Uncoordinated Hedging and Price Chain Reaction*

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ABSTRACT

We show that structured derivatives markets could cause a significant and long-lasting price dislocation of underlying stock due to a abrupt delta-hedging triggered by an event predefined in the payoff. Moreover, one event causes another: uncoordinated hedging creates a cascade of price impact on the underlying market. The stock market is susceptible to the sequential dislocation when corresponding derivatives are issued with a largely homogeneous payoff in a concentrated period. Using the unique features of Korean data, we find that the event-driven hedging contributes at least -5% of daily return on the event day. The price impact survives more than 1 week, and exacerbates itself by increasing probability of future events. Our results uncover a new feedback mechanism that amplifies a negative shock.

Keywords: Price Pressure, Delta Hedging, Uncoordinated Asset Sale, Over-the-Counter Derivatives Markets

JEL classification: G12, G14, G24

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In finance theory and also in practice, the value of derivatives contracts is computed with exogenous price dynamics of underlying assets. This procedure is true only if derivatives itself do not affect the underlying assets prices. In this paper, we show that this assumption does not hold; derivatives markets influence the underlying asset markets. This possibility suggests that pricing derivatives can be more complex than the extent that a typical option pricing model without the feedback might imply. This complexity is particularly severe in a case of over-the-counter (OTC) exotic derivatives. Those derivatives often involve dramatic transactions of the underlying assets, generating notable price impact. However, due to the lack of transparency of OTC derivatives and their non-standardized payoffs, it is difficult to clearly document their impact and potential risk to the underlying asset markets.

We examine this question by exploring the structured equity derivatives issued in Korea from 2006 to 2017. Several unique features of this market make it an ideal laboratory to study asset price implication of OTC derivatives. First, the size of Korean OTC equity derivatives market is very large relative to its underlying stock markets among other developed economies. Second, the payoff structure of the derivatives contracts is largely homogeneous to each other, sharing a particular feature that triggers a sudden liquidity demand via delta-hedging. Lastly, due to the fact that these products mainly target retail investors, the issuance is driven by investors' attention. A successful placement of a structured note leads them to demand more on the same underlying, causing issuance to concentrate in a short period of time.

The structure of the notes typically involves a swap of two exotic options.[1] The issuer sells a binary call option whose payoff is corresponding to the conditional coupon of the structured note to investors in exchange for knock-in barrier put option.[2] Issuers compete on the coupon because it determines the attractiveness of the investment products to retail investors. Therefore, if two notes on the same stock are issued at the similar time, the barrier levels of the put are also likely to be very similar. When the barrier is breached, the knock-in put suddenly becomes a vanilla put, dramatically shrinking the delta position. Accordingly, the knock-in event forces hedgers (issuers) to dump underlying stocks.

[1] About 80% of OTC derivatives in Korea has payoffs can be decomposed in the similar fashion.

[2] The put is typically has ATM strike and therefore a digital call with a higher coupon has to be exchanged with a put option with a higher barrier. Also, the net swap value is not zero because it includes issuers' upfront margin.

Due to the issuance concentration and homogeneity of payoffs, multiple knock-in events tend to simultaneously occur: when a knock-in barrier of a note is breached, it is likely that other notes on the same underlying would also provoke knock-in events, exacerbating the price pressure. Exploiting this mechanism, we first show that the triggered delta neutralization significantly dislocates the underlying stock price. Specifically, we observe "V"-shaped pattern of the abnormal return whose minimum point precisely coincides with the moment of events. The pattern also indicates that the price does not revert back immediately. It is not surprising to observe declining negative returns prior to knock-in events because, by definition, those events occur *due to* the negative returns. However, without the hedging-induced price impact, stock price would not necessarily correspond to a local minimum or a kink point at exact time of knock-in events.

To formally disentangle the hedging-related price from a price movement by firm fundamental change, we construct a proxy variable: the ratio of outstanding notional of the note to volume of the underlying stock *at the issuance*. We denote this variable by 'notional-to-volume (or $N2V$)' ratio. This ratio would be correlated with the hedging pressure because the dollar amount of position to be neutralized is proportional to the notional size. However, it is arguably orthogonal to the firm fundamental change around the events because this ratio is predetermined at the issuance. Given that it takes on average nine months since the issuance for a knock-in to occur, there is little reason that the ratio should be correlated with firm fundamentals.

Our result indicates that knock-in events are associates with about -10% abnormal return at the events when notional-to-value ratio is low. However, when it is high, knock-in events impose additional -5% of price discount only on the event day. This result is robust to unobserved heterogeneity regarding event time, industry, and their interaction, confirming that the hedging activities generate sudden and significant price dislocations. The price impact does not correct immediately. Focusing on a set of events that are apart from each other by more than our event window, we show that such a price impact lasts at least more than 2 weeks.[3]

Since the issuance is concentrated in time and the price-impact does not disappear quickly, a knock-in event may trigger another. We document this chain reaction by showing that a knock-in event

[3]There is a trade-off in setting the event window. A wide event window filters too many events also creates possible unknown heterogeneity between included and excluded events. A narrow event window alleviates those concerns but we are not able to observe long enough post-recovery process.

increases the probability of another event via a different structured note on the same underlying stock. This result has an important implication on the possibility of market destabilization. When there is a predetermined trading strategy (e.g., a stop-loss policy or a 5% Value-at-Risk (VaR) rule) and if it is largely homogeneous across traders, the uncoordinated policy-driven execution can cause an undesirable market-wide impact via the chain reaction mechanism.[4]

From the rational expectation perspective, it is natural to expect that such a risk is priced in. Upon a knock-in event, a rational trader would price the underlying asset reflecting the likelihood that another event-driven price drop may take place in the near future. In order to test this conjecture, we exploit a cross-event variation in terms of potential intensity of chain reaction. For a given event, we measure the intensity by the aggregated notional of outstanding pre-knock-in notes, normalized by trading volume of the underlying asset. We denote this measure by 'remaining-to-volume' (or $R2V$) ratio. If such expectation is priced in, then the intensity of price dislocation would be larger when an event is associated with a higher $R2V$ ratio, holding other variations constant.

However, we do not find any significant impact of $R2V$ ratio on the magnitude of price dislocation. It indicates that investors do not consider future events beyond the price pressure by the current knock-in event. The $R2V$ ratio is free from look-ahead bias as it only requires information available at the corresponding time. Therefore, our results suggest that, the expected price shocks are not fully reflected in the current pricing due to the non-transparent nature of OTC markets.

As a result of the price dislocation, one can imagine an investment strategy: upon a knock-in event, buy the corresponding underlying stock and hold it until the negative price discount recovers to the fundamental value. We implement this buy-and-hold strategy with 1 month holding period. Relative to the market, the strategy exhibits on average 2.9% of cumulative profit during the holding period. This finding indicates that one can earn economically significant premium by providing liquidity in the market upon knock-in events.

[4] A systemic intraday event in E-mini S&P 500 future market ("E-Mini") known as the "Flash Crash" occur in May 6, 2010. According to the CFTC-SEC (2010) report, the Flash Crash start by a large fundamental trader (a mutual fund complex) initiated a sell program to sell E-Mini contracts as a hedge to an existing equity position. This selling pressure drive the price of the E-Mini down approximately 3% in just four minutes from 2:41 p.m. to 2:44 p.m. This effect leads to the crisis in individual stock market. Even though after 2:45 p.m. prices in the E-Mini was recovering from its severe declines, sell orders placed for some individual securities and ETFs (including many retail stop-loss orders, triggered by declines in prices of those securities) found reduced buying interest, which led to further price declines in those securities.

This return can be further enhanced with the $N2V$ ratio. Since $N2V$ ratio is correlated with the intensity of price pressure but orthogonal to the firm fundamentals, implementing the strategy on the subset of events whose $N2V$ ratio is higher than a certain threshold would result better a outcome. We find that the abnormal investment profits are mainly driven by the set of events with high $N2V$ ratio, confirming this intuition.

We contribute to several strands in literature. Our results are consistent with earlier evidence that derivatives position can have a significant impact on the underlying assets (Conrad, 1989; Bansal, Pruitt, and Wei, 1989; Skinner, 1989; Sorescu, 2000; Dannhauser, 2017). In addition to their findings, we show that the market structure of derivatives or, more specifically, the way OTC derivatives are issued as well as the similarity across them also play an important role. On the other hand, several researchers document that option market contains price-relevant information that is not redundant to information content in the stock markets (Easley, O'Hara, and Srinivas, 1998; Roll, Schwartz, and Subrahmanyam, 2009). However, Muravyev, Pearson, and Broussard (2013) argue that equity options do not contain economic contents of price discovery process for the underlying stock price.Our results further generalize these findings that the option market information is not always reflected in the underlying asset market especially in the case of OTC derivatives.

Our paper is related to a strand of literature that predetermined trading strategies (e.g. stop-loss, VaR, or delta-hedging) catalyst a price drop because of temporary selling pressure. Huang and Wang (2008) illustrate a price drop mechanism due to selling pressure through equilibrium model when the financial market is not costless and in the absence of fundamental shock. On the other hand, many earlier researches show portfolio protection strategies triggers the crash in 1929 and 1987 stock market (Gennotte and Leland, 1990; Easley and O'Hara, 1991; Jacklin, Kleidon, and Pfeiderer, 1992). Osler (2005) argues that the stop-loss order catalyst price cascades because of order flow in currency markets. We find an empirical evidence that delta-hedging strategy arising from derivatives market can destabilize the underlying stock market.

We particularly find Ni, Pearson, and Poteshman (2005) relevant to our findings. They present evidence that option trading affects the prices of underlying stocks, at the expiration date for reasons related to hedge rebalancing and stock price manipulation. Our paper proposes an additional channel different from theirs: the price impact can occur before the expiration date and purely due to the hedging activities. Moreover, Ni, Pearson, Poteshman, and White (2018) find the evidence that option market maker hedge rebalancing has a pervasive effect on stock price at all times. Our work is also closely related to Ahn, Choi, Kim, and Liu (2010) in which the authors exploit OTC derivatives contracts in the same market. Beyond the investigation of single events, we make further expansions by focusing on the *sequential* price impact with implications of a market-wide destabilization. To the best of our knowledge, our paper is the first paper that examines the dynamic aspects of the price dislocation by derivative market structure.

More generally, our findings add additional empirical evidence that there is an implicit feedback channel from derivative markets to the underlying market. This is different from a set of assumptions that the typical option pricing theories are built upon, suggesting that option pricing can be much more complex when such a feedback effect is fully accounted for. Specifically, the feedback effect can be large for a certain type of exotic and complex derivatives. Factoring in this channel exacerbates the complexity of pricing already-complex derivatives.

