2020

Two Essays on Price Limits and One Essay on Health Insurance

Shawn McFarland

TWO ESSAYS ON PRICE LIMITS AND ONE ESSAY ON HEALTH INSURANCE

by

Shawn McFarland

A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

Major: Business Administration

The University of Memphis

May 2020

Dedication

This work is dedicated to Chelsey, Jaxton, Layla, Rhonan, and Nessah McFarland. Their love, support and light inspire all for which I strive and accomplish. I am forever grateful for their belief in me. They are the reason I endeavor. They are the reason I succeed. I am eternally theirs.

Acknowledgements

I am grateful to my dissertation committee, Dr. Thomas McInish, Dr. Pankaj Jain, Dr. Ronald Spahr, and Dr. David Kemme for their support, assistance, time, and energy in guiding me throughout my doctoral studies. I also thank Dr. Sunderman for his support and guidance through the research and dissertation process. Dr. Christine Jiang, Dr. Sandra Mortal, Dr. Quentin Chu, Dr. Sabatino Silveri, Dr. Jeff Black, Dr. Allen Carrion, and Dr. Konstatin Sokolov for providing invaluable in-class research instruction, seminar comments and discussions, and personal insight to aid and improve my research abilities. Finally, I am grateful to the University of Memphis staff, fellow students, and many family and friends who have supported me throughout my doctoral studies.

Preface

Chapter 1 and chapter 2 of this dissertation are combined into a single paper titled "Short Duration, Dynamic Price Limits: The Special Quote and Limit Up-Limit Down Rules" with Dr. Pankaj Jain and Dr. Thomas Mcinish. Chapter 3 "Efficient/Cost-Effective Healthcare Financing: A Three Tier Model" with Dr. Ronald Spahr and Dr. Mark Sunderman These chapters are prepared for submission to the Journal of Finance.

I thank Ayan Bhattacharya and the seminar participants at the Financial Infrastructure Stability and Cybersecurity (FISC) Center of Excellence at University of Memphis, the FMA Applied Finance conference, Securities and Exchange Commission Department of Economic Risk and Analysis, 2017 and 2018 Southwest Finance Association Annual Meetings, and the MMM Conference at Ole Miss. The opinions expressed are those of the authors and do not necessarily reflect those of the Office of Financial Research in the US Department of the Treasury, where Jain is a fellow.

Abstract

Shawn McFarland, Ph.D., The University of Memphis, April 2020

Two Essays on Price Limits and One Essay on Health Insurance

Major Professor: Thomas McInish, Ph.D.

The first two essays study the special quote (SQ) and limit up-limit down (LULD) rules. These rules are short duration price limits rules on the Tokyo Stock Exchange (SQ) and US stock exchanges (LULD). We present a novel research design where we create pseudo-event samples to test stock market behavior in the absence of these rules. The first essay examines price limit effects on delayed price discovery and the magnet effect. We find that neither SQ nor LULD delay price discovery. SQ exhibits evidence of the magnet effect at the upper price limit while LULD has no magnet effect. The second essay focuses on volatility spillover following a price limit event and microstructure noise during flash crashes. Consistent with previous findings regarding daily static price limits, we find little evidence that either SQ or LULD calm market volatility. Also, we find little evidence that LULD reduces intraday volatility during periods of extreme volatility such as flash crashes. The third essay strives to develop a more efficient, lower-cost health insurance/underwriting system. We divide healthcare coverage into three tiers. Tier 1 consists of low severity healthcare claims that occur regularly for essentially all people. Tier 2 covers relatively lower frequency and higher cost healthcare claims that present lower, more predictable underwriting risk and rarely involves prolonged, year to year, underwriting risks. Tier 3 involves catastrophic low frequency but high severity healthcare underwriting risks that may require larger volume insurers to achieve diversification through a more stable distribution of benefits. Tier 3 claims often result in long term and expensive future healthcare needs risks often terminating with the death of the insured. We show empirically that annual

health care expense is a function of claim frequency and claim severity. Further we show that claim frequency and claim severity are interrelated and that their covariant relation is non-homogeneous across the entire distribution of health care claims. Finally, we show that by segmenting health care insurance underwriting based on these three tiers, cumulative health insurance premiums are reduced. We propose policy recommendations to address social interests including affordable care and universal coverage.

Table of Contents

Table of Contents – Continued

List of Tables

Table Page

Chapter 1

Appendices

Chapter 2

Short duration, dynamic price limits: The special quote and limit up-limit down rules

We investigate short-duration, dynamic price limits designed to permit fundamental price changes, but curb temporary price changes due to irrational trading and order imbalances. Many markets have traditionally used static daily price limits, and these have been analyzed by academics (Cho, Russell, Tiao, and Tsay 2003, Brennan 1986, Chen, Gao, He, Jiang, and Xiong 2019, Kim and Rhee 1997, and Subrahmanyam 1994), but we are the first to examine the efficacy of dynamic intra-day price limits in a comparative framework. An early innovation in the area of dynamic, intra-day price limits is the special quotes (SQs) used by the Tokyo Stock Exchange (TSE) before 1985.[1] Another recent regulatory innovation is the Limit Up-Limit Down (LULD) Plan adopted by the US SEC at the end of May 2012 as a response to the flash crash of May 6, 2010.[2] Further, Short duration dynamic price limits are designed to overcome well know limitations of daily static price limits such as delayed price discovery, the magnet effect, and volatility spillover. Given the growing prevalence of dynamic price limits, it is useful to examine their efficacy and their interplay with many facets of price discovery, such as the speed with which prices incorporate information to arrive at new equilibrium prices, the magnet effect of price limits, trading volatility, and trading volume.

[1] Although outside the scope of our study, the London Stock Exchange's price monitoring threshold and the Hong Kong's volatility control mechanism are also other recent dynamic circuit breakers.

[2] Plan to Address Extraordinary Market Volatility, http://www.finra.org/sites/default/files/regulation-NMS-plan-to-address-extraordinary-market-volatility.pdf

The TSE and US price limits temporarily prevent trading at a price higher than an upper price limit (*UBND*) or lower than a lower price limit (*LBND*) to curb the effects of irrational trading, fat finger trades, algorithmic errors, outliers, and excessive order imbalances.[3] The reference price (*RP)* for determining the *UBND* and *LBND* is dynamic and changes for each stock as its price changes during trading. The *UBND*s and *LBND*s are symmetric around the *RP*.[4] Upon reaching the price limit, only trades that are within the prevailing *UBND* and *LBND* are allowed. Only under rare conditions is trading halted with no trading allowed, and, then, only for a few minutes. Trading may resume in different ways, depending on how market participants and the limit order book respond to the price-limit event. Both rules are similar in nature but the triggering mechanism, *RP*, magnitude of the *LBND* and *UBND*, and resolution mechanism differs between SQ and LULD. The dynamic nature of the reference price allows the incorporation of fundamental information and news into the stock price without subjecting trading to an unnecessarily fixed price range.

Our study is the first to compare and contrast the effects of two short duration, dynamic price limit rules on market quality. We find that SQ and LULD enhance price discovery and information price response. Intensified volatility is commonly documented (Fama 1989, Kuhn, Kurserk, and Locke 1991, Kim and Rhee 1997, and Lee, Ready, and Seguin 1994) following the end of circuit breaker trading halts. We find that SQ and LULD trading halts do not suffer from

[3] A complete list of definitions is in provided in Appendix A.

[4] For SQs, these short duration price limits are narrower than typical daily price limits.

these drawbacks and find evidence that at times of flash crashes, LULD reduces intraday volatility.

I. Circuit Breakers and Hypothesis Development

We focus on a particular type of circuit breaker—price limits that establish a floor (*LBND*) or ceiling price (*UBND*) beyond which a security is prohibited from trading. Proponents claim that price limits provide overexcited, misinformed, or uninformed market participants a cooling off period (Chou, Chou, and Chao 2013). Spiegel and Subrahmanyam (2000) develop a two-period model and show that the presence of trading halts increases (reduces) the probability of trading in the first (second) period. Critics cite evidence of volatility spillover (Fama 1989, Kuhn, Kurserk, and Locke 1991), which contributes to delays in price discovery and information price response.

Hamao and Hasbrouck (1995) describe many unique characteristics of the TSE, including a variation of the SQ rule and a similar 'warning quote' rule, but their focus is on immediacy in a market without designated dealers or market makers. Maskawa (2016) evaluates order behavior of market participants during SQ events and finds that market participants use order placement information of other participants to decide when to place their own order; this herding behavior may exacerbate volatility.

In a series of SEC white papers, Moise and Flaherty (2017), Hughes, Ritter, and Zhang (2017), Hughes (2017) provide detailed information about the working of the LULD rule. Moise and Flaherty (2017) evaluate the frequency of LULD events as well as erroneous trades surrounding the implementation of the LULD rule. They find no difference in the reduction of clearly erroneous trades. In addition, they find an increase in trading pauses for the Tier 2 securities, but a reduction in Tier 1 trading-pause frequency. Hughes, Ritter, and Zhang (2017) examine the LULD's effect on transitory volatility compared to the previous single stock circuit breaker pilot program. By constructing a variety of measures of large, short-term price reversals, they find that LULD reduces transitory volatility relative to the single-stock circuit breaker pilot. However, the results are dependent on the transitory volatility measure used. Hughes (2017) evaluates the effect of Amendment 10, an adjustment to the initial reference price methodology implemented in July 2016 and find that trading pauses are less frequent following the amendment.

A complementary working paper by Lin and Swan (2019) also examines the effect of LULD on market quality. These authors include the role of HFTs and maker-taker vs taker-maker market structures. Ours is a comparative study between both LULD and SQ whereas Lin and S restrict their study only to limit states and trading halts associated with LULD[5].

Traditionally, price limits are daily, static rules, and these are the focus of most previous studies.[6] Since 1950, the Tokyo Stock Exchange has employed daily price limits. Kim and Rhee (1997) examine the effect of Tokyo Stock Exchange's price limits on price discovery. These

[5] Moise and Flaherty (2017) identify a combined 965,602 limit state and trading halt events and 2,074,254 straddle state events. Due the less restrictive market conditions to trigger a straddle state, straddle states account for approximately 68% of LULD events. Straddle state restrict trading outside the price limits and quotes that are submitted outside the price limits during a straddle state are flagged as non-executable.

[6] The U.S. futures market has daily price limits (Brennan (1986)).

authors evaluate return series to determine the immediate price path following a price-limit event. They find that stocks that reach the price limit experience a price continuation in the following trading period more often than stocks that almost reach the price limit. Chen, Gao, He, Jiang, and Xiong (2019) study the daily price limit on the Shenzhen Stock Exchange and find that large traders' net buying on the limit-hitting day predicts stronger long-run price reversal. Bellia, Pelizzon, Subrahmanyam, and Uno (2016) evaluate the effect of HFTs on price discovery during the pre-opening, opening call auction, and continuous trading for the TSE and find that HFTs play an important role in price discovery and liquidity provision. Lehmann (1989) notes that price limits' impact on subsequent price behavior is uncertain because price limits curb rational investors as well as speculative overreaction. Note that LULD is meant to address extraordinary volatility and accommodate more fundamental price moves while SQ is meant to prevent wild price fluctuations. Given the above discussion, we test the following hypothesis:

> *Hypothesis 1: Price Discovery: Unlike static price limits SQ and LULD do not interfere with price discovery.*

Additionally, we explore the relative performance of SQ and LULD for price discovery.

Next, we focus on another significant concern about price limits, namely the magnet effect. The magnet effect is the notion that as traders observe the security price approach the price limit, fearing that they will be locked out by a forthcoming trading pause, these traders speed up their trading, which accelerates the movement of the price towards the price limit. However, unlike daily price limits, with SQ and LULD rules, buying or selling the stock before it hits the price limit induces the reference price itself to adjust in the direction of the price pressure, thus eliminating this risk in case of gradual price adjustments. Moreover, the pauses associated with the dynamic price limits are also temporary.

Spiegel and Subrahmanyam (2000) argue that in times of high information asymmetry informed market makers revise their estimates of short-term return variance upwards leading to wider spreads. In the context of SQ and LULD, the magnet effect can be characterized by informed liquidity suppliers, not traders, speeding up their revisions of price return variance in the face of a high information event. For SQ and LULD, the magnet effect should occur through quote revisions rather than trades. Cho, Russell, Tiao, and Tsay (2003) test the magnet effect on the Taiwan Stock Exchange. They find strong evidence that stock prices accelerate towards the *UBND* and weaker evidence that prices accelerate towards the *LBND*, supporting the magnet effect hypothesis. We test the following hypothesis:

> *Hypothesis 2: Magnet Effect: Unlike static price limits, LULD or SQ do not exhibit a magnet effect.*

Much of the empirical evidence dealing with trading halts supports the volatility spillover hypothesis. Subrahmanyam (1994) argues that price limits exacerbate price volatility by altering order placement strategies of large, sophisticated institutions. Circuit breakers increase ex ante price volatility and the probability of a price limit event by inducing discretionary traders to concentrate their trades in the first period. Gerety and Mulherin (1992) use the overnight closing of the market as a proxy for trading halts or other types of circuit breakers. They find that trading volume at the close has a positive relation to expected volatility and that trading volume at the open on the following day has a positive relation to both expected and unexpected volatility.

These authors argue that mandatory circuit breakers cost traders and that the risk of being locked into continued ownership makes the market more skittish. Kim and Rhee (1997) examine the effectiveness of the TSE price limits by testing whether there is volatility spillover. These authors find that volatility is higher after the halt than after a trading day when the price limit is almost reached.

Two studies test the volatility spillover hypothesis for Japanese stocks by comparing stocks that hit the price limits with those that get within 10% of the UBND or LBND. Kim and Rhee (1997) find that volatility is higher after the halt than after a trading day on which the price limit is almost reached. Deb, Kalev, and Marisetty (2017) use propensity scoring to construct matched pairs following Kim and Limpaphayom (2000) and find evidence of volatility spillover at the *UBND* only and conclude that price limits work well at the *LBND*.

Lee, Ready, and Seguin (1994) evaluate volatility and volume surrounding NYSE news-related trading halts by matching on non-halt control periods (dubbed “pseudo-halts”). These authors calculate three volatility measures and two volume measures to test for volatility spillover and determine that trading halts increase volatility and volume. We follow the Lee, Ready, and Seguin (1994) approach of examining volatility and volume; the relation between our measures and theirs is provided in Internet Appendix A.

Christie, Corwin, and Harris (2002) study the effects of alternative halt and reopening procedures. They find that liquidity and volatility effects are smaller if trading after a halt resumes on the same trading day rather than on the next day.

Farag (2013) studies the effect of changes to the width of price limits on stock returns and volatility on stock exchanges in Egypt, Thailand, and Korea, and finds that when these exchanges widen the limit parameters, prices do not fully reflect all information at the time the price limit is breached. Alternatively, Deb, Kalev, and Marisetty (2013) propose that flexible price-limit rules based on consecutive price limit hits reduce volatility spillover and allow prices to reflect all available information.

Lee, Ready, and Seguin (1994) evaluate the volatility spillover hypothesis. They measure post-halt volatility and volume against the same measures during matched periods of market activity that did not experience a halt. They find that volatility and volume are greater following halts suggesting that halting trading exacerbates rather than calms market volatility. SQ and LULD do not typically halt trading entirely. By allowing trading within the price limits during an LULD or SQ event, residual volatility may be decreased following an event. These considerations lead to the following hypothesis:

Hypothesis 3A: Volatility Spillover: SQ and LULD reduce volatility after a price-limit event.

Goettler, Parlour, and Rajan (2009) identify the volatility in microstructure noise as a deviation of the transaction price from estimated fundamental values. Dramatic deviations in transaction prices from fundamental prices are the principle adverse condition during a flash crash. The LULD rule, which came about as a direct result of the May 6, 2010, flash crash, is designed to allow for fundamental price changes while mitigating the extreme microstructure noise observed during the flash crash. This stated purpose of LULD leads us to our final hypothesis.

> *Hypothesis 3B: Volatility during Flash Crashes: LULD mitigates microstructure noise during flash crashes.*

We also investigate which rule performs better for Hypotheses 1, 2, and 3A.

Focusing on the Taiwan Stock Exchange and the Stock Exchange of Thailand, which impose 7% and 10% daily price limits, respectively, Kim and Limpaphayom (2000) document that small-cap, actively traded stocks with high volatility more often reach both the upper and lower trading bounds.

Examining order flow and liquidity surrounding NYSE trading halts, Corwin and Lipson (2000) argue that allowing traders to submit and cancel orders during a halt can mitigate the loss of information due to lack of trading. They find that submissions and cancelations of both market and limit orders significantly increase during trading halts.

II. Limit Up Limit Down and Special Quotes

A. How the SQ Rule Works

SQs, which are liquidity-demand based, are a unique feature of the Tokyo Stock Exchange (TSE). According to the exchange, the term "special quote" was first used in 1985, but the actual rule existed prior to that year.[7] According to the TSE website, SQs prevent short-term price fluctuations by mandating that the execution price of a trade must fall within a specified range

[7] Tokyo Stock Exchange, private correspondence.

based on the previous trade price, which becomes the *RP*. For example, when a security trades at a price of 100 JPY the limit parameter is ±5 JPY and the permissible price range is between 95 JPY and 105 JPY so that 95 JPY is the *LBND* and 105 JPY is the *UBND*. If a market order or marketable limit order to buy arrives when the best resting ask is higher than 105 JPY, the TSE issues a SQ, signaling to the market that there is an order imbalance.[8] The buy order is still executable, but only at a price within the price-limit parameters, and rests until it can be executed. While the SQ is being held, other orders are still accepted. If an order arrives that permits the execution of the entire resting buy order, a trade occurs and continuous trading resumes. However, if a sell order arrives that will only allow partial execution of the resting buy order, a call auction takes place. Continuous trading resumes when, through the call auction, all existing market orders are executed. If after 3 minutes all existing market orders are not able to execute within the price limit range, the price limit range is re-set to two times the original range. This process continues until the price limit range is sufficiently wide for trading to resume. According to the TSE's website, SQs are a mechanism that encourages the placement of orders to reduce or eliminate an order imbalance. Price-limit levels are dependent upon the prevailing stock price.

B. How the LULD Rule Works

In response to the May 6 flash crash, the SEC implemented the LULD rule (FINRA (2016)). Securities are classified as Tier 1 or Tier 2. Tier 1 securities are all stocks included in the S&P

[8] Appendix B provides a complete list of the TSE price limits at the time of our study.

500 index and/or the Russell 1000 index. High-volume, exchange-traded products are also included as Tier 1 securities. All remaining securities are Tier 2. The LULD rule prohibits trades outside an *UBND* and *LBND* that are symmetric around the *RP* and are disseminated to the public. The LULD *RP* for the first five minutes is the opening price on the security's primary listing exchange. Thereafter, the listing exchange calculates and carries forward the average trade price over the previous five minutes (*ATP*). When the *ATP* is 1% more or less that the current *RP*, the *ATP* becomes the new *RP*.

The *UBND* and *LBND* are as follows: *RP* >= $3.00, 5% for Tier 1 stocks and 10% for Tier 2 stocks; $0.75 <= *RP* < $3.00, 20%; *RP* < less than $0.75, the lessor of $0.15 or 75%. Trades cannot occur beyond these bands when they are in effect.

The LULD rule is triggered whenever the NBBO *quotes* are outside the prevailing *UBND* or *LBND*. This may occur two ways—a straddle state or limit state. A straddle state occurs when *ASK* > *UBND* > *BID* or *ASK* > *LBND* > *BID*. In this case, the primary listing exchange may, at its discretion, declare a five-minute trading pause for this stock. A limit state occurs when the *BID* = *UBND* or the *ASK* = *LBND* and the quotes are not crossed. When a limit state persists for more than 15 seconds, a mandatory five-minute trading pause is declared.

Regular trading resumes after an LULD event either by reopening trading following a trading pause or when the prevailing *ASK* and *BID* naturally move back to within the prevailing price limits, because of executions, cancellations, or updated price limits.

C. Comparison of SQ and LULD rules

The SQ and LULD rules differ significantly from traditional price limits in a variety of ways. The first, and perhaps most significant, is that SQ and LULD provide dynamic price limits. These price limits adjust as trading occurs allowing for large intra-day fundamental price changes while seeking to prevent very short-term uniformed or highly volatile trading. In contrast, traditional price limits are static; setting pre-determined daily *UBND*s and *LBND*s that are not adjusted to reflect significant information that alters the true equilibrium price. Secondly, SQ and LULD prevent trading in the affected stock outside the price limits only. SQ always allows trading within the price limits. LULD allows trading within the price limits at any time except when a 5-minute trading halt is in effect. Both rules are short duration and trading as usual resumes when the price limit event ends. Alternatively, traditional price limits halt all trading in the affected stock until the following trading day.

SQ and LULD also differ from each other in meaningful ways. A price limit parameter determines the magnitude of the *UBND* and *LBND*. Both SQ and LULD exhibit generally smaller price-limit parameters than traditional daily price limits. However, the LULD price-limit parameters are significantly larger than those for SQ. Moreover, the price-limit parameters are constructed in distinctly different ways. The SQ price-limit parameters are set as plus or minus a constant number of JPY around the *RP* and do not exceed 2.7% of the *RP*. In contrast, the LULD price-limit parameters are percentages with respect to the *RP*. Further, the *RP* by which the price limits are determined is calculated differently for SQ and LULD. For SQ, the *RP* is the previous trade price. For LULD, the *RP* is the arithmetic mean trade price of the previous five-minutes with special rules for the opening and extended periods of no trades. These differences highlight the more stringent price bands of the SQ and the longer memory of the LULD.

