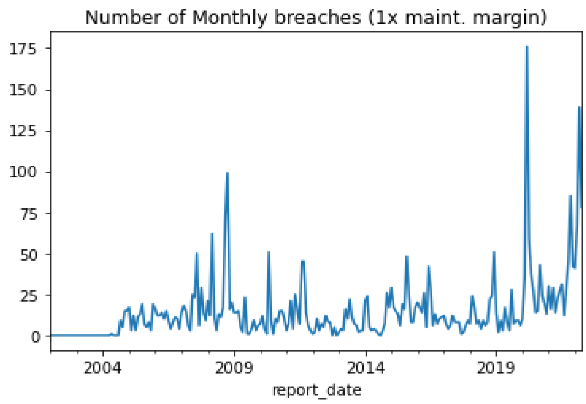


Figure 2: Monthly Breach Counts for sample markets
Number of monthly breach event counts in our sample. Breach events are calculated as in Equation 2 and we observe less than 7 of them on an average month. Spikes in the figure correspond to the great financial crisis and the Covid-19 market stress.



C. Market Level Data

In addition to trader level position data, we use market level information on prices, volumes and open interest, which is provided to the CFTC by the exchanges. Returns are calculated based upon the price and lagged price of the front-month contract for each market defined as the contract with the greatest volume on each day.

For our set of 92 markets, we calculate a set of daily market level variables to capture spill-over effects during liquidity shocks. These variables are $\Delta OI_{t,t+1}$, the daily change in open interest for a particular market; VOL_t^*, normalized volume; Ret_t, returns to the front contract of a given market; $illiquidity_t$, the Amihud illiqudity measure (Amihud (2002)), and $volatility_t$ measured by squared returns. In order to focus on markets with some minimum level of liquidity, we drop market observations where volume is less than 5,000 and open interest is below 2,500.

III. Traders' Reaction to Margin Breaches

We begin our analysis by investigating what traders do when they are faced with a large price move (triggering a margin breach) in one of the markets they have exposure to. We investigate changes to the trader's exposure in the market experiencing the large price move (the shocked market); in the trader's overall futures portfolio; and in the non-shocked markets.

To facilitate this analysis, we use the end-of-day position data described above. In Table I, we report descriptive statistics for the trader portfolio sample. The sample contains 13,311 unique traders with the median year in the sample containing 2,326 traders. The average portfolio of a trader in our sample is a little less than 6 billion dollars and median is almost 400 million dollars.

Next, we estimate the following model to understand how traders behave when faced with a margin breach:

Table I: Descriptive Statistics: Trader Portfolio Changes
The table provides simple statistics on trader portfolios. $Port_{i,t}$ is the size of trader i's portfolio at day t, $Exposure_{i,m,t}$ is the weight of trader i's portfolio on day t in the shocked market m, $\Delta Port\_weight_{i,m,t-1,t+1}$ is the percentage change in the share of market m in trader i's portfolio from day $t-1$ to day $t+1$, $\Delta port\_pct_{p\neq m,i,t-1,t+1}$ is the change in portfolio weight of markets other than market m in trader i's portfolio from day $t-1$ to day $t+1$, $\Delta Port\_pct_{i,t-1,t+1}$ is the change in portfolio weight of trader i a from day $t-1$ to day $t+1$.

Variable	Mean	Std. Dev.	Median
$Port_{i,t}$	5810.363	24609.444	391.294
$Exposure_{i,m,t}$	-0.007	0.272	0.000
$\Delta port\_weight_{i,m,t-1,t+1}$	-0.009	0.163	0.000
$\Delta port\_pct_{k\neq m,i,t-1,t+1}$	-0.015	0.234	0.000
$\Delta Port\_pct_{i,t-1,t+1}$	-0.018	0.249	0.000
VIX	19.846	9.698	17.110

$$\Delta Pos_{i,t-1,t+1} = \alpha + \beta_1 Exposure_{i,m,t} + \beta_2 breach\_ind_t + \beta_3 Exposure * breach\_ind + \beta_4 log(Port_{i,t}) + VIX_t + year_t + mkt_i + \epsilon \quad (3)$$

where $\Delta Pos_{i,t-1,t+1}$ represents the change in trader i's position in 1) commodity market m, 2) commodity markets $k \neq m$, and 3) whole portfolio from day $t-1$ to $t+1$. $Exposure_{i,m,t}$ is the weight of trader i's portfolio on day t in the shocked market m. $breach\_ind$ is an indicator variable equal to 1 when the market had a breach larger than the maintenance margin level on date t, 0 otherwise. Year and market effects are included in all models.

If a trader exits positions following a liquidity shock they may choose to either exit positions in the same market as the shock or to exit positions in the rest of their portfolio(non-shocked markets). In Model 1, we test this first scenario and measure the $t-1$ to $t+1$ change in portfolio weight for trader i in event market m. Notional position values and portfolios are measured using $t-1$ price levels. Resulting changes in portfolio weights are due changes in the number of contracts held in each position over the observation window. Model 2 shows the results for the second scenario where the aggregate portfolio weights in non-shocked markets are evaluated. Finally, Model 3 considers the overall change in size of the traders portfolio.

Table II reports these results. The $Breach_ind$ variable is insignificant in all 3 models as expected. Only traders who are exposed to the breach event are affected by the liquidity shock. For the $Exposure$ variable, the sample only consists of days with breach levels $< |-.25.|$ When faced with moderately negative returns, traders on average increase positions in other markets and do not necessarily change their positions in the event market itself. However, in extreme events where $BreachInd. = 1$, traders do begin altering the composition of their portfolios as seen in the interaction term. We do see traders exiting the affected market itself and traders on average reduce their positions in the shocked market by 3.6%, but the reaction in the non-shocked markets is larger with traders reducing the rest of their portfolio by 8.4%. $Port$ is a variable capturing the market size of the trader, and results suggest larger traders are likely to increase their portfolios, possibly because they are more likely to have access to additional capital or lines of credit they can draw upon to meet margin requirements rather than exit portfolio positions. VIX coefficient is negative suggesting that fire sales are larger during periods of greater market stress.