The rest of paper is organized as follows. Section I describes our data in detail. In Section II, we provide empirical evidence that the hedging-induced liquidity demand dislocates underlying stock price. Section III and Section IV discuss the chain reaction channel that the contemporaneous knock-in increases the future knock-in probability, and examine whether liklihood of negative price shock is priced in. Section V presents results of the trading strategy and several robustness checks. Section VI concludes.

I. Data Description

A. Aggregate pattern and background of OTC structured derivatives market

We first present the aggregate pattern of OTC structured derivatives note issuance in Korea. From 2003 to 2018, Figure 1 shows that the structured derivatives market has been growing rapidly with 22 percent annual growth rate in terms of outstanding amount. As a result, at the end of 2018, the total outstanding notional size of those securities reaches around 76 billion U.S. dollar equivalent [5],

[5]US dollar into south Korea Won exchange rate is used 1118.1, reported by the Bank of Korea at December 31, 2018.

accounting for almost 6.3% of total equity market capitalization. This relative size is particularly large compared to other developed markets. [6]

It is interesting to observe that the growth steepens after the 2008 Global Financial Crisis (19.4% versus 21.6%), during the period of low interest rate regime (Korea's benchmark rate on average is 2.1% in post-crisis versus 4.3% in pre-crisis period). Investors have been attracted by the higher yield of those investment products, although they look alike fixed income securities in terms of the way they are packaged and marketed. Like any typical bonds, investors initially invest par value of the note and are repaid the final payoffs ('coupon' and 'principal') when the note matures. The final payoffs and the maturity of the bond, however, depend on the underlying asset's performance and each note's payoff structure, precisely like a derivatives contract. These products are noticeably popular among retail investors as they are offered by their bank tellers, private bankers, or money managers. [7]

[Insert Figure 1 here]

B. Data construction

Due to the non-transparent nature of OTC derivatives contracts, we span several information sources to construct comprehensive data on structured equity derivatives issuance. We start from a commercial data provider called FnGuide that provides structured notes issuance history. The data well covers the issue events, however it does not include detail payoff structure (e.g., knock-in barrier level) of each issue. We augment detail contractual payoff by matching individual prospectus filed in Korea Security Depository (Securities Information Broadway) and Financial Supervisory Services (Data Analysis, Retrieval and Transfer system). During our sample period, from 2006 to 2017, we have 38,035 total number of publicly and privately placed structured equity derivatives note issuance.

[6] According to the market statistics of World Federation of Exchange in 2017, the Korea Exchange Market ranked second in notional turnover in the derivatives market and ranked fifth in total turnover of securitized derivatives, including warrants and callable bull/bear contracts.

[7] According to the report of Korea Financial Supervisory Services in 2018, retail investors hold 47% of the ELS and the channel is 76% by bank trusts, 12% by financial institutions, 10% by funds. The nominal amount of the ELS (combined both stock and index as underlying) break the highest record because of keeping interest rate at low levels. On the other hand, the trading volume of retail investors in exchange-traded derivatives accounts for only 13% of Korea's total trading volume in the exchanged-traded derivatives.

We use the following filters to construct selected samples for our study. First, we focus on notes whose at least one underlying asset is a stock. Typically these structured notes have a basket of underlying assets that could be a basket of individual stocks or mixture of stocks and indices. To concentrate on individual stock, we remove notes whose underlying asset is index (equity or other asset class) or a basket of indices. As a result, we are left with 16,736 of observations (unique number of notes).

Further we focus on notes that share a common contractual feature: knock-in barrier. It is because we treat knock-in events as an instrument that triggers extreme delta hedging activities. The resulting data set contains 8,174 unique number of notes, associating 90 unique number of underlying assets. Comparing with the previous number of notes, We note that almost 49 percent of notes involve the knock-in feature, conforming the homogeneity of payoff structure across different contracts.

From the payout details of each note and underlying stocks' price history, we find whether knock-in events have occurred and when they have occurred. With our sample, we identify 8,174 unique knock-in events that have happened on 1,301 unique knock-in event days. The fact that the number of events is more than the number event days implies that, on some days, there are more than one notes experiencing knock-in events. When the multiple knock-in events are associated with any identical stocks, we aggregate these and treat them as one knock-in event on the underlying, converting our data structure to event-day $\times$ stock level information.

Table I presents the summary statistics of our data set. Sorted by event year, the table shows total number of notes, total number of stocks and total notional size of structured notes newly issued (regardless of whether they are knocked-in or not during the corresponding event year) in the same year. We add columns that present total number of notes, total number of stocks and total notional size of notes that experience knock-in events in the corresponding year. Further, we augment the table by annual return and volatility of the benchmark market index (KOSPI).

[Insert Table I here]

C. Issuance herding and knock-in crowding

Since a large body of investors in the structured note markets is retail investors, the choice of underlying assets are significantly influenced by their attention. Once a product with attractive payoff (typically a higher coupon rate) is initially issued, it draws investors attention and leads them to demand another note with the equivalent terms. Issuers, therefore, try to issue additional notes with the same underlying stocks. This behavior creates the pattern of issuance herding: during a short period of time, a dis-proportionally large amount of notes on a particular underlying stock is being issued. Due to high competition between issuers, knock-in barrier of note under certain underlying stocks will be similar to provide attractive payoff to investor. If barrier is higher than average, investors will not buy the note or issuers need to sell note at low price. If barrier is lower than average, issuers have high probability of paying coupon at the maturity; hence, they will sell at high price. However, the supply of the note is limited because issuing these notes is equivalent of writing option contracts, and each issuer is bounded by its risk budget. Therefore, each issuer keep issuing the notes only until they max out their risk budget on the stock. This mechanism causes the aggregated issuance of those notes on a specific stock to be crowded in a certain time.

Panel (a) and Panel (b) in Figure 2 visualize this pattern. We select top 5 stocks from our data set (total 90 stocks) based on the total amount of note that experience the knock-in event on our sample period and put them along the vertical axis. We aggregate the amount and the contracts at month level. The horizontal axis of the figure represents the time, and the size of circles indicates the notional size (for panel (a)) and the number of contracts (for panel (b)) of newly issued notes corresponding to a stock and at a specific time. If there is no issuance herding, we expect that these circles are equisized and proportionally spread across the time. However, the figure show the contrary. We observe that larger circles are concentrated in time but in different times for different stocks, indicating the issuance herding.

Due to issuance herding with similar barrier level, the knock-in event is naturally concentrated at certain period. We define this phenomenon as knock-in crowding. Here is an example. Assume that (1) the underlying stock price is \$100, (2) the issuance of note based on underlying stock X is concentrated in year t, and (3) the barrier level is set between \$75 and \$85. In year t+1, the stock price is around \$90, nothing happens. However, if the stock price is now \$85 in year t+2, some of the concentrated notes start touch knock-in barrier. If price goes down further, the most of concentrated notes are knocked in. Furthermore, if hedging-related price pressure exists, minor effect of knock-in forces the stock price decrease, and it will lead to touch another knock-in barrier lower than \$85. Since numerous notes are concentrated between \$75 and \$85, the price will consecutively decrease at least \$75.

Panel (c) and Panel (d) in Figure 2 illustrate this pattern. We match the same firm with the panel (a). The size of circles are largely concentrated at the certain period. In comparison to the issuance herding, knock-in event is more crowded at specific point.

[Insert Figure 2 here]

D. Event window selection criteria

In our empirical analysis, we investigate the performance of the stock 10 days before and after the event day (21days). Unlike other event studies that each event windows are not overlapped, we note that the event window can be overlapped for total event samples because the knock-in events are crowded in certain period. Alternatively, we construct non-crowding knock-in samples, which are the unique sample in event window[8]. Therefore, total sample and non-crowding sample detect the different effects: the former display the knock-in effect of consecutive knock-in event and the latter reveal the effect of singular event.

The sample window selection has trade off between sample size of the non-crowding sample and observation of post event period. By choosing short term window (i.e. 5 days before the event day and 5 days after it), observations are not sufficient to monitor the long term performance of the stock after the event. To discover the pattern of price reversion after the event, a minimum event window is required. On the other hand, if we expand the window too wide, the non-crowding sample is not guaranteed because, by definition, non-crowding event is the unique knock-in event during the event window. In this case, we are not able to get the secure result from the lack of sample size. We decide our event window 10 days before and 10 days after the event day, to satisfy the both criteria: non-crowding knock-in cases and price reversion phenomenon. In robustness

[8] We define the event case is non-crowding when the consecutive knock-in event does not arise during the 30 days from the current event date. We do not consider the overlapped case before the current event date.

check, we present the result with different window to ensure that the results are not sensitive to window size.

II. Price Impact of Position Unwinding

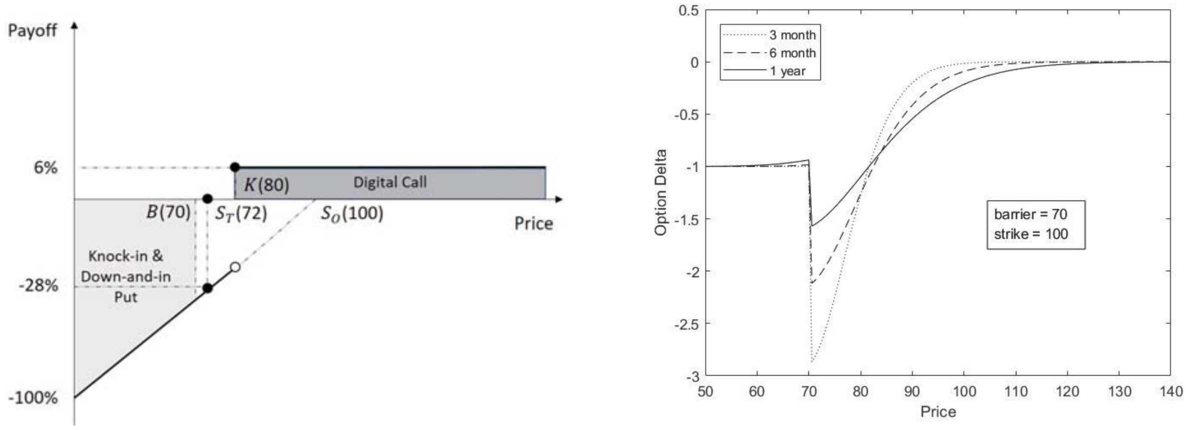
A. Equity-linked structured derivatives

Our empirical advantage to study derivatives-position-induced price impact relies on the fact that payoff structures across prevailing structured derivatives are largely homogeneous to each other. Typically, such OTC structure derivatives are composed of multiple individual assets. For a given underlying equity, the investor of the security buys a Bermudan style digital call options that can be exercised only on a set of dates (observation dates). The investor finances this purchase by selling a knock-in barrier put option on the same underlying to the issuer. This transaction forms a swap of the digital call and the knock-in put, with a complication that the swap is path-dependant: if the call option is in the money at any observation dates (redemption event), the entire structure is cancelled. Once the redemption event occurs, the investor receives a 'coupon' corresponding to the digital call payout. The issuer packages this swap in a note form by combining it with a zero coupon bond that will be called at par upon the redemption event. The note is therefore 'auto-callable' with the coupon as a call premium.