A second important difference between SQ and LULD is the mechanism used to provide for information dissemination. The SQ rule never formally halts trading. Trading can always occur within the price bands. However, the LULD imposes a mandatory five-minute trading pause during which no trades can occur when both the *BID* and *ASK* are equal to or outside the price limits. But even during this trading pause all quotes may be received and displayed

Finally, perhaps the most distinguishing difference between the SQ and LULD rules is that SQ is a trade-based rule and LULD is a quote-based rule. The SQ rule is triggered only when an order is received that would, if allowed, execute outside the price limits. Under this mechanism, only non-executable trades will notify the market that prices have moved beyond the price limits while quotes that are outside the price limits do not trigger a market wide notification. On the other hand, the LULD rule is triggered when either the best *BID* or *ASK* lies outside the prevailing price limits. For some thinly traded securities, a LULD event, and, potentially a halt, may occur at times when no trading is or would otherwise occur.

D. Daily Static Price Limits

The TSE also imposes a daily static price limit. The reference price for the daily price limit is the closing trade from the previous trading day and the *UBND* and *LBND* are set at approximately 20% to 30% above and below the reference price. Like SQ, the price parameters are a fixed amount of yen above and below the reference price, dependent on the reference price.

We test hypothesis 1, 2, and 3A for the TSE daily price limits to determine the relative performance of SQ and LULD. Our results are robust to daily static price limits as well.

III. Data and Event Identification

A. Data Sources

For January 2015, we collect trades and quotes for the US and Japan. Our US data are from DTAQ and comprise all trades and top-of-the-order-book quotes for all issues traded on the CTA participating markets. Observations for both trades and quotes are time stamped to the millisecond. These data allow us to identify the prevailing price limits, quotes that fall outside the prevailing price limits, and LULD-related trading halts. We observe the start and finish of each LULD event. The trade files allow us to identify price paths following a LULD event.

In addition, for January 2015, we collect Japanese data from the Nikkei Economic Electronic Databank System (NEEDS), which provides the price and depth in the limit order book for the best eight bid and ask price steps for all first and second section securities, Mothers, and ETFs. Observations are time stamped to the second and ordered chronologically within seconds. Observations are recorded when there is a change to the price or quantity of any price step on either side of the order book or when there is a trade. SQs are flagged.

Lastly, we collect daily open prices, intra-day high and low prices, and closing midpoints from the Center for Research in Security Prices (CRSP) data. We collect these data on all tickers traded on May 6, 2010, and August 24, 2015.

B. *Identification of LULD Events*

We begin by identifying all LULD events. Moise and Flaherty (2017) identify over 3 million LULD events over 122 trading days covering June 3 through August 2, 2013 and May 12 through August 29, 2014. To identify LULD events, these authors use SRO-provided data to identify each individual limit state, trading pause, and straddle state as well as orders arriving during each limit state. Using a different definition, we define an LULD event as a continuous period when at least one side of the NBBO is un-executable due to the LULD rule. We combine as a single LULD event instances where multiple LULD events occur in succession without trading between events. When the *ASK* (*BID*) crosses the *UBND* (*LBND*) price limit and quickly returns repeatedly multiple LULD events with identical post-event price paths and volatility and volume characteristics are created. The average amount of time between LULD events with no trade is 7 seconds with 0.2% lasting longer than 5 minutes. When these events occur in rapid succession with no trading occurring between them, we believe that they are essentially the same event.

Like Corwin and Lipson (2000), we remove delayed openings to identify trading activity and liquidity before and after halts. We further impose the restriction that a trade must occur both before and after the LULD event during the trading session to be included in our sample. As shown in Table 1, we identify 6,775 qualifying LULD events.[9,10]

C. Identification of SQ Events

When a marketable order is submitted that will transact beyond the *UBND* or *LBND* for a given stock on the TSE, the exchange issues a special quote (SQ) at the associated price limit. The issuance of a SQ marks the beginning of an SQ event. This SQ remains displayed until offsetting orders are submitted that permit the entire resting marketable order volume to transact. The first observance of an executed trade (*Fstpri*) following a SQ marks the end of the SQ event. Using similar filters as with LULD, we remove any SQ events that do not experience a trade both before and after the event during the same trading session. Because SQ events end with a

---

[9] Using the TAQ data, we find 6.3 million un-executable quotes due to LULD. This number is reduced to 2.6 million observations when we identify changes from one LULD condition to another. After combining consecutive LULD condition observations, we are left with 244,226 observations. Of those, 6,775 observations also have trades both before and after the event during the trading day. This is our final LULD sample.

[10] The change from 244,226 to 9,756 is quite dramatic. On July 18, 2016, after our sample period, amendment 10 was implemented. Amendment 10 changed the reference price determination when securities do not experience an opening transaction. Hughes (2017) finds that regulatory halts decreased by 80% but makes no formal assessment on the decrease in straddle state events or limit state events that do not result in a halt. Neither do we. However, the dramatic decrease in halts provides support for our decreased number of events due to the requirement of a trade prior to the event.

trade, there is no need to combine successive events without trades between them. As shown in Table 1, we identify 7,462 qualifying SQ events.

IV. Price Paths, Variables, and Associated Measurement Intervals

A. Price Continuations and Reversals

Price continuations and reversals constitute all price outcomes yet define many distinct price paths. We define five price paths. A price path that continues above (below) the *UBND (LBND)* following a *UBEVT* (*LBEVT*) event is labeled *Continue,* which we define as follows:

$$Continue = \begin{cases} 5MP > UBND \; if \; UBEVT \\ 5MP < LBND \; if \; LBEVT \end{cases} \tag{1}$$

where *5MP* is the average trade price (*ATP)* during the five-minute period beginning with the end of the price-limit event. Prior literature defines all other price paths as reversals. However, equilibrium price changes that occur near, but not beyond, the price limit are significantly different than highly volatile or illiquid market conditions that result in a price path at or near the opposite price limit. Our four reversal classifications are:

$$AT\_LIMIT = \begin{cases} UBND \geq 5MP \geq UBNDM \; if \; UBEVT \\ UBNDM \leq 5MP \leq LBND \; if \; LBEVT \end{cases} \tag{2}$$

$$Reversal = \begin{cases} UBNDM > 5MP > LUBNDM \; if \; UBEVT \\ LBNDM < 5MP < UBNDM \; if \; LBEVT \end{cases} \tag{3}$$

$$HIVT = \begin{cases} LBND \leq 5MP \leq LBNDM \; if \; UBEVT \\ UBND \geq 5MP \geq UBNDM \; if \; LBEVT \end{cases} \tag{4}$$

$$EXVT = \begin{cases} 5MP > LBND \; if \; UBEVT \\ 5MP > UBND \; if \; LBEVT \end{cases} \tag{5}$$

Our final price path designation is *NOTRD*. This occurs when no trades occur during the first five-minute, post-event interval. *NOTRD* is only possible following an LULD event. Our classification is exhaustive so the set of observations of *Continue*, *AT_LIMIT, Reversal, HIVT, EXVT*, plus *NOTRD* comprise all the observations.

We add controls for the price path following the event. These variables are equal to 1 when the observation's *POSTEVT* price path corresponds to the dummy variable and 0 otherwise. These price path dummy variables are *DContinue, DAT_LIMIT, DReversal, DHIVT,* and *DNOTRD*.

B. Variables

Although most of our variables are for intervals before or after an event, there are several exceptions. One is *Duration*, which is the length of each event in seconds. Returns can also span an event. For stock *i*, let $X = (P_t - P_{t-1})/P_{t-1}$ and $M, = (M_t - M_{t-1})/M_{t-1}$ where *M* is the synchronous market return. *ABRTN* = abs($X - M$), where t-1 is the second the event begins, and *t* is the second that the event ends. We also calculate a return, for which t-1 equals the second the event begins, and *t* is the price five minutes after the end of the event; this variable is $ABRTN_{5M}$.

Next, we define a set of dummy variables, many of which are similar to those of Cho, Russell, Tiao, and Tsay (2003). However, in the case of the SQ and LULD rules, we cannot use stock returns since the associated trades will induce the price limits to move. Instead, we employ quote revisions and use a dummy variable indicating that the *BID* or *ASK* is near the price limit. Let *DO* = 1 if *ASK* is >= *UBND* and *DU* = 1 if *BID* <= *UBND*. Let *DC* = 1 if *ASK* > *UBNDMID* and *DO* = 0. Let *DF* = 1 if *BID* < *LBNDMID* and *DU* = 0.

Changes to the *ASK* or *BID* can occur by quote revisions as well as through trades. However, for SQ and LULD, trades affect the *RP*, the *UBND*, and the *LBND*. In the case of LULD, the effect is observed sometime within the following 30 seconds. For SQ, the effect is instantaneous. As such, a change in the *ASK* (*BID*) is not always an adjustment towards the price limit for SQ and LULD as it is for daily static price limits. We develop a measure of nearness to capture changes towards and away from the price limits in an environment where price limits are ever changing. For measures of nearness of the *ASK* to the *UBND and LBND*, respectively, we define

$$UNear = \frac{ASK - RP}{UBND - RP} \tag{6}$$

$$LNear = \frac{RP - BID}{RP - LBND} \tag{7}$$

when *Near* is equal to 1 when the *ASK* (*BID*) is equal to the *UBND* (*LBND*).

As mentioned above, we follow Lee, Ready, and Seguin (1994) in measuring volatility and volume. Our five volatility measures are: *ABRET*, *HILO*; *SPDREV*; *MHILO*; *HILOP*. Our two volume measures are: *SHRS* and *TRDS*. We define five dummy variables, namely: *DMorning*, *DUP*, *DCall*, *Trade*, and *DTREAT.* We have one interaction variable, *I1*, which is the product of *DPE* and *DTREAT*. Our variables are defined in Appendix A.

C. Intervals

Because there is no trading during an event, most of our variables are for intervals before and after the event. We compare these to a reference sample baseline average (BL). Pre-event observations begin five minutes prior to the start of the price-limit event and end when the price limit begins. Pre-event measures, designated with the subscript pre, allow us to examine variables such as abnormal volatility and volume immediately prior to the price-limit event. Post-event observations, designated post, comprise the five-minute time interval beginning at the end of the price-limit event. Post-event measures allow us to examine variables following the event.

We calculate variables outside of events, which we designate BL. Let t_0 be the beginning of trading. Period 1[11] is t_0 through t_4; Period 2, t_5 through t_9; and so forth. BL1 is the mean daily period 1, BL 2 is the mean daily Period 2, and so forth. The BL measure for each pre-event interval is the mean daily period that includes the beginning time of the associated pre-event interval. The BL measure for each post-event interval is the mean daily period that includes the beginning time of the associated post-event interval. The BL measure is an average that captures normal levels for each security. Each volatility measure is calculated over five-minute daily periods throughout the trading day, excluding intervals from five minutes before to five minutes after each event.

We have discussed *RP*s, *UBND*s, and *LBND*s above. It may be useful to describe some variable that we use in relation to these. Exchange regulations establish the *RP* and a value X

---

[11] For period 1 we remove the first 20 seconds of the trading day to remove place holder quotes. Brownlees and Gallo (2006) notes that some 'quotes have a very large spread and there are often extremely large quotes or suspicious zeros.' Hasbrouck (2010) uses monthly TAQ to show how to identify the NBBO. In his example (Table 1) he begins 20 seconds after the opening. We find similar suspicious large or zero quotes that are typically resolved within 20 seconds of trading. Internet Appendix B shows an example of irregular quotes that are removed.

such that *RP* + X = *UBND* and *RP* – X = *LBND*. We define *UBNDMID* as *RP* + ½ X and *LBNDMID* as *RP* – ½ X.

D. Description Statistics

Table 1 reports descriptive statistics for SQ and LULD events. We present results for the total sample (All) and classified by whether the events are in the morning (*DMorning* = 1) or afternoon (*DMorning* = 0), initiated by a *UBND* (DC = 1) or *LBND* (DU = 0) condition, or occur during continuous trading (*Call* = 0) or the call auction (*Call* = 1). For LULD events, there is little difference between the number of morning and afternoon observations or between *UBND* and *LBND* observations. Durations are longer in the morning, but returns are lower. LULD event durations are highly skewed with the mean duration over 290 seconds, but median duration of 1 second or less. *UBND* events also have longer durations, but smaller returns. Also, the $ABRTN_{5M}$ is 3.35%. These results are unsurprising because the LULD events only occur at times of great market volatility and if they do not resolve themselves within fifteen seconds (for the limit state) a five-minute mandatory halt is imposed.

For SQ, there are substantially more events in the morning and of the *UBND* type. However, there is little difference in durations or returns. SQ events have shorter duration and smaller absolute returns than LULD events. Unsurprisingly, the duration for SQ events is also highly skewed with a mean duration of 134 seconds and a median duration of only seven seconds, indicating that SQ events resolve themselves rather quickly after they begin or near three-minute price band adjustment. The majority of SQ events are *UBEVT*.

Most SQ and LULD events occur during continuous trading.

E.1. Pseudo-Events

Kim and Rhee (1997) recognize that stocks that reach their limit are prevented from correcting their order imbalance. These authors overcome this obstacle by creating subgroups of stocks that ‘almost’ reach their price limit. Lin and Swan (2019) follow this approach. One limitation to this approach is that stocks that ‘almost’ reach their price limits may significantly differ from stocks that do reach the price limit, perhaps because they do not have similar informational shocks. Lee, Ready, and Seguin (1994) describe the ideal experimental design as one in which identical firms experience the same information event with some being subject to an NYSE halt while others are not. These authors create pseudo-halts by matching on time of day and stock returns net of market returns. We cannot identify pseudo-LULD events in the US data because any meaningful matching criteria will match to another LULD event. Lee, Ready, and Seguin (1994) did not face this problem because the NYSE halts they evaluate are called at the discretion of the floor specialist. However, as they point out, this matching process is not random and excludes halts with extremely large absolute price moves. As Kim and Rhee (1997) note: “halts are like price limits except that they are determined subjectively by exchange officials.”

We devise a novel experimental design that allows us to create pseudo-halt samples for both SQ and LULD that comprise stocks that reach or surpass the SQ and LULD limits, but that are not prevented from correcting their order imbalance. We do this by simulating LULD on the TSE and simulating SQ on the US market so that we create a control sample of firms that experience market conditions sufficient to trigger a price limit, but for which trading continues uninterrupted. There exist some important features of the US market that differs from the TSE that may affect our results. First, US listed firms have generally larger market capitalizations than TSE listed firms. Secondly, quoted spreads may differ significantly, not only across exchanges but across otherwise similar firms on the same exchange. Finally, the TSE imposes tick sizes that are increasing with security price increases. To control for these important characteristics we include market capitalization, quoted spread, and tick size as control variables in our regressions. However, since the firms are different and the exchanges are not open at the same time, we are not able to match on firm characteristics or by time of day. This is a limitation of our approach.

To create LULD pseudo-events (SLULD), we calculate a reference price, *RP*, for each TSE stock for each 30-second interval beginning at the opening of trading. For TSE stocks, we also calculate a contemporaneous *UBND* and *LBND* as a percentage of the *RP* using US rules. A SLULD occurs when either ASK > *UBND* or BID < *LBND*.

To create SSQ events, we identify a *RP*, which is the simply the most recent trade price for each stock at all times throughout the trading day. We calculate the contemporaneous *UBND* and *LBND* based on the stock price and in accordance with TSE SQ rules. A pseudo-event occurs when either *RP* > *UBND* or *RP* < *LBND.* Pseudo-events are identified separately for *UBND* and *LBND* events. Pre-event observations are for the five minutes prior to the first breach of the boundary and the post-event observations immediately follow the pre-event observations. To constitute a separate event, a new breach must occur more than five minutes after the previous breach and more than five minutes after any new breaches that occur during these five minutes.[12]

Our research design allows us to make four-way comparisons—LULD against SLULD, LULD against SSQ, SQ against SSQ, and SQ against SLULD.

E.2. Research Design

Slightly modifying Kim and Rhee's (1997) and Lin and Swan (2019) approach, we accommodate differences in short-term, dynamic price limits. SQ and LULD events can occur at either the *UBND* or *LBND*, regardless of the open-to-close return on the limit event date. We identify the *RP* as well as the *UBND* and *LBND* at the start of the event. TAQ and NEEDS data both allow us to identify the limit that has been reached. The first trade (*Fstpri*) following an SQ event must to be within the price limit if it occurs within 3 minutes. For LULD, the first trade following a LULD event may be forced to be within the price limits when a halt does not occur, can be at any price when a halt occurs, or may not occur until a significant amount of time has lapsed following the end of the event. Due to these important attributes of SQ and LULD, we observe the *Fstpri* as well as the *5MP* for each actual and simulated price limit event.

E.3. Do Circuit Breakers Interfere with Price Discovery?

[12] Stated differently, to constitute a separate event, a new breach must occur more than five minutes after the most recent breach. Hence, any new breaches within the five minutes follow an initial breach reset the clock for determining a separate event.

Table 2 reports the results of our preliminary analysis related to Hypothesis 1. For *Continue* there are significantly more SLULD events (6.25%) than LULD events (4.43%), and significantly more SSQ events (73.40%) than SQ events (26.07%). Hence, both SQ and LULD experience relatively fewer price continuations than their simulated counterparts. Therefore, contrary to Hypothesis 1, we find no evidence that these circuit breakers interfere with price discovery.

We further evaluate the delayed price discovery hypothesis using a probit regression model with *Continue* as our dependent variable. We separately pair our SQ and LULD samples with the SLULD and SSQ samples, in turn, to create four distinct comparisons. Our main RHS variable of interest is *DTREAT*. Our other RHS variables are our pre-event BL volatility and volume variables—*ABRET*, *HILO*, *SPDREV*, *MHILO*, *HILOP*, *SHRS*, and *TRDS*. We also include additional control dummy variables—*MORNING, CALL, DU, MRKT_CAP, SPREAD,* and *TICK_SIZE*. Finally, we include *Duration* as an additional control.

We report our probit results in Table 3. For both SQ and LULD, the coefficients of *DTREAT* (-1.277 and -0.544, respectively) are negative and significant. This result provides strong evidence that neither LULD nor SQ delay price discovery and strengthens our rejection of our Hypothesis 1. When compared to its simulated alternative, LULD has a significantly negative *DTREAT* coefficient of -2.46. The lone positive *DTREAT* coefficient of 1.145 is for the comparison of SQ with SLULD. This result likely reflects the fact that SQ has significantly more restrictive price-limit parameters.

Our results are robust in comparison to the TSE daily price limits as well. We identify 847 daily price limit events during our January 2015 sample period. We observe that 57.4% of daily price limits experience a price continuation on the trading day following the price limit event. Compared to LULD's 4.43% and SQ's 26.07% price continuation proportions, Both SQ and LULD interfere with or delay price discovery less often than daily static price limits.

E.4. Magnet Effect

To test for the presence of the magnet effect associated with LULD or SQ, we examine the behavior of liquidity providers as the *ASK* and *BID* approach the *UBND* and *LBND*.[13] We use an AR (3) model to identify the magnet effect at the *UBND* as follows:

$$U(Near)_t = \alpha_0 + \alpha_1 DC_{t-1} + \alpha_2 DO_{t-1} + \alpha_3 Trade + \alpha_4 U(Near)_{t-1} + \alpha_5 U(Near)_{t-2} + \alpha_6 U(Near)_{t-3} + \varepsilon \tag{8}$$

To identify the magnet effect at the *LBND*, our model becomes:

$$L(Near)_t = \alpha_0 + \alpha_1 DF_{t-1} + \alpha_2 DU_{t-1} + \alpha_3 Trade + \alpha_4 L(Near)_{t-1} + \alpha_5 L(Near)_{t-2} + \alpha_6 L(Near)_{t-3} + +\varepsilon \tag{9}$$

Both *U(Near)* and *L(Near)* are first differences. *DC (DF)* is a dummy variable equal to 1 when the *ASK* (*BID*) is nearer to the *UBND* (*LBND*) than to the *RP*. *DO (DU)* is a dummy variable

[13] Note that in investigating the magnet effect we focus on quotes rather than trades because trades cause *UBND* and *LBND* to change. Changes in *UBND* and *LBND* move the goal against which the magnet effect is measured.

equal to 1 when the *ASK* (*BID*) is higher (lower) than the *UBND (LBND)*. *Trade* is a dummy variable equal to 1 if the most recent quote follows a trade.

The magnet effect can exist only when there are price limits because it occurs when market participants speed up their activity in anticipation of halted or constrained trading upon reaching the price limit. Similar activity in the absence of a price limit is momentum. Comparing the actual events to the simulated events allows us to distinguish between the magnet effect and momentum.

Table 4 presents our magnet-effect results. We estimate our regression model for all stocks traded in both the US and TSE markets (Panels A and B) as well as for only those stocks that experience a price limit or pseudo-event (Panels C and D). If the magnet effect is present, we expect the coefficient of *DC* or *DF* to be positive and significant for LULD or SQ. Further, any positive and significant results for the coefficients of *DC* or *DF* in the simulated samples imply that at least some observed magnet effect might be explained by momentum.

Examining the results reported in Table 4, the *DF* coefficient of 0.007 for SQ for *UBND* for both the full sample (Table 4, Panel A) and event sample (Table 4, Panel C) is statistically significant, indicating that *SQ* exhibits the magnet effect. This conclusion is strengthened by the evidence of reversal shown by the significantly negative coefficient of -5.49 for the event SSQ sample (Table 4, Panel C). For LULD at the *UBND* and *LBND* (-0.343 and -0.479, respectively) as well as SQ at the *UBND* (-0.009), we find a reversion effect rather than a magnet effect for quotes. As they get nearer the price limits, quotes are more likely to be revised towards the *RP* than towards the price limit. A possible explanation for this is that market participants observe that in most cases—73.9% for SQ and 95.6% for LULD (Table 2)—prices remain at the price limit or revert towards the *RP*. The parameters set by the SQ and LULD signals to market participants when prices move beyond normal or typical parameters. This signal informs liquidity providers that conditions are favorable for submitting orders that are more aggressive. In addition, with traditional price limits, market participants speed up their activity as prices approach the limits because when the price limits are reached, trading is halted, and participants are unable to enter or exit positions. However, SQ and LULD allow trading to occur within the prevailing price limit range. The risk of not being able to trade is reduced for the SQ and LULD rules. These results are robust to momentum effects.