Overall, we find that traders react to margin breaches by reducing the size of their portfolios, possibly in order to be able to cover the margin call they receive as a result of the large price move. While this analysis tells us positions of these traders in other markets are also reduced, it doesn't provide us any analysis on how this impacts the non-shocked markets. It is possible that non-shocked markets may be impacted if enough traders reduce their exposure as a result of a margin breach in a different market. Next,

Table II: Large Trader Fire sale Results
Table presents regression estimates to Equation 3. Dependent variable in model (1) is the percentage change in the shocked market, in model (2) it is the percentage change in non-shocked markets, and in model (3) it is the percentage change in trader's whole portfolio. All regressions include year and contract fixed effects.

	Dependent variable: $\Delta Pos_{i,t-1,t+1}$		
	(1)	(2)	(3)
	Same Mkt	Other Mkts	Port
Exposure	0.0004	0.026^{***}	0.019^{***}
	(0.002)	(0.004)	(0.005)
Breach Ind.	−0.0003	0.004	0.003
	(0.002)	(0.003)	(0.003)
VIX	-0.0001^{***}	-0.0002^{***}	-0.0002^{***}
	(0.00002)	(0.00004)	(0.00004)
log(Port Size)	0.003^{***}	0.003^{***}	0.003^{***}
	(0.0001)	(0.0001)	(0.0001)
Exposure x Breach Ind.	-0.036^{*}	-0.084^{**}	-0.116^{**}
	(0.021)	(0.042)	(0.050)
Year Effects	Yes	Yes	Yes
Contract Market Effects	Yes	Yes	Yes
Adj. R Squared	0.003	0.001	0.001
Degrees of Freedom	1,224,697	1,224,697	1,224,697
Note:			*p<0.1; **p<0.05; ***p<0.01

we focus on market-level analysis to be able to answer this question.

IV. Spillovers within Connected Markets

The previous tests were conducted at the individual trader level. If trader portfolios are connected, this rebalancing activity in non-shocked markets could aggregate and be observable at the market level. Shocks could spill-over into other (unrelated) markets due to correlated patterns in portfolio holdings and fire-sale activity. We measure the level of connectedness between markets based upon trader portfolio positions test whether this measure can explain spill-overs between markets following liquidity shocks.

For cross-market spillovers we use market-level data, which captures connections between markets through common traders. In order to be able to measure this connection, we first propose a methodology of connecting various markets, even if they are not connected through fundamentals.

A. Methodology: Cross-Market Connection

Following Elliott, Golub and Jackson (2014) we develop a measure of market interconnectedness along two major dimensions: integration and diversification. The intuition here is that markets are more connected when there is greater overlap in positions (integration). However, the strength of this connection is attenuated by diversification. Shocks that affect a small fraction of a traders portfolio are unlikely to be transmitted to other portfolio positions. Similarly, if traders indeed rebalance their portfolio in response to a shock, the resulting trading activity will have limited effect on markets that are large relative to the shocked portfolios.

The connection between any two contracts, k and j is defined for traders T who hold both k and j as:

$$Connection_{k,j} = \frac{|Cross_{k,j}|}{Port_T} * \frac{Cross_{j,k}}{Size_j} \tag{4}$$

The first term captures the diversification component of our connection measure between markets k and j. Across the traders, T that hold both k and j in their portfolios, the cross-holdings are defined as: $Cross_{k,j} = \sum_t^T net\_position_{t,k}$. This is the notional value of positions in market k held by traders who also have positions in market j. Cross-holdings are scaled by the aggregate notional portfolio of traders, T, to capture how exposed traders in j are to market k. For any given day t, the aggregate portfolio of traders, I, is defined across all futures markets, M, as : $Port_I = \sum_m^M \sum_i^I abs(net\_pos_{i,m})$. Note that we take the absolute value of a trader's net position within a market so long and short positions across markets do not net each other out. When cross-holdings are large relative to portfolios, traders are more likely to have to rebalance their portfolios in response to a shock in market k creating the potential for spill-over effects to occur[8]. On the other hand, when $Cross_{k,j}$ is small compared to $Port_I$, the connection between k and j is low as traders will be less constrained following shocks to market k and face reduced pressure to rebalance their portfolios. Shocks to a diversified aggregate portfolio are less likely to be transmitted to other markets held by traders in k.

The second term of this equation measures the integration component of our connection measure. This term is the fraction of open interest in market j held by traders in market k and captures the impact rebalancing portfolio $Port_T$ may have on market j. In the numerator we have the cross-holdings between j and k, that is the notional value of positions in j by traders in both markets. This value is scaled by the notional open interest of market j, $Size_j$. The first term captures whether shocks may be transmit-

[8]It is worth noting that portfolio rebalancing in the face of a liquidity shock can be a complicated decision. Without any further information, we assume a uniform portfolio rebalancing in our approach in determining which markets will be affected by portfolio liquidations.

ted out of trader portfolios, and this second, integration term, measures whether those potentially transmitted shocks are large relative to the size of the affected markets, j, resulting in observable spillover effects.[9]

To ease interpretation of the sign of the connection measure, we chose to take the absolute value of the first component term. If both terms were signed, a positive connection value could mean traders were in aggregate net long in both k and j or net short with respect to the two markets. Similarly, with a negative connection value traders could be short in either market(but not both). Our primary interest is in measuring spillover effects in market j and by retaining the sign of the second term, the overall connection measure will have the same sign as $Cross_{j,k}$, the direction of the aggregate positions in market j. However, this design choice does introduce some amount of noise into our measure of the first term, $\frac{|Cross_{k,j}|}{Port_T}$. In response to a negative shock, we may be including some set of markets where the aggregate traders are net short who will not be constrained by the shock, but there is less noise in the measure of direction of aggregate effect to market j, our primary variable of interest. This noise in the measure of the first term is unlikely to bias our results in favor of finding a result as the direction of a portfolio rebalancing response on market j to a positive shock in market k is unclear.

B. Intermarket Correlation

Having established cross-market connections, our objective is to test whether connected markets are more likely to experience changes in their open interest (OI), volume, returns, and volatility during margin breaches. In Table III, we provide various statistics of the markets in our sample, including $\Delta OI_{t,t+1}$, which is percentage change in open interest from day t to $t+1$, trading volume normalized by market open interest, VOL_t^*, and Amihud Illiquidity measure calculated by dividing daily absolute returns in a market

[9] We provide a numerical example of our connection measure in the Appendix of the paper.

by the notional value of that market's trading volume.