The coupon and the barrier level trade off. To get a higher coupon the investor has to accept also a higher barrier, making the whole structure riskier.[9]

We simplify the payoff assuming that there is only one observation date, and illustrate it in the left panel of the following figure. The horizontal axis indicates the underlying stock price at the maturity (the only observation date). For this illustration, we assume that the stock price at the inception (S_0) is 100. The digital call strike is 80% of S_0 (80) with the payout of 6%. This means that the investor receives 6% of coupon if the underlying stock ends higher than 80 (redemption event). If the redemption event does not occur, the investor may experience loss because she is

[9]Since the note is sold at par, the maximum net swap value that the investor can afford is the difference between par and the discounted zero coupon bond. Since these products' main target is retail investor (Cha, 2017), issuers compete with the coupon rate. If two notes on the same underlying are issued in the same time, it is likely that their barrier levels are close to each other, coupons cannot be very different because they determine success of the placement.



(a) Simplified payoff (b) Delta of knock-in put

short the put. However, since it is a barrier option, the put option becomes active only when the knock-in barrier (70) is breached during the life of the option (knock-in event). There is no loss to the investor as long as the stock price stays above the barrier all the time even though redemption does not occur.

The knock-in event imposes a sudden change of the payoff. Suppose that the minimum stock price during the lifetime of the option was 71 (knock-in event not happened). If the stock price at the maturity is 72, the investor would not get the coupon but no loss incurs. However, if the minimum price was 70 (knock-in event happened), then she would lose 28% (=(100-72)/100) in spite of the same stock price at the maturity (72). This dramatic payoff change also heavily alters the risk profile of the derivatives upon the knock-in event.

The right panel of the same figure shows the delta of the knock-in put. While the minimum delta that a vanilla put can have is -1, the knock-in put delta can be much smaller than -1 prior to the knock-in event. Upon the knock-in event, the put option becomes a vanilla one, making its delta bounded above at -1. The issuer needs to build a long stock position to neutralize the negative delta of put. Prior to the knock-in event, the hedging position can be substantially big because of the large negative delta. When the knock-in barrier is touched, the put delta becomes much less negative and the delta-neutralizing issuer is left with excessive stock position, being forced to liquidate it immediately.

B. Measuring the price impact from knock-in event

In this section, we first test whether such hedging-driven liquidation imposes price pressure, causing the stock price to dislocate from the fundamental value. The biggest challenge is to distinguish the price changes due to the hedging-driven liquidation from the changes in the fundamental value. The position unwinding is triggered via knock-in event when the fundamental value also decreases. However, our set up has a particular advantage: the fundamental value is not necessarily very different in the neighbourhood of the barrier level. Therefore, should there be any price dislocation, its degree would be mostly pronounced precisely at the moment of knock-in event.

Furthermore, we construct a variable that is likely to be associated with the extent of hedging position liquidation, but unlikely to be correlated with fundamental value changes. The dollar value of delta is positively correlated with the size of the structure note (notional value). Given the issuance clustering (Figure 2 Panel (a) and (b)) and homogeneity of the payoffs, the knock-in events would also cluster (Figure 2 Panel (c) and (d)). For this reason, at a given day, there may exist multiple knock-in events from different notes on the same underlying. We reflect this possibility in the following 'notional-to-volume' or '$N2V$' measure.

For an underlying stock i, we aggregate each notional amount of a note k whose knock-in barrier is touched at day t.[10] We divide this by the average trading volume of stock i. Formally,

$$N2V_{i,t} = \frac{\sum_{k \in \mathbf{K}_{i,t}} Amount_k}{Volume_{i,S(\mathbf{K}_{i,t})}}, \tag{1}$$

where $\mathbf{K}_{i,t}$ is a set of notes whose underlying assets contain stock i and whose knock-in events are triggered at t, $Amount_k$ is the notional size of note $k \in K_{i,t}$, and $Volume_{i,S(\mathbf{K}_{i,t})}$ is the 6-month average dollar volume of stock i as of the earliest issue date among notes in $\mathbf{K}_{i,t}$ denoted by $S(\mathbf{K}_{i,t})$.

As we aggregate multiple notes on the same knock-in day t, the observation unit of $N2V$ becomes stock-level event j, pinning down the affected stock i at the knock-in event time t.[11] Therefore, we

[10] In many cases, a structured note has multiple underlying stocks, and the knock-in event is deemed to occur when *any* of those touches the knock-in barrier.

[11] A note that knocked-in k does not fully pin down stock-level event j because often the note's underlying is a basket of multiple stocks. However, once the note is knocked-in, the delta on each underlying experience the similar shock.

rewrite:

$$N2V_j = N2V_{i(j),t(j)}. \tag{2}$$

This specification predetermines $N2V$ at the time of note issuance, which is much before the knock-in event day t. [12] [13]

This way of aggregation take the fact that issuance as well as knock-in events are clustered in a particular time into the consideration. It is reasonable to expect that a higher $N2V$ would be associated with a larger price pressure on stock i. However, there is no obvious reason that a higher $N2V$ would be correlated with a bigger drop in fundamental value in the future, because it is difficult to envision that this predetermined variable in OTC derivatives market causes changes in the firm fundamental or that investors invest more on a firm whose fundamental value is expected to drop.

However, $N2V$ possibly correlates with future economic conditions. In particular, retail investors may chase the past stock return. A stock that recently had shown favorable return may draw their attention, driving a high issue cluster. When this issue timing is near the peak of the economic cycle, multiple notes will be simultaneously knocked-in (high $N2V$) sometimes during the downturn. If such clustered knock-ins happen in the middle of the downturn, then a high $N2V$ may coincide with a future negative return that causes more events by construction. To circumvent this concern, we use $N2V$ with an interactive fixed-effect of industry and calendar time corresponding to an event that controls for the heterogeneous economic condition.

C. Empirical design

As a first step, we examine the pattern of underlying stock prices movement around knock-in events. To this end, we use the event window between 10 trading days prior to and 10 trading days after a knock-in event. To focus on the stock-specific movement, we use a standard market-adjusted

[12] Average time gap between issuance date and knock-in event day is over 1 year (1.3 year)

[13] The trading volume around the knock-in events may be a consequence of hedging position liquidation. More generally, the volume appears to be correlated with price or volatility patterns, conditional on knock-in. In an unreported result, the trading volume increases significantly during (especially before two days after six days from) the knock-in event. Such an endogeneity discourages using the volume around knock-in and can be circumvented by using the volume at the issue date of event-experiencing-notes. As a robustness check, we use an alternative measure with the 6-month average dollar volume as of 1 day before the main event window starts. Our results remain qualitatively unchanged with this measure, as reported in the later section.

cumulative abnormal return (CAR) following (Ritter (1991) and MacKinlay (1997)). Specifically, CAR of stock i of event j at t during event day $\tau \in [-10, 10]$ is calculated in the following way:

$$CAR_{i(j),\tau} = \sum_{q=-10}^{\tau} \Big\{ R_{i(j),t(j)+q} - R_{m,t(j)+q} \Big\}, \tag{3}$$

where $R_{i,t}$ is the return of stock i at day t, $R_{m,t}$ is return of the market index (KOSPI Composite) at day t, $i(j)$ is the affected stock of event j, and $t(j)$ is the event day of j. The reference point of the CAR is 10 days prior to the event day $(t - 10)$ corresponding to the inception point of event window.

To show the event-time-variation price pattern, we use the following specification. For a given event j, we regress CAR of underlying stock i of event j, i.e, $i(j)$ on event-day-dummy variables:

$$CAR_{i,\tau} = \alpha_{I(i)\times M(j)} + \sum_{\tau=-10}^{10} \beta_\tau \cdot \mathbf{D}_\tau + \gamma X_{i,t(j)} + \varepsilon_{i,\tau}, \tag{4}$$

where $I(i)$ is the industry of stock i with Korea SIC 2-digit classification, $M(j)$ is the calendar month of the event j, $\mathbf{D}_\tau$ is an indicator variable whose value is 1 only at event day τ; otherwise 0, X is a vector of control variable using the most recent information of firm i known at $t(j)$. Although we adjust for market return via CAR, an economic condition for the associated industry around each event may be different. To address this possibility, we use Industry $\times$ Month fixed effect ($\alpha_{I(i)\times M(j)}$), corresponding to each event. Therefore, our results are robust to heterogeneity of industry-specific economic condition at event time. Lastly, since our events are partially overlapped within our event windows, intra-cluster correlation between abnormal return exists due to time serial correlation or cross-sectional correlation ((Kolari and Pynnönen, 2010; Kolari, Pape, and Pynnönen, 2018)). We reflect that the standard error allow for intra-event correlation in the model. Our coefficients of interest are β_τ ($\tau = \{-10, -9, ..., 10\}$). The estimated shape of the abnormal price pattern would suggest whether a knock-in event imposes a price dislocation.

More formally, we use $N2V$ measure in Equation (2) to distinguish the hedging liquidation effect from changes in firm fundamental. For a given event j, we regress CAR of underlying stock $i = i(j)$

of the event at the event day $t(j)$ on $N2V$ of the same event:

$$CAR_{i,t(j)} = \alpha_{I(i)\times M(j)} + \beta N2V_j + \gamma X_{i,t(j)} + \varepsilon_j. \tag{5}$$

Other variable definitions are identical to the previous equations. The coefficient β in Equation (5) differentiate CAR of the affected stock at the event date across variation of $N2V$. As a higher $N2V$ corresponds to a higher degree of price pressure from hedging activities, showing a significant and negative estimate for β would further confirm the price impact of hedging-driven liquidation, while alleviating the concern that the abnormal return is a consequence of unobserved firm fundamental changes that happen to be correlated with knock-in event.

