# Ex-ante and Ex-post Effects of Price Limits in Commodity Futures Markets

by

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*After October 1987, financial crisis, market regulators created dispositive called circuit breaks to contain high levels of volatility. As a type of circuit break, price limits were adopted not only on stock markets but in commodity futures contracts as well, however, its effects are not clear. The present study aimed to evaluate price limit ex-ante effects on the four major wheat futures markets by adopting Brogaard and Roshak (2015) methodology by estimating the probability of extreme movements and limit moves conditional to extreme movements and its ex-post effects on trading activity by contrasting the volume curve on limit days with a counterfactual volume curve that simulates a scenario where price limits were not hit. The results show that tighter limit levels decrease the probability of extreme movements by approximately 0.008% having an overall (four markets included) baseline probability of extreme moves equals 1.11% which agrees with the Holding Back hypothesis assuming extreme movements as a proxy for volatility. On the other hand, the probability of limit moves conditional to extreme movements increases when limit levels are tighter by approximately 0.066% with an overall baseline of 0.05% which supports the "Magnet" hypothesis. Regarding the ex-post effects, longer periods where prices stay at the limit level result in trading activity lost, however, if prices return to limit range but bounce back to a limit lock, the longer the gap between limit locks trading session experience an increase in trading activity. Moreoever, the ex-post effects on trading activity are more intense in Chicago relative to Kansas City because Chicago present a higher trading volume on average.*

**Key words:** circuit breaker, price limits, trading activity, ex-ante effect, ex-post effect

## Introduction

Commodity futures markets are used by producers and consumers as a risk management tool to hedge themselves against price risk. Therefore, futures prices need to be trustworthy benchmarks of the actual value of the underlying commodity. To guarantee price integrity, futures market prices should be subject to volatility derived from fundamental supply and demand factors but not volatility coming from non-fundamental reasons. In particular, futures prices should not be subject to bubbles and other feedback loops where high prices lead to even higher prices. Exchanges use mechanisms called circuit breakers which aiming to halt trading when this latter kind of volatility causes prices to overreact. Trading halts and price limits are examples of circuit breaks used by exchanges around the globe and cast multiple viewpoints about its effectiveness. Proponents would say that circuit breaks work as a speed bump in a rapid decline or increase. Critics would say that circuit breaks that interruptions inhibit efficient pricing.

To illustrate how they work, trading halts were created after the October 1987 market crash and are based on levels of change in price relative to the previous close. For instance, On S&P 500 index, NYSE sets three levels of change in price as their threshold, 7%, 13%, and 20%. If the index has a change in the price of 7% up or down, there is a trading halt of 15 minutes. After this period trade resumes and, if the second level gets hit, then another trading halt of 15 minutes is triggered. In case the third level gets hit, then trading stops for the rest of the day.

For price limits, let's consider that a certain exchange based on previous price behavior set a price limit of 55 cents for the corn futures contract. If the previous settlement price was $3.75 per bushel, the limit range would be between $ 4.30 and $3.20 per bushel. As a form of "too far, too fast” condition to restrict volatility, price limits are set based on current market information aiming to resemble a realistic volatility status. In more detail, the limit range is established daily by a specific amount higher or lower than the previous day’s settlement price. Nonetheless, restrict price to freely ranges brings questions regarding its effects on price behavior before and after a limit move. Price limits are the most used method to mitigate price volatility in commodity futures markets since the 20th century and is the focus of this study since its effects on this markets are still unclear Daily price limits may affect trading activity and prices after prices hit limit bounds (ex-post) and before a limit hit (ex-ante). In theory, price limits were developed to restrain excessive volatility that could drive prices quickly to levels not sustained by fundamental reasons, but skeptical to the policy would say the opposite due to its effect on trading behavior. Moreover, with limits, there is no direct way to calculate the impairment caused on trading activity since the alternative scenario where limits do not apply doesn’t apply to the same market circumstances. With that, what are the ex-ante effects of price limits that could influence prices to get to the limit? Moreover, what is the comportment of trading activity before, when the limit gets hit and after?

Price limits ex-ante effects could be reflected in trade behavior. Traders could use limit levels as a signal to develop their strategies. In face of a high volatility period and extreme move in price leading it to the limit level, traders could anticipate their trades as they visualize a real chance that price hits the limit which Subrahmanyam (1994) addresses as the “Magnet” hypothesis. The opposite could also happen, where traders in face of a high volatility period would delay their orders for a stillness moment when prices would be subjected to regular levels of volatility described by Subrahmanyam (1997). A good way to untangle this dilemma is to estimate the likelihood of extreme moves or limit hits conditional to price limits in the commodity futures market.

Trading activity empirically is affected on both moments, before and after a limit hit essentially being shifting back and forward, however, its main change is observed from an ex-post perspective. Right before a limit hit, volume tends to spike to levels relatively similar to the open or close decreasing drastically during the period where the limit is locked and resuming with another peak if prices return to levels below the limit. This market phenomenon fairly looks like another U-shaped pattern investigated by Admati and Pfleiderer (1988) inside the day. This shift in trading activity would certainly impose a cost. Without a scenario where price limits are not applied, one way to overcome this obstacle is to estimate this cost by calculating the difference in trading activity between the volume in a limit day and a counterfactual scenario that would represent the absence of price limits.

This paper assesses the effects of price limits on price behavior before and after limits are hit. We also estimate the realized costs of imposing price limits in terms of shifted trading activity. Both efforts rely on the presence of other unconstrained or less constrained markets to estimate the relevant counterfactual and trading activity that would have occurred in the absence of price limits. To better identify this counterfactual, we apply our analysis to the wheat futures complex, the four actively traded and liquid wheat futures contracts originally based in Chicago, Kansas City, Minneapolis, and Paris.

In the ex-ante sphere, we use a similar methodology as Brogaard and Roshak (2015) on estimating the probability of a limit move and an extreme move conditional to specific features of the commodity futures market through a Difference-in-difference linear probability model. In our study, three elements are crucial to set our model. First is the possibility to test price limit policy as our treatment by using the Paris wheat futures contract as our control which is feasible by not being under the price limit regime. Second is based in the fact that after the commodity boom in 2008, due to frequent large price changes, CME Group abandoned a constant price limit and established a periodical review on limit levels for various commodities which is the treatment in our model to answer if a tighter limit level increase or decrease the likelihood of a limit move. Third is in our definition of extreme movements. Price changes equivalent to 25 cents are addressed as extreme movements. Knowing the likelihood of extreme movements can enlighting the ex-ante effects of price limit on price behavior.

Trading activity could also be subjective to the ex-post effects of price limits. Admati and Pfleiderer (1988) investigate intraday patterns in stocks evoking the U-shaped theory over volume. We can apply this concept in commodity futures since empirically daily volume behaves in a U-shaped curve (volume peak at the opening following by lower levels throughout the trading session and surging again at the end of the trading session). Theoretically, if there is an ex-post effect of price limits, a volume U-shaped pattern could be observed where volume peak at the moment prices hit the limit level and reduces as prices keep locked at the limit level following by a considerable increase when prices return to price range. Unfortunately, a little has been discussed in the literature about trading activity and price limits in agricultural commodity markets, therefore this is study throw light on the subject.

As our ex-ante effects estimates, a tighter limit level reduces the probability of an extreme movement for both treated and control variables, which corroborate with the "Holding Back" hypothesis taking extreme movements as a proxy for volatility as Brogaard and Roshak (2015). However, regarding the probability of limit moves conditional to extreme movements, we observe the opposite conclusion. A tighter limit level increases the likelihood of a limit move corroborating with the "Magnet" hypothesis suggested by (Subrahmanyam, 1994). Ex-post effects of price limit on trading activity have a similar ambiguous behavior. Trading activity has a unique behavior when prices are about to hit the limit. Around a limit hit, trading activity shifts concentrating seconds before a limit hit and creating a peak on volume. Seconds before the hit, trading activity tends to reduce drastically surging again if prices return inside the limit bound. This behavior is subject most by how long prices will stay at the limit level and/or if prices will hit the limit level multiple times in a session. Our results indicate that the longer is the period where prices are at the limit, the greater is the trading activity loss in comparison with a possible scenario where price limits would not apply which is expressed by our counterfactual volume curve. Moreover, if prices hit the limit level multiple times in a session and the time between hits are longer, the trading session can experience an increase in trading activity since volume speak right before the limit hit is not compensated by the loss in trading activity when price stay at the limit for a longer time.