Table III: Descriptive Statistics: Market Level
Table presents simple descriptive statistics for the markets in our sample. $\Delta OI_{t,t+1}$ is the percentage change in open interest from day t to $t+1$. VOL^*_t is daily trading volume normalized by open interest. Amihud Illiquidity measure calculated by dividing daily absolute returns in a market by the notional value of that market's trading volume.

var	mean	sd	med
Open Interest (in thousands)	210.156	510.281	497.410
$\Delta OI_{t,t+1}$	0.013	0.178	-0.003
Volume (in thousands)	230.131	497.931	572.210
VOL^*_t	0.279	1.172	0.213
Ret_t	-0.271	2.129	-0.029
$volatility_t$	5.094	11.483	0.815
Amihud Illiqudity	0.001	0.003	0.000
Ted Spread	0.439	0.618	0.240
VIX	25.432	13.579	21.560

C. Connected Portfolios

We calculate market connectedness, $CONN_{k,j,t}$ using the method described above. Table IV reports a number of example market pairs taken from across the connection distribution. *Tdr_Count* is the number of large traders holding both markets in the portfolio. Portfolio weights in markets k and j are reported. This is the mean weight the market is in each traders portfolio, not weight in the joint aggregate portfolio. Mkt OI is the integration component of the connection measure. This is the fraction of open interest in each market held by the group of traders holding markets k and j. As markets become less connected we observe smaller portfolio weights and lower integration between the pairs.

Table IV: Descriptive Statistics: Connection Measure
Table presents randomly picked examples of market pairs with different levels of connection, as defined in Equation 4. Table also reports the number of common traders between these two markets and the portfolio weight of these markets in these traders' portfolios.

Mkt_k	Mkt_j	Connection(x1000)	Tdr_Count	$Weight_k$	$Weight_j$	Mkt K OI	Mkt J OI
UST 10Y NOTE	GASOLINE RBOB	5.608	73	0.287	0.012	0.093	0.232
UST 5Y NOTE	S&P 500 STOCK INDEX	3.635	29	0.260	0.125	-0.041	0.113
UST 10Y NOTE	FED FUNDS	3.079	87	0.287	0.158	-0.140	0.124
UST 2Y NOTE	LEAN HOGS	2.755	75	0.371	0.004	0.039	0.213
UST 2Y NOTE	NIKKEI STOCK AVERAGE YEN DENOM	0.049	35	0.371	0.427	0.015	0.008
UST BOND	COCOA	0.018	46	0.151	0.003	0.005	0.041
NAT GAS NYME	E-MINI S&P 500	0.012	122	0.219	0.184	0.126	0.006
ULTRA UST BOND	AUSTRALIAN DOLLAR	0.012	21	0.162	0.005	0.031	0.003
HENRY HUB LAST DAY FIN	HENRY HUB PENULTIMATE NAT GAS	-0.529	38	0.216	0.021	-0.302	-0.074
UST 10Y NOTE	S&P 500 STOCK INDEX	-0.598	32	0.287	0.134	-0.017	-0.051
S&P 500 STOCK INDEX	E-MINI S&P FINANCIAL INDEX	-5.373	9	0.220	0.026	0.163	-0.381
NIKKEI STOCK AVERAGE YEN DENOM	MSCI EM INDEX	-6.223	38	0.633	0.031	0.082	-0.192

D. Regression Analysis

We treat $CONN$ as an indicator variable for a pair of markets whose connection is within the top quintile in a given month. This indicator variable can be thought of as the set of markets j that are highly exposed to traders in market k, which is the shocked market.

As we analyze how connection between markets matters for changes in non-shocked markets, it is important to note that the changes a market experiences might be due to its fundamentals, which might also be the cause of the margin breach in the shocked market. In order to control for this, we first run our analysis only for markets that are not fundamentally connected to the shocked market, which we call *uncorrelated markets*. We first measure rolling annual price correlations between every pair of markets in our sample and for each market k, we identify correlated markets where annual price correlation is greater than .70, and uncorrelated markets where annual price correlation is less than .15. We argue that within the set of uncorrelated markets, market level spillover effects are more likely to be driven by market connectedness rather than information effects from the shock.

For a set of breach events, we estimate the following model:

$$X_{j,t} = \alpha + \beta_1 CONN_{k,j,t} + \beta_2 Ted_t + \beta_3 log(Size)_{it} + \beta_4 VIX_t + year_t + mkt_j + key\_mkt_k + \epsilon \tag{5}$$

For each event in the sample, we have a market, k, which experienced a breach and a set of connection measures between the breached market, k, and the other markets, j in the sample. The connection coefficient is testing if markets that are highly connected through shared cross-holdings by the traders in the breached market experience spillover effects, $\mathbf{X_{j,t}}$, which include change in open interest, normalized volume, market return, Amihud illiquidity measure, and volatility. As control variables, we include the Ted Spread and VIX as general measures of market sentiment along with the interaction between the Ted Spread and the connection indicator. Lastly, year effects and fixed effects for both the shocked market k and affected market j are included.

Traders experiencing a shock have the opportunity to raise external capital instead of exiting their portfolio positions. However, their capability to do this is limited by the cost and availability of external funds. We use the Ted Spread to control for the availability of capital (through funding cost) since we believe when capital costs are high, traders are more likely to respond to a liquidity shock with by a significant reduction in their portfolios.

Table V reports the results for the set of markets uncorrelated with the shocked market during event days. The coefficient on the connection indicator captures spillover effects between markets. On its own, this variable is generally not significant. However, when interacted with the Ted Spread, we see significant spillover results with negative returns and increased illiquidity in connected markets. That is, when funding costs are high, connected markets experience spillover effects during portfolio fire sales. In general market size is a mitigating factor in reducing spillover effects while VIX amplifies spillovers between markets.

As a robustness check, we repeat the above tests for the group of correlated markets comparing correlated connected and unconnected markets. Table VI reports these results. Generally results are even more pronounced for related markets; namely when funding liquidity is constrained, more connected markets observe a significant drop in open interest on top of lower returns and higher illiquidity.

Table V: Market Connection Results: Uncorrelated Markets
Table presents regression estimates from Equation 5 for the impact of negative price shocks in uncorrelated markets. Dependent variables for the five models are ΔOI, normalized volume, market return, Amihud illiquidity measure and volatility respectively. All regressions include year, contract market, and shocked market fixed effects.