D. *Dynamic price impact and cross-sectional variation*

Panel (a) of Figure 3 show the event-time pattern of CAR defined in Equation (3). We plot the point estimates of each β_τ and its 95% confidence interval. For this practice, we use a event case of non-crowding whose the consecutive knock-in event does not arise during the 10 days from the current event date. Therefore, total sample size of Panel (a) is 10,017 (477 events $\times$ 21 days). We note, on the day of knock-in (vertical line), the CAR becomes noticeably negative with 12 percent on average. This magnitude is both economically and statistically very significant. Prior to the event, CAR is already negative. It may simply reflect the fact that knock-in event occurs due to the negative return. Additionally, the possibility that the note issuers may start unwinding the position in the expectation of the knock-in may contribute to this pattern. However, the pattern of negative CAR is dramatically flipped over after the knock-in. It exhibits the recovery pattern right after the event. In section V, we expand the window to include after 30 trading days from the event and find that CAR revert back to the point that it is statistically insignificant from 0.

This notable "V" shape of CAR provide an implication regarding the source of the negative CAR. The negative CAR itself cannot sufficiently imply dislocation from fundamental value. However, if the negative CAR peaks precisely at the moment of the knock-in event and CAR recovers right after, it suggest that the negative CAR is mainly driven by any event-driven market activities: delta position liquidation.

[Insert Figure 3 here]

Table III presents the result of Equation (5). Since our events occur in different times and with different stock, we have time-series as well as cross-sectional heterogeneity. In order to address this, we have used five different specifications of control variables including firm-specific variables (size and book-to-market) as well as past market information (past return, volatility of the affected stock and market return). Across these specifications, the coefficient β are consistently negative and highly significant. Upon a knock-in event, there is a substantial price pressure on the underlying stock via hedging related liquidation. Quantitatively, 1 standard deviation increase of $N2V$ corresponds to 59 basis points of more negative CAR.[14]

Furthermore, our result implies that when knock-in events are clustered in time, the downward price pressure will be severe. In a case when numerous structured notes are knocked-in on the same day, the aggregated shares to be liquidated would be large, making $N2V$ higher. Such a big amount of unwinding, relative to the stock's intrinsic volume, would result in a larger degree of price dislocation. Given the clustered issue pattern, multiple knock-in events on a day is plausible. Since the knock-ins are monitored continuously, a certain daily stock price movement can make a set of knock-in barriers nearby breached on the same day.

Several patterns regarding control variables are worth noting. The price dislocation is more severe when the firm is smaller as measured by natural log of book value of asset. Also, a higher degree of negative abnormal return is associated with a higher level of return volatility of the affected stock [15]. These patterns are consistent with Duffee (1995) who provides evidence that stock return is negatively correlated with its volatility, and also shows that this relation is strongest among small firms. During the event period when the affected stock return is likely to be negative, smaller firms with higher volatility show relatively worse return.

[Insert Table III here]

Finally, we repeat the estimation of the dynamic pattern separately for each subset of event by $N2V$. In particular, we categorize our sample events into three groups using the tercile of $N2V$.

[14] The mean of $N2V$ is 0.10 and standard deviation is 0.19. Marginal effect of $N2V$ is -0.03. Therefore, the marginal effect of increment of one standard deviation of $N2V$ is -0.59% (-0.0059=0.19*(-0.03)).

[15] Return volatility is annualized volatility using 1-month return of stock.

We report the regression result with the subsample of top and bottom tercile in Panel (b) of Figure 3. This figure displays the point estimates of β_τ in Equation (4) when the events have low $N2V$ (triangle marker) versus high $N2V$ (circle marker).

Both patterns show the similar V shape. We further note that, on the event day, the CAR from events with high $N2V$ is significantly lower than the case of low $N2V$. This result further bolsters our claim that the delta-hedging unwinding imposes price dislocation. Interestingly, they are not statistically different from each other prior to the event, suggesting that issuers do not unwind the position beforehand at least proportionally to the amount to be liquidated. The reversion speed also appears to be similar. However, due to the bigger drop on the event day, it takes longer for high-$N2V$ events to recover from the liquidation shock.

E. Distribution comparison between the different distance to the knock-in barrier

In the previous section, we find that higher exposure to hedging liquidation leads to more severe price dislocation. In the following analysis, we take a parametric approach to test whether price dynamics are different near the barriers. The figure shows a simplified illustration of the stage classification by distance to barrier. To measure the distance to barrier($DB_{i,k,t}$), we use the distance-to-default ratio according to the KMV approach as follows: for stock i of note k,

$$DB_{i,k,t} = \frac{ln\left(\frac{P_{i,t}}{B_{i,k}}\right) + \left(r_t - \frac{\sigma_{i,t}^2}{2}\right)(T-t)}{\sigma_{i,t}\sqrt{T-t}}, \tag{6}$$

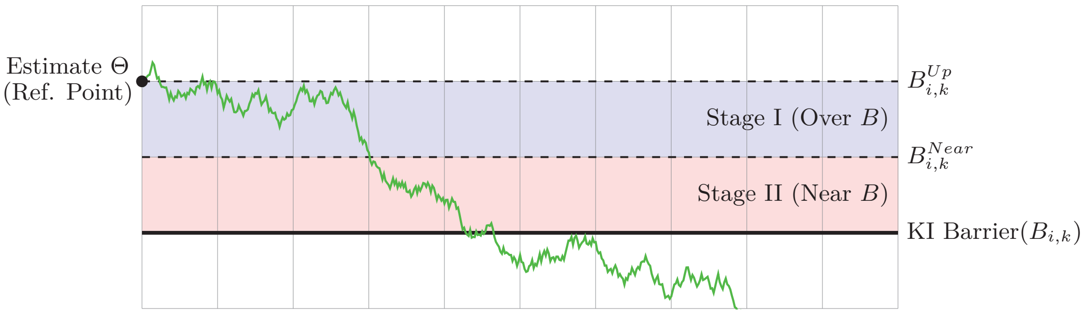
where $P_{i,t}$ is stock price of firm i, $B_{i,k}$ is barrier level of firm i of note k. r_t is risk-free rate and we use 91 days Certificate of Deposit. We estimate $\sigma_{i,t}$ via Maximum Likelihood Estimation (MLE) using prior 21-day (1-month) observations when the stock price initially touches the upper threshold.

Under equation (6), we define two price thresholds around the knock-in barrier, $B_{i,k}$, for each underlying stock i of note k. We estimate the second threshold at first based on the barrier level. The second threshold is closer to $B_{i,k}$: $B_{i,k}^{Near}$. Then, we estimate the first threshold corresponds a point based on the second thresholds where the underlying stock price is far above $B_{i,k}$: $B_{i,k}^{Up}$. Accordingly, these thresholds yield the intervals as below:

$$\text{Stage I (Over KI Barrier)}: \quad P_{i,k} \in [B_{i,k}^{Near},\ B_{i,k}^{Up})$$

$$\text{Stage II (Near KI Barrier)}: \quad P_{i,k} \in [B_{i,k},\ B_{i,k}^{Near})$$

Stage I implies that the stock price is far above the knock-in barrier, specifically when it lies between $B_{i,k}^{Near}$ and $B_{i,k}^{Up}$. Stage II indicates the stock price is closer to the barrier but the barrier is not breached yet. We notice that the each stage has the same probability to touch the downside barrier. For stage I, the probability of starting at the top of the Stage I ($B_{i,k}^{Up}$) and touching the bottom ($B_{i,k}^{Near}$) is equal to the probability of starting at the top of the Stage II ($B_{i,k}^{Near}$) and touch the barrier level ($B_{i,k}$). The following figure illustrates how we define these thresholds, for a given knock in barrier, and the two stages of interest.



Unlike the previous tests using only the knocked-in cases, this analysis is using all notes regardless of their knocked-in state. One thing to notice is that the notes may not have a return observation for each stage as the range of the stage is not touched. If the stock price has remained above the range of Stage I ($B_{i,k}^{Up}$) until the note expires, there would be no stage-specific sample for that note. In addition, if the stock price has arrived to barrier level ($B_{i,k}$) at least once, the return will not be counted even if the stock price rises and enters to Stage I or Stage II because the note already experienced knock-in. Likewise, We also select the samples in Stage I and Stage II under consideration that each note can have multiple underlying assets. Hence, we do not select samples of one underlying asset in Stage I and Stage II, if the other underlying asset has already experienced a knock-in event.

In each event p where stock i that underlies note k touches down the point $B_{i,k}^{Up}$, we classify the actual return by stage g (g=I or II) during the contract period and estimate sample mean and standard deviation of each stage.

Moreover, we define a reference date when the stock price first belongs to the Stage I. We estimate $\Theta = \{\mu_p^{MLE}, \sigma_p^{MLE}\}$ at reference point via Maximum Likelihood Estimation (MLE), using 1-month prior daily return history.

The chart in Figure 4 plots the actual distribution for the sample mean and sample variance against the normal distribution given by the Gaussian distribution. Red dotted line is the normal distribution with averaged μ_p^{MLE} and σ_p^{MLE} by event p. The histogram represents the return distribution of actual mean ($\mu_p^{act,g}$) and standard deviation ($\sigma_p^{act,g}$), and blue solid line shows the normal distribution with actual parameters.

Figure 4 compares how the actual return distribution is different from the one estimated in each stage. According to the plot, the sample mean of the actual return distributions of the Stage I is similar to the MLE estimation. However, the actual return distribution of the Stage II has noticeably more negative mean and more volatile. We call this phenomenon magnetic effect because knock-in barrier functions like a magnet. When stock price is far higher than the barrier, the mean of return is not different from the MLE estimation (Stage I). When the distance between stock price and the barrier becomes closer, the barrier draws down the stock price to the barrier.

To analyze the magnetic effect more robustly, we implement controlled distribution comparison. For event p,

$$\mu_p^{'} = \alpha_{i(p)\times M(p)} + \beta \cdot \mathbf{I}_{2,p} + \gamma X_{i,p} \varepsilon_p, \tag{7}$$

where $\mu_p^{'}$ is the difference between sample mean and mean by MLE within the same event p. $\mathbf{I}_{2,p}$ is indicator function, equal to 1 when actual mean is estimated in Stage II. Stage I is the omitted category. $\alpha_{i(p)\times M(p)}$ is the firm $\times$ Month fixed effect corresponding to each event, and Stage I is the omitted category.