**Methodology**

For this study, we use daily and intraday wheat futures contracts price and volume data from January 2007 to April 2019 for the world wheat futures market complex: the Chicago Mercantile Exchange (CME) Soft Red Winter Wheat (SRW) and Kansas City Hard Red Winter Wheat (KC HRW) contracts, the Minneapolis Grain Exchange (MGEX) Hard Red Spring Wheat (HRSW) contract, and Euronext Milling Wheat N° 2 (EBM) contract. For brevity, we refer to each contract using the city with which it is commonly associated (i.e. Chicago, Kansas City, Minneapolis, and Paris, respectively). For Paris data, prices are converted to US currency and quantity aiming to match CME price and contract specification.

Daily price data were collected from Bloomberg Terminal. For each year, all delivery months are collected it, however after 2015, Euronext changes its delivery months for wheat contracts. For Euronext EBM contracts, the delivery months are November (X), January (F), March (H) and May (K) until May 2015 and then September (U), December (Z), March (H) and May (K) from September 2015 onwards. In respect to CME contracts, SRW and KC HRW cover March (H), May (K), July (N), September (U) and December (Z).

Intraday price and volume data were purchased from CQG Inc. Data is available for the Kansas City, Chicago, and Paris contracts. This data reports the price and volume for every trade in each market in chronological order, time-stamped to the minute.

There are two sections in our methodology. The first one describes all procedures and models to estimate the ex-ante effects of price limits by estimating the probabilities of extreme movements and limit movements under different conditions. The second describes all procedures to estimate ex-post effects of price limit on volume by constructing a counterfactual volume curve to project what would happen with trade activity if there were no limit hits. With that, we compare our counterfactual volume with the actual volume during limit days to assess price limits effect on trading activity and estimate its costs.

*Price limit ex-ante evaluation*

To evaluate ex-ante effects of price limits, market moments and factors have to be taken into consideration whereas they could influence price trajectory towards the limit. Our selected market moment is the existence of extreme movements. Large price move could be associated with limit hits as traders could use those as a signal to anticipate or delay their orders. Moreover, price limit levels and even other market factors like volatility, more active market, and public report releases could affect the likelihood of an extreme movement or even a limit hit. Therefore, to assess the ex-ante effects of price limits we estimate the probability of extreme movements and the probability of limit moves conditional to extreme movements in the wheat futures market complex, in a difference-in-difference approach using Linear Probability Model (LPM) adapted from Brogaard & Roshak (2015). With that we estimate:

- *P(extreme movements)*

The Probability of extreme movements due to different markets, limit levels, limit level changes through time, volume, days to expiration, delivery period, and exogenous variables such as VIX Index, and fundamental reports (i.e. WASDE).

- *P(Limit movements | extreme movements)*

Probability of limit movements given extreme movements happened due to different markets, limit level, limit level changes through time, volume, days to expiration, and exogenous variables such as VIX Index, and fundamental reports (i.e. WASDE).

The Difference-in-difference approach is possible since Paris contracts do not use daily price limit policy. Moreover, CME Group resets the daily price limit every six months since 2014 which gives variation in the "treatment" variable across time. The analysis imposes extreme movements as an oscillation in price greater or equal to 25 cents. For limit move, change in price relative to the previous day price close must be biding with the respective daily limit on the given day. CME group reset the daily price limit levels every six months since 2014. Figure 1 shows how daily price limit levels behave through time. Before 2014, limit levels were constant and just had a reset process in 2008 due to the commodity boom prices which made limit moves more frequent since limit levels were not effective to those volatility levels. The first reset happens in May based on the average of the settlement price from the 45 consecutive days of the nearest July contract before and on the business day before April 16th. The calculated average multiplied by 7% and rounded to the nearest 5 cents per bushel, or 30 cents per contract, whichever is higher, will be the preliminary initial price limit. The same procedure is done to KC HRW contract and the higher preliminary initial price limit will be the new initial price limit for Wheat futures and will become effective on the first trading day in May until the last trading day in October.

The second reset occurs on the first trading day in November based on the average of the settlement price from the 45 consecutive days of the nearest December contract before and on the business day before October 16th. The calculated average multiplied by 7% and rounded to the nearest 5 cents per bushel, or 30 cents per contract, whichever is higher, will be the preliminary initial price limit. The same procedure is applied to the Kansas City contract and the higher preliminary initial price limit will be the new initial price limit for Wheat futures and will become effective on the first trading day in November until the last trading day in next April. Those changes in price limit levels are important to our model to evaluate the effect of price level changes through time on estimate probabilities. Minneapolis's daily limit is fixed in 30 cents for the whole period.

*Extreme move probability models*

Our study proposes two models for each extreme move probability estimative. The first model estimating the probability of extreme movements discriminating price limit in levels. The second model discriminate price limit levels as "tight" or not relative to the previous price limit level. Our first model for *P(Extreme movements)* is shown in Equation 1.

$$(1)\ Extreme_{m,c,t} = \beta_0 + \sum_{m=1}^{4} \beta\, Markets_{m,t} + \beta_5 Limit50_{m,c,t} + \beta_6 Limit35_{m,c,t} + \beta_7 Limit30_{m,c,t} + \sum_{n=1}^{10} \beta\, Reset_{m,c,t} + \beta_{18} LagExtreme_{m,c,t} + \beta_{19} LagLimitMove_{m,c,t} + \beta_{20} Life_{m,c,t} + \beta_{21} Delivery_{m,c,t} + \beta_{22} VIX_t + \beta_{23} REPORTS_t$$

*Extreme* is a dummy variable equal to 1 if, on market *m*, contract *c* at day *t* experienced an extreme movement. *Markets* are dummy variables to discriminate which of the four markets the contract *c* belongs (i.e CBOT, KC, MGEX or Euronext-Paris) at day *t. Limit50*, *Limit35,* and *Limit30* are dummy variables to express the price limit levels on market *m*, contract *c* at day *t*. *Limit50* is equal to unity for price limit levels less or equal to 50 cents and 0 otherwise. *Limit35* is equal to unity for price limit levels less or equal to 35 and 0 otherwise and *Limit30* is equal to unity for price limit levels less or equal to 30 and 0 otherwise. The ten *Reset* variables are dummy variables for each reset on price limit levels in CBOT and KC which happens every 6 months. *Lag Extreme* for market *m*, contract *c*, and day *t* is a dummy variable equal to one if the previous day experienced a extreme movement. *Lag Limit Move* for market *m*, contract *c*, and day *t* is a dummy variable equal to one if the previous day experienced a limit move. *Life* variable corresponds to days before the expiration on market *m*, for contract *c* at day *t*. *Delivery* is a dummy variable standing for the delivery period (last twelve days of the contract) when price limits are not applied and are equal to 1 when contracts are at this period or 0 otherwise. The exogenous variables are *VIX* for CBOE Volatility index and *REPORTS* is expressed as a dummy variable equals to 1 for time t when a fundamental report is released (i.e. WASDE).

$$(2)\ Extreme_{m,c,t} = \beta_0 + \sum_{m=1}^{4} \beta\, Markets_{m,t} + \beta_5 Tight_{m,c,t} + \sum_{n=1}^{10} \beta\, Reset_{m,c,t} + \beta_{16} LagExtreme_{m,c,t} + \beta_{17} LagLimitMove_{m,c,t} + \beta_{18} Life_{m,c,t} + \beta_{19} Delivery_{m,c,t} + \beta_{20} VIX_t + \beta_{21} REPORTS_t$$

The second model for P(Extreme movements) is shown in equation 2. All variables are the same except that *Limit50*, *Limit35*, and *Limit30* are replaced by *Tight* which is a dummy variable equals to unity when the daily limit is narrower relative to the previous level and 0 otherwise. The *Tight* variable is an attempt to synthesize the dynamic effect of limit levels due to its periodical reset. In theory, tighter limits could increase the probability of extreme movements and limit move since the price range allowed is narrow in comparison with the previous price range established by the limit bounds.