Comparatively, both SQ and LULD exhibit evidence of a reversionary effect. However, LULD appears to improve market quality better by exhibiting this effect and both the *UBND* and *LBND.*

Following our same methodology as with short duration dynamic price limits we extend our analysis of the magnet effect to the TSE daily price limit as well. The wider price limit parameters associated with the daily price limits may mean that *UNear* (*LNear*) being equal to 0.5 is not meaningfully near enough to the price limit to alter traders' behavior. We also estimate our AR(3) regressions by altering our threshold for *DC* (*DF*) being equal to 1 when *UNear* (*LNear*) is greater than or equal to 0.75 and yet again at 0.90.[14] We find evidence of the magnet effect at the LBND. We estimate a significant DF coefficient at the lower limit equal to 0.002,

[14] Full regression results reported in Internet Appendix G

0.005, and 0.017 when *LNear* is greater than or equal to 0.5, 0.75, and 0.90 respectively. We find that the short duration dynamic price limits fare at least as well as daily price limits in association with the magnet effect. LULD performs better at not exhibiting a magnet effect at all.

E.5. Volatility Spillover

Finally, we turn our attention to the volatility spillover hypothesis (Hypothesis 3A). For each firm for each LULD event *t*, for the five-minute, pre-event observations, we calculate $ABRET_t$. We segment the day into successive five-minute intervals beginning at the market open. We identify the interval that includes the time of day that corresponds to the beginning of event t. We calculate the mean for *ABRET* for all the days in January 2015, excluding the day on which event t occurs; this is $Statistic_{BL,t}$. We define S_t as $ABRET_t / Statistic_{BL,t}$ and *Mean Abnormal Statistic* as the mean of S_t over all *t* times 100.

Following Lee, Ready, and Seguin (1994), the *Mean Abnormal Statistic* represents firm-specific, time-controlled volatility relative to BL values. We continue our analysis with our group of pseudo-events that experience the same informational shock but are not subject to the LULD or SQ price limits. Our pseudo-halt samples allow us to compare the pre- and post-price-limit event to other events with similar large and sudden price movements. Calculate

$$\frac{1}{Q}\sum_{i=1}^{Q}\frac{Pseudo\_Event\ Statistic_i}{Pseudo\ Statistic_{BL}} * 100 \tag{10}$$

where Q= Number of events in the Pseudo-event sample.

We report the *Mean Abnormal Statistic* in Table 5, Panel A. The value of 1,310 indicates that the event statistic is about 13 times larger than the base-period statistic. We replicate this analysis for the remaining variables (*HILO, HILOP, MHILO, TRDS,* and *SHRS,* in turn) and report the results in Table 5, Panel A. We replicate the entire analysis for SQ pre-event observations, and for both SQ and LULD post-event observations (Table 5, Panel B). Tables 5 *p*-values refer to the difference between the mean abnormal statistics for each event and pseudo-event pairing.

For both SQ and LULD, volatility and volume are significantly higher across all measures both before and after an LULD or SQ event (except for pre- and post-event *MHILO* for LULD).[15] However, by design, SQ and LULD events should occur at times of elevated volatility when we would expect pre-event volatility to be abnormally high. We also conclude from these results that the price and volume adjustment is incomplete at the end of a price-limit event. Comparing SQ and LULD events to their baseline measure as well as to pseudo-events allows us to control for both time of day effects and the magnitude of the information release.

For the TSE daily price limit we measure our five volatility statistics and two volume statistics on the day of each daily price limit event, the following day, and a baseline measure for all non-event days. We also exclude all days following an event from our baseline measure. As with SQ and LULD, we again find mixed results for the TSE daily price limits to calm market volatility. *ABSRET* and *MHILO* are significantly reduced following a daily price limit event, but all other measures of volatility and volume are not significantly different following a daily price

[15] Internet Appendix C includes more detailed reporting of our results.

limit event. SQ and LULD perform at least as well in reducing volatility as daily price limits but without halting trading for extended periods of time. We conclude from these results that compared to daily static price limits, SQ and LULD perform well while allowing for information flow through trading.

Contrary to Hypothesis 3A, we find that neither SQ nor LULD show consistent reductions in volatility and volume. Our results are similar to the Lee, Ready, and Sequin (1994) findings regarding NYSE trading halts[16].

E.6. Extreme Market Conditions

The May 6th, 2010 flash crash gave rise to LULD. This event is well known and characterized by sudden and dramatic price changes that were immediately followed by price reversals. Proctor and Gamble, for example opened trading at $61.91 and closed at $60.75 yet traded briefly as low as $39.37. This represents more than a 35% intra-day decline on a trading day that recorded a -1.8% return. On August 24th, 2015 a flash crash like the one seen on May 6th, 2010 occurred. The SEC's Office of Analytics and Research's note on equity market volatility (2015) remarks that equity and equity related futures "markets experienced unusual price volatility, particularly during the period surrounding the 9:30 a.m. E.T." We extend our study to examine the effectiveness of LULD to mitigate volatility during flash crashes by comparing May 6th, 2010 (May) to August 24th, 2015 (Aug).

[16] Internet Appendix D reports similar results with an OLS regression analysis. Internet Appendix E reports similar results with a difference in difference regression analysis

We begin by measuring *Intraday Volatility* as

$$Intraday\ Volatility = \ Daily\ High\ Price - Daily\ Low\ Price \tag{11}$$

We measure *Intraday Volatility* for each stock on each day and perform a standard *t*-test of the difference in means. We also include this same measure for all trading days in January 2015 for a comparison with normal activity. Table 6, Panel A, reports our results. The mean *Intraday Volatility* of $3.38 for Aug is significantly smaller than $4.28 for May. For stocks with a 5% LULD price parameter, we find similar results with an Aug mean value of $6.97 compared to $8.52 for May. *Intraday volatility* on these days captures the magnitude of the flash crash and we find that the Aug flash crash, when LULD is in effect, is less severe than the May flash crash.

The conditions during the flash crash are described by Goettler, Parlour, and Rajan (2009) as microstructure noise. They define microstructure noise as a deviation of transaction prices from estimated fundamental values but do not offer a formal measure of it. Larger daily price ranges are expected when larger daily equilibrium price changes occur so *intraday volatility* only provides a partial view of *microstructure noise*. To more fully measure the amount of microstructure noise, for May and Aug, we divide Equation (11) by the absolute value of the open price less the closing price. This measure allows us to analyze the magnitude of *intraday volatility* relative to daily equilibrium price changes. The implication is that *microstructure noise* is dependent on both *intraday volatility* and daily equilibrium price changes. For the entire sample, for 5% and 10% parameters, we find that despite LULD's ability to reduce *intraday volatility,* LULD does not show a mitigating effect on microstructure noise. A possible explanation is that during the first 15 minutes of trading, the price parameters for LULD are two times their normal magnitude. The Aug flash crash occurred at the market open and so the *microstructure noise* mitigating benefits of LULD may have been muted during this period given the larger price parameters in effect. These results fail to support Hypothesis 3B that LULD mitigates microstructure noise at times of flash crashes.

E.7. Electronically Traded Funds

Both SQ and LULD apply to electronically traded funds as well as single stocks (ETFs). ETFs should trade at prices equal to the weighted average price of the fund constituents. Given this quality, ETFs should reach the *UBND* or *LBND* only when a significant number of the funds' constituents equilibrium price move beyond their respective price limits.

E.8. Special Quotes' Dynamic Limit Parameters

SQs price limit parameter is also dynamic. If a SQ event has not ended after three minutes, the price bands widen to double their original magnitude. SQ events that persist past the three-minute mark represent the most extreme SQ events. We evaluate the expansion process for each of our hypotheses. Our results are reported in Table 7.

Beginning with price discovery, we allow our price-path definitions to adjust so that the *UBND* and *LBND* are defined by the newly adjusted price limit rather than the original price limit. We find that 13.2% of SQ events that last for three minutes or longer experience a price continuation. This is less than 26.07% of price continuations for all SQ events and 73.4% of price continuations for all SSQ events. We conclude that the parameter adjustment process also does not interfere with or delay price discovery.

Longer lasting SQ events imply greater short-term price uncertainty. This elevated price uncertainty is likely marked by widening spreads. This behavior could be construed as a magnet effect when in-fact it is simply a reflection of price uncertainty. We remove the securities that experience long lasting SQ events from our magnet effect sample of securities and re-estimate (8) and (9). At the upper limit, where we find evidence of the magnet effect, we estimate the D(C) coefficient to be 0.011 and is significant at the 1% level. This is larger than the 0.007 estimated coefficient on the full sample. We conclude that the observed magnet effect is not the result of widening spreads at times of high price uncertainty. Further, it appears that the price limit adjustment process involved with SQ is beneficial in reducing the magnet effect in the most extreme cases.

Finally, we compare pre-event volatility to post-event volatility for each SQ event that last for three minute or longer. For each of our five volatility and two volume measures we calculate the mean abnormal statistic and perform a t-test to determine the difference between the pre-event abnormal statistic and post-event abnormal statistic. Again, we find mixed results for SQ's ability to calm market volatility. *HILOP*, *SHRS*, and *TRDS* are significantly reduced, *ABSRET*, *HILO*, and *SPDREV* are significantly increased, while *MHILO* remains unchanged. These results are consistent with our findings regarding volatility for our entire sample.

V. Conclusion

Special quotes (SQ) in Japan and limit-up limit-down (LULD) in the U.S. are short-term, dynamic price limits. These price limits are distinguished by the fact that they (1) adjust throughout the trading day based on trading activity, and (2) allow trading to resume shortly after the price limit event begins rather than waiting until the following trading day. However, SQ and LULD differ from each other in important ways. First, LULD's price limit parameters are significantly larger than SQ's. Secondly, LULD's reference price is based on the previous five minutes of trading while SQ is equal to the previous trade price. Finally, LULD is a liquidity-supply-driven rule whereas SQ is liquidity-demand-driven.

We examine SQ and LULD events to test for price discovery, volatility spillover effects, and the magnet effect. To determine the effect of SQ and LULD on the market, we devise a novel pseudo-halt approach by simulating SQs of US markets and LULD on the TSE. We find that neither LULD nor SQ delay price discovery. We find that SQ suffers from the magnet effect at the *UBND.* At the *LBND* for SQ as well as the *UBND* and *LBND* for LULD, we find a reversal effect. Finally, we find mixed results for both SQ and LULD regarding how well either rule calms the market. It is apparent that the price and volatility adjustment process is not complete at the end of either LULD or SQ, but that some measures of volatility are improved with SQ and LULD while others are not. Finally, we test the efficacy of LULD at mitigating microstructure noise during the flash crashes of May 6th, 2010 and Aug 24th, 2016. We find that microstructure noise is significantly higher on Aug 24th compared to May 6th.

We conclude that SQ and LULD enhance market quality by allowing trading to occur within the prevailing price limits, but without the threat of prolonged trading halts. SQ and LULD's performance and market enhancing qualities are particularly strong when compared to traditional daily static price limits.

References

Bellia, Mario, Loriana Pelizzon, Marti G. Subrahmanyam, Jun Uno, and Darya Yuferova, 2016, Low-latency trading and price discovery: Evidence from the Tokyo Stock Exchange in the pre-opening and opening periods, SAFE Working Paper Series, No. 144.

Brennan, Michael J., 1986, A theory of price limits in futures markets, *Journal of Financial Economics* 16, 213-233.

Brownlees, Christian T. and Giampiero Gallo, 2006, Financial econometric analysis at ultra-high frequency: Data handling concerns, *Computational Statistics and Data Analysis* 51, 2223-2245.

Chen, Ting, Zhenyu Gao, Jibao He, Wenxi Jiang, and Wei Xiong, 2019, Daily price limits and destructive market behavior, *Journal of Econometrics* 208, 249–264

Cho, David D., Jeffrey Russell, George C. Tiao, and Ruey Tsay, 2003, The magnet effect of price limits: Evidence from high-frequency data on Taiwan Stock Exchange, *Journal of Empirical Finance* 10, 133-168.

Chou, Pin-Huang, Robin K. Chou, Kuan-Cheng Ko, and Chao, Chun-Yi Chao, 2013, What affects the cool-of duration under price limits?, *Pacific-Basin Finance Journal* 24, 256-278.

Christie, William G., Shane A. Corwin, and Jeffrey H. Harris, 2002, Nasdaq trading halts: The impact of market mechanisms on prices, trading activity, and execution costs, *Journal of Finance* 57, 1443-1478.

Corwin, Shane A., and Marc L. Lipson, 2000, Order flow and liquidity around NYSE trading halts, *Journal of Finance* 55, 1771-1801.

Deb, Saikat S., Petko S. Kalev, and Vijaya B. Marisetty, 2013, Flexible price limits: The case of Tokyo Stock Exchange, *International Financial Markets, Institutions and Money* 24, 66-84.

Deb, Saikat S., Petko S. Kalev, and Vijaya B. Marisetty, 2017, Price limits and volatility, *Pacific-Basin Finance Journal* 45, 142-156.

Fama, Eugene F, 1989, Perspectives on October 1987, or what did we learn from the crash?, in Robert J. Barro, Robert W. Kamphuis Jr., Roger C. Kormendi, and J.W. Henry. Watson, eds.: *Black Monday and the Future of the Financial Markets* (Dow Jones-Irwin, Homewood, IL).

Farag, Hirsham, 2013, Price Limit bands, asymmetric volatility and stock market anomalies: Evidence from emerging markets, *Global Finance Journal* 24, 85-97.

FINRA (Financial Industry Regulatory Authority), 2016, Plan to address extraordinary market volatility submitted to the Securities and Exchange Commission pursuant to Rule 608 of Regulation NMS under the Securities Exchange Act of 1934, (Short title: Limit up/limit down (LULD) plan).

Gerety, Mason S. and J. Harold Mulherin, 1992, Trading halts and market activity: An analysis of volume at the open and the close, *Journal of Finance* 47, 1765-1784.

Goettler, Ronald L., Christine A. Parlour, and Uday Rajan, 2009, Informed traders and limit order markets, *Journal of Financial Economics* 93, 67-87

Hamao, Yasushi and Joel Hasbrouck, 1995, Securities trading in the absence of dealers: trades and quotes on the Tokyo Stock Exchange, *Review of Financial Studies* 8, 849-878.

Hasbrouck, Joel, 2010, The best bid and offer: A short note on programs and practices, available at SSRN: https://ssrn.com/abstract=1699426 or http://dx.doi.org/10.2139/ssrn.1699426

https://www.jpx.co.jp/english/equities/trading/domestic/04.html

Hughes, Paul, 2017, The effect of amendment 10 of the limit up-limit down pilot plan. U.S. Securities and Exchange Commission.

Hughes, Paul, John Ritter, and Hao Zhang, 2017, Limit up-limit down pilot plan and extraordinary transitory volatility, U.S. Securities and Exchange Commission.

Kim, Kenneth A. and Piman Limpaphayom, 2000, Characteristics of stocks that frequently hit price limits: Empirical evidence from Taiwan and Thailand, *Journal of Financial Markets* 3, 315-332.

Kim, Kenneth A. and S. Ghon Rhee, 1997, Price limit performance: Evidence from the Tokyo Stock Exchange, *Journal of Finance* 52, 885-901.

Kuhn, Betsy A., Gregory J. Kurserk, and Peter Locke, 1991, Do circuit breakers moderate volatility? Evidence from October 1989, *Review of Futures Markets* 10, 426-434.

Lee, Charles M. C., Mark J. Ready, and Paul J. Seguin, 1994, Volume, volatility, and the New York Stock Exchange trading halts, *Journal of Finance,* 49, 183-214.

Lehmann, Bruce N., 1989, Commentary: Volatility, price resolution, and the effectiveness of price limits, *Journal of Financial Services Research* 3, 205-209.

Lin, Yiping and Peter L. Swan, 2019, Limit up limit down, exchange access fees, and high frequency trading around price limits, working paper, University of New South Wales.

Maskawa, Jun-ichi, 2016, Collective behavior of market participants during abrupt stock price changes, *PLoS ONE* 11(8).

Moise, Claudia E. and Paca Flaherty, 2017, Limit up-limit down pilot plan and associated events, U.S. Securities and Exchange Commission, White paper.

SEC Staff of the Office of Analytics and Research Division of Trading and Markets, 2015, Research note: Equity market volatility on August 24, 2015.

Spiegel, Mathew and Avanidhar Subrahmanyam, 2000, Asymmetric Information and Disclosure Rules, *Journal of Financial Intermediation* 9, 363-403.

Subrahmanyam, Avanidhar, 1994, Circuit breakers and market volatility: A theoretical perspective, *Journal of Finance* 49, 237-254.

Appendix A

Definitions of terms

General definitions	
ASK	The best ask.
Average Trade Price (ATP)	The average trade price over the preceding 5-minutes. For LULD, the *ATP* becomes the *RP* when the *ATP* is more than 1% higher or lower than the *RP*
BID	The best bid.
BL (*Baseline Average*)	A representation of the normal level of volatility. *BL*s are measured for *ABRET*, *HILO*, *HILOP*, *SPDREV*, *SHRS*, *TRDS*, and *MHILO*. Each volatility measure is calculated over five-minute daily periods throughout the trading day, excluding intervals from five minutes before to five minutes after each event. Let t0 be the beginning of trading. Daily period_1 is t0 through t4, daily period_2 t5 through t9, and so forth. BL_1 is the mean daily period_1; BL_2 is the mean daily period_2, and so forth. The *BL* measure for each *pre-event interval* is the mean daily period that includes the beginning time of the associated *pre-event interval*. The *BL* measure for each *post-event interval* is the mean daily period that includes the beginning time of the associated *post-event interval*. Calculated baseline statistics are denoted with a subscript '*BL*.'
BLstat	The BL statistic from the reference distribution corresponding to the *i*th event in each sample.
Continuous trading	During this period trades occur whenever two counterparties agree on a price. For continuous trading *DCall* = 0
DTREAT	A dummy variable equal to 1 for each LULD or SQ observation and equal to 0 for each SLULD and SSQ observation
Event	A market condition in which marketable orders are not executed because execution requires a trade price > *UBND* or < *LBND*. For LULD the event begins with the first observation of the NBBO outside the current UBND-LBND range. A LULD event ends in one of two ways. When there are no NBBOs observed outside the current *UBND-LBND* range or after a 5-minute trading pause.

	A SQ event begins with the first issuance of a special quote and ends with the next trade.
Interaction	*DTREAT x DPE.*
LBEVT	A disallowed trade or quote is at a price lower than *LBND*.
LBND (Also called the *lower bound* or *lower price limit)*	The lowest price that a stock is allowed to trade at a given point in time. For LULD, *LBND* is price dependent, time dependent, and Tier dependent. For Tier 1 stocks priced \$3.00 or more the *LBND* = 0.95 X *RP* beginning 15 minutes after the market opens until 25 minutes before the market close. During the first 15 minutes and final 25 minutes of trading the *LBND* = 0.90 X *RP*. For Tier 2 stocks priced \$3.00 or more the *LBND* = 0.90 X *RP* beginning 15 minutes after the market opens until 25 minutes before the market close. During the first 15 minutes and final 25 minutes of trading the *LBND* = 0.80 X *RP*. For Tier 1 and Tier 2 stocks that are priced between \$0.75 and \$3.00, *LBND* = 0.80 X *RP* beginning 15 minutes after the market opens until 25 minutes before the market close. During the first 15 minutes and final 25 minutes of trading the *LBND* = 0.60 X *RP*. For Tier 1 and Tier 2stocks that are priced less than \$0.75, *LBND* is the lessor of 0.25 X *RP* or \$0.15. For SQ, both the *UBND* is and LBND are price dependent and is a set number of JPY rather than a percentage or the *RP*.
LBNDM	The midpoint between the *LBND* and the *RP*.
Limit Parameter	The price range between the *RP* and the *UBND (LBND).*
Magnet Effect	A tendency for stock prices to accelerate toward the *UBND* or *LBND* as prices approach the *UBND or LBND*.
Pseudo Event	A simulated price-limit event on an exchange other than the one with the price limit rule. LULD pseudo-events are SLULD events on the TSE. SQ pseudo-events are SSQ events in US.
RP *(Reference Price)*	The midpoint between the *UBND* and *LBND.* For LULD, at the start of trading the *RP* is the opening price on the listing exchange. Thereafter, the *RP* is the arithmetic mean trade price during the immediately preceding 5 minutes. For SQ, the *RP* is the previous trade price except at the market open where the *RP* is the closing price from the previous trading day. For both the SQ and LULD, *LBND* and *UBND* are the same distance from the *RP*.
Tier 1	All NMS stocks included in the S&P 500 Index, the Russell 1000 Index, and select exchange-traded products
Tier *2*	All NMS stocks that are not included in Tier 1.