Similarly, we execute regression on standard deviation as follows:

$$\sigma_p^{'} = \alpha_{i(p)\times M(p)} + \beta \cdot \mathbf{I}_{2,p} + \gamma X_{i,p} + \varepsilon_p.$$

where $\sigma_p^{'}$ is the difference between sample standard deviation and standard deviation by MLE within the same event p.

In Table IV, we find the difference between parametric and non-parametric mean in Stage II is significantly heterogeneous from the difference in the stage I. The first table ($\mu^{'}$) shows that β is significantly negative in all combinations of the control variables. After controlling the firm and the month fixed effect, the actual mean of Stage II, compared to Stage I, is relatively lower by -0.41 %. The result means that after adjusted the mean of MLE, the mean of Stage II is statistically lower than mean of the Stage I. The second table ($\sigma^{'}$) presents that the actual standard deviation of Stage II is more volatile after adjusted the the standard deviation of MLE.

[Insert Figure 4 and Table IV here]

III. Price Chain Reaction

A. Knock-in cascade

Due to the issuance clustering and issuer competition, the knock-in barriers of notes on the same underlying are likely to close to each other. [16] Given the magnitude and the slow recovery process, a price dislocation from one event may cause another, creating a cascade of knock-in events. To formally test this conjecture, we first verify the current knock-in event triggers the other knock-in event.

However, such issuance clustering imposes a challenge. Since issue time is not evenly distributed, a currently occurring event may be followed by substantially different upcoming knock-in barriers. Suppose that there are two issue waves of structured notes on a particular underlying stock. For the aforementioned reason, knock-in barriers within a cluster would be similar. However, if those clusters are sufficiently apart from each other in time, average barrier levels across clusters may differ. Therefore, as the last remaining note from the first wave knocks-in, regardless of its magnitude

[16] As a result of examining the difference between the barriers based on the day when the issuance is the greatest during the sample period, the number of notes is 179 notes with 49 underlying stocks. Excluding underlying stocks with a unique note (at lease two notes required to calculate the difference between barriers), the number of notes is 160 with 30 underlying stocks (about 5 contracts per underlying asset). The percentage of note with less than or equal to 5% barrier difference is 73%, less than or equal to 10% barrier difference is 79%, and less than or equal to 20% barrier difference is 92%.

of price dislocation, the event may not meaningfully affect the future events in the second cluster whose average barrier level is much lower. Nevertheless, it is difficult to separate each cluster and perform within-cluster analysis because such clusters are not separated by clear boarders.

We overcome this challenge through a variable that identifies, for each contemporaneous event, potential notes whose barriers remain untouched and are within a certain proximity. Specifically, for each event j, its corresponding stock $i = i(j)$ and event time $t = t(j)$, we construct the variable as follows:

$$Proximity_{i,t} = \frac{1}{N[\mathbf{K}'_{i,t}]} \sum_{k \in \mathbf{K}'_{i,t}} DB_{i,k,t}, \tag{8}$$

where $\mathbf{K}'_{i,t}$ is a set of notes whose underlying assets include stock i that are issued before t but remain un-knocked-in as of t, $N[\mathbf{K}'_{i,t}]$ is a number of notes in a set $\mathbf{K}'_{i,t}$, and finally $DB_{i,k,t}$ is the distance to barrier defined in equation 6. We average the distance-to-barrier over multiple notes in $\mathbf{K}'_{i,t}$, making the observation units of *Proximity* stock-day level. A higher *Proximity* implies that the remaining notes have knock-in barriers close to the one in concurrent event j.

B. *Empirical design*

We propose a formal model to test whether the price pressure caused by a contemporaneous knock-in event increases the future knock-in probability. To this end, for each event j, we first construct an indicator variable $KI_{i(j),t(j)}$ that gives 1 if there are any knock-ins from notes on the same underlying $i(j)$ in the next 10-days from concurrent event time $t(j)$; otherwise 0.

As the first step, we only consider $N2V$ the measure of the price dislocation from the current event: for each event j, its corresponding stock $i = i(j)$ and event time $t = t(j)$, we specify Probit model as follows:

$$KI_{i,t} = \Phi\Big(\alpha_{I(i)\times M(j)} + \beta N2V_j + \gamma X_{i,t} + \varepsilon_{i,t}\Big), \tag{9}$$

where $\Phi(\cdot)$ is the standard normal cumulative density function, $KI_{i,t}$ is defined above, and all other variables' definitions are identical to ones in Equation (4). The coefficient β of the above equation would uncover whether the price shock driven by one event would lead another to occur, underpinning the chain reaction.

Further, to address the barrier heterogeneity across clusters, we divide total events into 2-quantile by $N2V$ and by $Proximity$ respectively, and check the interaction effect in the categorical Probit regression. We use the interaction of $N2V$ with $Proximity$ in the following specification:

$$\begin{aligned} KI_{i,t} = \Phi\Big(&\alpha_{I(i)\times M(j)} + \beta_1 N2V_j^{High} + \beta_2 Proximity_j^{High} \\ &+\beta_3 N2V_j^{High} \cdot Proximity_j^{High} + \gamma X_{i,t} + \varepsilon_{i,t}\Big), \end{aligned} \tag{10}$$

where $Proximity$ is defined in Equation (8) and definitions of all other variables are identical to the previous equations. The coefficient of interest is β_3 as it indicates that a higher degree of price pressure causes other knock-in events of notes with only *adjacent* barriers, uncovering the chain reaction mechanism.

C. Results on knock-in cascade and price chain reaction

Table V presents the estimation result of Equation (9). We report 5 specifications with different sets of control variables. Across all specifications, it shows that higher $N2V$ increases future knock-in probability. Time varying industry-specific economic conditions are controlled for via the fixed effects. Our results imply that the event-driven liquidity demand pushes price down, leading other structured note to knock-in. The effect on the future knock-in is not only statistically but also economically significant. Using the specification in Column (5) of the same table, we estimate that one standard deviation increase of $N2V$ increases the future knock-in probability by 6% keeping all other explanatory variables at their mean.[17]

Table VI report the regression result of Equation (10). Across all the different specifications, we consistently show that price pressure by a event (measured by $N2V$) increases future knock-in probability only when remaining notes on the same underlying stock have barrier levels close to each other (high $Proximity$). Not only do these results provide additional support for the chain reaction of knock-in events, but also they further alleviate the concern that $N2V$ correlates with a market condition in a particular way.

[17]The mean of $N2V$ is 0.10 and standard deviation is 0.19. Marginal effect of $N2V$ at the mean level is 0.29. Therefore, the marginal effect of increment of one standard deviation of $N2V$ at the mean is 6% (0.0551=0.19*0.29).

In the previous analysis on *contemporaneous* events with $N2V$, we address this with the fixed effect of industry $\times$ calendar-month. However, as we examine *future* events, *Proximity* helps us further ruling out the possibility of spurious relationship between $N2V$ and future knock-ins. We particularly concern that, for any reasons, $N2V$ is larger in the period of declining price. Then, the future knock-ins are more likely to occur because of the negative momentum, not because of the liquidity demand. However, during the period of negative return, the *Proximity* would continue to be smaller as more notes from the same cluster-vintage experience knock-ins and disappear in the calculation. As an illustration, suppose that there is only one note whose barrier remains untouched from a vintage. Its knock-in event must be followed by a substantial negative return (because it is the last one in the batch) and imposes a large $N2V$ as we concern. On the other hand, corresponding *Proximity* would be small since it is entirely based on notes of another issue-cluster with a different barrier level. Therefore, if there is a latent variable positively correlated with $N2V$ and future knock-in probability, the positive correlation between $N2V$ and future knock-ins must be stronger when *Proximity* is *small*.

Our results show the opposite: the $N2V$ is positively correlated with future knock-in *only* when *Proximity* is higher. This finding bolsters the explanation based on the chain reaction mechanism that a knock-in leads another knock-in to occur, and rules out the potential spurious relationship.

[Insert Table V and Table VI here]

IV. Decomposition of Price Impact

A. *Expectation of future knock-in effect at Knock-In Event*

In the previous chapter, we show that the sudden event-triggered liquidity demand imposes a negative price impact, that does not appear to be corrected immediately. As a result, one knock-in event triggers another, especially when remaining notes on the same underlying have the similar barrier level close to the one currently experiencing the event. Through this mechanism, if another price shock is foreseeable, one may expect that such a likelihood would be reflected in the price upon the concurrent event.

To formally examine this, we construct 'remaining-to-volume' or '$R2V$' measure. It is similarly defined as $N2V$ that measures price impact of the contemporaneous event, except that $R2V$ considers future knock-in events that is likely to occur in the future excluding the current one. Specifically, for underlying stock i and event time t corresponding to each event j (i.e., $i = i(j), t = t(j)$), we aggregate notional amount of note k in the relevant set $\mathbf{K}''_{i,t}$ defined below, and then normalize it by volume of stock i at day t:

$$R2V_{i,t} = \frac{\sum_{k \in \mathbf{K''_{i,t}}} Amount_k}{Volume_{i,S(\mathbf{K}''_{i,t})}}, \tag{11}$$

where $\mathbf{K}''_{i,t}$ is a set of outstanding notes whose underlying assets include stock i and that remain un-knocked-in as of t but likely to be knocked-in. We collect the remain un-knokced-in notes when the stock price ($P_{i,k}$) at t locates in the Stage II range (between $B^{Near}_{i,k}$ and $B^{Up}_{i,k}$) as specified in Equation (6). All other variables' definitions are identical to Equation (4). Simply put, while $N2V$ accounts for the price impact due to current liquidity demand, $R2V$ measures the price impact by the unrealized but foreseeable negative shock.

B. Empirical design

First, we examine whether the knock-in expectation has any effect on the current price. As in Equation (5), we regress CAR of underlying stock $i = i(j)$ at day $t(j)$ corresponding to event j on $R2V_{i,t(j)}$:

$$CAR_{i,t(j)} = \alpha_{I(i)\times M(j)} + \beta R2V_j + \gamma X_{i,t(j)} + \varepsilon_j, \tag{12}$$

where all other variable definitions are identical to ones in Equation (5). Our coefficient of interest is β as it would indicate if the expectation for the future events is priced in.