	Dependent variable:				
	(1)	(2)	(3)	(4)	(5)
	ΔOI	Normalized Volume	Return	Illiquidity	Volatility
Conn Ind.	0.0004	0.030	0.016	−0.00003	0.605*
	(0.006)	(0.036)	(0.069)	(0.0001)	(0.349)
Ted Spread	−0.005	−0.110***	−0.095	0.001***	2.151***
	(0.004)	(0.027)	(0.067)	(0.0001)	(0.419)
Ted Spread x Conn Ind.	−0.001	−0.022	−0.289***	0.0003***	0.372
	(0.004)	(0.029)	(0.080)	(0.0001)	(0.481)
VIX	0.0002	0.016***	−0.012***	0.00000	0.126***
	(0.0002)	(0.001)	(0.002)	(0.00000)	(0.015)
log(Size)	0.064***	−0.123***	0.195***	−0.001***	−0.340
	(0.004)	(0.023)	(0.049)	(0.00005)	(0.264)
Year Effects	Yes	Yes	Yes	Yes	Yes
Contract Market Effects	Yes	Yes	Yes	Yes	Yes
Key Market Effects	Yes	Yes	Yes	Yes	Yes
Adj. R Squared	0.046	0.158	0.154	0.533	0.278
Degrees of Freedom	12,589	12,589	12,589	12,589	12,589
Note:					*p<0.1; **p<0.05; ***p<0.01

Table VI: Market Connection Results: Correlated Markets
Table presents regression estimates from Equation 5 for the impact of negative price shocks in correlated markets. Dependent variables for the five models are ΔOI, normalized volume, market return, Amihud illiquidity measure and volatility respectively. All regressions include year, contract market, and shocked market fixed effects.

	Dependent variable:				
	(1)	(2)	(3)	(4)	(5)
	ΔOI	Normalized Volume	Return	Illiquidity	Volatility
Conn Ind.	0.004	−0.040	0.277***	−0.0004***	−1.051**
	(0.006)	(0.040)	(0.077)	(0.0001)	(0.523)
Ted Spread	−0.011**	−0.232***	0.193***	0.0004***	−1.628***
	(0.004)	(0.029)	(0.061)	(0.0001)	(0.469)
Ted Spread x Conn Ind.	−0.011***	−0.030	−0.174***	0.0003***	0.220
	(0.003)	(0.024)	(0.058)	(0.0001)	(0.476)
VIX	0.0003	0.019***	−0.060***	0.00002***	0.525***
	(0.0002)	(0.001)	(0.002)	(0.00000)	(0.020)
log(Size)	0.047***	−0.097***	0.056	−0.001***	−1.743***
	(0.004)	(0.026)	(0.057)	(0.0001)	(0.411)
Year Effects	Yes	Yes	Yes	Yes	Yes
Contract Market Effects	Yes	Yes	Yes	Yes	Yes
Key Market Effects	Yes	Yes	Yes	Yes	Yes
Adj. R Squared	0.072	.171	.327	0.608	.395
Degrees of Freedom	11,048	11,048	11,048	11,048	11,048

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

D.1. Positive Shocks

So far, we have analyzed the impact of a significant drop in the settlement prices of our shocked markets, however a significant jump in the price would create margin breaches for traders with long exposure as well. Hence, using the same breach definition, we can test the effect of positive shocks (i.e. breach levels greater than 1) on spill-over effects between connected markets using the set of bottom quintile connections (i.e short exposure to market j).

Table VII estimates the same model but for the set of positive shock events on uncorrelated markets. We observe that similar to a significant price drop causing margin breaches, in the case of price jumps returns in connected markets are also negatively impacted when the Ted Spread is high. Unlike the negative price shocks, we do not observe a change in illiquidity in the connected market, but we observe an increase in volatility.

Overall, our results point to an important connection measure between futures contracts that is dependent on common traders between markets, and that also can propagate shocks across contracts when funding costs are high.

V. Case Study: MF Global

One of the biggest shocks to the U.S. futures markets happened in the fall of 2011. Trading futures contracts requires going through brokerage firms, called Futures Commission Merchants (FCMs). MF Global was one of the biggest FCMs in the market when they filed for bankruptcy on October 31st, 2011.

The way FCMs work is that they collect collateral, called margin, from customers for the leveraged futures positions customers hold. MF Global's collapse, which was due to the liquidity constraint issues by the FCM as well as the eventual downgrade of the

Table VII: Positive Liquidity Shocks: Uncorrelated Markets
Table presents regression estimates from Equation 5 for the impact of positive price shocks in uncorrelated markets. Dependent variables for the five models are ΔOI, normalized volume, market return, Amihud illiquidity measure and volatility respectively. All regressions include year, contract market, and shocked market fixed effects.

	Dependent variable:				
	(1)	(2)	(3)	(4)	(5)
	ΔOI	Normalized Volume	Return	Illiquidity	Volatility
Conn Ind.	0.008	0.058	0.013	0.0002**	−0.194
	(0.008)	(0.044)	(0.102)	(0.0001)	(0.577)
Ted Spread	−0.002	−0.293***	0.186***	0.001***	0.834**
	(0.005)	(0.026)	(0.070)	(0.0001)	(0.378)
Ted Spread x Conn Ind.	−0.001	−0.018	−0.203**	−0.0001	1.102**
	(0.006)	(0.029)	(0.086)	(0.0001)	(0.506)
VIX	0.0001	0.018***	−0.035***	0.00001***	0.279***
	(0.0002)	(0.001)	(0.003)	(0.00000)	(0.015)
log(Size)	0.046***	−0.074***	−0.047	−0.001***	−1.971***
	(0.005)	(0.027)	(0.065)	(0.0001)	(0.371)
Year Effects	Yes	Yes	Yes	Yes	Yes
Contract Market Effects	Yes	Yes	Yes	Yes	Yes
Key Market Effects	Yes	Yes	Yes	Yes	Yes
Adj. R Squared	0.041	0.172	0.146	0.531	.349
Degrees of Freedom	9,416	9,416	9,416	9,416	9,416

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

FCM's rating (Heckinger (2014)), was one of the biggest FCM failures in futures history.

When an FCM goes bankrupt, one of the first actions is to transfer the positions of customers to other FCMs, along with their margins. However, in MF Global's case, some of the customer funds had been used up by MF Global to fund the margin calls on the FCM's own proprietary trades. This resulted in transfer of customer futures positions to other FCMs, but not all of their margins (Peterson (2013)), which meant customers received a margin call from their new FCMs as a result.