*Limit move probability models*

We design two models to estimate the probability of limit moves. The third model uses the same concept as those models before, however, it estimates a conditional probability of a limit movement given an extreme movement occurrence and is shown in Equation 3:

$$(3)\ LimitMove_{m,c,t} = \beta_0 + \sum_{m=1}^{4} \beta\, Markets_{m,t} + \beta_5 Limit50_{m,c,t} + \beta_6 Limit35_{m,c,t} + \beta_7 Limit30_{m,c,t} + \sum_{n=1}^{10} \beta\, Reset_{m,c,t} + \beta_{18} LagExtreme_{m,c,t} + \beta_{19} LagLimitMove_{m,c,t} + \beta_{20} Life_{m,c,t} + \beta_{21} VIX_t + \beta_{22} REPORTS_t$$

*LimitMove* is a dummy variable equals to unity when the difference in price relative to previous day close price on market *m*, contract *c*, at day *t* is binding with the limit level at day *t* or 0 otherwise. All other variables are the same as Equation 1 except for *Delivery* which during that period price limits do not apply.

As our fourth model, a conditional probability of a limit movement given an extreme movement occurrence is shown in Equation 4. The variables are the same as Equation 3, however, limit levels are replaced by *Tight* variable, which is a dummy variable equal to unity when the limit price level is tighter or equal relative to the previous price limit level.

$$(4)\ LimitMove_{m,c,t} = \beta_0 + \sum_{m=1}^{4} \beta\, Markets_{m,t} + \beta_5 Tight_{m,c,t} + \sum_{n=1}^{10} \beta\, Reset_{m,c,t} + \beta_{16} LagExtreme_{m,c,t} + \beta_{17} LagLimitMove_{m,c,t} + \beta_{18} Life_{m,c,t} + \beta_{19} VIX_t + \beta_{20} REPORTS_t$$

After evaluating the probabilities estimated for each model, the models with greater performance are used to display estimate probabilities using our control (Paris) data and other three markets

(CBOT, KC, and MGEX) aiming to evaluate our treatments (reset window period) in a difference-in-difference layout. The plots are confronted with the regression coefficients for each probability estimate.

*Price limit ex-post evaluation*

To estimate the ex-post effects of price limits we assess how limit moves affect trading activity using intraday data of wheat futures contract from two major markets, Chicago and Kansas City. Our data are composed of 392 limit days occurred in Chicago and Kansas City from 2008 until 2017.The data shows that trading activity can be shifted according to limit hit and its duration. The longer price limits bind the more likely it becomes that trading volume is curtailed. In contrast, a short period with limit bonded, could likely behave as a price shock and increase trading activity. Additionally, volume peak could happen moments before the limit hit, thus indicating a lag effect of price limits on trading activity. Changes in trading activity could result in costs such as a decrease in price discovery and trading activity lost. Consequently, we estimate the ex-post effect of price limits on trading activity by observing the behavior of volume during a limit move day and compare it with a counterfactual volume curve which is a representation of what could happen with volume if there was no limit hit.

The intraday data used has a minute resolution allowing to identify the exact minute when prices hit the limit, however not exactly when inside the minute. Since electronic trading enables a larger number of orders to be executed in seconds, this resolution prevents us to measure how much trading activity we have before, before, at the limit, and during the limit lock. To overcome this limitation, since the filled orders are placed chronologically in the data, we manage it to equally distribute all trades that happened within a minute yielding a “sequential intra-minute” time-bin resolution. After arranging the data to this resolution, we construct our counterfactual volume curve. We measure the net loss or gain of trading activity due to limit hits as the difference between actual volume on the limit day and counterfactual volume before, during, and after the period where a lock-limit event occurs. The counterfactual volume series estimates what would have happened if trading was not halted due to the limit. To preserve any market condition in favor of a realistic comparison we estimate counterfactual volume using the average intraday volume in each time-bin using the average over the last 5-7 days. To accommodate higher average trading volume in general on limit move days we adjust our counterfactual volume series to narrow any possible gap between volume levels since days that are not limit move days and are used to compute our counterfactual tend to present lower daily volume on average.

$$(5)\quad Adjusted\ Counterfactual\ Volume_{m,c,t,i} = Counterfactual\ Volume_{m,c,t,i}\ \frac{\sum_{i=1}^{n} Actual\ Volume\ limit\ day_{m,c,t,i}}{\sum_{i=1}^{n} Counterfactual\ volume_{m,c,t,i}}$$

Where the *Adjusted Counterfactual Volume* on market *m*, contract *c*, day *t* at time bin *i* is equal to the *Counterfactual Volume* for market *m*, contract *c*, day *t* at time bin *i* multiplied by the ratio between the total *Actual Volume* and the total *Counterfactual Volume* on market *m*, contract *c*, day *t* at time bin *i*. With the counterfactual adjusted, the data is merged based on the time-bin stamp and the *Net Trade* variable on market *m*, contract *c* at limit day *t* is calculated which is essentially the difference between the total *Adjusted Counterfactual Volume* on limit day *t* for all time-bin *i* and the total *Actual Volume on limit day t* for all time-bin *i*.

$$(6)\ Net\,Trade_{m,c,t} = \sum_{i=1}^{n} Adjusted\ Counterfactual\ Volume_{m,c,t,i} - \sum_{i=1}^{n} Actual\,Volume\ limit\ day_{m,c,t,i}$$

Trading volume generally is larger than the counterfactual right before and at the period when the limit hits and lower when the limit has been hit for a long time. When prices return to levels inside the limit bound, trading volume peaks again creating a similar U-shaped pattern. This illustrates that price limits have a lag effect on trading activity. Therefore, three variables are created to capture those effects. The *Min. Lock* variable, which is the sum of minutes when prices stayed locked on the limit level on market m, contract c at limit day t is created to capture the duration effect. Since prices are locked at the limit level, some market participants understand that prices are not realistic and reduce their trades at this level thus reducing trading activity. The *Min. lock with Gap* variable is the period starting from the moment of the first limit hit until the end of the last limit hit on market *m*, contract *c* at limit day *t* and is calculated to make able to get our third variable The *Gap* variable is essentially the total minutes that prices are not locked at the limit level between the moment of the first limit hit until the end of the last limit hit and controls the lag effect of price limits on trading activity.

$$(7)\ \ Gap_{m,c,t} = Min.Lock_{m,c,t} - Min.LockWithGap_{m,c,t}$$

## *Trading activity dynamic models*

Positive values of net trade indicate trading activity loss because the counterfactual volume is higher than the actual volume. Due to the limit hit, part of the volume who was supposed to exist based on our counterfactual volume curve is lost. On the other hand, negative values of net trade indicate trading activity gain. The actual volume during a limit day is greater than our counterfactual volume curve which shows an increment on trade activity due to the limit hit.

To identify relationships between our measure of the trading volume change in trading volume caused by the imposition of price limits, we estimate five regression models with net trade as the dependent variable. The first model considers the level of *Net Trade* as a function of *Min Lock, Gap*, *Total Volume* and our control variables *Lag Extreme*, *Vix*, *Report,* and *Life* used on previous models for our ex-ante analysis. The second model estimates exclusively the level trade loss (positive net trade values) using the same controls as the first model control variables and the third one estimates exclusively the level of trade gains (negative net trade values) using the control variables used before. Our fourth and fifth model is similar to second and third, however, our dependent variables are expressed in natural logarithm form to provide margin effects in percentage (Log-level coefficients)

For the first model, we use *Net trade* on market *m*, contract *c* at limit day *t* as our dependent variable without distinguishing positive and negative values. As our control variables, *KC* is a dummy variable equals unity when *Net trade* happens on Kansas City wheat contract *c* at limit day *t*. *Min.Lock* is the sum of minutes that price stayed locked on the limit level on market *m*, contract *c* at limit day *t*. The *Gap* is the total amount of minutes where the price is not locked at the limit level between the moment of the first limit hit until the end of the last limit hit on market *m*, contract *c* at limit day *t*. The variables KC_Min.lock and KC_Gap are interaction variables between our Market variable *KC* and our variables of interest *Min.lock* and *Gap.* They are created in order to know the intensity of the effect of our variables of interest on trading activity for both markets, Kansas City and Chigaco. *TotalVol* is the total volume on market *m*, contract *c* at limit day *t*. *LagExtreme* is a dummy variable equals to unity when the day before a limit day *t*, on market *m* and contract *c* (price change equals or greater than 25 cents). *VIX* represents the CBOE Volatility index at limit day *t*. *Report* is a dummy variable equals unity when any supply and demand related report is release at limit day *t* and *Life* is the number of days before the expiration of contract *c*, on market *m* at limit day *t*.