Further, we conduct decomposition of the price dislocation into a portion due to the contemporaneous liquidity demand and a portion corresponding to investors' rational expectation that takes imminent negative shock in the consideration. For this task, we simultaneously include the measure of contemporaneous effect ($N2V$) and future effect ($R2V$) of knock-in events as below:

$$CAR_{i,t(j)} = \alpha_{I(i)\times M(j)} + \beta_1 N2V_j + \beta_2 R2V_j + \gamma X_{i,t(j)} + \varepsilon_j. \tag{13}$$

$R2V$ is defined in Equation (11) and all other variable definitions are identical to previous equations (e.g., Equation (12)). Comparison of β_1 and β_2 would show the relative importance of two different causes for the negative price impact.

Unlike issuers of the note subject to the current event, other investors do not need to act only at the moment of knock-in. They may liquidate the asset in advance, facing a soon-to-be-realized negative shock from future knock-ins. If this is the case, a set of stocks heavily contingent on the probable negative price shock may suffer from a larger degree of price pressure *before* the time of current event. For this possibility, we investigate CAR in the dynamic set up as in Equation (4) during the pre-period ([-10,0]) by the tercile of $R2V$ separately.

We examine only pre-period to avoid a potential sample selection issue. In the dynamic analysis (Figure 5), recall that we impose the condition that event time is at least 10-days apart to each other to circumvent having multiple events during the event window [-10,+10]. However, in this case, requiring the same condition may select stocks with certain characteristics that price pressure from future knock-ins are highly expected at the event time (high $R2V$) however do not experience any knock-ins in the following 10 days.

C. Result of price impact decomposition

Table VII and Table VIII present the result of the Equation (12) and (13), respectively. From Table VII, we do not find strong evidence that the imminent risk is priced in. Moreover, in Table VIII, the decomposition result of CAR indicates that $R2V$ does not have any explanatory power relative to $N2V$. The coefficients regarding $R2V$ are consistently statistically insignificant and R^2 of the regression largely stays unchanged relative to the case with $N2V$ only, as reported in Panel (a) of Table III.

Figure 5 shows the dynamic CAR estimation specified in Equation (4) but only during the pre-period [-10,0] by the top (triangle-marker) and the bottom tercile (circle-marker) of $R2V$ using 479 events. We find that the price impacts are not significantly different by the probable negative price impact prior to the knock-in event. This finding complement our interpretation for the result of Table VIII that the stock market does not fully integrate information in OTC derivatives market.

These results are intriguing. If the market is sufficiently efficient, the possibility of the future shock must have price-relevant implication. When a negative and long-lasting price shock is probable, a rational trader would require a higher degree of risk premium and further push the price down. Our findings suggest that the information of OTC derivatives market is not fully reflected in the stock prices. Due to the less-transparent nature, as well as a difficulty of information collection, investors do not appear to pay much attention to information in the OTC market.

[Insert Table VII, Table VIII and Figure 5 here]

V. Additional Analyses

A. Trading strategy

Via previous analyses, we document the price dislocation due to the knock-in events and its slow recovery pattern. Based on this finding, we implement a trading strategy that simultaneously involves proving liquidity to the stock at knock-ins and selling the benchmark portfolio. Our strategy requires zero investment because we finance the provided liquidity by going short on the benchmark portfolio. We hold this long-short portfolio for one month (20 trading days) and close the position. For the benchmark portfolio, we consider market portfolio as well as industry portfolio specific to the stock we buy.

The strategy return is therefore calculated by benchmark-adjusted cumulative abnormal return which we denote it by PnL^b_τ, where benchmark $b = \{\text{Market, Industry}\}$ and holding period $\tau = \{1, .., 20\}$. Specifically, for stock i at day t corresponding to each event j, i.e., $i = i(j), t = t(j)$, we first calculate daily profit and loss at strategy-day q using benchmark b as follows:

$$\Delta PnL^{j,b}_q = R^i_{t+q} - R^b_{t+q}, \tag{14}$$

where R^i_t is the return of stock i, R^b_t is the return of benchmark portfolio b at day t. We next take average of $\Delta PnL^{j,b}_q$ across all events, constructing ΔPnL^b_τ. Accordingly, the average strategy return with τ-day holding period using benchmark b is calculated as:

$$PnL^b_\tau = \sum_{q=1}^{\tau} \Delta PnL^b_q. \tag{15}$$

We implement the strategy always at the next day of event $q = 1$ instead of $q = 0$, because the knock-in event can be sometimes based on the last price. In this case, the earliest possible day to implement our strategy is the next day. For returns of the benchmark portfolio, we use KOSPI Composite return when $b =$ Market, and use KOSPI Industry Group Index as industry return. [18]

Panel (1) of Figure 6 presents 20-day performance of our strategy adjusted for two different benchmark returns ($PnL^b_{\tau=1,\ldots,20}$), using total 1301 number of events. The results indicates that this strategy is strongly profitable. 1-month (20 trading day) holding period strategy return is as high as 2.9% against the market and 1.7% against the corresponding industry return.

We further examine the investment performance with respect to the degree of liquidity demand $N2V$ with approximately 430 events per each group. By tercile of $N2V$, we report the investment performance of the top and bottom tercile to highlight the variation in Panel (b) of Figure 6. For the sake of brevity, we only present the industry-adjusted performance PnL^{Industry}. This analysis shows that the return is mainly driven by high $N2V$ events. The high $N2V$ group shows almost 2.5% of the return, as opposed to 1% return of the low $N2V$ group. This result further confirms that the sudden liquidity demand driven by the market structure of OTC derivatives imposes a significant price dislocation, and its degree is well captured by the $N2V$ measure.

[Insert Figure 6 here]

B. Robustness with various event windows

As we discussed the event window selection in section I, we determine the event window [-10,+10] to satisfied the two different criteria: (1) enough non-crowding events to implement empirical test and (2) appropriate time period after the event to confirm the price reversion. In this section, we select different window size to focus on one criteria at the expense of the other criteria. We select two different window size: [-10,+30] and [-5,+5].

On one hand, in order to check the long-term reversion pattern after the knock-in event, we expand a event window to [-10,+30]. In our empirical analysis, we investigate the performance of the stock in a roughly two-month window, starting 10 days before the event day and ending 30 days after it

[18] KOSPI Industry Group Index is classified by the Korea Exchange (KRX) and has 22 different industry portfolio.

(41 days). The event window is unbalanced, skewed more on the post event, to analyze the pattern of the post event period. Our main focus is to detect knock-in effect at event date and over 1-month of the performance variation after the event. Panel (a) of Figure 7 plot the point estimates β_τ and its 95% confidence interval defined in Equation 16 when the events have low $N2V$ (triangle marker) versus high $N2V$ (circle marker): for a given event j, we regress CAR of underlying stock i of event j, i.e, $i(j)$ on event-day-dummy variables,

$$CAR_{i,\tau} = \alpha_{I(i)\times M(j)} + \sum_{\tau=-10}^{30} \beta_\tau \cdot \mathbf{D}_\tau + \gamma X_{i,t(j)} + \varepsilon_{i,\tau}, \tag{16}$$

where all the settings are exactly same with Equation 4 except the period of windows ($\tau = \{-10, -9, ..., 30\}$). Our coefficients of interest are β_τ. Now, our post-event window is large enough to detect reversion patterns.[19] In Panel (a), we find a more explicit "V" shape of CAR at the event, and it takes 15 days for CAR to revert back to the point that it is statistically insignificant from 0. Since the fundamental value cannot satisfactorily explain this explicit "V" shape of CAR variation, we find the evidence that this variation is more likely to arise due to hedging-driven effect. Furthermore, although the number of events declines, the CAR in high $N2V$ group is still statistically lower than the CAR in low $N2V$ group only at the event date.

On the other hand, in an effort to securely collect non-crowding events, we reduce our window size to [-5,+5] and increase events from 477 to 589 events at the expense of after event period. Panel (a) of Figure 7 illustrate the point estimates β_τ and its 95% confidence interval defined in Equation 16 when the events have low $N2V$ (triangle marker) versus high $N2V$ (circle marker). The big difference is that the confidence interval of point estimate is more tight due to increment of the non-crowding case. This result clearly shows that the CAR in high $N2V$ group significantly lower than CAR in low $N2V$ group. This result support our argument that delta-hedging unwinding forces to draw down its underlying stock price.

[Insert Figure 7 here]

[19] At the expense of widening window, our total non-crowding events are decreased from 477 events to 360 events due to the definition of non-crowding.

C. *Robustness of Knock-in effect with different measure calculation*

In this section, we look at issues of volume trading used in existing $N2V$ (defined in Equation (2)) and $R2V$ ratio (defined in Equation (11)), and to verify if the alternative measure reach the same result. In the existing ratio, the trading volume is used for the average trading volume for six months from the time of issuance. The reason for this is that it is orthogonal to fundamental because it is pre-determined at the issuance date, Another important reason is the variation of trading volume around the knock-in event. The movement may be the result of the liquidation of the hedged position. Although we did not report, we found that the volatility of the trading volume increases statistically significance increases from 2 days before to 6 days after the time of the event. If the transaction volume around the event is used, the volume increases greatly around the event, causing an endogenous problem that underestimates measures. However, since the the average period between knock-in date and the issuance date is more than one year, the trading volume at the issuance date may have a problem that trading volume is disable to reflect current situation properly. Therefore, we construct alternative measure to reconcile these issues. Alternatively, the date for calculating the trading volume is set to 11 days before the event period. Because our major research event window is [-10,+10], it is independent and closest to the event date. The adjusted $N2V^a$ measure defined as follows: for an underlying stock i, we aggregate each notional amount of a note k whose knock-in barrier is touched at day t, we divide this by the average trading volume of stock i:

$$N2V_{i,t}^{a} = \frac{\sum_{k \in \mathbf{K}_{i,t}} Amount_k}{Volume_{i,t-11}}, \tag{17}$$

$Volume_{i,t-11}$ is the 6-month average dollar volume of stock i at the 11 days before the event day. All other variables' definitions are identical to Equation (1).

Similarly, the adjusted $R2V^a$ measure defined by following equation: for underlying stock i and event time t corresponding to each event j (i.e., $i = i(j), t = t(j)$), we aggregate notional amount of note k in the relevant set $\mathbf{K}''_{i,t}$ defined below, and then normalize it by volume of stock i at day t:

$$R2V_{i,t}^{a} = \frac{\sum_{k \in \mathbf{K''_{i,t}}} Amount_k}{Volume_{i,t-11}}, \tag{18}$$

$Volume_{i,t-11}$ is the 6-month average dollar volume of stock i at the 11 days before the event day.

All other variables' definitions are identical to Equation (11).