While margin calls are normally driven by changes in the market fundamentals such as abnormal volatility, in MF Global's case it was driven by the FCM's decision to use some of the segregated customer funds to cover it's own liquidity needs, which constitutes a quasi-natural experiment in terms of looking at how customers react in the face of a large, exogenous margin call. We use this shock to study which customers had to liquidate their positions in a short window of time (fire sales) to cover the unexpected margin calls. We find that decision to liquidate positions depends on what percentage of a customer's futures portfolio was held at MF Global. We also show the resulting fire sales had a sizeable impact on impacted markets.

A. Data Preparation

A.1. Calculate portfolio measures

For our results on MF Global, we restrict the sample to just a two year period window around the MF Global bankruptcy and only consider customers who held some portion of their portfolio with MF Global.

Customer portfolio values may change from day-to-day due to either trading or price movements. To isolate portfolio effects that are driven by customer decisions, notional portfolio values are calculated with a fixed price level using prices on Nov 1, 2011 while customer positions are taken as of the end of day at time t.

Figure 3: Aggregate Notional Portfolio for MF Global Customers
Figure presents the aggregate notional value of MF Global customer positions (using Nov 1, 2011 prices) held at MF Global and other FCMs

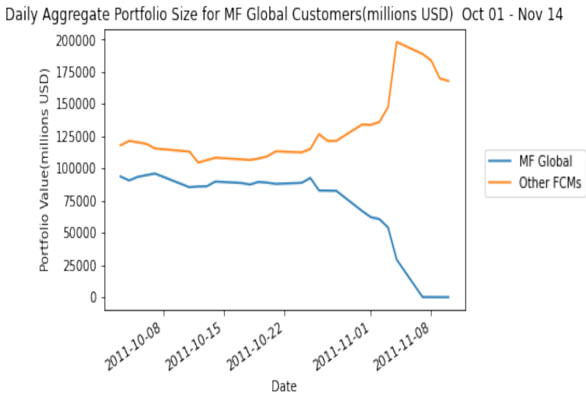


Figure 3 depicts the aggregate notional value of positions (using Nov 1, 2011 prices) for MF Global customers and the split between positions held at MF Global and other FCMs.

Portfolio values are relatively stable throughout October. Following the bankruptcy, there is a sharp rise in positions held at other FCMs with a corresponding drop in positions at MF Global as positions were transferred to other FCMs. By Friday, 11-04, $61 billion in notional positions were transferred out of MF Global to other FCMs. Starting the following Monday, 11-07, MF Global customers began reducing their portfolio exposures by $30 billion over the following week. Mechanically, all of the positions were transferred over between MF Global to the other FCMs, but a portion of the customer margins stayed with MF Global resulting in customers receiving margin calls once the transfer was completed. If customers wanted to maintain their portfolio in its entirety, additional margin was required. Otherwise, liquidations were required to match the initial margin required on the customers portfolio with the available funds in the customers new account.

Table VIII: Notional Portfolio Summary Stats on Oct 31, 2011
Table presents portfolio summary of three different groups of traders depending on their exposure level to MF Global. Mean, standard deviation, and median are in millions USD.

	count	mean	standard deviation	median
High Exposure MF Port	284	208.910	1628.146	16.190
High Exposure Non-MF Port	269	30.584	66.505	9.070
Mid Exposure MF Port	59	80.917	146.891	25.129
Mid Exposure Non-MF Port	59	112.060	253.233	28.450
Low Exposure MF Port	55	51.247	122.534	12.422
Low Exposure Non-MF Port	55	2305.268	6300.350	275.260

A.2. Distribution between MF Global and other FCMs

Customers may allocate their positions across multiple FCMs, and that introduces a customer level variation in exposure to the bankruptcy of MF Global. Customers are divided into three groups based on the percentage of their reported futures portfolio held at MF Global. Large and small exposures to MF Global are defined as having greater than 75% or less than 25% of portfolio positions in MF Global accounts respectively while the remaining traders are included in the mid-exposure group. Traders with only a small portion of their portfolio in MF global accounts are largely unaffected by the bankruptcy and will have little reason to liquidate their portfolio. As seen in Table VIII, most MF Global customers tend to only use MF Global, but a number of large traders split their positions between MF Global and other FCMs.

B. Changes in Positions Held by Group

The relative size of the margin call experienced by MF Global customers is dependent on the portion of the customers portfolio held at MF Global. Customers with the majority of their portfolio held at non-MF Global FCMs will receive margin calls after the transfer on just a small portion of their overall portfolio. On the other-hand, customers who had the entirety of the portfolio at MF Global will have a margin call that is proportionally much greater.

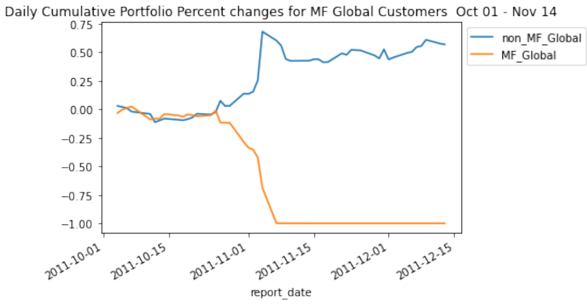
In the below figures, daily notional portfolio changes are calculated using lagged prices to capture the change in portfolio value due to the active trading decisions by the investor by adjusting the number of contracts held. For each customer we sum the change in portfolio value between two days using prices as of Nov 1, 2011 across all markets held by the customer: $\sum_m^M c_{m,t} * p_{m,t} - c_{m,t} * p_{m,t}$, where $c_{m,t}$ is the number of contracts held by investors in market m on day t. We then take the cumulative sum of daily portfolio changes to measure the aggregate trading decisions of MF Global customers within each exposure group.

Figure 4 shows the cumulative percentage change in MF Global customer notional portfolios split between MF Global and other FCMs from October 1, 2011 to November 15, 2011. From October 1 to October 28(the Friday before the bankruptcy) the cumulative percentage change in customer portfolios was relatively stable. Aggregate combined(MF Global and other FCMs) portfolios decreased by 3.6%. Positions held at non-MF Global FCM's increased by 2.97%.