$$(7)\ Net\ trade_{m,c,t} = \beta_0 + \beta_1 KC_t + \beta_2 Min.Lock_{m,c,t} + \beta_3 KC\_Min.lock_{m,c,t} + \beta_4 Gap_{m,c,t} + \beta_5 KC\_Gap_{m,c,t} + \beta_6 TotalVol_{m,c,t} + \beta_7 LagExtreme_{m,c,t} + \beta_8 VIX_t + \beta_9 Report_t + \beta_{10} Life_{m,c,t}$$

The second model uses as the dependent variable levels of *Trade loss* (Net trade positive values) on market *m*, contract *c* at limit day *t* which are all positive values of net trade variable previously calculated. All other control variables are like the first model.

$$(8)\ Tradeloss_{m,c,t} = \beta_0 + \beta_1 KC_t + \beta_2 Min.Lock_{m,c,t} + \beta_3 KC\_Min.lock_{m,c,t} + \beta_4 Gap_{m,c,t} + \beta_5 KC\_Gap_{m,c,t} + \beta_6 TotalVol_{m,c,t} + \beta_7 LagExtreme_{m,c,t} + \beta_8 VIX_t + \beta_9 Report_t + \beta_{10} Life_{m,c,t}$$

Our third model uses as the dependent variable levels of *Trade gain* on market *m*, contract *c* at limit day *t* which is all negative values of net trade variable previously calculated. This variable is adjusted to positive values to facilitate coefficient interpretation. All other control variables are similar to the last model described.

$$(9)\ Tradegain_{m,c,t} = \beta_0 + \beta_1 KC_t + \beta_2 Min.Lock_{m,c,t} + \beta_3 KC\_Min.lock_{m,c,t} + \beta_4 Gap_{m,c,t} + \beta_5 KC\_Gap_{m,c,t} + \beta_6 TotalVol_{m,c,t} + \beta_7 LagExtreme_{m,c,t} + \beta_8 VIX_t + \beta_9 Report_t + \beta_{10} Life_{m,c,t}$$

The fourth and fifth models are based on the same concept as the second and third models, however, our dependent variable for both is expressed in natural logarithm form. We design those models to obtain coefficient interpretation in percentage (Log-level model).

$$(10)\ ln(Tradeloss)_{m,c,t} = \beta_0 + \beta_1 KC_t + \beta_2 Min.Lock_{m,c,t} + \beta_3 KC\_Min.lock_{m,c,t} + \beta_4 Gap_{m,c,t} + \beta_5 KC\_Gap_{m,c,t} + \beta_6 TotalVol_{m,c,t} + \beta_7 LagExtreme_{m,c,t} + \beta_8 VIX_t + \beta_9 Report_t + \beta_{10} Life_{m,c,t}$$

$$(11)\ ln(Tradegain)_{m,c,t} = \beta_0 + \beta_1 KC_t + \beta_2 Min.Lock_{m,c,t} + \beta_3 KC\_Min.lock_{m,c,t} + \beta_4 Gap_{m,c,t} + \beta_5 KC\_Gap_{m,c,t} + \beta_6 TotalVol_{m,c,t} + \beta_5 LagExtreme_{m,c,t} + \beta_6 VIX_t + \beta_7 Report_t + \beta_8 Life_{m,c,t}$$

## Results and Discussion

In this section, we discuss our results for both approaches: 1) ex-ante effects of price limits and; 2) ex-post effects of price limits. For the former, we present results from a set of linear probability models including the estimated change in the probability of limit moves in the presence of different price limit levels. For the latter, I present estimates of the difference between actual and counterfactual volume on limit move days and consider correlation between this outcome and a set of covariate factors.

### *Ex-ante effects*

Limit moves are not common market events. Table 1 presents a descriptive overview of the data. The baselines for extreme and limit moves are displayed for each market in our study. The sample we use includes the four major wheat markets, CBOT, Kansas City, Minneapolis, and Paris composing a total of 37584 daily observations where each observation is a day in a contract for each market from January 2014 to April 2019. The sample presents a well-distributed share among all the markets, 26.06% (CBOT), 25.06% (KC), 21.79% (MGEX), and 22.49% (Paris). Including all markets, our baseline probability for extreme moves is 1.11%.

When compared with other markets, Minneapolis presents the higher extreme move baseline probability of 1.47% followed by Chicago and Kansas city with 1.21% and 1.40%, respectively. On the other hand, Paris has the lowest baseline of 0.32%.The close extreme move baseline between Chicago and Kansas City can be explained by the fact that these prices are highly correlated, which maximizes the chance that an extreme move in a Chicago contract is transmitted to Kansas City and vice-versa.

For limit moves, we can observe the uncommonness of the event. Overall, 0.05% is the frequency that a limit move occurs, which gives us only 19 events throughout the entire sample. Evaluating the markets, Chicago and Kansas City have almost the same baseline with 0.09% and 0.10%, respectively. MGEX baseline is low due to just one limit move and also because of the fixed daily price limit. The daily price limits for CBOT and KC pass by a reset every six months. Observing the variables Limit50, Limit35, Limit30 we concluded that CBOT has a longer period when the daily price limit is more restrictive (i.e. Limit35) than KC. MGEX has a daily price limit set at 60 cents since January 2014 without changing. The changing in daily price limits is an important feature from our sample because we are evaluating ex-ante relationships between the daily price limit levels and the probability of those thresholds to be crossed.

In our sample, extreme movements happen mostly in 2014 (153 observations, 36.34%) and 2017 (121 observations, 28.74%) which present an annual average VIX of 14.82 and 11.24, respectively and is the period where CME established the limit level reset policy. The VIX can serve as a parameter for volatility, but commodity markets (especially wheat) can have other volatility proxies that could be hard to measure. When evaluating limit moves, most of them happened in 2017 and 2018 on CBOT and KC wheat contracts.

Table 3 displays the results for four regressions. The first two estimate the probability of extreme movements as a function of (1) limit levels of 50, 35, 30 cents and (2) a *Tight* variable which describes whether the actual limit level was decreased or unchanged (=1) or increased (=0) relative to the level over the previous six months. Overall, models 1 and 2 show a global F test significant at 1% level and Adjusted R-squared of 0.045 and 0.044, respectively. Observing the market's coefficients, KC contracts present on average a higher increase (0.017%) in the probability of extreme movements which has a baseline of 1.11% for the whole sample and 1.40% only counting Kansas City relative to Paris. The second model shows KC and CBOT with higher results, 0.014% and 0.012% increase on average for each market, respectively relative to Paris. The limit's coefficient shows a negative impact on the probability of extreme movements. However, just *Limit30* displays a significant coefficient of -0.009%. The variable *Tight* was statistically significant at 1% level and shows a negative impact (0.008%) on the likelihood of an extreme movement relative to its previous 6 month limit level period. This result corroborates with our first model where tighter limit levels can increase the probability of extreme movements. Lag extreme variable ($Extreme_{t-1}$) and Lag Limit move, which is one of our controls and represents the occurrence of an extreme move and limit move on the previous day, respectively, presents a relatively large positive effect on the probability of an extreme move for both models. Significant at 1%, the increment caused by an extreme move on the previous day is 0.152% on average in an overall baseline of 1.14% and for the occurance of a limit move on the previous day increase the probability by 0.138% on average. This variable behaves as a hindsight for limit moves which could work as a signal for traders to develop their strategies. Variables such as Vix, Volume (expressed in the natural log), Contract Life (Life) and Delivery Period are included as controls aiming to clear the effect of limit levels and tightness. The Reset windows variables are included to analyze price limit levels using the Difference-in-difference model.

After adjusting for differences in the probability of limit moves across markets, we consider the time variables for all models to control the effect of the variation previded by every 6-month reset on limit levels. The impact of those variables expressed on their coefficients are only valid for the time period under analysis, but can enlighten some information. Except for the first 2017 reset window for model 1 (which shows no statistical significance), all of them presented negative impact on the extreme movement likelihood and were statistically significant.  displays the estimated likelihood of extreme movements from model 1 using control (Paris) and all other three market data on a six months average basis. The period before 2014 is our reference for comparison since it was excluded from our models to avoid singularity issures.