UBEVT	A disallowed trade or quote is at a price higher than *UBND*.
UBND (Also called the *upper bound* or *upper price limit.)*	The highest price that a stock is allowed to trade at a given point in time. For SQ, both the *UBND* is and LBND are price dependent and is a set number of JPY rather than a percentage or the *RP*.
UBNDM	The midpoint between the *UBND* and the *RP*.
MRKT_CAP	Firm market capitalization
SPREAD	The mean quoted spread for each firm
TICK_SIZE	The minimum tick size as allowed by the exchange. The TSE imposes an increasing tick size based on the security's trading price

Event variables	
ABRTN	The absolute return on the stock during the LULD or SQ price limit event. Computed as the first trade price after an LULD or SQ event less the last trade price prior to the price limit event scaled by the last trade price prior to the event.
$ABRTN_{5M}$	The absolute return on the stock during the LULD or SQ price limit event. Computed as the last trade price in the *post-event interval* less the last trade price prior to the price limit event scaled by the last trade price prior to the event.
DCall	A dummy variable equal to 1 when the resolution mechanism is a call auction and 0 for continuous trading.
DMorning	A dummy variable equal to 1 when the event begins during the morning session of the TSE or during the first half of the trading day in the US, and equal to 0 otherwise
DUP	A dummy variable equal to 1 for *UBEVT* and 0 for *LBEVT*
Duration	The length of time that a price limit lasts measured in seconds.
Event Statistic	The statistic from the *i*th event in each sample. Since there is no trading during an event, these statistics are for the five-minute period before and after the event.
Mean Abnormal Statistic	Firm-specific, time-controlled volatility and volume. For each event *t*, for each firm, for variable *X*, we calculate the mean value of *X* over all days other than the event day for the five-minute interval at the same time of day to obtain X_{BL}. The *Mean Abnormal Statistic* is X_t/X_{BL}.
Intraday Volatility	A measure of volatility throughout the trading day $Intraday\ Volatility = \ Daily\ High\ Price - Daily\ Low\ Price$
Daily Volatility	A measure of volatility over an entire trading day $Daily\ Volatility = \ Abs(Closing\ Price - Opening\ Price)$

Microstructure Noise	A ratio to measure the intra-day price range relative to the daily price range. $$Microstructure\ Noise = \frac{Mean\ Intraday\ Volatility}{Mean\ Daily\ Volatility}$$
	Path dummy variables
DAT_LIMIT	A dummy variable equal to 1 when the observation's *Post-event* price path is *AT_LIMIT* and 0 otherwise.
DC, (DF)	A dummy variable equal to 1 when the *ASK* (*BID*) is nearer to the *UBND* (*LBND*) than to the *RP*.
DContinue	A dummy variable equal to 1 when the observation's *Post-event* price path is *Continue* and 0 otherwise.
DHIVT	A dummy variable equal to 1 when the observation's *Post-event* price path is *HIVT* and 0 otherwise.
DNOTRD	A dummy variable equal to 1 when the observation's *Post-event* price path is *NOTRD* and 0 otherwise.
DO, (DU)	A dummy variable equal to 1 when the *ASK* (*BID*) is higher (lower) than the *UBND (LBND)*.
DReversal	A dummy variable equal to 1 when the observation's *Post-event* price path is *Reversal* and 0 otherwise.
DTrade	A dummy variable equal to 1 when a change in the *ASK* or *BID* is due to a trade.
Near	A ratio to measure how near the *BID* (*ASK*) is to the *LBND (UBND)*. $$U(nearness) = \frac{ASK - RP}{UBND - RP}$$ $$L(nearness) = \frac{RP - BID}{RP - LBND}$$
Reversion Effect	The opposite of the magnet effect. A condition in which prices or quotes are more likely to adjust towards the reference price rather than towards the price limit when prices are near to the price limits.
Trade	A dummy variable equal to 1 if the most recent quote follows a trade.
	Post-event variables
5MP	Average trade price during the *Post-event* period.
DPE	A dummy variable equal to one for observations during the post-event interval.
Fstpri	The first trade price *Post-event*.

Post-event interval	The five-minute period immediately following the end of a price limit event. Calculated statistics during the post-event interval are denoted with a subscript '*post.*'
Pseudo Event	A simulated price-limit event on an exchange other than the one with the price limit rule. For LULD, events on the TSE; for the TSE, events of a US exchange. FOR LULD, these are designated SLULD and for the TSE they are designated as SSQ.
	Pre-event variables
Pre-event interval	The five-minute period immediately preceding the start of a price limit event. Calculated statistics during the pre-event interval are denoted with a subscript '*pre.*'
	Price-path variables
AT_LIMIT	A condition where the price path of a stock remains near or at the applicable price limit. For a *UBEVT*, *UBNDM* ≤ *Fstpri* or 5MP ≤ *UBND*. For a *LBEVT*, *LBND* ≤ *Fstpri* or 5MP ≤ *LBNDM*.
Continue	For an *UBND event*, a *UBND* < *Fstpri* or *UBND* < *5MP*. For a *LBND event*, *Fstpri* < *LBND* or 5MP < *LBND*.
EXVT *(Extreme Volatility)*	Extreme volatility. A condition where the price path of a stock reverses in the opposite direction to continue beyond the opposing price limit. For *UBEVT*, *Fstpri* < *LBND* or *5MP* < *LBND*. For *LBEVT*, *UBND* < *Fstpri* or *5MP* < *Fstpri*.
HIVT *(High Volatility)*	A condition where the price path of a stock reverses in the opposite direction as the applicable price limit. For *UBEVT*, *LBND* ≤ *Fstpri* or 5MP ≤ *LBNDM*. For *LBEVT*, *UBNDM* ≤ *Fstpri* or *5MP* ≤ *UBND*.
Reversal	A condition where the price path of a stock returns to the *reference price* level. For any LULD or SQ event, *LBNDM* < *Fstpri* or 5MP < *UBNDM*.
	Variables measured over 5-minute intervals
ABRET	The absolute return. Computed as the last trade price in an interval less the first trade price in an interval scaled by the first trade price in an interval.
HILO	The absolute difference between the highest and lowest trade price in an interval.
HILOP	The *HILO* variable scaled by the lowest trade price in an interval.
MHILO	The highest midpoint less the lowest midpoint scaled by the lowest midpoint during the interval.
SHRS	The number of shares traded in an interval.

SPDREV	The number of revisions to the BBO midpoint in an interval.
TRDS	The number of trades in an interval.

Appendix B

Trade-to-trade price limits

For the Tokyo Stock Exchange, we present the trade-to-trade price limits, which vary according to the price of each stock. Columns 3 and 4 are calculated by dividing the absolute price limit by the stock price at the lower and upper range of the price category, respectively. These data are obtained from the TSE web site. All prices are in JPY

Stock price	Absolute JPY limit	Price limit as % of	
		LBND	*UBND*
0 to 200	± 5		± 2.5%
200 to 500	± 8	± 4%	± 1.6%
500 to 700	± 10	± 2%	± 1.4%
700 to 1,000	± 15	± 2.1%	± 1.5%
1,000 to 1,500	± 30	± 3%	± 2%
1,500 to 2,000	± 40	± 2.7%	± 2%
2,000 to 3,000	± 50	± 2.5%	± 1.7%
3,000 to 5,000	± 70	± 2.3%	± 1.4%
5,000 to 7,000	± 100	± 2%	± 1.4%
7,000 to 10,000	± 150	± 2.1%	± 1.5%
10,000 to 15,000	± 300	± 3%	± 2%
15,000 to 20,000	± 400	± 2.7%	± 2%
20,000 to 30,000	± 500	± 2.5%	± 1.7%
30,000 to 50,000	± 700	± 2.3%	± 1.4%
50,000 to 70,000	± 1,000	± 2%	± 1.4%
70,000 to 100,000	± 1,500	± 2.1%	± 1.5%
100,000 to 150,000	± 3,000	± 3%	± 2%
150,000 to 200,000	± 4,000	± 2.7%	± 2%
200,000 to 300,000	± 5,000	± 2.5%	± 1.7%
300,000 to 500,000	± 7,000	± 2.3%	± 1.4%
500,000 to 700,000	± 10,000	± 2%	± 1.4%
700,000 to 1,000,000	± 15,000	± 2.1%	± 1.5%
1,000,000 to 1,500,000	± 30,000	± 3%	± 2%
1,500,000 to 2,000,000	± 40,000	± 2.7%	± 2%
2,000,000 to 3,000,000	± 50,000	± 2.5%	± 1.7%
3,000,000 to 5,000,000	± 70,000	± 2.3%	± 1.4%
5,000,000 to 7,000,000	± 100,000	± 2%	± 1.4%
7,000,000 to 10,000,000	± 150,000	± 2.1%	± 1.5%
10,000,000 to 15,000,000	± 300,000	± 3%	± 2%

15,000,000 to 20,000,000	± 400,000	± 2.7%	± 2%
20,000,000 to 30,000,000	± 500,000	± 2.5%	± 1.7%
30,000,000 to 50,000,000	± 700,000	± 2.3%	± 1.4%
Over 50,000,000	± 1,000,000	± 2%	

Tables

	N	Duration	ABRTN	$ABRTN_{5M}$
Panel A: LULD				
All	6,775	290.56	0.236	3.345
		(0.01)	(0.0)	(0.231)
DMorning = 1	3,243	493.11	0.140	2.048
		(0.01)	(0.0)	(0.292)
DMorning = 0	3,532	104.59	0.342	4.536
		(0.01)	(0.0)	(0.200)
DU = 1	3,471	370.87	0.284	1.613
		(0.01)	(0.0)	(0.177)
DU = 0	3,304	214.13	0.191	5.164
		(0.01)	(0.0)	(0.333)
DCall = 0	6,747	285.44	0.228	3.348
		(0.01)	(0.0)	(0.231)
DCall = 1	28	1,526.22	2.276	2.656
		(315.01)	(0.053)	(0.394)
Panel B: SQ				
All	7,058	133.99	0.011	0.013
		(7.0)	(0.008)	(0.015)
DMorning = 1	4,170	134.01	0.012	0.015
		(5.5)	(0.015)	(0.017)
DMorning = 0	2,888	133.95	0.009	0.011
		(8.5)	(0.001)	(0.004)
DU = 1	5,862	115.90	0.011	0.018
		(5.0)	(0.006)	(0.008)
DU = 0	1,196	222.62	0.007	0.021
		(29.0)	(0.015)	(0.020)
DCall = 0	7,056	133.99	0.011	0.013
		(6.5)	(0.008)	(0.015)
DCall = 1	2	135	0.00	0.00
		(135)	(0.00)	(0.00)

Table I. Descriptive statistics for SQ and LULD events
We examine LULD (Panel A) for all U.S. exchanges and SQ (Panel B) events for the TSE during the month of January 2015. For both Panels, we present results for the total sample (All) and classified by whether the events are in the morning (*DMorning* = 1) or afternoon (*DMorning* = 0), initiated by a *UBND* (DU = 1) or *LBND* (DU = 0) condition, or occur during continuous trading (*DCall* = 0) or the call auction (*DCall* = 1). For each event, we present the number of observations, *Duration* (in seconds); *ABRTN* and $ABRTN_{5M}$. Mean and median values (in parentheses) are reported.

	Fstpri		5MP	
Panel A: LULD (n = 6,775)				
Continue		0.89%		4.43%
All Reversal types		86.58%		83.03%
AT_LIMIT	11.79%		0.87%	
Reversal	74.60%		82.11%	
HIVT	0.15%		0.01%	
EXVT	0.04%		0.04%	
NOTRD		12.53%		12.53%
Total		100.00%		100.00%
Panel B: SQ (n = 7,058)				
Continue		13.88%		26.07%
All Reversal types		86.13%		73.92%
AT_LIMIT	41.73%		19.95%	
Reversal	43.44%		41.03%	
HIVT	0.79%		6.64%	
EXVT	0.17%		6.30%	
Total		100.00%		100.00%
Panel C: SLULD (n = 447)				
Continue				6.25%
All Reversal types				35.78%
AT_LIMIT			10.99%	
Reversal			24.57%	
HIVT			0.22%	
			0.00%	
NOTRD				57.97%
Total				100.00%
Panel D: SSQ (n = 10,453)				
Continue				73.40%
All Reversal types				26.59%
AT_LIMIT			15.69%	
Reversal			10.27%	

Table II – Continued

HIVT	0.34%	
EXVT	0.29%	
Total		100.00%

Panel E: TSE Daily Price Limit (n = 847)

Continuation	57.38%
Reversal	42.62%
Total	100.00%

Table II. Classification of trades following LULD, SQ, SLULD, and SSQ events

We examine LULD (Panel A), SQ (Panel B), SLULD (Panel C), and SSQ (Panel D) events. For each event, we identify the *Fstpri* and the *5MP* following the event. We classify these as a *Reversal*, *AT_LIMIT*, *Continue*, *HIVT*, and *EXVT* using *Fstpri* and *5MP*, in turn. In Panel E we include the same analysis on the TSE daily price limit 5MP.

	LULD vs SLULD	SQ vs SSQ	LULD vs SSQ	SQ vs SLULD
Intercept	-1.73**	0.727**	0.685**	-1.667**
DTREAT	-0.544**	-1.277**	-2.460**	1.145**
MRKT_CAP	-0.001**	-0.001**	-0.001**	-0.001**
TICK	-0.162*	0.045**	-6.029*	0.006
SPREAD	-0.520	0.678**	0.472**	17.26**
$ABRET_{PRE}$	2.905**	0.139	4.882**	-2.908*
$HILO_{PRE}$	0.004**	-0.001**	-0.003**	-0.001
$HILOP_{PRE}$	-0.134	-6.288**	-1.970*	6.241**
$TRDS_{PRE}$	0.001**	-0.001*	0.001**	-0.001**
$SHRS_{PRE}$	-0.001	-0.001**	-0.001**	-0.001**
$SPDREV_{PRE}$	-0.001**	0.001	-0.001	0.001
$MHILO_{PRE}$	-0.002**	7.202**	-0.022	0.989**
$ABRET_{BL}$	28.56**	14.042**	28.40**	15.41
$HILO_{BL}$	0.001	-0.001	0.053**	-0.001
$HILOP_{BL}$	-19.06**	-23.60**	-27.14**	-12.23*
$TRDS_{BL}$	0.001	0.001*	0.001	0.001**
SHRS	-0.001	-0.001**	-0.001**	-0.001**
$SPDREV_{BL}$	0.001	-0.001*	-0.001	-0.001*
$MHILO_{BL}$	-0.383	1.041**	-0.001	-5.638
DMorning	0.659**	0.176**	0.20**	0.172**
DCall	1.528**	6.684	1.344**	5.067
DUP	-0.229**	-0.197**	-0.063*	-0.574**
Duration	-0.0012	0.001**	-0.001**	0.001**

Table III. Probit analysis for investigation of delayed price discovery

We examine the market conditions preceding LULD, SQ, SLULD, and SSQ events. We group LULD with SLULD, SQ with SSQ, LULD with SSQ, and SQ with SLULD. Using a probit model, we regress *Continue* on our pre-event volatility and volume measures. Our primary RHS variable is *DTREAT*, which equals 1 for each LULD or SQ observations. Our control variables include the volatility and volume pre-event and BL measures. We include market capitalization, average quoted spread, and tick size as well as dummy variables for time of day (*DMorning*), resolution mechanism (*Call*), and to distinguish *UBEVT* from *LBEVT* (*DUP*). Our final control variable is *Duration.* Positive (negative) coefficients that are less (greater) than 0.001 (-0.001) are rounded to 0.001 (-0.001). * and ** indicate significance at the 0.05 and 0.01 levels, respectively.

	LULD	SLULD	SQ	SSQ	Daily

Panel A: UBND (all stocks)					
Intercept	0.022**	-0.004**	-0.007**	0.154**	
DC	-0.343**	0.004**	0.007**	-0.195	
DO	-24.8**	-0.032**	-0.037**	-5.409**	
Trade	-0.009**	0.014	0.010	-0.246**	
$Near_{t-1}$	-0.338**	-0.975**	-0.930**	-0.655**	
$Near_{t-2}$	-0.056**	-0.227**	-0.327	-0.039**	
$Near_{t-3}$	-0.141**	-0.173**	-0.277*	-0.236**	
Panel B: LBND (all stocks)					
Intercept	0.091**	-0.004**	-0.003**	0.091**	
DF	-0.479**	-0.003**	-0.009**	-0.479 **	
DU	-6.234**	-0.057**	-0.058**	-6.324**	
Trade	-0.076**	0.011**	0.005**	-0.076	
$Near_{t-1}$	-0.004**	-0.718**	-0.658**	-0.004**	
$Near_{t-2}$	0.001**	-0.075**	-0.270**	0.001**	
$Near_{t-3}$	-0.001**	-0.205**	-0.143**	-0.001**	
Panel C: UBND (only stocks with events)					
Intercept	0.042**	-0.007**	-0.009**	0.102**	0.001
DC	-0.258**	-0.007**	0.007**	-0.549**	-0.003**
DO	-2.140*	-0.029**	-0.018**	-1.491**	-0.028**
Trade	-0.058*	0.028**	0.018**	-0.129**	-0.926**
$Near_{t-1}$	-0.153**	-1.034**	-0.838**	-0.259**	-0.159**
$Near_{t-2}$	-0.048**	-0.294**	-0.341**	0.091**	-0.121**
$Near_{t-3}$	-0.038**	-0.217**	-0.184**	-0.286**	0.001*
Panel D: LBND (only stocks with events)					
Intercept	0.028**	-0.009**	-0.008**	0.028**	-0.001**
DF	-0.066**	-0.004**	-0.002**	-0.066**	0.002**
DU	-0.627**	-0.039**	-0.033**	-0.627**	-0.025**
Trade	0.014**	0.028**	-0.014**	-0.014**	-0.752**
$Near_{t-1}$	-0.898**	-0.868**	-0.705**	-0.898**	0.002**
$Near_{t-2}$	-0.528**	-0.175**	-0.272**	-0.528**	-0.121**
$Near_{t-3}$	-0.277**	-0.225**	-0.135**	-0.277**	-0.001**

Table IV. Investigation of magnet effect due to LULD and SQ price-limit rules

For January 2015, we identify *UBND* and *LBND* for each event type using NBBOs from DTAQ. For *UBND*, in Panel A, we report the results of our estimate of the following AR(3) time series regression model:

$$U(Near)_t = \alpha_0 + \alpha_1 DC_{t-1} + \alpha_2 DO_{t-1} + \alpha_3 Trade + \alpha_4 U(Near)_{t-1} + \alpha_5 U(Near)_{t-2} + \alpha_6 U(Near)_{t-3} + \varepsilon$$

Similarly, for *LBND*, in Panel B, we report the results of our estimate of the following regression model:

$$L(Near)_t = \alpha_0 + \alpha_1 DF_{t-1} + \alpha_2 DU_{t-1} + \alpha_3 Trade + \alpha_4 L(Near)_{t-1} + \alpha_5 L(Near)_{t-2} + \alpha_6 L(Near)_{t-3} + +\varepsilon$$

We replicate the analysis using only stocks that have an event and report the results in Panels C and D, respectively. Variables definitions are in Appendix A. * and ** indicate significance at the 0.05 and 0.01 levels, respectively.

	N	ABRET	HILO	HILOP	SPDREV	MHILO	SHRS	TRDS
Panel A: Pre-event								
LULD	6,362	1,310**	465**	474**	187**	590	580**	241**
SLULD	292	1,053**	718	707**	465**	306**	1,099**	437**
p-value		0.159	0.007	0.012	<0.001	0.200	0.297	0.001
SQ	6,592	449**	406**	395**	630**	518**	659**	399**
SSQ	10,452	93.3**	45.8**	61.3**	26.7**	22.6**	70.3*	47.9
p-value		<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Panel B: Post-event								
LULD	6,498	556**	378**	431**	346**	297	444**	217**
SLULD	437	363**	396	384**	702**	1,059**	417**	462**
p-value		0.008	0.718	0.548	<0.001	0.310	0.003	0.056
SQ	6,623	326**	400**	364**	684**	384**	407**	368**
SSQ	9,914	410**	217**	418**	37.3**	29.1**	155**	128**
p-value		0.117	<0.001	0.645	<0.001	<0.001	<0.001	<0.001

Panel C: TSE Daily

	ABSRET	HILO	HILOP	SPDREV	MHILO	SHRS	TRDS
Pre-event	296**	234**	229**	366**	253**	518**	442**
Post-event	199**	232**	209**	321**	210**	505**	423**
Difference	96.6	2.22	19.5	45.4	42.8	13.1	19.4
p-value	0.001	0.9223	0.338	0.522	0.008	0.932	0.882

Table V. Actual and pseudo values

For LULD, SQ, SLULD, and SSQ, we report pre-event (Panel A) and post-event (Panel B) mean abnormal statistics. We test the null hypothesis that each mean abnormal statistic is equal to its comparable mean BL statistic (not tabulated) and indicate significant differences with * and ** at the 0.05 and 0.01 levels, respectively. We report pre- and post-event statistics for TSE daily price limit (Panel C) for comparison. We also compare the means of the actual and pseudo values using a standard t test and report the *p*-values.

	N	January 2015	May 6th, 2010	August 24th, 2015	Difference	*p-value*
Panel A: Intraday Volatility						
Full Sample	4,389	\$0.931	\$4.276	\$3.384	\$0.892**	<*0.001*
5% Price Parameter	1,187	\$1.511	\$8.518	\$6.969	\$1.549**	<*0.001*
10% Price Parameter	2,666	\$0.757	\$2.640	\$2.009	\$0.631**	<*0.001*
Panel B: Microstructure Noise						
Full Sample	4,389	3.542	7.424	10.341	-2.917**	<*0.001*
5% Price Parameter	1,187	4.273	9.142	13.779	-4.637**	<*0.001*
10% Price Parameter	2,666	3.368	6.749	8.995	-2.246**	<*0.001*

Table VI. The flash crashes of May 6th, 2010 and August 24th, 2015
LULD came about as a response to the May 6th, 2010 flash crash. August 24th, 2015 saw a similar flash crash at a time that LULD was in effect. For both May and August, we evaluate the effectiveness of LULD by comparing *Intraday Volatility* (Panel A) and *Microstructure Noise* (Panel B) where these two variables are:

$$Intraday\ Volatility = \ Daily\ High\ Price - Daily\ Low\ Price$$

$$Microstructure\ Noise = \frac{Intraday\ Volatility}{Abs(Closing\ Price - Opening\ Price)}$$

For each stock. We test whether the differences are statistically different from zero and report the *p*-values in the last column. Column 3 in Panels A and B reports results for January 2015 to allow comparison with normal values. Using a standard *t*-test, we compare May and August and report the *p*-values.

n=997							
Panel A: Price Discovery							
	5MP						
Continuation	13.24%						
Reversal	86.76%						
Total	100%						
Panel B: Magnet Effect							
	SQ						
UBND							
DC	0.011**						
LBND							
DF	-0.017**						
Panel C: Volatility							
	ABSRET	HILO	HILOP	SPDREV	MHILO	SHRS	TRDS
Pre-event	411**	398*	396**	391**	462**	456**	289**
Post-event	3,703**	3,393**	276**	478**	402**	268**	217**
Difference	-3291	-2,995	120	-87.14	60.4	188	71.9
p-value	0.001	0.012	0.038	0.011	0.408	0.001	0.001

Table VII. Special quote's dynamic price bands

We examine the dynamic nature of special quote's price bands. We test for price discovery interference (Panel A), the magnet effect (Panel B) and volatility spillover (Panel C). In Panel A we identify the *5MP* for each event. We classify these as *Reversal* or *Continuation*. In Panel B we remove securities that experience a SQ event with duration greater than 180 seconds. We estimate (8) and (9) and report the results of the *DC* and *DF* variables. Full regression results are reported in Internet Appendix F. In Panel C we report mean abnormal statistics pre-and post-event periods. We report the mean difference using a t-test and report the *p*-values. * and ** indicate significance at the 0.05 and 0.01 levels, respectively.