Table IX summarize the nested regression of the main regressions with new measure. Overall, the result is almost similar but the scale is minutely decreased because the noise of volume trading around event date hinder the measure to capture the effect clearly. From first three column, the result is the regress CAR on the alternative measures. The first column present the impact of the liquidity effect on CAR by the $N2V^a$. With alternative measure, the liquidity effect is still significantly negative. In the second column, the expectation effect is not significant. The third column , likewise to the previous result, only the $N2V$ ratio is significant and the $R2V$ and the interaction term are not significant. From last two column, the table shows the result of regression on knock-in indicator, equal to 1 when the events experience the future knock-in. In fourth column, we still find the result that the liquidity effect triggers the future knock-in event with alternative $N2V^a$. In fifth column, we interacted the $N2V$ and the $Proximity$ measure. Similarly, interaction term is the only term with statistical significance. As a result, we confirm that our results are robust by producing qualitatively same with the alternative measures.

[Insert Table IX here]

VI. Conclusion

In this paper, we document a salient case in which the structure of derivatives market imposes a substantial feedback effect on the underlying asset prices via delta hedging. Particularly, a certain type of structured derivatives triggers a sudden and dramatic change in the delta position, forcing the hedgers to quickly unwind a large position. This event happens when the stock price breaches some lower boundary. Such a liquidity demand dislocates the underlying stock price from the fundamental value by a significant degree and for a considerable time period.

This mechanism can be amplified in two aspects. The magnitude becomes bigger when the amount of liquidation is large relative to the underlying stocks intrinsic trading volume. The shock lasts longer when one liquidation event causes another, creating the chain reaction of the events. This type of structured derivatives are issued competitively among financial institutions without any effort to coordinate. As a result, we show that issuance of notes on a particular stock is concentrated in a short time period with a largely homogeneous payoff structure. We show that when the current market structure of derivatives, therefore, amplifies the feedback effect in both ways.

Our finding has an theoretical implication on the option pricing. Pricing without considering this potential risk is likely to be incorrect because a typical pricing model assumes that the underlying asset parameters are exogenous to the derivatives prices and markets. In other words, option pricing with the risk due to lack of coordination can be much more complex. Also, our paper provides an important policy implication. Lack of a system that facilitates issuer coordination in OTC market may exacerbate the downturn via price chain reaction.

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Figure 1. Trend of Structured Derivatives Market

This figure shows aggregate pattern of OTC structured derivatives note issuance in Korea. From 2003 to 2018, the overall growth rate is 34 percent in terms of outstanding amount. Solid line represents aggregate outstanding amount of structured derivatives and the dotted line illustrates the portion of this market compared to total equity market capitalization. The growth steepens after the 2008 Global Financial Crisis (19.4% versus 21.6%), during the period of low interest rate regime (Korea's benchmark rate on average is 2.1% in post-crisis versus 4.3% in pre-crisis period).

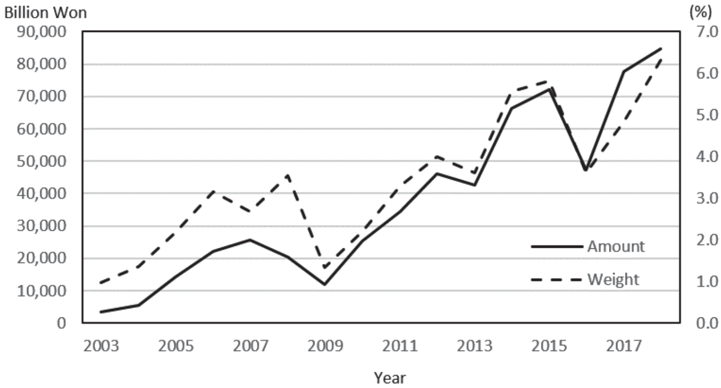
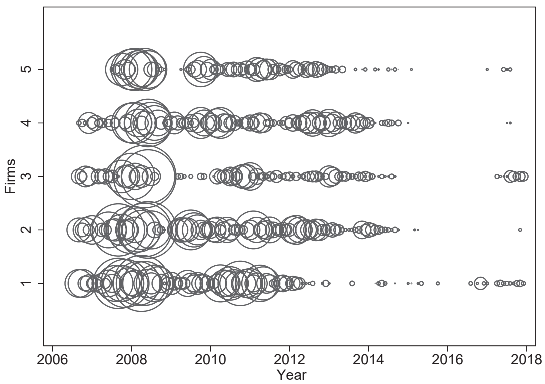
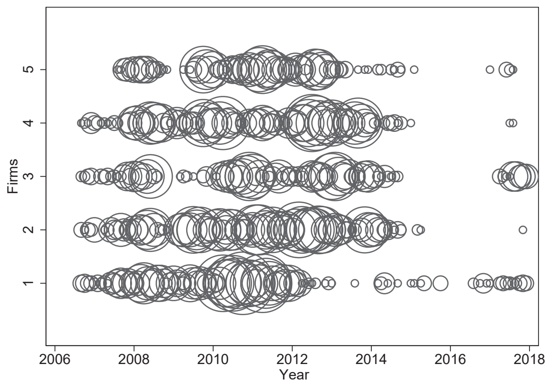


Figure 2. Issuance Herding and Knock-in Crowding

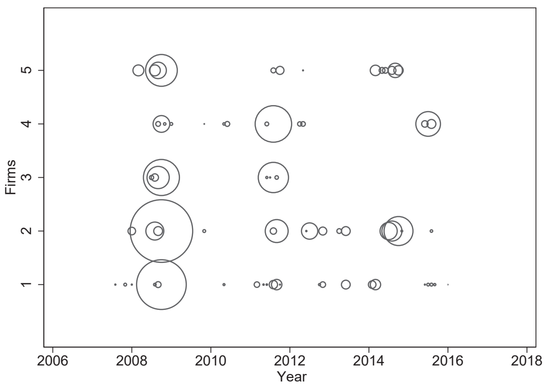
This figure shows the issuance and knock-in events are crowded in a specific time. We select top 5 stocks from our data set (total 90 stocks) based on the total amount of note that experience the knock-in event on our sample period and put them along the vertical axis. We aggregate the amount and the contracts at the month level and visualize the circles based on these values. The horizontal axis of the figure represents the time, and the size of circles indicates the notional size (for panel (a) and (c)) and the number of contracts (for (b) and (d)) corresponding to a stock and at a specific time. If there is no issuance herding, we expect that these circles are equisized and proportionally spread across the time. However, the figure shows that larger circles are concentrated in time but in different times for different stocks, indicating the issuance and knock-in event crowding.



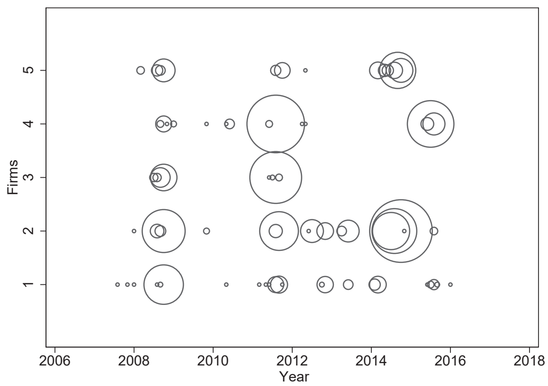
(a) Issuance Herding (Amount)



(b) Issuance Herding (Unit)



(c) Knock-in Crowding (Amount)



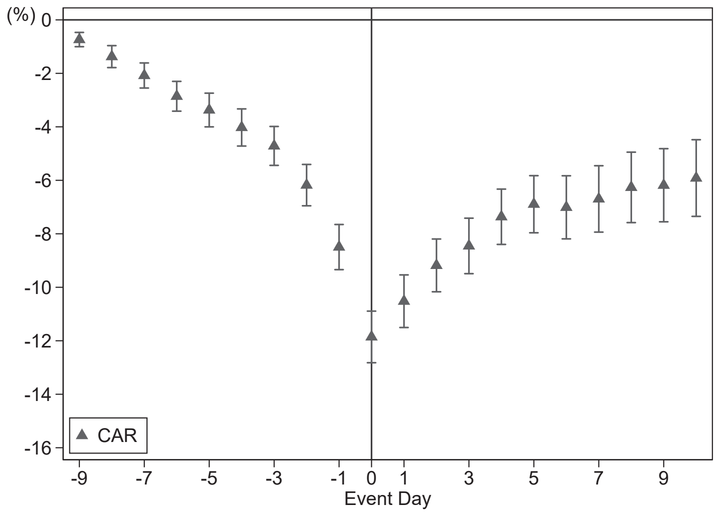
(d) Knock-in Crowding (Unit)

Figure 3. Cumulative Abnormal Return Variation around Knock-in Event [-10,+10]

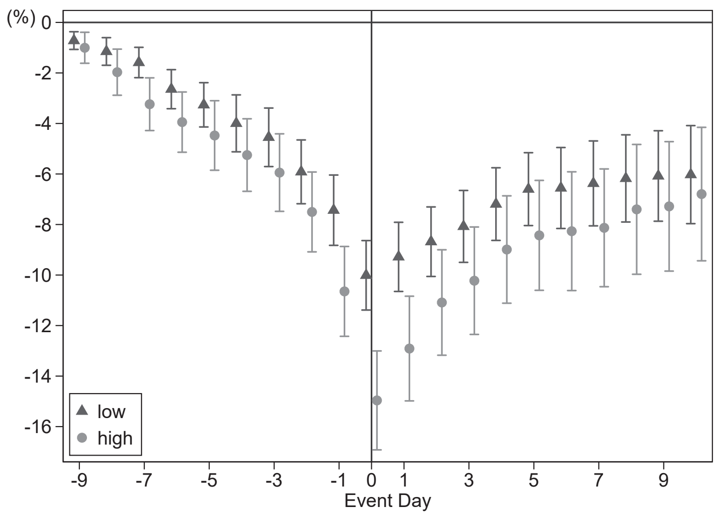
This figure plots the event-time pattern of CAR defined in as follows:

$$CAR_{i,\tau} = \alpha_{I(i)\times M(j)} + \sum_{\tau=-10}^{10} \beta_\tau \cdot \mathbf{D}_\tau + \gamma X_{i,t(j)} + \varepsilon_{i,\tau},$$

where for a given event j, we regress CAR of underlying stock i of event j, $I(i)$ is the industry of stock i with Korea SIC 2-digit classification, $M(j)$ is the calendar month of the event j, $\mathbf{D}_\tau$ is an indicator variable whose value is 1 only at event day τ; otherwise 0, X is a vector of control variable using the most recent information of firm i known at $t(j)$. $\alpha_{I(i)\times M(j)}$ is Industry $\times$ Month fixed effect corresponding to each event. The figure present the point estimates of each β_τ ($\tau = \{-10, -9, ..., 10\}$) and its 95% confidence interval. Panel (a) shows average knock-in effect of non-crowding samples on CAR is in Panel (a) and sample size is 10,017 (477 events $\times$ 21 days). In Panel (b), we categorize our sample events into three groups using the tercile of $N2V$. Panel (b) displays the point estimates when the events have low $N2V$ (triangle marker) versus high $N2V$ (circle marker). Sample size of Panel (b) for the low $N2V$ ratio is 3,318 (158 events $\times$ 21 days) and for the high $N2V$ ratio is 3,339 (159 events $\times$ 21 days). The estimated shape of the abnormal price pattern would suggest whether a knock-in event imposes a price dislocation.