In early 2014, the limit levels reset from 60 cents to 45. This considerable reduction (tighter limit level) impacted negatively the probability of extreme movements in comparison to the period before when price limits were static. According to our models the first 2014 reset window coefficient is one of the largest ones in magnitude. We observed a considerable decrease in the probability of extreme movements for both control and markets from the first 2015 reset window until late 2016 in comparison with the static period which consists of tight reset windows with negative statistically significant coefficients. The first 2017 reset window (Positive coefficient) indicates a period when the probability of extreme move would return to similar levels as the static period (before 2014) as Figure 2 shows. Those levels would be significantly greater (approximately 3.5%) than our data baseline of 0.24% for Paris (Control) and 1.4% for the other markets on average in daily terms, however not statistically significant

The next period of tighter reset windows occurred from late 2017 until late 2018 with an ambiguous behavior. Late 2017, the daily limit stayed at the same level as of late 2016, however, this period shows the higher probability levels only reducing late 2018. In this period is clear to see the difference in reaction over Paris and other markets. The level's magnitude and how sharp is the response in CBOT, KC, and MGEX can be seen through this period. The results from the first models are aligned with the Holding back hypothesis (Subrahmanyam 1997) that price limit helps to decrease volatility which in our analysis can be observed as a contraction in the probability of extreme movements. Brogaard and Roshak (2015) conclude that circuit breaks such as price limit can improve market stability by decreasing large movements and our present results so far can lead us to a similar conclusion. However, some trade-off would probably be involved to acquire this stability, such as a reduction in price discovery.

The next two models estimate the probability of a limit move given the occurrence of an extreme movement. The same description of the first two models applies to those, where we use the limit levels variable and tightness. Our third model overall presents an Adjusted R-squared of 0.303 and a global F test significant at a 1% level. With a better goodness-of- fitness relative to the past models, the 30-cent limit level coefficient presented statistically significant at 1% with a relatively large positive effect on the probability of a limit move (0.168% increase over a 0.05% overall baseline). The result is intuitive. Since 30 cents is the most restrictive limit level in our limit level historical series it is logical to show an increment in the probability of limit move given extreme movements. However, considering that our coefficient is based relative to our control (Paris), we can assume that the positive marginal effect on the conditional probability of a limit move supports the Magnetism hypothesis (Subrahmanyam (1994), Chan et.al. (2005) and Treynor, (2019)). Another powerful insight is regarding the Lag Limit move variable. This variable gives a hindsight on the probability of a limit move that could help market participants to place their orders and strategies. The occurrence of a limit move on the previous day increase the probability by 0.678% with a base line of 0.05%.

The last model considers tightness. It presents an Adjusted R-square of 0.276 and a global F test statistically significant at 1% level. Besides present a lower goodness-of-fit, the variable Tight is significant at 1% level and corroborates with the conclusion observed for the third model where the Magnet hypothesis is supported since it counts for all restriction increase throughout all limit level.

Figure 3 displays the estimated probability of limit moves conditional to extreme movements occurrence in MGEX, KC, and CBOT using model 4 due to the tight variable presence. The same periods from Figure 2 are highlighted and the coefficient effects are only valid for comparions throughout the period analyzed. We find opposite results from our first two models observing the shaded area from the first reset window in 2015 to second in 2016. This period presents limit levels with negative marginal effects on the probability of extreme moves on the first two models, however, our estimates for the probability of limit moves conditional to extreme moves increase in those periods. Those tight windows marginal increments on the probability of a limit move after the occurrence of an extreme move corroborate with the "Magnet" hypothesis taking limit moves as a proxy for volatility. Paris was not displayed because the probability of hit the limit is always zero (since it is our control).

The second period highlighted from late 2017 to late 2018 shows a loose limit level. The last two windows were classified as loose since the limit level starts to get wider (from 30 cents to 35 for both Chicago and KC contracts). Even with negative effects on the coefficients, the probability of limit moves drastically drops on this period which empirically still corroborates with our positive relationship between tightness and probability of limit moves conditional to extreme moves. This section of our series supports the Magnetism hypothesis and is aligned with our regression results for model 4 where a tight limit level increases the probability of limit move (loose limit level decrease probability of limit move).

Our findings on the second probability estimation regarding limit move conditional to extreme movement occurrence support the Magnetism hypothesis in a certain way, where tighter limit levels increase the probability of a limit move. It is known that our sample size for limit moves conditional to extreme movements is small (416 observations) and only 19 days where price reached the limit threshold. Etienne, Irwin, and Garcia (2015) evaluate price explosiveness on corn, soybeans and wheat futures markets from 2004-2013. On their findings, only 2% of the whole sample experience a price explosive moment and, regarding wheat contracts, only ten, twenty-five and twenty-seven business days had price explosiveness for CBOT, Kansas City and Minneapolis contracts. Their conclusion reinforces how rare those events are but still could generate substantial implications for the market.

### *Ex-post effects*

The ex-post effects of price limits are evaluated in this study by observing trading volume during limit days and through the use of an estimated counterfactual for trading volume in that market-contract-day, infer price limit effects on trading volume.

To better understand our results, the first step is to evaluate the duration of all limit moves observed in our data sample against net trade, which is the difference between our adjusted counterfactual volume and the actual volume at the limit move day and is expressed by the variable Min.lock.  shows the ex-post data summary statistics. The greater sum of minutes with price locked at the limit level is 190 and is related with a max net trade loss of approximally 9200 contracts. For net trade gains, the data shows a max sum of minutes equals to 164. Our data shows a greater number of observations where net trade gains happened in comparison with net trade loss, but the max net trade loss (9159 contracts) is greater than the max net trade gain (3576 contracts) observed.

To better understand this relationship between limit lock duration and net trade behavior those two dimensions are displayed in Figure 4 and Figure 5 for trade losses and gains. For both, it is possible to observe a positive relationship between long periods of limit locks and trade gains and losses, however, this behavior is more evident for trade losses. It is worth mentioning that this relationship seen in those figures are not for a continuous limit lock but by the total sum of minutes that prices stayed at the limit level. Observing the data, we notice different trading activity responses according to how long and if there were gaps within limit locks.

Trading volume doesn't respond immediately to a limit hit. Volume tends to shift around a limit hit where a peak is evident before prices bind with the limit taking a moment to reduce to lower levels. This delay effect of price limits on trading volume could restate the classical U-shaped volume curve inside a trading session where a volume peaks would be seen around a limit hit and another one right after prices come back to the range. To investigate this effect,  enlights the subject. Our five models are displayed in the table where the first, second and third are implemented with levels of net trade as our dependent variable. The last two use the natural logarithm aiming more comprehensible coefficients.

All models present an F statistic significant at 1% level. All models presented a fair goodness-of-fit with the higher adjusted $R^2$ for model 2 (0.422) and lowest for model 1 (0.116).  Among the level models, *Min.lock* coefficient presented statistically significant at 1%. The marginal effect of an extra minute locked at the limit level is positive for both trade loss and gain, however, on average its impact is greater for losses (26 contracts for an additional minute locked at the limit level). Moreover, the overall model using net trade variable as a linear variable (accounting for positive (trade losses) and negative (trade gains)) shows a positive marginal effect for *Min.lock* which increases trading activity loss by approximately 13 contracts for an additional minute. The same conclusion can be seen from our Log-level models. The marginal effect of an additional minute in the sum of minutes where prices stay at the limit level increase more trading activity losses (6.1% for an additional minute) than trading activity gains (2.3% for an additional minute).

The delay effect of price limits can be explained through the *Gap* coefficient. Empirically we can see that short limit locks our limit days with large gaps show the occurrence of a U-shaped pattern in the volume curve. Practically, the peak in volume due to a limit hit is not compensated by the halt on trading activity if prices would stay locked at limit levels. The coefficients of our level models show this. The longer the gap, the greater is trading activity gain.

In the level models, the marginal effect of an additional minute for the gaps increases trading activity gains. In the trade loss model, an additional minute in the gap reduces trade loss by 0.868 contracts and in the trade gain model, 0.281 contracts. In our log-level models, the results are in the opposite direction where an additional minute in the gap between limit hits reduces trading activity gains by 1%. One reason for the increment in trading activity could be that non-commercial traders reduce their net short and net long positions when an upper and lower limit gets hit to cover their margin calls (Janardanan et.al., 2019).