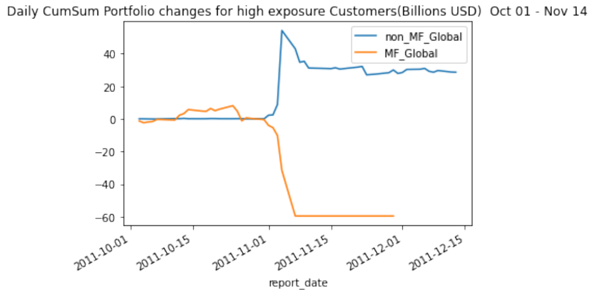
During the week following the bankruptcy announcement, we see a symmetric trend between MF Global and Other FCMs as positions were transferred. On November 4th, positions held at other FCMs increased 68% from the October 1st levels. Starting Monday, November 7th, positions at other FCMs started to decline and by Friday November 10th, positions at other FCMs were only 42% above the initial levels. Aggregate combined(MF Global and other FCMs) portfolios were 20.65% smaller than October 1st levels.

The remaining panels of Figure 4 show the cumulative sum of daily portfolio changes across the 3 subgroups of MF Global customers. Customers with the largest exposure to MF Global had comparatively larger portfolio reductions in the post-bankruptcy period

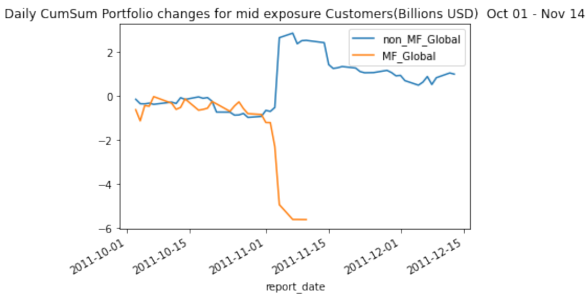
Figure 4: Portfolio Changes of MF Global Customers Around the Collapse
Figure shows the changes in portfolios of various groups of MF Global customers around the FCM's collapse. Top left figure shows portfolio changes experienced by all customers of MF Global, top right figure shows portfolio changes experienced by large exposure customers, bottom left figure shows portfolio changes experienced by mid exposure customers, and bottom right figure shows portfolio changes experienced by small exposure customers.



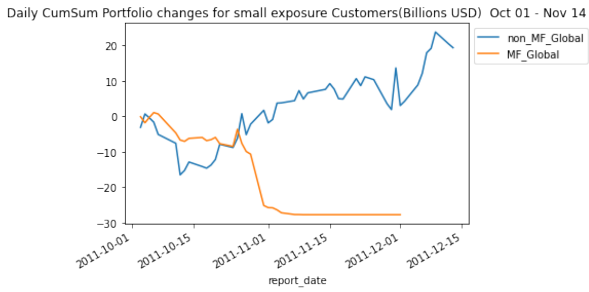
(a) MF Global sum of customer portfolio changes (all customers)



(b) MF Global sum of customer portfolio changes (high exposure customers)



(c) MF Global sum of customer portfolio changes (mid exposure customers)



(d) MF Global sum of customer portfolio changes (small exposure customers) relative to customers with medium or small MF Global exposures.

Table IX reports the daily aggregate portfolio changes for the group of large exposure customers. In the week prior to the bankruptcy, there is little trading activity in other FCMS by these customers. Approximately 47 billion USD was transferred to these FCMs on November 4th, and by the end of the week traders had reduced their positions by 32.9 billion.

In parenthesis, Table IX shows z-score test statistics for the daily portfolio changes. These test statistics are calculated based upon the mean and standard deviation of the daily portfolio changes for the same group of customers over the November 2010 to September 2011 period. Trading during the pre-bankruptcy October period is largely insignificant. While position exits during the fire sale week of November 11 are consistently significant.

B.1. Regression Tests

We can use a regression framework to test whether pre-bankruptcy exposure to MF Global can explain the cross-section of post-transfer portfolio liquidations by MF Global clients. We calculate the change in portfolio size between November 1, 2011 and November 10, 2011. This covers the period from the beginning of the bankruptcy to the end of the transfer period. Notional portfolios are calculated using prices as of November 1, 2011 to control for changes in market conditions over the observation window. Changes in notional portfolio size by customers are driven by trading decisions over the sample period.

The following model is estimated:

$$\Delta Port_i = \alpha + \beta_1 MF\_Port\_PCT_i + \beta_2 Initial\_port\_size_i + \epsilon \tag{6}$$

Table IX: Daily Aggregate Trading by High Exposure MF Global Customers(billions USD)

Table presents z-score test statistics for the daily portfolio changes around the MF Global's bankruptcy dates. These test statistics are calculated based upon the mean and standard deviation of the daily portfolio changes for the same group of customers over the November 2010 to September 2011 period.

Date	Other FCMs	MF Global
2011-10-25	0.030	-3.125
	(0.080)	(-0.185)
2011-10-26	0.000	-5.900
	(0.066)	(-0.341)
2011-10-27	-0.051	2.435
	(0.043)	(0.127)
2011-10-28	0.118	1.640
	(0.120)	(0.083)
2011-10-31	-0.034	-0.819
	(0.051)	(-0.055)
2011-11-01	2.751	-3.605
	(1.324)	(-0.212)
2011-11-02	1.322	-1.476
	(0.671)	(-0.092)
2011-11-03	6.478	-4.796
	(3.029)	(-0.279)
2011-11-04	46.817	-21.499
	(21.479)	(-1.216)
2011-11-07	-10.777	-27.940
	(-4.863)	(-1.578)
2011-11-08	-8.172	-0.002
	(-3.672)	(-0.010)
2011-11-09	-10.052	-0.002
	(-4.531)	(-0.010)
2011-11-10	-3.884	-0.000
	(-1.711)	(-0.009)
2011-11-14	-0.462	-0.007
	(-0.145)	(-0.010)
2011-11-15	-0.084	-0.003
	(0.027)	(-0.010)

Where $\Delta Port_i$ is the percentage difference in customer aggregate portfolio size between Nov 1 and Nov 10, 2011. $MF\_Port\_PCT_i$ is the percentage of the customers portfolio held at MF Global on November 1, 2011. We hypothesize that greater exposure to MF Global is associated with larger portfolio reductions as the resulting margin call will be proportionally larger for clients who predominantly trade through MF Global. $Initial\_port\_size_i$ is the size of the customers notional portfolio in billions USD.