Supplemental Material

Internet Appendices to

Short duration, dynamic price limits:
The special quote and limit up limit down rules

Internet Appendix A

Definitions of terms

Relation of Lee, Ready, and Seguin (1994) abnormal statistic to ours

Lee, Ready, and Seguin (1994) define the average abnormal statistic as:

$$= \frac{1}{n}\sum_{i=1}^{n}\frac{Halt\ Statistic_i - Matched\ Statistic_i}{Average\ Statistic_i}$$

where n = number of halts; *Halt Statistic* = the statistic from the *i*th halt; *Matched Statistic* = the statistic from the *i*th matched pseudo-halt; *Average Statistic* = the average statistic from the reference sample.

We likewise define our average abnormal statistics the same way. However, in our research design, neither n nor *Average Statistic* is constant between the price limits (halts) and the pseudo-events (matched). Our average abnormal statistic is defined as follows:

$$\frac{1}{n}\sum_{i=1}^{n}\frac{Event\ Statistic_i}{Average\ Statistic_i} - \frac{1}{q}\sum_{j-1}^{q}\frac{Pseudo - Event\ Statistic_j}{Average\ Statistic_j}$$

where: n = number of price limit events; q = number of pseudo-events; *Event Statistic* = the statistic from the *i*th event. The *Event Statistic* is the same variables as *Halt Statistic* from Lee, Ready, and Seguin (1994). We use the term '*Event*' because not all price limit events result in a halt. *Pseudo-Event Statistic* = the statistic from the *j*th pseudo-event; *Average Statistic*$_i$ = Average statistic from the event reference sample; *Average Statistic*$_j$ = Average statistic from the pseudo-event reference sample.

Proof

Our average abnormal statistic measure is defined as follows:

$$\frac{1}{n}\sum_{i=1}^{n}\frac{Event\ Statistic_i}{Average\ Statistic_i} - \frac{1}{q}\sum_{j=1}^{q}\frac{Pseudo - Event\ Statistic_j}{Average\ Statistic_j}$$

This is a general form of the equation used by Lee, Ready, and Seguin (1994).

When *n* and *q* are equal

$$\frac{1}{n}\sum_{i=1}^{n}\frac{Event\ Statistic_i}{Average\ Statistic_i} - \frac{1}{n}\sum_{j=1}^{n}\frac{Pseudo - Event\ Statistic_j}{Average\ Statistic_j}$$

When *Average Statistic*$_i$ and *Average Statistic*$_j$ are equal and derived from the same sample

$$\frac{1}{n}\sum_{i=1}^{n}\frac{Event\ Statistic_i}{Average\ Statistic_i} - \frac{1}{n}\sum_{j=1}^{n}\frac{Pseudo - Event\ Statistic_j}{Average\ Statistic_i}$$

When each event is matched to only one pseudo-event

$$\frac{1}{n}\sum_{i=1}^{n}\frac{Event\ Statistic_i}{Average\ Statistic_i} - \frac{1}{n}\sum_{i=1}^{n}\frac{Matched\ Statistic_i}{Average\ Statistic_i}$$

When simplified:

$$\frac{1}{n}\sum_{i=1}^{n}\frac{Event\ Statistic_i - Matched\ Statistic_i}{Average\ Statistic_i}$$

This special case of our general equation is equal to the average abnormal statistic used by Lee, Ready, and Seguin (1994):

$$\frac{1}{n}\sum_{i=1}^{n}\frac{Halt\ Statistic_i - Matched\ Statistic_i}{Average\ Statistic_i}$$

Internet Appendix B

The limit order book during the opening and closing seconds

We present a sample of the limit order book during the opening and closing seconds. Beginning with the open, we document suspicious quote activity during the first few seconds of the trading day. The *ASK* is either missing or at a price as high as one thousand times higher than the *BID.* These values do not accurately depict typical quote or trade prices for the stock. This condition is generally resolved within the first twenty seconds of trading and is not observed again until the final twenty seconds of trading. Column 1 is the *i*th observation of the NBBO beginning at the open.

Suspicious quotes at the open 01/02/2015						
Observation	Ticker	Time	seconds	ASK	BID	Midpoint
1	AIRI	9:30	0	0.00	6.90	crossed
2	AIRI	9:30	0	249,999.98	8.55	125,004.27
3	AIRI	9:30	0	42,949.00	6.90	21,477.95
33	AIRI	9:30	1	21.60	7.50	14.55
34	AIRI	9:30	1	13.46	10.00	11.73
35	AIRI	9:30	1	13.20	7.50	10.35
36	AIRI	9:30	1	13.46	9.30	11.38

We find similar suspicious behavior at the close similar the open. In the closing seconds of the trading day, we find *Ask* quotes that are missing or many thousand times higher than normal trade prices. We also find *Bid* quotes that are at or near zero.

Suspicious quotes at the close 01/05/2015						
L-16	OCC	4:00	0	5.88	3.28	4.58
L-4	OCC	4:00	0	5.88	0.01	2.935
L-1	OCC	4:00	0	199,999.99	0.0001	99,999.995
L (Last)	OCC	4:00	0	0	0.0001	Crossed

Internet Appendix C

Comparison of event time and control time statistics

Following Lee, Ready, and Seguin (1994), *Mean Abnormal Statistics* represent firm-specific and time-controlled volatility relative to BL values. We report the *Mean Abnormal Statistic* in Table C1, Panel A. The value of 1,310 indicates that the event statistic is about 13 times larger than the base-period statistic. We replicate this analysis for the remaining variables (*HILO*, *HILOP*, *MHILO*, *TRDS*, and *SHRS*, in turn) and report the results in Table C1, Panel A. We replicate the entire analysis for SQ pre-event observations (Table C1, Panel B), and for both SQ and LULD post-event observations (Table C2, Panels A and B, respectively).

For both SQ and LULD, volatility and volume are significantly higher across all measures both before and after an LULD or SQ event (apart from pre- and post-event *MHILO* for LULD).[17] However, by design, SQ and LULD events should occur at times of elevated volatility when we would expect pre-event volatility to be abnormally high. We also conclude from these results that the price and volume adjustment is incomplete at the end of a price-limit event. While our research design controls for time-of-day and firm-specific effects, we do not control

[17] We find only 2 qualifying SQ events that are resolved with a call auction. We find that no trades occur in the five minutes preceding either of these events. *ABRET*, *HILO*, *HILOP*, *SHRS*, and *TRDS* are all equal to 0 for these events and the *Mean abnormal statistic* is equal to 0. Abnormal statistics are markedly lower following call auction resolved events as well. These results are contrary to Hypothesis 3.

for the magnitude of the price move due to information release or order imbalance. Our results are similar to the Lee, Ready, and Sequin (1994) findings regarding NYSE trading halts.

	Volatility measures					Volume measures	
	ABRET	HILO	HILOP	SPDREV	MHILO	SHRS	TRDS
Panel A: LULD (n = 6,362)							
All	1,310**	465**	474**	187**	590	580**	241**
DMorning=1	503**	387**	420**	224**	898	495**	272**
DMorning=0	1,918**	525**	514**	156**	360	648**	217**
Call = 0	1,313**	466**	474**	187**	600	581**	241**
Call = 1	558**	411*	405**	169	226	280	260
DUP = 0	1,043**	445**	451**	131**	694	747**	214**
DUP = 1	1,623**	489**	500**	248**	492	395**	272**
Panel B: SQ (n = 6,592)							
All	449**	406**	395**	630**	518**	659**	399**
DMorning=1	445**	400**	388**	635**	553**	684**	388**
DMorning=0	453**	414**	404**	624**	470**	625**	413**
Call = 0	449**	406**	395**	630**	518**	659**	399**
Call = 1	0**	0**	0**	3.3**	22.1**	0**	0**
DUP = 0	591**	486**	488**	579**	719**	415**	300**
DUP = 1	425**	393**	380**	640**	481**	705**	417**

Table CI. Pre-event statistics

For each five-minute, pre-event period t, we calculate the value of $ABRET_t$ and $Statistic_{BL,t}$. Let t_0 be the beginning of the trading. Period 1 is t_0 through t_4; period 2, t_5 through t_9; and so forth. For each firm for each event, BL_t is the period that includes the beginning time of the associated pre-event interval. $Statistic_{BL,t}$ is the mean value of *ABRET* over all BL_t's, excluding the event day. We define S_t as $ABRET_t / Statistic_{BL,t}$ and *Mean Abnormal Statistic* as the mean of S_t over all t times 100. We test whether the null hypothesis that the means for all pre-event $ABRET_t$'s and the corresponding $Statistic_{BL,t}$'s are equal using a standard t test. We report S_t for LULD events in Panel A and for SQ events in Panel B. We repeat the entire analysis for *HILO*, *HILOP*, *SPDREV*, *MHILO*, *SHRS*, and *TRDS*, in turn. * and ** indicate significance at the 0.05 and 0.01 levels, respectively.

	Volatility measures					Volume measures	
	ABRET	HILO	HILOP	SPDREV	MHILO	SHRS	TRDS
Panel A: LULD (n = 6,498)							
All	556**	378**	431**	346**	297	444**	217**
DMorning = 1	223**	229**	368**	317**	273	312**	156**
DMorning = 0	862**	517**	490**	475**	321**	575**	277**
Call = 0	558**	380**	433**	347**	297	446**	218**
Call = 1	99.41	77.9	53.1	166	470	41.8	27.9*
DUP = 0	303**	351**	458**	211**	223	546**	188**
DUP = 1	840**	409**	401**	489**	377	337**	248**
Panel B: SQ (n = 6,623)							
All	326**	400**	364**	684**	384**	407**	368**
DMorning = 1	315**	416**	387**	721**	391**	454**	403**
DMorning = 0	334**	390**	350**	691**	380**	376**	345**
Call = 0	326**	400**	364**	685**	384**	407**	368**
Call = 1	45.1	68.7	67.9	91.7**	43.0	195	139
DUP = 0	415**	498**	480**	845**	547**	403**	405**
DUP = 1	311**	383**	344**	653**	353**	407**	361**

Table CII. Post-event statistics

For each five-minute, post-event period *t*, we calculate the value of $ABRET_t$ and $Statistic_{BL,t}$. Let t_0 be the beginning of the trading. Period 1 is t_0 through t_4; period 2, t_5 through t_9; and so forth. For each firm for each event, BL_t is the period that includes the beginning time of the associated post-event interval. $Statistic_{BL,t}$ is the mean value of *ABRET* over all BL_t's, excluding the event day. We define S_t as $ABRET_t / Statistic_{BL,t}$ and *Mean Abnormal Statistic* as the mean of S_t over all *t* times 100. We test whether the null hypothesis that the means for all post-event $ABRET_t$'s and the corresponding $Statistic_{BL,t}$'s are equal using a standard *t* test. We report S_t for LULD events in Panel A and for SQ events in Panel B. We repeat the entire analysis for *HILO*, *HILOP*, *SPDREV*, *MHILO*, *SHRS*, and *TRDS*, in turn. * and ** indicate significance at the 0.05 and 0.01 levels, respectively.

Internet Appendix D

Additional test of Hypothesis 3A

We extend our analysis of hypothesis 3A and perform an OLS regression to isolate the market's response to the trading pause by estimating the following volatility and volume regressions. For volatility, our regression is:

$$X = \alpha + \beta_1 DTREAT + \beta_2\, SHRS_{post} + \beta_3\, TRDS_{post} + \beta_4\, Duration + \beta_5 DMorning + \beta_6 DCall + \beta_7 DU + \beta_8 DContinue + \beta_9 DAT\_LIMIT + \beta_{10} DReversal + \beta_{11} DHVT + \beta_{12} DNOTRD + \varepsilon$$

For volume, our regression is:

$$X = \alpha + \beta_1 DTREAT + \beta_2\, ABRET_{post} + \beta_3\, HILOP_{post} + \beta_4\, SPDREV_{post} + \beta_5\, MHILO_{post} + \beta_6\, Duration + \beta_7 DMorning + \beta_8 DCall + \beta_9 DU + \beta_{10} DContinue + \beta_{11} DAT\_LIMIT + \beta_{12} DReversal + \beta_{13} DHVT + \beta_{14} DNOTRD + \varepsilon$$

Our LHS variable, *X*, is one of the event statistics *ABRET*, *HILOP*, *SPDREV*, *MHILO*, *SHRS*, and *TRDS*, in turn. Our RHS variable of interest is *DTREAT*, which equals 1 for each *LULD* or *SQ* observation and 0 for *SLULD* or *SSQ* observations. We regress each post-event volatility dependent variable on each securities' post values of *SHRS* and *TRDS* excluding the variable on the LHS. We regress each post-event volume dependent variable on each securities' post values of *ABRET*, *HILOP*, *SPDREV*, and *MHILO* excluding the variable on the LHS. We include various dummy variables. We control for time of day with *DMorning*, for event type with *DU*=1 for *UBEVT*, and for the resolution mechanism with *DCall*. We add controls for the price path following the event: *DContinue, DAT_LIMIT, DReversal, DHIVT,* and *DNOTRD*.

We report results in Table D1 results do not support Hypothesis 3A. LULD, when compared with SLULD, has lower *post-event SPDREV* (-106), but is significantly greater across all other measures of volatility. Likewise, when SQ is compared to SSQ the *DTREAT* coefficient is negative only for *HILOP* (-0.007) while all other measures of volatility and volume have a significantly positive *DTREAT* coefficient. When compared to the same simulated rule, both SQ and LULD shows evidence of greater *post-event* volatility. This evidence is weaker when the comparison is with the alternate price limit.

SQ and LULD are reactionary rules designed to halt market activity partially only when abnormally high volatility has already entered the market. Indeed, our results confirm that pre-event volatility and volume are abnormally high. We conclude that at least some of the post-event activity is a continuation of pre-event volatility.

	Volatility measures				Volume measures	
	ABRET	HILOP	SPDREV	MHILO	SHRS	TRDS
Panel A: LULD vs SLULD (n =7,222)						
Intercept	-0.004	0.006	582	-2.889	439,332	-156
DTREAT	-0.003	-0.008*	364**	3.518	34,733	62.4*
$ABRET_{BL}$					-262,319**	1,462**
$HILOP_{BL}$					2,417726**	6,136**
$SPDREV_{BL}$					-18.27**	0.184**
$MHILO_{BL}$					-30.94	-0.012
$SHRS_{BL}$	-0.001**	0.001**	-0.001**	-0.001		
$TRDS_{BL}$	0.001**	0.001**	1.040**	-0.002		
Duration	-0.001	-0.001	0.308**	-0.001	-13.42	-0.061**
DMorning	-0.004**	-0.017**	-117*	-6.795	-178,797**	-1.463
DCall	0.004	0.003	530	-1.646	-175,334	-205*
DU	0.016**	0.024**	-692**	8.109	-283,015**	74.4**
DContinue	0.007	0.010	-724	4.058	-91,155	245
DAT_LIMIT	0.002	0.006	-367	0.097	-119,036	25.6
DReversal	0.008	0.020	-312	4.433	136,940	12.89
DHIVT	-0.004	-0.007	-579	0.400	-84,212	160
DNOTRD	-0.001	0.001	-428	2.386	-123,854	69.6
MRKT_CAP	-0.001**	-0.001**	0.001**	0.001	-0.001	0.001**
SPREAD	0.002	-0.009	-331	-9.113	-441,980*	-60.9
TICK_SIZE	0.001*	0.001*	-5.78**	0.005	-454	-0.497
Panel B: SQ vs SSQ (n =17,511)						
Intercept	0.084**	0.001**	29.9**	0.020**	259,053**	94.8**
DTREAT	0.012**	-0.007**	57.3**	0.009**	90,038**	59.7**
$ABRET_{BL}$					-308,392**	-248**
$HILOP_{BL}$					987,969**	1,140**
$SPDREV_{BL}$					209**	0.603**
$MHILO_{BL}$					2,618,863**	1,894**
$SHRS_{BL}$	0.001**	0.001**	0.001**	0.001**		
$TRDS_{BL}$	0.001**	0.001**	0.438**	0.001**		
Duration	0.001**	0.001**	-0.014**	0.001**	-27*	-0.026**
DMorning	-0.007**	0.003**	16.4**	0.003**	-2,863	2.711
DCall	-0.012	-0.011	-77.6	-0.020	107,133	92.6
DU	-0.005**	-0.002**	-3.576	-0.002**	19,549**	10.5*
DContinue	-0.067**	-0.026**	-21.8*	-0.012**	-303,360**	-126**

Table DI.—Continued

DAT_LIMIT	-0.067**	-0.018**	-21.3*	-0.014**	-337,740**	-157**
DReversal	-0.065**	-0.018**	-48.3**	-0.017**	-191,133**	-80.5**
DHIVT	0.216**	0.020**	-26.4*	0.024**	-6,767	148**
MRKT_CAP	0.001	0.001	0.001**	0.001	0.001	0.001**
SPREAD	-0.001	0.001	-6.679	-0.004*	-19,720	-27.5
TICK_SIZE	0.001	0.001	-0.113	0.001	-360	-0.129
Panel C: LULD vs SSQ (n =17,228)						
Intercept	0.054**	0.068**	74.8	0.693	111,265	-371**
DTREAT	-0.016**	-0.012**	92.4**	3.880	299,716**	201**
$ABRET_{BL}$					-2,173,264**	-2,131**
$HILOP_{BL}$					3,040,275**	7,787**
$SPDREV_{BL}$					-10.4	0.076**
$MHILO_{BL}$					-39.2	-0.005
$SHRS_{BL}$	0.001	0.001	0.001**	0.001		
$TRDS_{BL}$	0.001**	0.001**	0.402**	-0.001		
Duration	0.001	0.001*	0.308**	0.001	-20.7**	-0.026**
DMorning	-0.001	-0.006**	0.475	-2.211	-70,873**	-0.790
DCall	0.005	0.001	564**	-2.216	-205,062	-122*
DU	0.003**	0.002**	39.2**	3.188	-105,270**	58.7**
DContinue	-0.045**	-0.047**	-29.5	-0.079	17,855	231**
DAT_LIMIT	-0.035**	-0.033**	-36.7	-0.186	2,225	133*
DReversal	-0.029**	-0.025**	-23.6	0.525	88,324	83.3
DHIVT	-0.005	-0.010	-329	0.566	-17,752	181*
DNOTRD	-0.038**	-0.047**	-218	-1.343	-226,614	112
MRKT_CAP	0.001**	0.001**	0.001**	0.001	0.01	0.001**
SPREAD	0.007**	0.014**	-64.8	-0.558	-46,687	-138**
TICK_SIZE	-0.368**	-1.127**	-17,607**	-185	-9,897,724**	6,699**
Panel D: SQ vs SLULD (n = 7,505)						
Intercept	0.105**	0.036**	148**	0.102**	186,367**	2.965
DTREAT	0.012	-0.003	-101**	-0.056**	57,810	91.8**
$ABRET_{BL}$					-92,221	-86.7**
$HILOP_{BL}$					5,347,566**	2,652**
$SPDREV_{BL}$					277**	0.994**
$MHILO_{BL}$					118,182	-83.2
$SHRS_{BL}$	0.001	0.001**	0.001**	0.001*		
$TRDS_{BL}$	0.001**	0.001**	0.615**	0.001**		
Duration	0.001*	0.001**	-0.001	0.001*	9.565	-0.002
DMorning	-0.017**	0.005**	14.7**	0.004**	-6,578	-2.183

Table DI.—Continued

DCall	-0.022	-0.028	-108	-0.029	148,544	106
DU	-0.014**	-0.004**	0.379	-0.016**	57,147**	7.044
DContinue	-0.056**	-0.009**	25.7**	-0.007*	-286,899**	-97.5**
DAT_LIMIT	-0.081**	-0.017**	22.0*	-0.018**	-293,723**	-123**
DReversal	-0.077**	-0.020**	-30.4**	-0.018**	-100,838**	-21.6
DHIVT	0.227**	0.020**	-48.9**	0.024**	-95,875*	93.4**
DNOTRD	-0.082**	-0.028**	-63.6**	-0.023**	-128,876	21.8
MRKT_CAP	0.001	0.001**	0.001**	0.001	0.001	0.001
SPREAD	-0.017	-0.287**	-1,610**	-0.592**	-3,740,138**	-2,384**
TICK_SIZE	0.001	0.001	-0.104	0.001	-288	-0.077

Table DI. Effect of price limit rules on volatility and volume (full results)

We regress post-event volatility and volume measurements on *DTREAT* to measure the volatility spillover due to SQ and LULD rules. For volatility measures, our regression model is:

$$X = \alpha + \beta_1 DTREAT + \beta_2\, SHRS_{post} + \beta_3\, TRDS_{post} + \beta_4\, Duration + \beta_5 DMorning + \beta_6 DCall + \beta_7 DU + \beta_8 DContinue + \beta_9 DATLMT + \beta_{10} DReversal + \beta_{11} DHVT + \beta_{12} DNOTRD + \beta_{13} MRKT_{CAP} + \beta_{14} SPREAD + \beta_{15} TICK_{SIZE} + \varepsilon$$

For volume measures, our regression model is:

$$X = \alpha + \beta_1 DTREAT + \beta_2\, ABRET_{post} + \beta_3\, HILOP_{post} + \beta_4\, SPDREV_{post} + \beta_5\, MHILO_{post} + \beta_6\, Duration + \beta_7 DMorning + \beta_8 DCall + \beta_9 DU + \beta_{10} DContinue + \beta_{11} DATLMT + \beta_{12} DReversal + \beta_{13} DHVT + \beta_{14} DNOTRD + \beta_{15} MRKT\_CAP + \beta_{16} SPREAD + \beta_{17} TICK\_SIZE + \varepsilon$$

where the LHS variables are the event statistics *ABRET*, *HILOP*, *SPDREV*, *MHILO*, *SHRS*, and *TRDS*, in turn. *X* is a vector of five variables from the set *ABRET*, *HILOP*, *SPDREV*, *MHILO*, *SHRS*, and *TRDS*, excluding the variable on the LHS. These variables are included for the pre, post, and BL intervals so that there are fifteen variables in total. Our sample comprises price-limit events and matched pseudo-events. We report our results in Panel A. Only the coefficient of *DTREAT* is reported. We repeat our analysis with *HILOP*, *SPDREV*, *MHILO*, *SHRS*, and *TRDS*, in turn, as the LHS variable, which allows us to complete Panel A. We repeat the entire analysis for SQ and SSQ combined (Panel B), for LULD and SSQ combined (Panel C), and for SQ and SLULD combined (Panel D). * and ** indicate significance at the 0.05 and 0.01 levels, respectively.