The intensity of gains and losses on trading activity are different according to our model. The Kansas City interaction variables KC_Min.lock and KC_gap help to understand the different intensities the effect of our variables of interest have on both markets. To obtain the effect of an extra minute locked at the limit and the effect of an extra minute in a gap for Kansas City we need to calculate the sum of Min.Lock and Gap coefficient and the interaction coefficients, respectively. In this case, the marginal effect of an extra limit locked at the limit in Kansas City is relatively small (approximately 3 contracts) to Chicago. The same conclusion can be seen for the gap interaction variable. Overall, a gap between limit hits increase trading activity gains. However this effect is lower in Kansas City relative to Chicago due to the sum of coeffients (Gap and KC_Gap) being almost zero. A reasonable evidence to support this result is the difference in magnitude of trade gains and losses observed on both markets. Figure 6 illustrate this difference in magnitude by displaying the amount of minutes locked at the limit versus trade gains and losses. Clearly, CBOT values for trade gains and losses are fairly greater than KC showing that by the fact that CBOT wheat contracts presenting a higher volume on average compared with KC makes the effect of limit move on trading activity more intense in CBOT. The same pattern can be seen for gap values.

## Conclusions

In this study, we use future price and volume data from the four major wheat futures markets, Chicago , Kansas City, Minneapolis, and Paris to estimate the ex-ante and ex-post effects of price limits. We estimate the impact of changing price limits on the probability of extreme movements and the probability of limit moves conditional on the occurrence of extreme movements similar to Brogaard and Roshak (2015). For the ex-post effects, we investigate how trading activity behaves before, during and after a limit hit.

In our ex-ante assessment, the results indicate that tighter limit levels decrease the probability of extreme movements by 0.008% with a baseline probability of 1.11% for all four markets studied. In essence, exchanges with the procedure to revise their limit levels periodically, when revised to a tighter level, on average reduce the probability of extreme movements based on the results generated by the period analyzed in this study. These findings support the "Holding Back" hypothesis suggested by Subrahmanyam (1997) with the caveat that extreme movements have to be used as a proxy for volatility. However, our estimate for the probability of a limit move conditional to extreme movements points the contrary. Logically, tighter limit levels increase the probability of limit moves when extreme moves happen which supports the "Magnet" hypothesis implied by Subrahmanyam (1994) when we confront the results with our control (Paris) where price limits do not apply. Moreover, the occurance of a limit move on the day before could be used as a hindsight information since the marginal effect of our Lag Limit move is positive and relatively larger when compared with our base line for limit move (0.05%)

The ex-post effects of price limit on trading activity are consistent with our empirical investigation. Trading activity has a unique behavior when prices are about to hit the limit where a U-shaped volume curve traditionally observed in a trading session can repeat itself. This behavior is subject most by how long prices will stay at the limit level and/or if prices will hit the limit level multiple times in a session. Our results indicate that the longer is the period where prices are at the limit, the greater is the trading activity loss in comparison with a possible trading activity gain. Moreover, if prices hit the limit level multiple times in a session and the time between hits is longer, the trading session can experience an increase in trading activity. The intensity of those effects change through markets as well. Due to its lower daily volume compared with Chicago, Kansas City react less to ex-post effects relative to Chicago.

The results could help market participants by increasing their information regarding the effects of this rare market events and help them navigate efficiently through the commodity markets. For policymakers and exchanges, this study could enlighten more information about price limit effects on price and trading activity thus supporting them to implement these circuit breaks effectively.

Further researches could collaborate with the subject by evaluating intraday datasets with higher resolutions and for other markets where price limits are constantly hit it and that could show inefficient such as Live Cattle and Lumber. Moreover, evaluating the behavior of order in the order book could increment the analysis and clarify price limit effects.

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**Table 1 - Extreme and limit move descriptive statistics for the wheat futures market**

| | Full Sample | | CBOT | | KC | | MGEX | | EBM | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Mean or % | Sum | Mean or % | Sum | Mean or % | Sum | Mean or % | Sum | Mean or % | Sum |
| **Regular Moves** | 92.76% | 34863 | 92.33% | 9668 | 91.99% | 8709 | 93.40% | 8062 | 99.66% | 8424 |
| **Extreme Moves** | 1.11% | 416 | 1.21% | 127 | 1.40% | 133 | 1.47% | 127 | 0.32% | 29 |
| **Limit Moves** | 0.05% | 19 | 0.09% | 9 | 0.10% | 9 | 0.01% | 1 | 0.00% | - |
| **Limit 60** | 76.04% | 26826 | 100.00% | 9795 | 100.00% | 8842 | 100.00% | 8189 | 0.00% | - |
| **Limit 50** | 49.09% | 17320 | 92.91% | 9101 | 92.95% | 8219 | 0.00% | - | 0.00% | - |
| **Limit 35** | 36.66% | 12933 | 73.35% | 7185 | 65.01% | 5748 | 0.00% | - | 0.00% | - |
| **Limit 30** | 16.27% | 5739 | 31.01% | 3037 | 30.56% | 2702 | 0.00% | - | 0.00% | - |
| **N** | 35279 | - | 26.06% | 9795 | 25.06% | 8842 | 21.79% | 8189 | 22.49% | 8453 |

**Table 2 - Ex-post data summary statistics**

| | Full Sample | Trade Loss | Trade Gain |
|---|---|---|---|
| Variable | Sum | Sum | Sum |
| **Max min. lock** | 190 | 190 | 164 |
| **Min min. lock** | 1 | 1 | 1 |
| **Median min. lock** | 14 | 11 | 15 |
| **Average min. lock** | 24.69 | 26.98 | 23.36 |
| **Max Gap** | 1128.67 | 1128.67 | 1101.92 |
| **Min Gap** | 0 | 0 | 0 |
| **Median Gap** | 48.87 | 37 | 57.6 |
| **Average Gap** | 122.01 | 131.47 | 117.56 |
| **Max Net trade** | 9159.27 | 9159.27 | 3576.13 |
| **Min Net trade** | -3576.13 | 0.001 | 0.001 |
| **Median Net trade** | -9.1 | 9.02 | 50.63 |
| **Average Net trade** | 0.95 | 382.2 | 218 |
| **N** | 392 | 143 | 249 |

## Table 3 - Regression Results from the four linear probability models

| | Extreme | | Limit Move | |
|---|---|---|---|---|
| | **Limit level** | **Tightness** | **Limit level** | **Tightness** |
| | (1) | (2) | (3) | (4) |
| **CBOT** | **0.016***** (0.004) | **0.012***** (0.002) | 0.009 (0.050) | 0.027 (0.039) |
| **KC** | **0.017***** (0.004) | **0.014***** (0.002) | 0.005 (0.050) | 0.007 (0.042) |
| **MGEX** | **0.008***** (0.002) | **0.008***** (0.002) | 0.009 (0.041) | -0.025 (0.040) |
| **Limit50** | -0.007 (0.005) | | 0.009 (0.052) | |
| **Limit35** | -0.001 (0.003) | | 0.030 (0.046) | |
| **Limit30** | **-0.009***** (0.003) | | **0.168***** (0.055) | |
| **Tight** | | **-0.008***** (0.002) | | **0.066*** (0.035) |
| **$\text{Extreme}_{(t-1)}$** | **0.152***** (0.005) | **0.153***** (0.005) | **0.062**** (0.028) | 0.040 (0.028) |
| **$\text{Limit Move}_{(t-1)}$** | **0.138***** (0.025) | **0.136***** (0.025) | **0.625***** (0.077) | **0.678***** (0.077) |
| **Life** | **-0.00004***** (0.00001) | **-0.00004***** (0.00001) | -0.0001 (0.0001) | -0.0001 (0.0001) |
| **Delivery** | **0.023***** (0.004) | **0.024***** (0.004) | | |
| **Vix** | **-0.0004**** (0.0002) | **-0.0004**** (0.0002) | -0.003 (0.006) | -0.003 (0.006) |
| **Report** | **0.011***** (0.003) | **0.011***** (0.003) | **0.100***** (0.039) | **0.116***** (0.039) |
| **Reset14_1(45¢/50¢) T/T** | **-0.023***** (0.004) | **-0.023***** (0.003) | -0.020 (0.056) | -0.049 (0.051) |
| **Reset14_2(35¢/40¢) T/T** | **-0.017***** (0.004) | **-0.016***** (0.003) | -0.022 (0.046) | -0.057 (0.041) |
| **Reset15_1(40¢/40¢) L/T** | **-0.011***** (0.004) | **-0.013***** (0.003) | -0.014 (0.045) | -0.028 (0.031) |
| **Reset15_2(35¢/35¢) T/T** | **-0.024***** (0.004) | **-0.024***** (0.003) | -0.036 (0.065) | -0.066 (0.058) |
| **Reset16_1(30¢/35¢) T/T** | **-0.029***** (0.004) | **-0.029***** (0.003) | | |
| **Reset16_2(30¢/30¢) T/T** | **-0.024***** (0.004) | **-0.029***** (0.003) | -0.011 (0.181) | -0.014 (0.183) |
| **Reset17_1(30¢/30¢) T/T** | 0.003 (0.004) | -0.002 (0.003) | -0.056 (0.049) | 0.022 (0.044) |
| **Reset17_2(30¢/30¢) T/T** | **-0.023***** (0.004) | **-0.028***** (0.003) | 0.006 (0.096) | 0.143 (0.091) |
| **Reset18_1(35¢/35¢) L/L** | **-0.020***** (0.004) | **-0.024***** (0.003) | 0.025 (0.051) | 0.048 (0.036) |
| **Reset18_2(35¢/35¢) L/L** | **-0.031***** (0.004) | **-0.035***** (0.003) | -0.053 (0.101) | -0.034 (0.093) |
| **Constant** | **0.035***** (0.004) | **0.037***** (0.004) | 0.044 (0.099) | 0.047 (0.098) |
| Observations | 35,265 | 35,265 | 416 | 416 |
| $R^2$ | 0.045 | 0.045 | 0.336 | 0.308 |
| Adjusted $R^2$ | 0.045 | 0.044 | 0.303 | 0.276 |
| Residual Std. Error | 0.106 (df = 35242) | 0.106 (df = 35244) | 0.175 (df = 395) | 0.178 (df = 397) |
| F Statistic | 75.914*** (df = 22; 35242) | 83.039*** (df = 20; 35244) | 10.010*** (df = 20; 395) | 9.795*** (df = 18; 397) |