Table X: Portfolio Liquidations and Exposure to MF Global
Table presents the estimates from the Equation 6 regression. $\Delta Port_i$ is the percentage difference in customer aggregate portfolio size between Nov 1 and Nov 10, 2011. $MF\_Port\_PCT_i$ is the percentage of the customers portfolio held at MF Global on November 1, 2011. $Starting\_port\_size_i$ is the size of the customers notional portfolio in billions USD.

	coef	**std err**	**z**	**P> |z|**
Intercept	0.0030	0.041	0.075	0.941
MF_Port_PCT	-0.1009**	0.049	-2.077	0.038
Initial_port_size	-0.0076	0.016	-0.470	0.638
Adj. R Squared	0.012			
Degrees of Freedom	321			
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table X provides the estimates for the change in MF Global customer portfolio size. We show that a 1% increase in MF Global exposure is associated with an expected .1% decrease in portfolio size at the end of the transfer period. Customers with 50% of their positions with MF Global are expected to reduce their portfolio size by 5%.

C. MF Global Returns

We can test whether these MF global fire-sales had observable market level affects. If MF Global clients liquidate \$60 billion USD in notional value in fire-sales, this mass-selling activity may disrupt the markets being sold if these customers are exiting positions from

Table XI: Comparison of Actual vs Sector Returns for sold positions
Table presents the realized returns of MF Global markets and the realized returns to other markets within comparable sectors, as well as their difference and t-statistics.

Date	Markets	return	sector ret	diff	T-Stat	p value 5%
Nov 7	69	0.011	0.004	0.007	1.367	-0.007
Nov 8	11	-0.028	0.001	-0.029	-2.025	-0.027
Nov 9	14	-0.035	-0.012	-0.023	-2.124	-0.018

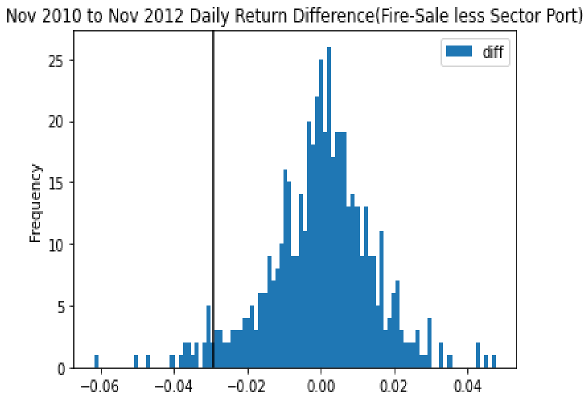
the same set of markets. These market disruptions are not driven by information about the particular market, but instead by the liquidity constraints of MF Global customers who are exiting positions in a fire sale who just happen to be holding positions in the same market.

For November 7 through November 9 when the fire sales occurred, we identify the group of markets where MF Global customers exited more than .75% of open interest. We also filter for markets that had a minimum of 500 contracts in open interest and positive settlement prices. To control for potential market information effects, we calculate benchmark returns using the mean sector return for each contract[10].

For a two year window around the MF Global bankruptcy, we calculate the difference between the realized return of each market and its benchmark to measure the distribution of excess returns. On November 8, 2011, when MF Global clients were exiting their positions, this set of 12 markets under-performed the benchmark by 2.9%. The 5% left tail of the 2 year excess return distribution is -2.7%. Using this realized distribution of excess returns, we compute a T-value of -2.025 for the November 8 under-performance. These statistics are presented in Table X and Figure 5 depicts the distribution of actual returns for the 11 markets against the benchmark returns.

[10]For the purposes of calculating benchmark returns, market sectors are defined as the leading two digits of the CFTC commodity code listed in the publicly available Commitments of Traders Report (COT Report)

Figure 5: Distribution of abnormal market returns Nov. 8 2011
Figure presents the distribution of abnormal returns for all the markets in our sample. The vertical black line marks the return of 11 MF Global markets on November 8, 2011.



VI. Conclusion

In this paper we explore how large price shocks can initiate margin breaches, which lead to fire sales. We provide evidence on how large price shocks can cause traders to reduce their exposure in their total futures portfolio, including in non-shocked markets. We show that this is specifically true when funding costs (TEDrate) are high, however not if the trader is a large trader suggesting well-capitalized traders are not as impacted.

Next, we use common traders to connect markets. We specifically show how shocks can propagate to other markets when markets are strongly connected through common traders. In order to control for the possibility of fundamentals driving shocks in both markets, we focus on shock propagation to uncorrelated markets. We find that returns and liquidity in uncorrelated markets are both adversely impacted due to spillovers from shocked markets.

Finally, we use the MF Global collapse as a quasi-experimental identification methodology. The collapse of MF Global was an exogenous shock to the positions of MF Global customers, who had to come up with considerable margin to keep their futures positions. Our estimates suggest customers with 50% of their positions with MF Global are expected to reduce their portfolio size by 5%.

References

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2015. "Systemic Risk and Stability in Financial Networks." *American Economic Review*, 105(2): 564–608.

Amihud, Yakov. 2002. "Illiquidity and stock returns: cross-section and time-series effects." *Journal of Financial Markets*, 5(1): 31–56.

Anton, Miguel, and Christopher Polk. 2014. "Connected Stocks." *The Journal of Finance*, 69(3): 1099–1127.

Babus, Ana, and Péter Kondor. 2018. "Trading and Information Diffusion in Over-the-Counter Markets." *Econometrica*, 86(5): 1727–1769.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler. 2005. "Comovement." *Journal of Financial Economics*, 75(2): 283–317.

Barbon, Andrea, Marco Di Maggio, Francesco Franzoni, and Augustin Landier. 2019. "Brokers and Order Flow Leakage: Evidence from Fire Sales." *The Journal of Finance*, 74(6): 2707–2749.

Basak, Suleyman, and Anna Pavlova. 2013. "Asset Prices and Institutional Investors." *American Economic Review*, 103(5): 1728–58.

Braverman, Anton, and Minca Andreea. 2014. "Network of Common Asset Holdings: Aggregation and Measures of Vulnerability." Mimeo, Available at SSRN: http://ssrn.com/abstract=2379669.

Brunnermeier, Markus K, and Lasse Heje Pedersen. 2009. "Market liquidity and funding liquidity." *The review of financial studies*, 22(6): 2201–2238.