Internet Appendix E

Additional tests of Hypothesis 3

Using each variable from the set—*ABRET*, *HILOP*, *SPDREV*, *MHILO, SHRS,* and *TRDS*—in turn, as the LHS variable, we estimate the following model:

$$X = \alpha + \beta_1 DPE + \beta_2 \, DTREAT + \beta_3 I1 + \beta_4 \boldsymbol{Y} + +\beta_4 Z + \varepsilon$$

where *DPE* equals 1 for all post-event observations and *DTREAT* equals 1 for all SQ and LULD observations. *I1* = *DTREAT x DPE*. *Y* is a vector of control variables, for the interval BL, comprising all the variables from the set *ABRET*, *HILOP, SPDREV*, *MHILO, SHRS,* and *TRDS,* excluding the variable on the LHS. *Z* is the vector of the following dummy variables: *DMorning*, *DCall*, *Duration*, *DU* and price path dummy variables *DContinue, DAT_LIMIT, DReversal*, *DHIVT*, *and DNOTRD*. We report results in Table 1.

The regression results in Table E1 provide mixed support for Hypothesis 3 and do not consistently suggest an increase or decrease in volatility measures between the stocks experiencing a price-limit and those that do not. It is also unclear whether LULD or SQ performs better in reducing market volatility.

	Volatility measures				Volume measures	
	ABRET	HILOP	SPDREV	MHILO	SHRS	TRDS
Panel A: LULD vs SLULD (n =7,222)						
Intercept	-0.017	-0.010	-48.5	417,736	-253	-1.822
DPE	-0.007	-0.003	53.3	19,040	28.1	0.011
DTREAT	0.004	-0.001	225*	65,595	133	6.013**
I1	-0.021**	-0.006	300*	-70,742	72.7	-2.206
MRKT-CAP	0.001**	0.001**	0.001**	0.001	0.001**	0.001**
SPREAD	0.007	-0.005	-370*	-383,982	-198**	-10.1*
TICK_SIZE	0.001	0.001	-4.043**	-47.5	-0.823	0.003
$ABRET_{BL}$		1.147**	40,340**	-14,603,106	-45,746**	186**
$HILOP_{BL}$	1.133**		-38,407**	11,658,356	40,319**	-193**
$SPDREV_{BL}$	0.001**	0.001**		-142	0.617**	-0.002**
$MHILO_{BL}$	0.001	0.001	-0.026		-0.148	0.001
$SHRS_{BL}$	0.001	0.001**	-0.003**	-124		-0.018**
$TRDS_{BL}$	0.001**	0.001**	5.505**	1,248	0.001**	
Duration	0.001*	0.001	0.147**	-15.9	-0.011*	-0.001*
DMorning	-0.010**	-0.021**	-246**	-215,238	-95.5**	-5.981**
DCall	0.009	0.001	262	-218,559	-266	-1.833*
DU	0.029**	0.030**	-299**	-315,817	346**	7.127**
DContinue	-0.006	-0.008	0.231	-30,479	808	6.245**
DAT_LIMIT	0.005	0.006	156	21,933	-74.8	1.165
DReversal	0.007	0.020	305	180,123	-28.3	7.257
DHIVT	0.016	0.024	342	151,797	-337	-0.773
DNOTRD	0.011	0.012	124	-57,426	-122	0.225
Panel B: SQ vs SSQ (n =17,511)						
Intercept	0.142**	0.029**	61.6**	0.026**	273,851**	221**
DPE	0.009**	0.014**	6.671*	0.002**	4,553	7.329
DTREAT	0.009**	0.020**	77.4**	0.025**	208,658**	134**
I1	0.008**	-0.020**	-8.836*	-0.011**	-193,363**	-41.1**
MRKT-CAP	0.001	0.001	0.001**	0.001*	0.001	0.001**
SPREAD	-0.002	-0.003*	-15.3	-0.006**	-37,483	-38.2**
TICK_SIZE	0.001	0.001	-0.120	0.001	-374	-0.133
$ABRET_{BL}$		0.884**	-1,441**	-0.234**	-7,600,881**	-4,898**
$HILOP_{BL}$	0.339**		1,773**	0.736**	6,762,989**	5,594**
$SPDREV_{BL}$	0.001	0.001**		0.001**	-611**	0.421**
$MHILO_{BL}$	0.001	0.001*	-0.167		2,347	-0.847
$SHRS_{BL}$	0.001*	0.001**	0.001**	0.001**		0.001**

Table EI.—Continued

$TRDS_{BL}$	0.001	0.001**	0.807**	0.001**	1,369**	
Duration	0.001**	0.001**	-0.023**	0.001**	-60**	-0.044**
DMorning	-0.003**	0.002**	13.7**	0.002**	4,366	6.398*
DCall	-0.014	-0.019	-132	-0.025*	-148,710	-148
DU	-0.003**	-0.002**	-4.475*	-0.001**	20,803**	0.454
DContinue	-0.140**	-0.033**	-65.9**	-0.026**	-299,840**	-251**
DAT_LIMIT	-0.140**	-0.030**	-70.8**	-0.029**	-338,257**	-271**
DReversal	-0.140**	-0.029**	-75.4**	-0.031**	-149,791**	-219**
DHIVT	-0.106**	-0.012**	-14.2	-0.015**	173,626**	-95.3**
Panel C: LULD vs SSQ (n =17,228)						
Intercept	-0.005	0.007	-166	2.148	152,787	74.5
DPE	0.009**	0.014**	6.671	0.002	4,553	7.329
DTREAT	0.010**	0.007**	1.278	8.929**	300,875**	329**
I1	-0.037**	-0.023**	348**	-2.191	-56,512**	92.9**
MRKT-CAP	0.001**	0.001**	0.001**	0.001	-0.001**	0.001**
SPREAD	0.006**	0.013**	-27.5	-1.638	4,406	-155**
TICK_SIZE	-0.418**	-1.185**	-14,723**	-86.4	-11,974,91**9	941
$ABRET_{BL}$		0.929**	5,507**	79.6	-7,655,503**	-31,569**
$HILOP_{BL}$	0.873**		-4,789**	-90.9	5,133,328**	28,655**
$SPDREV_{BL}$	0.001**	0.001**		-0.002	-3.627	0.166**
$MHILO_{BL}$	0.001	0.001	0.026		-165	-0.102
$SHRS_{BL}$	0.001**	0.001*	-0.001**	0.001		0.002**
$TRDS_{BL}$	0.001**	0.001**	1.988**	-0.014	1,458**	
Duration	0.001*	0.001	0.151**	-0.001	-22.2**	-0.012**
DMorning	-0.005**	-0.009**	30.1**	-1.978	-90,656**	-9.242
DCall	0.003	-0.009	384**	-2.699	-253,124*	-76.3
DU	0.011**	0.012**	47.4**	2.667*	-124,932**	178**
DContinue	-0.005	-0.011	194	-1.461	18,703	-208**
DAT_LIMIT	-0.001	-0.004	178	-1.484	25,535	-272**
DReversal	0.002	0.005	138	-0.315	94,559	-438**
DHIVT	0.001	-0.003	220	-0.259	12,127	-178
DNOTRD	0.005	-0.005	-14.6	-7.376	-206,801*	-606**

Table EI. Effect of price limit rules on volatility and volume (full results)

Let X represent the set of variables *ABRET*, *HILOP*, *SPDREV*, *MHILO*, *SHRS*, and *TRDS.* Using each of the variables, in turn, as the LHS variable, we estimate the following model:

$$X = \alpha + \beta_1 DPE + \beta_2 DTREAT + \beta_3 I1 + \beta_4 \boldsymbol{Y} + +\beta_4 Z\ \varepsilon$$

where *DPE* equals 1 for all post-event observations and *DTREAT* equals 1 for all SQ and LULD observations. *Y* is a vector of control variables comprising all the variables from the set *ABRET, HILOP, SPDREV, MHILO, SHRS*, and *TRDS*, excluding the variable on the LHS, for the interval BL. Z is the vector of the following dummy variables: *DMorning*, *DCall, Duration*, *DU* and price path dummy variables *DContinue, DAT_LIMIT, DReversal, DHIVT, and DNOTRD*. We report results for LULD and SLULD in Panel A, for SQ and SSQ in Panel B, for LULD and SSQ in Panel C, and for SQ and SLULD in Panel D. * and ** indicate significance at the 0.05 and 0.01 levels, respectively.

Internet Appendix F

Addition results for Table 7

Panel A: UBND	
Intercept	-0.008**
DC	0.011**
DO	-0.018**
Trade	0.011**
$Near_{t-1}$	-0.968**
$Near_{t-2}$	-0.324**
$Near_{t-3}$	-0.318**
Panel B: LBND	
Intercept	-0.001**
DF	-0.017**
DU	-0.083**
Trade	0.001**
$Near_{t-1}$	-0.550**
$Near_{t-2}$	-0.274**
$Near_{t-3}$	-0.148**

Table FI. Table VII full regression

For January 2015, we identify *UBND* and *LBND* for each SQ event with a duration of 180 seconds or longer. For *UBND,* in Panel A, we report the results of our estimate of the following AR(3) time series regression model:

$$U(Near)_t = \alpha_0 + \alpha_1 DC_{t-1} + \alpha_2 DO_{t-1} + \alpha_3 Trade + \alpha_4 U(Near)_{t-1} + \alpha_5 U(Near)_{t-2} + \alpha_6 U(Near)_{t-3} + \varepsilon$$

Similarly, for *LBND,* in Panel B, we report the results of our estimate of the following regression model:

$$L(Near)_t = \alpha_0 + \alpha_1 DF_{t-1} + \alpha_2 DU_{t-1} + \alpha_3 Trade + \alpha_4 L(Near)_{t-1} + \alpha_5 L(Near)_{t-2} + \alpha_6 L(Near)_{t-3} + +\varepsilon$$

Variables definitions are in Appendix A. * and ** indicate significance at the 0.05 and 0.01 levels, respectively.

Internet Appendix G

Additional results for Table 8

	Near=0.50	Near=0.75	Near=0.90
Panel A: UBND			
Intercept	0.001	0.001	0.001*
DC	-0.003**	-0.010**	-0.040**
DO	-0.028**	-0.028**	-0.028**
$Near_{t-1}$	-0.926**	-0.926**	-0.924**
$Near_{t-2}$	-0.159**	-0.159**	-0.158**
$Near_{t-3}$	-0.121**	-0.120**	-0.120**
Panel B: LBND			
Intercept	-0.001**	-0.001**	-0.001**
DF	0.002**	0.005**	0.017**
DU	-0.025**	-0.025**	-0.026**
$Near_{t-1}$	-0.752**	-0.753**	-0.752**
$Near_{t-2}$	0.002**	0.001**	0.001**
$Near_{t-3}$	-0.121**	-0.122**	-0.122**

Table GI. Table VIII full regression results

For January 2015, we identify *UBND* and *LBND* for each TSE daily price limit events. For *UBND*, in Panel A, we report the results of our estimate of the following AR(3) time series regression model:

$$U(Near)_t = \alpha_0 + \alpha_1 DC_{t-1} + \alpha_2 DO_{t-1} + \alpha_3 Trade + \alpha_4 U(Near)_{t-1} + \alpha_5 U(Near)_{t-2} + \alpha_6 U(Near)_{t-3} + \varepsilon$$

Similarly, for *LBND*, in Panel B, we report the results of our estimate of the following regression model:

$$L(Near)_t = \alpha_0 + \alpha_1 DF_{t-1} + \alpha_2 DU_{t-1} + \alpha_3 Trade + \alpha_4 L(Near)_{t-1} + \alpha_5 L(Near)_{t-2} + \alpha_6 L(Near)_{t-3} + +\varepsilon$$

Variables definitions are in Appendix A. * and ** indicate significance at the 0.05 and 0.01 levels, respectively.

Efficient/Cost-Effective Healthcare Financing: A Three Tier Model

A common error regarding healthcare models is to conflate the scope of healthcare services provided and the financing of healthcare. These two important components of a healthcare system should be treated somewhat independently; however, obviously a greater scope of healthcare provided results in higher healthcare costs. First, the desired scope of healthcare services provided should be defined, then healthcare financing should be determined, given the parameters defining the scope of desired healthcare services. Our proposed model for healthcare financing attempts to identify an efficient/cost-effective healthcare financing using a three-tier model. Each tier of the three-tier model assumes a different payer/underwriter and a different probability distribution of healthcare claims.

Given high and rapidly rising healthcare costs in the United States and elsewhere in the world, mitigating this increasing trend and possibly reducing the high cost of quality healthcare is an important issue for citizens, politicians, policy makers, as well as academics.

Hartwig (2008) finds that health care expenditures are rising in virtually all OECD countries. However, differing hypotheses exist regarding contributing factors and causes for the rising healthcare cost trend. Suggested factors causing increases in healthcare costs include: defensive medicine, Studdert, et al (2005) and Kessler and McClellan (1996); supplier-induced demand McGuire and Pauly (1991) and Cromwell and Mitchell (1986); technology-driven demand, Smith, Newhouse, and Freeland (2009) and Weisbrod (1991); comorbidities, Egede Simpson and Zheng (2002); rising administration costs, Woolhandler, Campbell and Himmelstein (2003); regulatory compliance costs, Bodenheimer (2005) and price inflation in general, Thus, all of these identified driving factors contribute to this trend. In addition, waste and fraud undoubtedly underlie many, if not all, healthcare cost growth drivers as well.

Rising healthcare expenditures also drives an increasing demand for health insurance. Borger, Rutherford and Won (2008) develop a model that forecasts future consumer demand for both health insurance and health care, suggesting a two-goods economy consisting of medical goods and non-medical goods. They cite that between 1948 and 2004 U.S. health care expenditure rose from 4% of GDP to 16% and that this trend is expected to continue, where, increases in healthcare expenditures have resulted in increased demand for health insurance. Ahking, Giaccotto and Santerre (2009), Cameron, Trivedi, Milne and Piggott (1988) and Marquis and Long (1995) illustrate the increasing importance of healthcare insurance underwriting. In addition, Cohen and Siegelman (2010); Manning and Marquis (1996); Baicker and Chandra (2005); Kronick and Gilmer (1999) and Cooper and Schone (1997) show that in addition to rising healthcare costs, these vicissitudes lead to other undesirable consequences related to moral hazard, adverse selection, and labor market problems.

Health insurance underwriting risk is complicated by the general publics' desire for universal health coverage, including coverage for preexisting conditions and catastrophic healthcare events, thus expediting rising health care costs and increasing premiums for households, employers and governments. However, absent from much of the ongoing discussion is the efficiency of healthcare insurance underwriting and how it is or should be financed.

Our unique proposed, cost-effective approach to healthcare is to first define healthcare scope/coverage parameters and then, given the defined healthcare parameters and associated estimated costs, we identify an underwriting financing structure potentially spread across stakeholders: households/insureds, insures and government, that will substantially reduce healthcare cost and equitably distribute cost across all stakeholders.

We formulate an underwriting approach by first identifying and clarifying specific costs, cost drivers and cost trends for each cost driver. Then, we postulate recommendations for the future healthcare policy structure, underwriting and payers. Our objective is to identify cost drivers and cost trends, given defined healthcare parameters, that will provide improved and attainable quality healthcare to all Americans. Then, we identify an underwriting payment/financing structure that will substantially and equitably reduce healthcare cost for all stakeholders.

We identify inefficiencies in our current healthcare underwriting and financing system and improve on the current structure of U.S. healthcare expenditures and financing in three ways. First, we segment patient healthcare cost into three tiers: Tier 1, high frequency/low severity healthcare; Tier 2, medium frequency/medium severity healthcare, and Tier 3: high severity/low frequency across the entire distribution of insureds, but possibly high frequency healthcare cost for the segment of the healthcare distribution that incurs catastrophic healthcare events. Second, we estimate frequency of healthcare events and cost severity per healthcare event for each tier, allowing us to determine underwriting cost pure premiums for each tier. It is possible in a given year for a single insured to be included in all three tiers, if he or she experiences a catastrophic health event. Third, we measure serial healthcare costs for a single insured by measuring year to year cost covariances by following the same patient across multiple years. Thus, we posit that each tier of the healthcare probability distribution will result in substantially different statistical parameters and unique distributions.

For each tier, we analyze claim severity and frequency and their covariance for each year and year over year serial correlation for insureds. We expect to find high frequency of healthcare claims, but low severity in Tier 1, medium frequency and medium severity for those insureds reaching Tier 2 and possibly high frequency and high severity of healthcare claims in catastrophic coverage for those insureds reaching Tier 3. We posit that claim frequency and claim severity depend on the seriousness and cost of patient healthcare needs.

Currently, healthcare underwriting generally estimates total healthcare paid claims/costs across the entire distribution of insureds and estimates a mean pure premium for the entire sphere of covered healthcare events. Inherently, this is very inefficient, if distributions explaining healthcare costs are unstable across the entire distribution. Thus, for simplicity, we propose a three-tier model that will better define more homogeneous underwriting distributions and parameters for each tier.

Patients who have higher and more costly healthcare needs, during a given year, may experience higher claims in subsequent years. Thus, decomposing healthcare cost into three tier levels for each year and also estimating the impact of serial claims in subsequent years, facilitates identifying different payers for different insurance tiers and improved policy decisions that may curtail high and rising healthcare costs.

We expect no identifiable pattern for frequency and severity or serial dependency for tier 1, since much of tier 1 is higher frequency but less-serious healthcare events. Insureds reaching tier 2 may display dependencies between frequency and severity of insurance claim, where this tier would be represented by less frequent claims, but higher severity, for example minor operations. Tier 3, catastrophic healthcare events, may represent by only a small proportion of the entire distribution of insured individuals, but for the smaller number of insureds reaching tier 3 in a given year, their distribution of paid claims may exhibit high frequency and high severity of healthcare claims. Tier 3 may also represent end of life healthcare events. However, the percentage, in a given year, of individuals reaching tier 3 level of paid claims is quite small.

The remainder of our paper is organized as follows: section 2 is a review of literature of healthcare financing and insuring of interdependent claims. Section 3 describes our data and methodology. Section 4 closes with our findings and conclusions.

I. Literature Review and Hypothesis Development

Kleiman (1974), Newhouse (1977), Parkin et al. (1987), Milne and Molana (1991), Getzen and Poullier (1991), Gerdtham and Jönsson (1991), Gerdtham et al. (1992) and Hitiris and Posnett (1992) find a correlation between health care spending and GDP. Other than GDP growth as a cost driver, Hitiris and Posnett (1992), Di Matteo and Di Matteo (1998) and Zweifel et al. (1999) find that proximity to death appears to be the strongest driver of healthcare costs. However, we strive to further identify these and other cost drivers as causes of healthcare cost growth.

Financing healthcare treatment is unique because the treatment of provided healthcare is unique for each individual, thus, healthcare financing may also be unique for each individual insured. Costs to treat a specific healthcare ailment varies from patient to patient because of unique factors determined by the specific ailment and other factors determining the quantity and cost of healthcare services provided and the recovery period for the individual patient. For example, Egede Simpson and Zheng (2002) find that patients with comorbidities is more costly.

Many types of insurance assume that the frequency of claims and their cost/severities are independent; however, this most likely is not the case for specific levels of healthcare insurance. Generally, we posit that healthcare frequency of claims and severity of claim may be correlated; however, not homogeneously across the paid claims’ distribution. A significant healthcare encounter today may increase the likelihood of future healthcare encounters and higher healthcare claims. Thus, an expensive healthcare encounter today increases the probability of future costly healthcare encounters. This observation leads us to our first hypothesis.

Hypothesis 1: Claim frequency and claim severity are interdependent (correlated) with non-homogeneous covariances across the paid claim distribution.

Total realized annual charges or claims for an individual patient/insured is a function of an individual's expected annual claim frequency and expected claim severity. Specifically, expected annual total charges/claims are the product of a patient's expected paid claim frequency and expected claim severity. Also, annual claim frequency and average claim severity may display different covariances across the entire paid claims' distribution. Therefore, we posit that the product of the expected annual claim frequency and average annual expected claim severity, if we ignore their covariance, differs from expected total annual charges/claims for each individual.

Hypothesis 2: Expected mean annual paid claims per insured increases non-linearly across the distribution of healthcare claims/costs.

A majority of healthcare encounters are initiated due acute, resulting from minor illnesses for example, colds and flu, not chronic events, or may be preventive in nature, for example, physicals, wellness checks, annual check-ups and immunizations. Thus, a predominance of healthcare encounters occur to maintain health or to treat minor healthcare events, where, these encounters are relatively inexpensive. However, if the cost of preventive healthcare is too high, patients may forego preventive care, betting that they will be unafflicted. Differences in motivation to treat healthcare events, preventive/maintaining health versus restoring health, leads to our third hypothesis.