*Source: Study's results using futures data from Bloomberg terminal* *p<0.1 **p<0.05 ***p<0.01

*Note:Reset variables present the period of change (i.e Year_half), limit levels established on each market (CBOT/KC) in cents, and Tight/Loose limit levels (CBOT/KC)*

## Table 4 - Regression results from ex-post effect model designs

| | Nominal | | | Logarithm | |
|---|---|---|---|---|---|
| | **All Data** | **Trade Loss** | **Trade Gain** | **Log Trade Loss** | **Log Trade Gain** |
| | (1) | (2) | (3) | (4) | (5) |
| **Min.lock** | **12.952*****| **26.371*****  | **5.251***** | **0.061***** | **0.023*** |
| | (1.940) | (3.475) | (1.346) | (0.014) | (0.014) |
| **KC_Min.lock** | **-12.566***** | **-23.841***** | -3.470 | 0.009 | **0.118***** |
| | (3.626) | (6.283) | (2.423) | (0.026) | (0.025) |
| **Gap** | **-1.199***** | **-2.542***** | **0.827***** | -0.003 | 0.002 |
| | (0.323) | (0.639) | (0.195) | (0.003) | (0.002) |
| **KC_Gap** | **1.165***** | **2.612***** | **-0.847***** | 0.005 | **-0.023***** |
| | (0.418) | (0.797) | (0.260) | (0.003) | (0.003) |
| **Total Vol** | **0.007***** | **0.015***** | 0.001 | **0.00002**** | 0.00000 |
| | (0.002) | (0.003) | (0.001) | (0.00001) | (0.00001) |
| **KC** | **219.389**** | -124.499 | -85.338 | **-2.416***** | **-2.394***** |
| | (108.456) | (199.271) | (70.921) | (0.811) | (0.741) |
| **Extreme$_{(t-1)}$** | -2.146 | -190.114 | **-132.468*** | -1.181 | -0.648 |
| | (126.212) | (261.731) | (74.493) | (1.065) | (0.779) |
| **Vix** | 0.780 | 6.636 | -0.538 | 0.005 | -0.033 |
| | (4.579) | (11.389) | (2.586) | (0.046) | (0.027) |
| **Report** | -132.911 | -256.530 | -50.517 | 0.204 | -0.863 |
| | (143.444) | (338.580) | (81.563) | (1.378) | (0.853) |
| **Life** | **3.168**** | **6.135**** | 0.348 | 0.006 | -0.010 |
| | (1.411) | (2.365) | (0.954) | (0.010) | (0.010) |
| **Constant** | **-709.153***** | **-981.101***** | 82.689 | 0.643 | **4.975***** |
| | (192.715) | (372.052) | (124.820) | (1.514) | (1.305) |
| Observations | 392 | 143 | 249 | 143 | 249 |
| $R^2$ | 0.139 | 0.463 | 0.263 | 0.330 | 0.429 |
| Adjusted $R^2$ | 0.116 | 0.422 | 0.232 | 0.280 | 0.405 |
| Residual Std. Error | 792.546 (df = 381) | 894.224 (df = 132) | 388.033 (df = 238) | 3.640 (df = 132) | 4.057 (df = 238) |
| F Statistic | **6.137***** (df = 10; 381) | **11.378***** (df = 10; 132) | **8.481***** (df = 10; 238) | **6.511***** (df = 10; 132) | **17.914***** (df = 10; 238) |

*Source: Study's results using futures data from Bloomberg terminal and CQG intraday data* $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$
*Notes: Trade loss and Trade gain are distinguished by the sign. Net trade positive values are trade loss and negative values are gain*