Coval, Joshua, and Erik Stafford. 2007. "Asset fire sales (and purchases) in equity markets." *Journal of Financial Economics*, 86(2): 479–512.

Diebold, Francis X, Laura Liu, and Kamil Yilmaz. 2017. "Commodity connectedness." National Bureau of Economic Research.

Edmans, Goldstein, and Jiang. 2012. "The Real Effects of Financial Markets: The Impact of Prices on Takeovers." *The Journal of Finance*, 67(3): 933–971.

Elliott, Matthew, Benjamin Golub, and Matthew O. Jackson. 2014. "Financial Networks and Contagion." *American Economic Review*, 104(10): 3115–53.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T. Lundblad. 2011. "Regulatory pressure and fire sales in the corporate bond market." *Journal of Financial Economics*, 101(3): 596–620.

Greenwood, Robin, Augustin Landier, and David Thesmar. 2015. "Vulnerable banks." *Journal of Financial Economics*, 115(3): 471 – 485.

Heckinger, Richard. 2014. "MF Global: a case study of liquidity risks." *Journal of Financial Market Infrastructures*, 79–96.

Huang, Sheng, Matthew C. Ringgenberg, and Zhe Zhang. 2022. "The Information in Asset Fire Sales." *Management Science*.

Kahraman, Bige, and Heather Tookes. 2019. "Margin Trading and Comovement During Crises*." *Review of Finance*. rfz019.

Kruttli, Mathias, Phillip Monin, and Sumudu Watugala. 2019. "The Life of the Counterparty: Shock Propagation in Hedge Fund-Prime Broker Credit Networks." , (19-03).

Maggio, Marco Di, Francesco Franzoni, Amir Kermani, and Carlo Sommavilla. 2019. "The relevance of broker networks for information diffusion in the stock market." *Journal of Financial Economics*, 134(2): 419–446.

Peterson, Paul, E. 2013. "Behind the Collapse of MF Global." *Choices*, Quarter 2.

Shleifer, Andrei, and Robert Vishny. 2011. "Fire Sales in Finance and Macroeconomics." *Journal of Economic Perspectives*, 25(1): 29–48.

A. Appendix - Connection Example

In this section we provide a numerical example of our connection measure.

A. Connection Example

Let us assume that there are four traders (T_1, T_2, T_3, T_4) trading in three markets (A, B, C). Note that each market has a different size and traders can have long or short positions in each market. Table A1 shows a hypothetical example of how each one of these four traders has exposure in each market.

Table A1: Example of Trader Positions in Different Markets

	A	**B**	**C**
T_1	30	-15	1
T_2	-12	0	4
T_3	-18	5	0
T_4	0	10	-5

We aggregate this trader position matrix M into a cross-holdings matrix, C. First we define H as a $0, 1$ indicator matrix to identify if a trader has a position in a given market. Next, the cross-holding matrix is defined as $C = H^{'}M$ and diagonal of C is defined as the size of each market in M. Market sizes are calculated as: $((abs(Long) + abs(Short))/2$, where $Long$ and $Short$ represent the sum of long and short contracts in that market, respectively[11].

Table A2 shows the calculated cross-holdings matrix, C. For example, element $(A, B) = -10$ indicates that traders with at least 1 position (long or short) in market A have a net short position of $-10 exposure in market B.

Table A2: Example of Cross Market Holdings of Traders

	A	**B**	**C**
A	30	-10	5
B	12	15	-4
C	18	-5	5

For the first term of the connection measure, we need to calculate aggregate joint portfolios, $Port_T$. For the joint portfolio of traders in markets A and B we calculate row sums of the rows with non-zero elements for these two markets in our market matrix M which would be T_1 and T_3. In our example, the joint portfolio vector is:

[11]While normally long contracts should equal short contracts in futures markets, we do not observe positions of 100% of the traders in our data since those who hold positions below a certain limit do not have to report. See section II for more details

Table A3: Example of Cross Market Holdings of Traders

	(A,B)	**(A,C)**	**(B,C)**
Joint Portfolio	69	62	61

In matrix C each element, (k, j), has a corresponding joint portfolio computed in Table A3. For instance in matrix C, element $(k = B, j = C)$ has the value of -4 and a corresponding joint portfolio (A, B) of 61. We divide each element, (k, j), of matrix C by the associated joint portfolio value. The diversification component of the connection matrix is the absolute value of the transpose of this matrix. Additionally, the diagonal of this matrix is set to 0 as markets do not have a connection to themselves. In Table A4, traders in market C hold 18 contracts of market A which has a weight of .290 in the combined (A, C) portfolio of 62 units. In other words, a shock to market A affects 29% of the aggregate portfolio of traders holding both market A and C.

Table A4: Diversification Component

	A	**B**	**C**
A	0	.174	0.290
B	0.145	0	0.082
C	0.081	0.066	0

The market integration term in Table A5 is matrix C divided element-wise by its diagonal. This value measures the portion of open interest in market j by traders in market k. In our example, traders in market B hold -4 contracts in market C which has an open interest of 5 or 80% of the short open interest in the contract. This suggests that market C is highly integrated with market B as 80% of the short open interest in C is held as part of a portfolio that is exposed to B. This integration matrix is not symmetric. Traders in C hold -5 contracts in market B, or one third of the open interest in B. Market B is less integrated with market C as traders T_1 and T_2 hold market B but have little or no exposure to market C.

Table A5: Integration Component

	A	**B**	**C**
A	1	-.667	1
B	.4	1	-0.8
C	0.6	-0.333	1

Finally, to compute the final connection matrix, Table A6, we take the cross-product of the diversification and integration component matrices.

The connection example in table A6 shows that market A (row 1) has strong connections to markets B and C. Traders in market A make up large portions of the open

Table A6: Connection Matrix

	A	**B**	**C**
A	0	-0.115	0.29
B	0.058	0	-0.66
C	0.048	-0.022	0

interest in markets B and C (high integration). Shocks to market A also affect a large portion of the aggregate trader portfolios (A, B) and (A, C)(low diversification).

In our example, market C has weak connections to markets A and B. While C is highly integrated with markets A and B, this integration is attenuated by the small portfolio weight traders in A and B allocate to market C in the aggregate portfolio. Any shocks that occur in market C are unlikely to be transmitted outside of the trader portfolios as the shocked positions are small relative to the overall trader portfolios (A, C) and (B, C).