Hypothesis 3: Claim frequency, claim severity and their covariance is heterogeneous across the entire distribution of healthcare claims, thus the paid claims distribution should be *segmented into more relatively homogeneous segments/tiers to facilitate underwriting and payer determination.*

Given our proposition that covariances for claim frequency, f, and claim severity, s, are heterogeneous over the full distribution of healthcare claims, estimates of total annual mean pure premiums (MPPs) over the entire claim distribution may be significantly bias as compared to estimating MPPs for each tier, where, this bias may affect the accuracy and fairness of estimated annual healthcare premiums.

We show, empirically, that healthcare claims are neither normally distributed nor bounded at the upper level, and the non-constant covariance over the full distribution of total paid claims results in biased/inaccurate estimates for MPPs. Thus, segmenting the distribution of healthcare paid claims into three tiers based on each tier's unique frequency, severity and covariance of frequency and severity. This serves to reduce estimation MPP bias and more accurately estimates each tier's underwriting costs MPP, thus facilitating the estimation of MPPs for each tier and improve efficiency in determining best payers for each tier.

Hypothesis 4: Segmenting financing MPPs into three tiers based on relative homogeneity of frequency and severity may reduce cumulative MPPs rather than estimating MPPs over the entire claims' distribution. Also segmenting into three tiers facilitates identifying optimal payer structures among individual insured, private insurer and government insurers.

Thus, we posit that cumulative estimated mean MPPs across the three tiers is lower than estimated MPPs calculated for the entire distribution of paid claims, thus, facilitating the identification of payers among individual insured, private insurer and government insurers for each tier.

MPP estimation errors may be measured as the difference between actual paid claims and model estimated MPPs. Smaller errors suggest greater model estimation efficiency.

Insurance policies premiums, including healthcare insurance, are generally for one year, and estimated MPPs are random variable estimates of actual annual healthcare paid claims/losses, or charges paid by the insurer, where, annual insurer losses may be broken down to loss severity, cost of each services/paid claim, and frequency, times per year service is provided or number claims received annually by the insurer. We allow covariance between frequency and severity, where, in general, higher frequency, the number of claims per year per insured, generally results in higher annual paid claims per insured individual. Thus, insured individuals who access health care services more often in a year generally submit higher annual paid claims to insurers.

Another advantage of estimating MPPs as functions of frequency and severity within each insurance tier is that similar procedures vary in severity and costs across patients and service providers. Factors affecting frequency and severity may include patient age, location, comorbidities, unexpected complications and service provider. Mean annual estimated MPPs measure averages but fail to measure uniqueness across different tiers or account for changes across healthcare encounters.

II. Data and Methodology

A. Cerner HealthFacts

Our primary data source is the electronic health records (HER), Health Facts EMR data, made available through Center for Biomedical Informatics at the University of Tennessee Health Science Center, UTHSC. ***Data in Health Facts are extracted directly from the EMR from hospitals in which Cerner has a data use agreement. Encounters may include pharmacy, clinical and microbiology laboratory, admission, and billing information from affiliated***

patient care locations. All admissions, medication orders and dispensing, laboratory orders and specimens are date and time stamped, providing a temporal relationship between treatment patters and clinical information. Cerner Corporation has established Health Insurance Portability and Accountability Act-compliant operating policies to establish de-identification for Health Facts.

Healthfacts data include over 49 million distinct patients with more than 290 million patient encounters from 2000 through 2015. Healthfacts is comprised of sequenced, time stamped encounter, events level data for individual patients from both Cerner and non-Cerner participating facilities. An encounter refers to each time a patient is seen for services with a participating provider.

Each encounter begins upon admission and ends at discharge. A clinical visit to a provider that last at least an hour will be a single encounter with a length of stay of 1 day. Longer-term inpatient stays, usually in a hospital, for example, in the ICU and subsequently transferred to a recovery floor within the same hospital prior to discharge will also be considered a single encounter but with a longer length of stay. Total charges for an encounter are the summation of all provider related charges for that encounter.

Charges for outpatient prescriptions, when written by a primary care provider but not filled during a clinical visit, excluded from total charges. However, inpatient prescriptions administered by the provider during the encounter are included in total charges. For length of stays longer than 1 day, we are unable to identify the breakdown of charges, thus we do not include them. For example, ICU patients are likely to have the bulk of their charges front-loaded during their stay; however, an emergency department patient, admitted for less than 48 hours, may have charges evenly distributed across both days. Further, patients with longer length of stays may incur charges clustered together but may include some days with relatively few charges.

Data also provide a wide range of healthcare descriptive variables, including acute and non-acute care settings, both in hospitals and in clinics, the census region for each care setting, care setting size measured by licensed beds as well as dummy variables for teaching hospitals and rural versus urban locations. Care settings associated with health systems may be tracked across clinic, hospital, and ER visits within the system. In outpatient clinics not associated with a health system, each patient may be tracked across visits to that single provider.

Additional variables provide information on each patient, including current medical condition and needs. For example, the patient's age, gender, marital status, race and payer source are provided. Also provided in the data is the major diagnostic category, the reason for the visit as well as more granular descriptions of each patient's ailments. Secondary diagnosis and co-morbidities also are provided. To some extent the admission source and care setting is included in the data, but only for a fraction of the observations.

With respect to healthcare costs, the Healthfacts data provide insight into five major categories of patient care: clinical, economic, process, functional, and satisfaction, including billing data on many patient encounters. 95% of inpatient encounters include data on at least one of three areas: medication, laboratory or billing, where, data is available for 60% of outpatient encounters and 70% of ER encounters. Billing data is our primary focus for identifying factors affecting levels and increases healthcare expenditures.

Regarding billing data, the total charges variable represents hospital invoice charges prior to receiving any deductions in received/reimbursed payments. As is generally the case, payments remitted by insurance companies to healthcare providers are reduced by agreements between parties and may also be reduced because of co-pays and patient deductibles.

Deductibles represent amounts patients are personally responsible for; however, often self-pay patients may be offered or may negotiate reduced amounts for upfront cash payments. Also, indigent patients, despite their inability to pay, cannot be turned away for many services, such as ER visits. Thus, the total charges variable may overstate actually paid health care expenses.

We recognize the potential overstatement nature of the data; however, the deduction rate, as measured by the billed amounts less total paid amounts divided by billed amounts should remain relatively stable across years, thus this data bias does not pose a major problem for the validity of our results. In addition, while different health care systems and providers may differ cross sectionally, aggregate amounts should also remain relatively stable year over year.

B. Descriptive Statistics

Our analysis includes only patients with billing data. Using this data, we evaluate the scope of total patient healthcare expenditures by reviewing admission sources and discharge dispositions to identify patients who are expected to have additional encounters. This approach facilitates our developing parameters for estimating and capturing health care expense. We apply our filters to ensure that we include only those patients for whom we have a majority of claim data. Given our filters, our sample covers 2000 through 2014, and includes over 12 million unique patients with over 23 million patient years. A patient year is the estimated total healthcare costs incurred by a single patient in a single year. Table 1 reports descriptive statistics regarding patients, encounters, and annual charges by year.

[Table 1 Here]

We observe a highly skewed distribution of annual healthcare expense. Mean annual charges per insured, averaged across years, are approximately $8,000 with a standard deviation of .Median charges are while the maximum annual charges exceed $8 million.

A high level of loss variable skewness is problematic with regard to risk pooling and diversification, where, a few large losses, in a given year, significantly affect MPPs. MPP estimation is additionally problematic with unbounded annual losses, substantially increasing variances, making it difficult for underwriters to accurately estimate reasonable MPPs and to estimate confidence intervals around MPPs. Figure 1 is a histogram of patient annual healthcare costs and shows the degree of skewness in the distribution.

[Figure 1 here]

Table 2 shows the percentiles in the distribution.

[Table 2 here]

C. Variables Definitions and the Mean Pure Premium (MPP) calculations

Spahr and Escolas (1986) developed a model for private mortgage insurance (PMI) contingent on economic states where mortgage loan defaults (frequency) and each mortgage losses (severity) were correlated. Their model observed that during an economic environment, such as a severe recession, individual home loan defaults increased substantially because of a contagion effect caused by other homes in the community simultaneously defaulting as well. Thus, catastrophic home loan defaults increase the supply of homes, and along with an economic recession where less homebuyers exist, home values decreases precipitously, causing greater/unsustainable unexpected losses to PMI insurers, causing some PMI insurers to fail. This scenario not only played out in the 1980s, but also occurred during the 2007-09 recent severe recession. Their model is similar to ours, where we also posit that claim frequency and claim severity may also display dependency. To test our hypotheses, the following model is proposed to consider relevant parameters for individual (an insured family or an individual) insured underwriting risk per insured and the resulting pure risk premiums for each insurance tier.[1] Definitions and variables for this model are:

AHE (Annual Healthcare Expense) = the summation of individual annual healthcare expenses;

f = frequency, # of annual claims per insured;

s = severity of annual claim losses per insured (per family or for each individual);

p = pure risk annual premium per insured;

T = annual total losses/paid claims incurred in a population of insureds;

E(f) = expected annual frequency of claims per insured;

σ^2_f = variance of annual frequency of claim occurrence;

E(s) = expected annual per encounter loss severity for each encounter/claim, per insured. Calculated as total annual paid claims per insured individual divided by the number of claims/encounters (frequency) for that insured individual;

σ^2_s = the variance of loss severity per encounter/claim;

Cov(f,s) = covariance between annual frequency and per encounter severity for each insured;

$E(p_i)$ = the expected mean pure risk premium (hereafter MPP) for insured in the ith tier;

σ^2_i = the variance of MPP for each insured in the ith tier;

Cov(i,j) = the covariance between the MPP per insured between the ith and jth tier;

$E(T_i)$ = expected annual total incurred loss for the population of N insureds in ith tier;

[1] While the model allows for the interdependence of default and severity rates, it does not impose such a condition if it is not present.

σ^2_{Ti} = variance of annual total incurred losses in ith tier for the insured population.

$\rho_{i,j}$ = correlation between the ith and jth tier losses/paid claims.

The mean and variance for individual pure risk premiums, which may be estimated for the full distribution of healthcare claims or for each tier are:

$$MPP = E(p) = E(f \bullet s) = E(f)E(s) + Cov(f,s) \quad (1)$$

and

$$\text{Variance } MPP = \sigma^2_p = E(f)^2\sigma^2_f + E(s)^2\sigma^2_s + 2E(f)E(s)Cov(f,s).^{2} \quad (2)$$

For individual risk units (families or individuals) healthcare claims, we posit that Cov(f,s) will be heterogeneous across different tiers of the full healthcare cost distribution, e.g. severity of claim losses are allowed to be correlated, positively or negatively, with the frequency of claim losses.

We begin with the simple proposition that the annual mean pure premium (MPP) is equal to the mean expected annual healthcare expenses (AHE) incurred by an insured individual. The MPP is one way to estimate annual healthcare premiums, which is the expected underwriting losses for an individual insured risk unit underwritten by an insurer. In our case of health insurance an individual risk unit is an insured individual. We estimate an OLS regression to

[2] According to Goodman (1960, p. 708-713), the variance of the product of two dependent random variables is

$$o^2_p = E(f)^2\sigma^2_s + E(s)^2\sigma^2_f + 2E(f)E(s)E_{11} + 2E(f)E_{12} + 2E(s)E_{21} + E_{22} - E_{11}^2$$

where,

$E_{11} = Cov(f,s)$

$E_{12} = E(f - E(f))\ (s - E(s))^2$

$E_{21} = E(f - E(f))^2(s - E(s))$ and

$E_{22} = E(f - E(f))^2(s - E(s))^2$

Given these relationships, it is easily shown that equation (2),

$$\sigma^2_p = E(f)^2\sigma^2_f + E(s)^2\sigma^2_s + 2E(f)E(s)Cov(f,s)$$

is a good approximation for determining the variance of the annual pure premium per insured for underwriting healthcare insurance coverage in each tier for an insured individual.

determine what, if any a priori observed factors aid in predicting an individual's AHE. We estimate the following four models.

$$AHE = B_1 + B_2 Female + B_3 Age + B_4 Year$$

$$AHE = B_1 + B_2 Female + B_3 Age + B_4 Year + B_5 Urban + Gender\ FE + Marital\ FE + Census\ Location\ FE$$

$$AHE = B_1 + B_2 Annual\ Frequency$$

$$AHE = B_1 + B_2 Annual\ Frequency + B_3 Female + B_4 Age + B_5 Year + B_6 Urban + Gender\ FE + Marital\ FE + Census\ Location\ FE$$

Where *Urban* is a dummy variable equal to 1 for all patients of urban hospitals and *GENDER FE* are gender fixed effects, *Marital FE* are marital status fixed effects, and *Census Location FE* are fixed effects for US census region. In our final two models we include the variable *Annual Frequency*. We include *Annual Frequency* to show that while the other factors are by in large statistically significant, the inclusion of *Annual Frequency* is what provides any explanatory power to the regression models. Table 3 reports our results. *Annual Frequency* is not observable in estimating underwriting losses because it occurs simultaneously with underwriting losses and are therefore unusable for estimating the MPP. We therefore conclude that the mean AHE is our best initial estimate for MPPs.

[Table 3]

Estimating *Annual Daily Charges* as E(s) and *Annual Frequency* as E(f) using the above regressions yields a maximum R^2 of 0.0508. So these are poor ways of estimating these variables as well. Same result for daily charges per encounter. This suggests that mean daily charges per encounter is the best estimate for E(s) and mean frequency per encounter is best estimate of E(f).

D. Calculating Mean Pure Premiums

Hypothesis 1: Claim frequency and claim severity are interdependent (correlated) with non-homogeneous covariances across the paid claim distribution, alleges that frequency and severity dependencies are heterogeneous across the full distribution of healthcare cost data. However, this dependency relation may extend in both directions for different tiers. Serious health events, requiring lengthier, more invasive, more expensive treatments and possibly numerous treatments throughout a year and possibly across years, may exhibit positive covariances between frequency and severity. Whereas, those insured not accessing healthcare nor incurring substantial healthcare costs in a given year, will likely incur subsequently fewer healthcare costs during other years. Thus, these scenarios justify the existence of significant covariances, especially in different tiers.

We test hypothesis 1 by estimating, for each patient for each year, claim severity, frequency and correlation (CORR) and covariance (COV). CORR and COV are reported in table 3. For all years in our sample, we observe positive and significant covariances and correlations between claim frequency and severity, thus supporting part of hypothesis 1, that claim frequency and severity exhibit dependencies over the full claim distribution.

[Table 4 here]

Table 4 shows that claim frequency and claim severity are interdependent upon each other. In testing hypothesis 1, Table 4 reports that claim severity and claim frequency are significantly positively correlated for all study years. However, we posit that correlations between claim frequency and severity is stronger as claim frequency and claim severity increase, growing at a non-linear rate. The positive correlations for each year between frequency, and severity is biased towards the few patients with very high frequency and extremely severe health encounters, where, these cases are outliers compared to the overall population, but overwhelm possibly negative frequency-severity relationships found in the lower frequency-severity encounters. However, low frequency and severity encounters account for the vast majority of observed healthcare encounters. Subsequently, we test whether frequency and severity correlation are different in each of the three tiers of the paid claim distribution

To determine if this interdependent relation is heterogenous across all health care claims we subdivide the distribution of health care claims at approximately the 50th percentile and the 99th percentile. This subdivision allows us to define three tiers of health care claims. Tier 1 encompasses each individual's cumulative annual health care claims up to $2,000. Tier 3 includes each individual's cumulative annual health care claims in excess of $2,000 but not exceeding $100,000. Tier 3 comprises all cumulative annual health care claims for each individual in excess of $100,000. We estimate COV(f,s) for each claim for each year in our sample period. Table 5 reports our results. We show that the covariant relation is negative for Tier 1 and generally shifts positive towards Tier 3. This result supports our hypothesis that the claim frequency and claim severity covariant relation is non-homogeneous across the full distribution of health care claims.

[Table 5 here]

MPPs are estimated from Cerner reported data annual healthcare expenses (AHE) for our entire sample period. Alternatively, insurer underwriting losses may be broken down to frequency and severity of healthcare claims to estimate means and variances of MPPs that may be used to set premiums for an individual insured patients using equations (1) and (2)

If covariance between frequency and severity increase with higher frequency and severity levels and hypothesis 2 (*mean annual paid claims per insured increases non-linearly across the distribution of healthcare claims)* are true, it follows that estimating MPPs from (1), but ignoring the covariance term should yield a lower annual MPP than when covariance terms are included. We test hypothesis 2 by estimating MPPs using equation (1) with and without covariance terms and observe the differences. Table 4 reports our results. In each year of our sample period we observe that equation (1) overestimates the MPP as compared to equation (2). These findings support our second hypothesis.

[Table 6 here]

Testing hypothesis 2, our results strengthen our hypothesis that covariance of frequency and severity is heterogeneous across claim types. It is possible that by segmenting claim types based on the covariance of frequency and severity may result in a more efficient financing stratagem. Thus, we propose a three-tiered healthcare financing system that segments claims by total annual claims per insured that also groups insured by healthcare claim frequency and severity; hereby, reducing overall healthcare cost/insurance premiums.

The first tier in our model generally consists of low severity claims that are experienced by virtually the entire population. These claims include maintenance and preventive care encounters as well as minor healthcare encounters that are not expected to result in future encounters or prolonged treatments. For simplicity we define the parameters of each tier based on total annual cumulative healthcare expense. Tier1 comprises all healthcare claims up to $2,000 per year per individual. Individual annual cumulative healthcare claims in excess of $2,000 and up to $100,000 comprise tier2. Tier3 include all Individual annual cumulative healthcare claims in excess of $100,000. Based on the annual healthcare claims percentiles more than half of all patients will only experience healthcare claims in tier1. At the other end of the extreme, approximately 1% of the population will incur enough annual healthcare expenses to extend into tier3.We modify our calculation of the MPP for each tier by including the probability of a patient incurring costs in each of the three tiers. Our new formulas for calculating the MPP for each tier is:

$$MPP_{T1} = P(T1) \ * \ (E(f_{T1}) * E(s_{T1}) + COV(f_{T1}, s_{T1}) \tag{4}$$

$$MPP_{T2} = P(T2) \ * \ E(f_{T2}) * E(s_{T2}) + COV(f_{T2}, s_{T2}) \tag{5}$$

$$MPP_{T3} = P(T3) \ * \ E(f_{T3}) * E(s_{T3}) + COV(f_{T3}, s_{T3}) \tag{6}$$

Frequency and severity can only be positive and can only increase through time. Claims cannot have a negative severity, and, by extension, additional claims only increase cumulative annual claims. By designing our tiered financing system in this way, we not only identify the changing covariant relation across healthcare claims but also simultaneously control for the positive covariance caused by the non-negative nature of encounter frequency and severity.

[Table 5 here]

Using equations (4) (5), and (6) we test our third and fourth hypothesis. Table 5 reports our results. We find that for all years in our sample we find a negative COV(f,s). This result supports our third hypothesis that low severity claims generally have the effect of preventing future severe (expensive) healthcare encounters. Furthermore, we find mixed results for COV(f,s) relation for tier2 and tier3 encounters. Despite the mixed results the magnitude of the COV(f,s) is greater for tier3 than for tier2. Also, while we isolate the negative COV(f,s) in tier1, much of the overall positive COV(f,s) in the entire distribution is removed when we control for the non-negative nature of frequency and severity. We expect to find then that the summation of the Tier1 MPP, Tier2 MPP, and Tier3 MPP should be less than the MPP for the entire distribution. To test our fourth hypotheses, we estimate the MPP for each tier and sum them up. We compare the summation of MPPs for each tier to the MPP for the entire distribution and report their differences in table 6. We find that for each year in our sample the sum of the Tier’s

MPPs is less than the MPP for the entire distribution. These results support our fourth hypothesis that financing healthcare over tiers is less expensive than financing the entire distribution on a single policy.

[Table 6 here]

E. Policy Recommendations

Healthcare coverage as a social good has long been a topic of debate among policymakers. On the one hand, untreated healthcare declines may result in significant and irreversible adverse consequences for those afflicted. On the other, the cost of providing healthcare coverage to the entire population presents significant social costs that many are unwilling to bear. We propose a three-tiered health insurance model wherein the first and second tier are privately financed, and the third tier is publicly financed.

The first tier, covering all healthcare costs up to $2,000 annually. Tier one encounters comprise low severity claims that are experienced by the entire population. First tier coverage may be optimally financed through individual savings, tax advantaged health savings accounts, or direct primary care models[3]. The second tier covers all annual charges in excess of $2,000 and up to $100,000. Traditional private insurance models are best suited to cover the second tier of health insurance. Second tier encounters include high severity encounters experienced by relatively few individuals. The third tier comprises all healthcare claims in excess of $100,000 cumulative annual charges. Third tier encounters are generally catastrophic in nature and are experienced by very few patients. These encounters are catastrophic to the patients physical and financial health and are likely to result in long term care, disability, or even death. Also, the third tier is unbounded on the right side of the distribution. For all practical purposes, incurred

[3] A primary care model is when a primary care physician charges a monthly fee that covers office visits, consultations, and certain medical examinations.

healthcare costs are virtually unlimited. For these reasons, we propose that the third tier of health insurance be socially financed by government entities. We filter our sample to include only those encounters for which we have payer information. We evaluate the proportion of encounters currently paid for by government entities. Table 7 shows that for tier three encounters the government currently covers approximately two-thirds of encounters, measured both in number of encounters and dollars.

[Table 7 here]

III. Conclusion

Many have argued that healthcare is becoming increasingly prohibitively expensive. We evaluate the relation between claim frequency and claim severity. We find that claim frequency and claim severity have a positive covariant relation. We find that expected total annual charges are a function of expected frequency and expected severity and that calculating MPPs considering this relation provides a less biased estimation. We also examine the covariant relation and find that at the low severity end of the distribution the claim frequency-severity covariance is negative. Finally, we find that by financing health insurance over tiers provides a less expensive model of financing than covering all healthcare losses in a single policy.