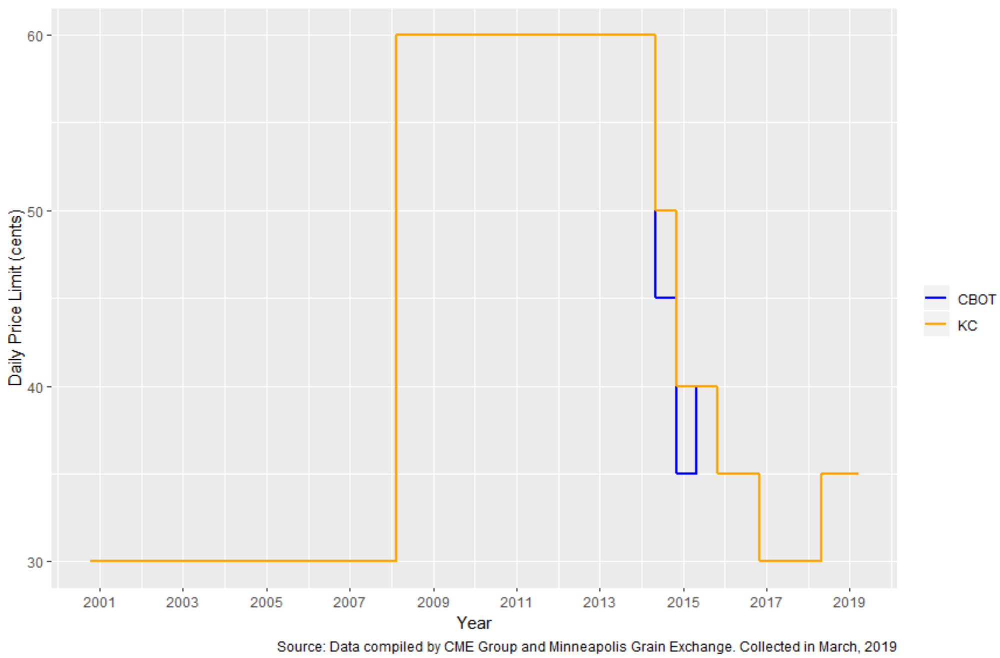


**Figure 1 - Historical daily limit levels for CBOT and KC**

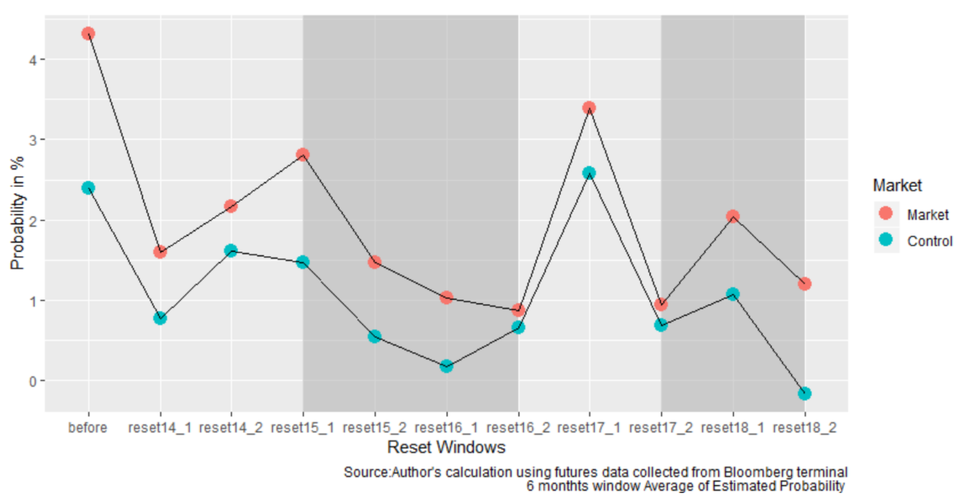


**Figure** 2 **- Probability of extreme movement for control (Paris) and Markets (including CBOT, KC, and MGEX)**

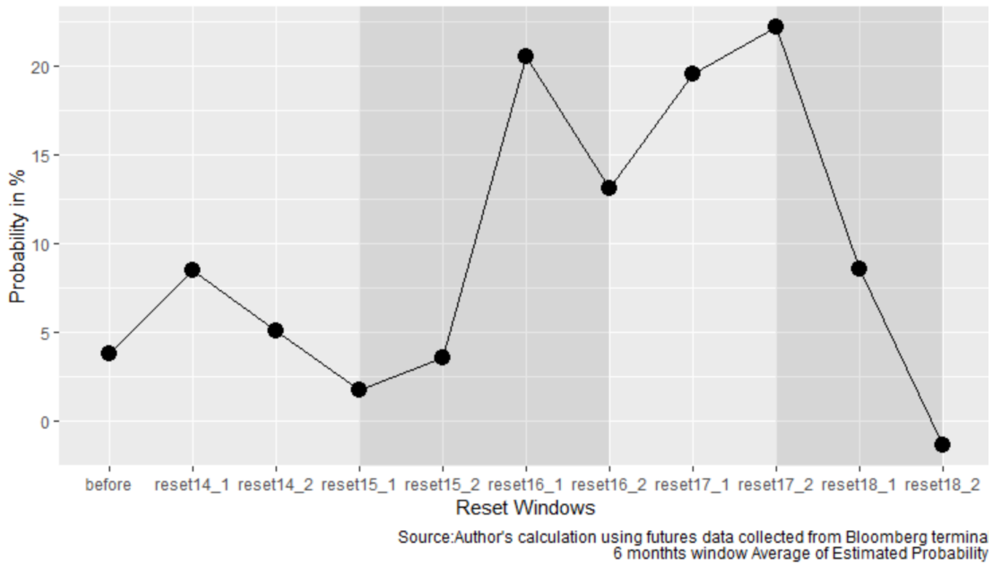


**Figure 3 - The estimated probability of limit moves in markets CBOT, KC, and MGEX conditional to extreme movements in markets and Paris.**

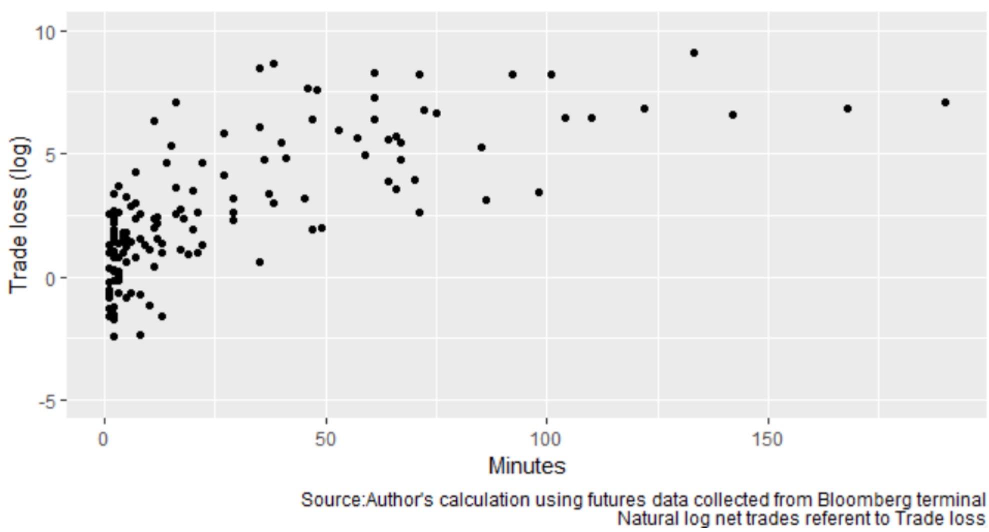


**Figure 4 - Trade loss and the total length time of limit lock**

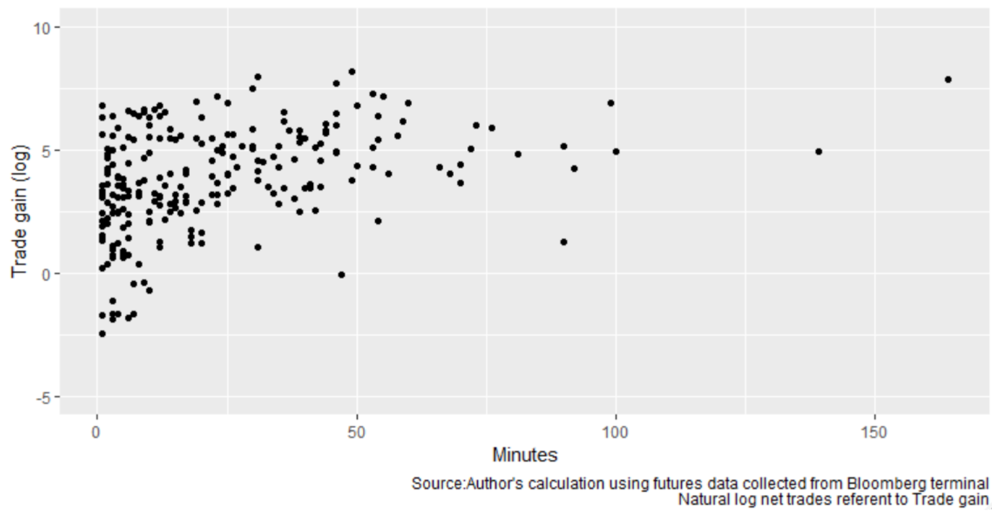


**Figure 5 - Trade gain and the total length time of limit lock**

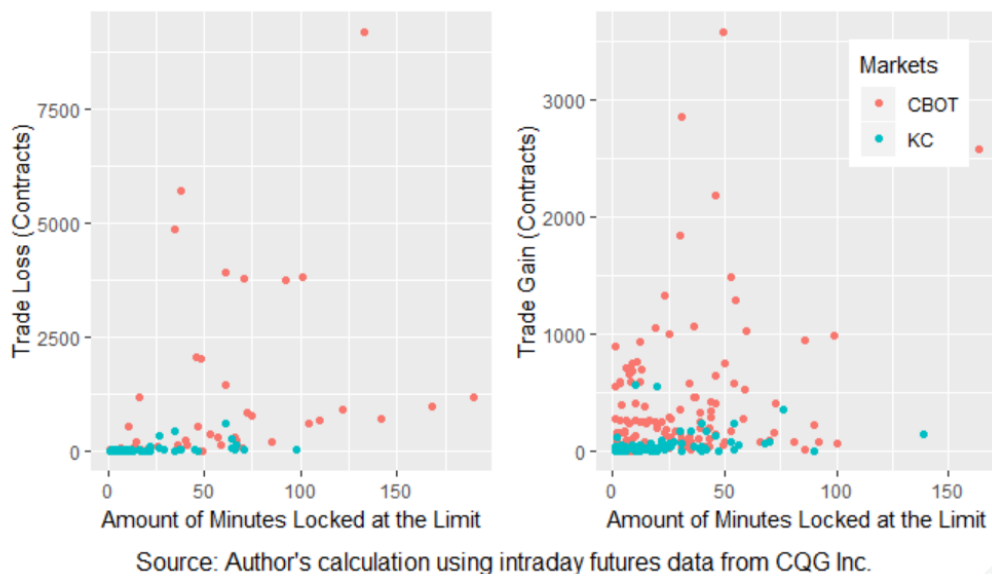


**Figure 6 - Trade gains and losses for Chicago and Kansas City contracts in nominal level (contracts)**