References

Ahking, Francis W., Carmelo Giaccotto, and Rexford E. Santerre, 2009, The Aggregate Demand for Private Health Insurance Coverage in the United States, *Journal of Risk & Insurance*, 76, 133-157.

Baicker, Katherine, and Amitabh Chandra, 2005, The Labor Market Effects of Rising Health Insurance Premiums, NBER Working Paper No. 11160.

Bodenheimer, Thomas, 2005, High and rising health care costs. Part 1: seeking an explanation, *Annals of Internal Medicine* 142, 847-854.

Borger, Christine, Thomas F. Rutherford, and Gregory Y. Won, 2008, Projecting Long Term Medical Spending Growth, *Journal of Health Economics*, 27, 69-88.

Baumol, William J., 1967, Macroeconomics of unbalanced growth: the anatomy of urban crisis, *The American economic review*, 415-426.

Cameron, A. Colin, Pravin K. Trivedi, Frank Milne, and J. Piggott, 1988, A Microeconometric Model of the Demand for Health Care and Health Insurance in Australia, *The Review of Economic Studies*, 55, 85-106.

Centers for Medicare and Medicaid Services (CMS), 2016, https://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/nationalhealthexpenddata/nhe-fact-sheet.html

Cohen, Alma and Peter Siegelman, 2010, Testing for Adverse Selection in Insurance Markets, *Journal of Risk and Insurance*, 77, 39–84.

Cooper, Phillip F., and Barbara S. Schone, 1997, More Offers, Fewer Takers for Employment-Based Health Insurance: 1987 and 1996, *Health Affairs*, 16, 142-149.

Cromwell, Jerry, and Janet B. Mitchell, 1986, Physician-induced demand for surgery, *Journal of Health Economics* 5, 293-313.

Di Matteo, Livio, and Rosanna Di Matteo, 1998, Evidence on the determinants of Canadian provincial government health expenditures: 1965–1991, *Journal of Health Economics* 17, 211-228.

Egede, Leonard E., Deyi Zheng, and Kit Simpson, 2002, Comorbid depression is associated with increased health care use and expenditures in individuals with diabetes, *Diabetes care* 25, 464-470.

Gatti, James F. and Ronald W. Spahr, 1997, The Value of Federal Sponsorship: The Case of Freddie Mac, *Real Estate Economics*, 25, 453-485.

Getzen, Thomas E., and Jean-Pierre Poullier, 1991 An income-weighted international average for comparative analysis of health expenditures, *The International Journal of Health Planning and Management* 6, 3-22.

Gerdtham Ulf, Jes Søgaard, Fredrik Andersson, Bengt and Jönsson, 1992, An econometric analysis of health care expenditure: a cross-section study of the OECD countries, *Journal of Health Economics* 11, 63-84.

Gerdtham, Ulf, and Bengt Jönsson, 1992 International comparisons of health care expenditure conversion factor instability, heteroscedasticity, outliers and robust estimators, *Journal of Health Economics* 11, 189-197.

Hartwig, Jochen, 2008, What Drives Health Care Expenditure?—Baumol's Model of 'Unbalanced Growth' Revisited, *Journal of Health Economics,* 27, 603-623.

Hitiris, Theo, and John Posnett, 1992, The determinants and effects of health expenditure in developed countries, *Journal of Health Economics* 11, 173-181.

Kessler, Daniel, and Mark McClellan, 1996, Do doctors practice defensive medicine?, *The Quarterly Journal of Economics*, 111, 353-390.

Kleiman, Ephraim, 1974, The determinants of national outlay on health, *The Economics of Health and Medical Care*. Palgrave Macmillan UK, 1974. 66-88.

Kronick, Richard, and Todd Gilmer, 1999, Explaining the Decline in Health Insurance Coverage, 1979-1995, *Health Affairs,* 18, 30-47.

Manning, Willard, and M. Susan Marquis, 1996, Health Insurance: The Tradeoff Between Risk Pooling and Moral Hazard, *Journal of Health Economics*, 15, 609-639.

Marquis, M. Susan, and Stephen Long, 1995, Worker Demand for Health Insurance in the Non-Group Market, *Journal of Health Economics,* 14, 47-63.

McGuire, Thomas, and Mark Pauly, 1991, Physician response to fee changes with multiple payers, *Journal of Health Economics* 10, 385-410.

Milne, Robin, and Hassan Molana, 1991, On the effect of income and relative price on demand for health care: EC evidence, *Applied Economics* 23, 1221-1226.

Newhouse, Joseph, 1977, Medical-care expenditure: a cross-national survey, *The Journal of Human Resources* 12, 115-125.

Parkin, David, Alistair McGuire, and Brian Yule, 1987, Aggregate health care expenditures and national income: is health care a luxury good?, *Journal of Health Economics* 6, 109-127.

Smith, Sheila, Joseph Newhouse, and Mark Freeland, 2009, Income, insurance, and technology: why does health spending outpace economic growth?, *Health Affairs* 28, 1276-1284.

Spahr, Ronald W. and Edmond L. Escolas, 1986, Mortgage Guarantee Insurance: A Unique Style of Insurance, *Journal of Risk Insurance*, 53, 308-319.

Spahr, Ronald W. and Mark A. Sunderman, 2014, The U.S. Housing Finance Debacle, Measures to Assure its Non-Recurrence and Reform of the Housing GSEs, *Journal of Real Estate Research*, 36, 59-86.

Spahr, Ronald W., Mark A. Sunderman, and Chukwaka Amalu, 1991, Corporate Bond Insurance: Feasibility and Insurer Risk Assessment, Journal of Risk and Insurance, 58, 418-437.

Studdert, David, Michelle Mello, William Sage, Catherine DesRoches, Jordan Peugh, Kinga Zapert, and Troyen Brennan, 2005, Defensive medicine among high-risk specialist physicians in a volatile malpractice environment, *Jama* 293,2609-2617.

Weisbrod, Burton, 1991, The health care quadrilemma: an essay on technological change, insurance, quality of care, and cost containment, *Journal of Economic Literature* 29, 523-552.

Woolhandler, Steffie, Terry Campbell, and David Himmelstein, 2003, Costs of health care administration in the United States and Canada, *New England Journal of Medicine* 349, 768-775.

Zweifel, Peter, Stefan Felder, and Markus Meiers, 1999, Ageing of population and health care expenditure: a red herring?, *Health Economics* 8, 485-496.

Figures

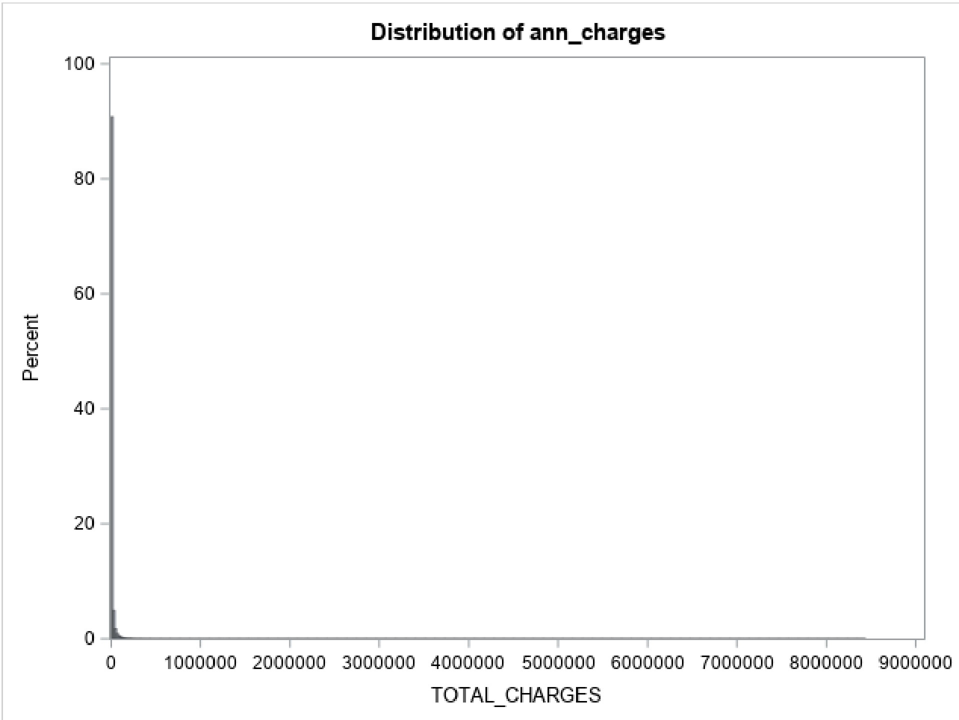
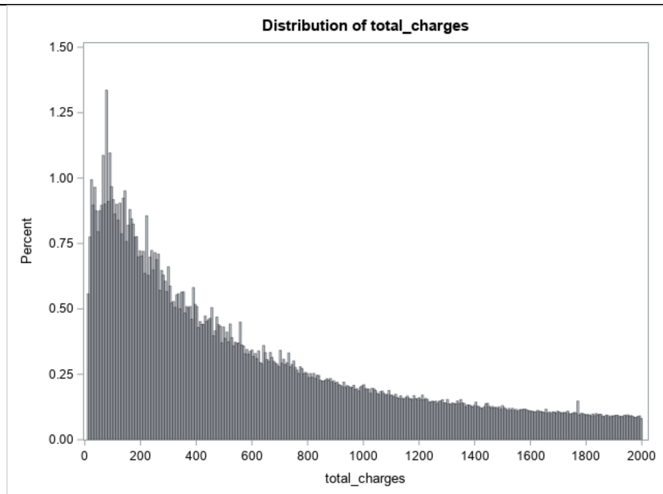


Figure I: Histogram for entire distribution of annual healthcare expense

Shows a histogram of individuals annual health care charges. Our data covers years 2000 through 2014. We show that the overwhelming proportion of patients incur very few charges while a small minority incur overly large amount of annual charges. Further we show that annual charges are virtually unbounded in the tail.

Panel A: Tier 1



Panel B: Tier 2

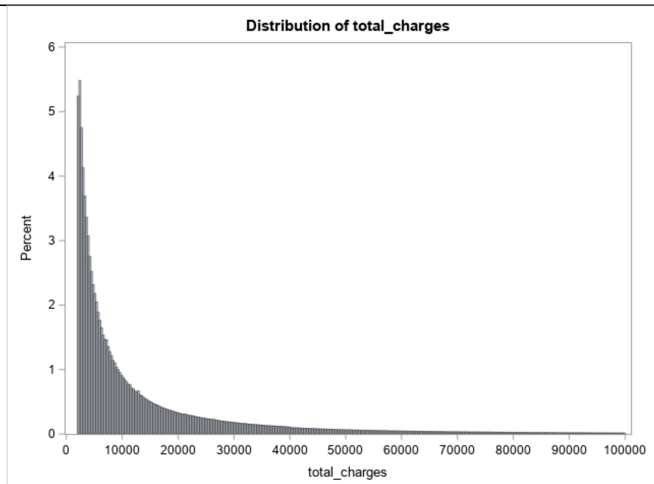


Figure II – Continued

Panel C: Tier 3

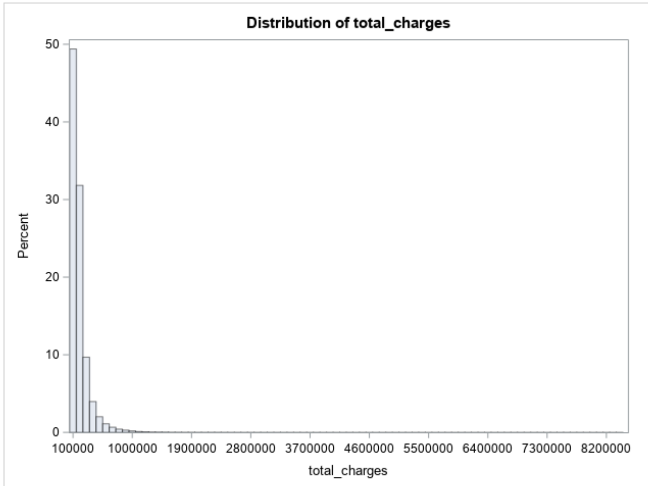


Figure II: **Histograms for each tier**

Shows a histogram of individuals annual health care charges for each tier. Our data covers years 2000 through 2014.WE find that each tier is positively skewed, and that the skewness increases with each tier.

Tables

	N	Mean Charges	Median Charges	Standard Deviation of Charges	Skewness of Charges	Min Charges	Max Charges
Total Patients	12,236,959						
Patient Years	22,778,271	$8,144	$1,156	$29,931	22.96	$9.01	$8,432,869
Women	13,509,087	$7,489	$1,121	$26,745	25.55	$9.01	$8,432,869
Men	9,4443,335	$8,925	$1,177	$33,580	20.54	$9.01	$6,160,271
Other	22,862	$2,584	$467	$10,915	21.05	$9.02	$520,808
NB-18	4,387,704	$4,692	$801	$27,205	40,48	$9.01	$6,160,271
18-65	13,542,968	$7,253	$1,121	$26,458	22.42	$9.01	$4,984,151
>65	5,044,612	$13,220	$1,821	$38,315	16.56	$9.01	$8,432,869

Table I: Descriptive Statistics
We examine the Cerner Healthfacts data for the years 2000 to 2014. We report the total number of unique patients (*Total Patients*) as well as total costs per patient per year (*Patient Years*). We report minimum, maximum, and mean annual charges. We subdivide *Patient Years* by gender and age.

Year	N	25	50	75	90	95	99	Max
2000	171,881	$404	$1,667	$7,629	$23,639	$42,161	$114,958	$2,856,421
2001	593,911	$200	$782	$5,092	$18,758	$31,886	$133,264	$2,843,629
2002	711,762	$210	$722	$3,350	$12,842	$26,905	$91,327	$2,418,552
2003	829,567	$261	$891	$4,095	$15,104	$30,911	$95,514	$1,710,055
2004	879,486	$294	$1,014	$4,384	$14,838	$30,308	$91,501	$5,551,445
2005	986,654	$312	$1,039	$4,296	$14,029	$28,036	$86,961	$2,259,747
2006	1,150,406	$337	$1,100	$4,585	$15,386	$30,955	$96,837	$2,428,437
2007	1,534,623	$365	$1,189	$4,743	$16,335	$32,915	$108,232	$3,482,904
2008	2,046,256	$506	$1,805	$7,183	$22,641	$40,138	$119,416	$4,865,327
2009	2,672,558	$493	$1,728	$7,091	$22,896	$41,147	$119,714	$8,432,869
2010	2,562,039	$474	$1,701	$7,313	$23,508	$42,579	$124,209	$6,160,271
2011	2,342,051	$250	$874	$3,820	$15,263	$31,331	$105,060	$5,299,914
2012	1,778,776	$262	$924	$4,158	$16,477	$33,352	$110,320	$4,778,221
2013	2,028,404	$209	$768	$3,615	$15,061	$31,927	$106,003	$3,194,463
2014	2,686,910	$269	$979	$4,466	$17,177	$34,929	$111,030	$5,269,692
Full Sample	22,975,284	$325	$1,143	$5,096	$18,269	$35,316	$110,032	$8,432,869

Table II: Individual annual healthcare cost percentiles

We calculate each individual's annual healthcare costs each year over the sample period of 2000 through 2014. We report the annual distributions. We report the 25^{th}, 50^{th}, 75^{th}, 90^{th}, 95^{th}, and 99^{th} percentiles. We also report the maximum annual charges each year.

	Model 1	Model 2	Model 3	Model 4
R^2	0.0108	0.0179	0.4664	0.4606
Annual Frequency			3,334***	3,337***
Intercept	3,582***	-5,986***	-10,250***	-3,221***
Age	121.7***	117.9***	18.12***	
Year	19.95***	70.29***	-0.66	
Urban		4,300***	6,693***	
Gender FE	Yes	Yes	Yes	No
Marital FE	No	Yes	Yes	No
Location FE	No	Yes	Yes	No

Table III: OLS estimated annual healthcare expense

We estimate OLS regressions to determine factors that predict individual patient's AHE. *Annual Frequency* is the total number of calendar days a patient access health care in a year. *Age* is the patient's age in years, *Year* is the calendar year, *Urban* is a dummy variable equal to 1 for patient's that access an Urban provider. We include fixed effects for gender, marital status, and US census location. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels respectively.

Year	COV(f,s)	CORR(f,s)	*p-value*
2000	1,969	0.162	*<0.001*
2001	1,881	0.191	*<0.001*
2002	1,348	0.231	*<0.001*
2003	1,332	0.165	*<0.001*
2004	1,182	0.194	*<0.001*
2005	1,093	0.202	*<0.001*
2006	1,224	0.119	*<0.001*
2007	1,246	0.135	*<0.001*
2008	1,199	0.104	*<0.001*
2009	1,284	0.126	*<0.001*
2010	1,352	0.138	*<0.001*
2011	1,126	0.174	*<0.001*
2012	1,149	0.165	*<0.001*
2013	1,043	0.165	*<0.001*
2014	1,144	0.182	*<0.001*

Table IV: Claim frequency and severity covariance

We calculate the covariance and correlation coefficient between frequency and severity for each year in our sample period. For each observation, frequency is the number of calendar days that the encounter covers while severity is the daily average cost for the encounter. We also report p-values for the correlation coefficient.

	Tier 1	Tier 2	Tier 3
Year	COV(F_{T1},S_{T1})	COV(F_{T2},S_{T2})	COV(F_{T2},S_{T2})
2000	-553	625	-523
2001	-594	-1,098	5,804
2002	-428	153	1,899
2003	-521	431	1,410
2004	-580	144	546
2005	-578	-38.2	-1,244
2006	-652	-213	-6,527
2007	-644	-334	-6,772
2008	-1,132	-1,092	-6,891
2009	-1,104	-826	-6,183
2010	-1,125	-858	-5,616
2011	-654	-239	-2,549
2012	-696	-88.0	-4,213
2013	-618	-256	-4,328
2014	-758	-90.4	-2,874

Table V: Claim frequency and severity by tier
We divide our sample into three tiers at approximate values for the 50th percentile and the 99th percentile. Tier 1 comprises all claims for individuals up to $2,000 of cumulative annual health care expense. Tier 2 comprises all cumulative individual health care expenses in excess of $2,000 and up to $100,000. Tier 3 is all cumulative individual annual health care expenses in excess of $100,000.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year	AHE	E(f)	E(s)	COV(f,s)	MPP	Difference
2000	9,671	4.4	1,511	1,969	8,617	1,054
2001	8,348	3.7	1,331	1,881	6,806	1,542
2002	6,300	3.3	1,146	1,348	5,130	1,170
2003	6,899	3.4	1,349	1,332	5,919	980
2004	6,813	3.2	1,496	1,182	5,969	844
2005	6,513	3.1	1,506	1,093	5,762	751
2006	7,169	3.2	1,612	1,224	6,382	787
2007	7,752	3.3	1,628	1,246	6,618	1,134
2008	9,634	3.5	2,354	1,199	9,438	196
2009	9,769	3.6	2,264	1,284	9,434	335
2010	10,039	3.6	2,275	1,352	9,542	497
2011	7,310	3.3	1,469	1,126	5,974	1,336
2012	7,675	3.3	1,560	1,149	6,297	1,378
2013	7,141	3.4	1,396	1,043	5,789	1,352
2014	7,807	3.3	1,656	1,144	6,609	1,198

Table VI: **Estimated annual MPP**

We estimate annual MPPs as estimated AHE as well as a function of the interdependent variables E(f) and E(s) as in equation (1). We compare the estimated MPPs for each method. Column (2) is the MPP as measured by AHE. Column (3) is the annual E(f), column (4) is annual E(s) and column 5 is the annual COV(f,s). Column (6) is the MPP as calculated using equation (1). Column (7) is the difference in MPPS and is calculated as column (2) – column (6).

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year	MPP(T1)	MPP(T2)	MPP(T3)	Total MPP	AHE	Difference
2000	1,153	5,314	598	7,065	9,671	2,606
2001	839	3,843	757	5,439	8,348	2,909
2002	781	3,187	215	4,183	6,300	2,117
2003	838	3,672	173	4,683	6,899	2,216
2004	876	3,386	158	4,420	6,813	2,393
2005	887	3,230	157	4,274	6,513	2,239
2006	926	3,545	314	4,785	7,169	2,384
2007	925	3,513	428	4,866	7,752	2,886
2008	1,064	4,545	474	6,083	9,634	3,551
2009	1,050	4,633	477	6,160	9,769	3,609
2010	1,051	4,769	452	6,272	10,039	3,767
2011	811	3,152	362	4,325	7,310	2,985
2012	831	3,281	393	4,505	7,675	3,170
2013	750	3,105	345	4,200	7,141	2,941
2014	842	3,502	330	4,674	7,807	3,133

Table VII: Estimated annual MPP for each tier

We calculate MPPs for each tier based on E(f), E(s), and COV(f,s) parameters for each tier. We compare the sum of the tiers' MPPs to the MPP calculated as mean AHE. For each year we find substantially reduced premiums when financing is segmented into tiers.

	Total Encounters	Total Government Encounters	Government Proportion Encounters	Total Dollars	Total Government Dollars	Government Proportion Dollars
Tier 1	24,294,977	10,582,536	0.4356	58,282,841,833	30,935,751,440	0.5308
Tier 2	18,614,468	10,049,896	0.5399	104,802,684,281	60,242,426,280	0.5748
Tier 3	991,774	645,397	0.6508	37,434,908,908	24,375,185,562	0.6511

Table VIII: Government proportion of paid claims

We report the proportion of encounters for each tier that are paid by government entities. We filter our sample to include only those observations that include payer information. Government payer indicators include military dependents, Medicare, Medicaid, and Other Government. We identify the total encounters and total dollars as well as the number of encounters and dollars paid by government entities. We report the proportion of government paid encounters for each tier.