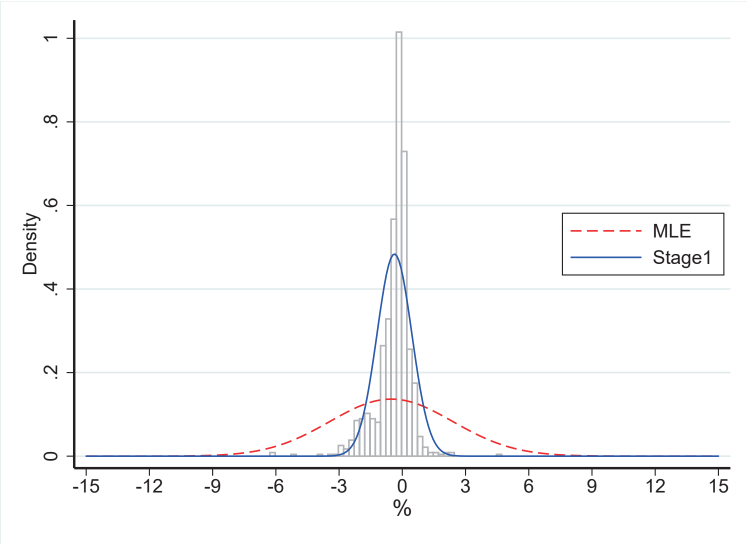
(a) Average Knock-in Effect on CAR



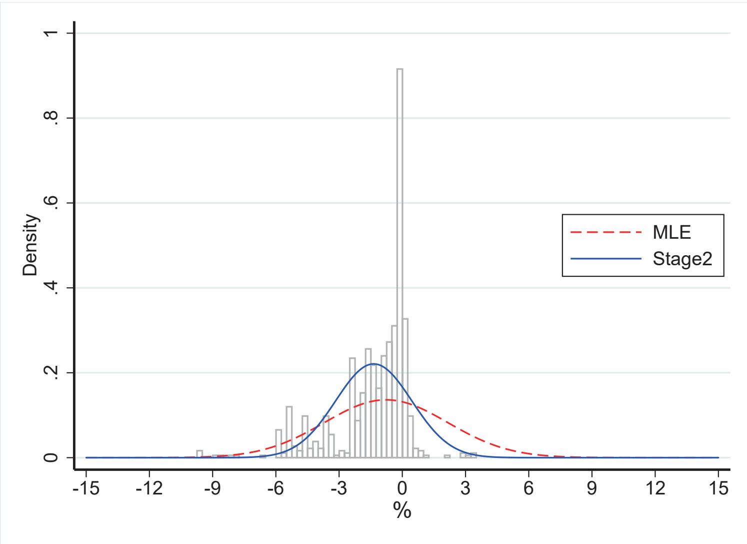
(b) Knock-in Effect on CAR by Low and High N2V

Figure 4. Distribution Comparison in Different Stage

The chart plots the actual distribution for the sample mean and sample variance against the normal distribution given by the Gaussian distribution. For event p when stock i of note k hits its upper barrier of each stage, red dotted line is the normal distribution with averaged μ_p^{MLE} and σ_p^{MLE} by event p. The histogram represents the return distribution of actual mean ($\mu_p^{act,g}$) and standard deviation ($\sigma_p^{act,g}$), and blue solid line shows the normal distribution with actual parameters.



(a) Stage I: Over Barrier



(b) Stage II: Near Barrier

Figure 5. Cumulative Abnormal Return Variation across R2V during Pre-event Period [-10,0]

Figure illustrates the point estimate and its 95% confidence interval of the dynamic set up as following equation during the pre-event period [-10,0] by the tercile of $R2V$ separately:

$$CAR_{i,\tau} = \alpha_{I(i)\times M(j)} + \sum_{\tau=-10}^{0} \beta_\tau \cdot \mathbf{D}_\tau + \gamma X_{i,t(j)} + \varepsilon_{i,\tau},$$

where for a given event j, we regress CAR of underlying stock i of event j, $I(i)$ is the industry of stock i with Korea SIC 2-digit classification, $M(j)$ is the calendar month of the event j, $\mathbf{D}_\tau$ is an indicator variable whose value is 1 only at event day τ; otherwise 0, X is a vector of control variable using the most recent information of firm i known at $t(j)$. $\alpha_{I(i)\times M(j)}$ is Industry $\times$ Month fixed effect corresponding to each event. It displays the point estimates when the events have low $R2V$ (triangle marker) versus high $R2V$ (circle marker). Sample size for the low $R2V$ ratio is 1,760 (160 events $\times$ 11 days) and for the high $R2V$ ratio is 1,749 (159 events $\times$ 11 days). We find that the price impacts are not significantly different by the probable negative price impact prior to the knock-in event. This finding complement our interpretation for the result of Table VIII that the stock market does not fully integrate information in OTC derivatives market.

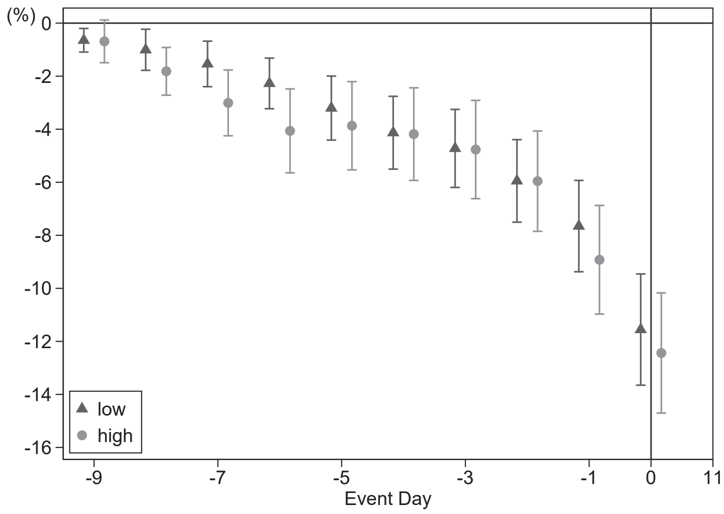
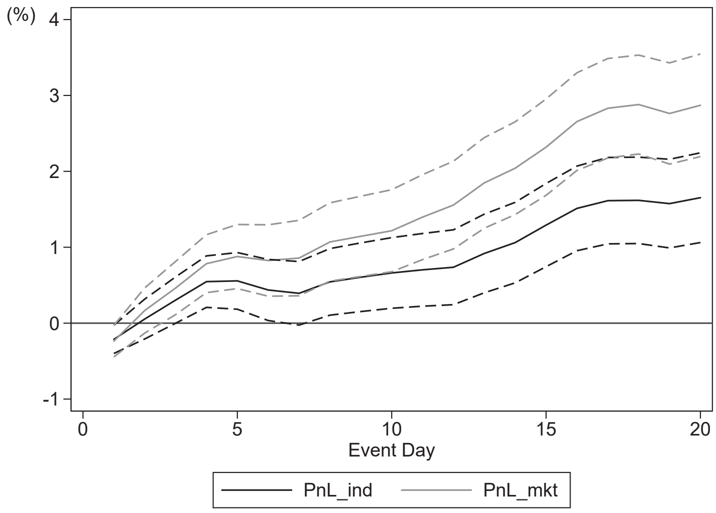


Figure 6. 20-day Trading Strategy Performance after the Knock-in Event

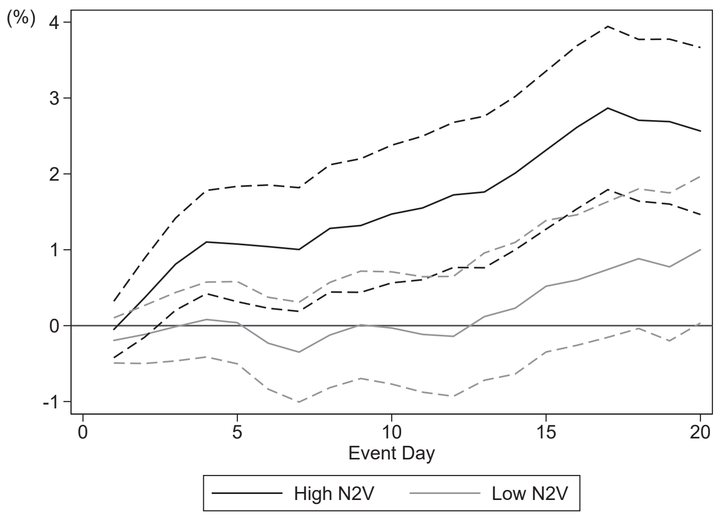
Figure shows the performance of the 20 day trading strategy that long portfolio when the knock-in event occurs and short benchmark portfolio. The benchmark portfolio used market portfolio and industry portfolio specific to the stock we buy. For returns of the benchmark portfolio, we use KOSPI Composite return as market return, and use industry return classified by Korea Exchange SIC (KRXSIC) return as industry return. We construct zero investment portfolio and the strategy return is calculated by benchmark-adjusted cumulative abnormal return which we denote it by PnL^b_τ, where benchmark $b = \{\text{Market, Industry}\}$ and holding period $\tau = \{1, .., 20\}$. Accordingly, the average strategy return with τ-day holding period using benchmark b is calculated as:

$$PnL^b_\tau = \sum_{q=1}^{\tau} \Delta PnL^b_q.$$

Panel (a) shows $PnL^{Industry}$ (black solid) and PnL^{Market} (grey solid) performance of total events and its 95% confidence interval (dotted line with the same color by each PnL. Panel (b) compares the PnL between high and low $N2V$ in industry-adjusted return. ($PnL^{Industry}$).



(a) Comparison of PnL between Benchmark-adjusted Return



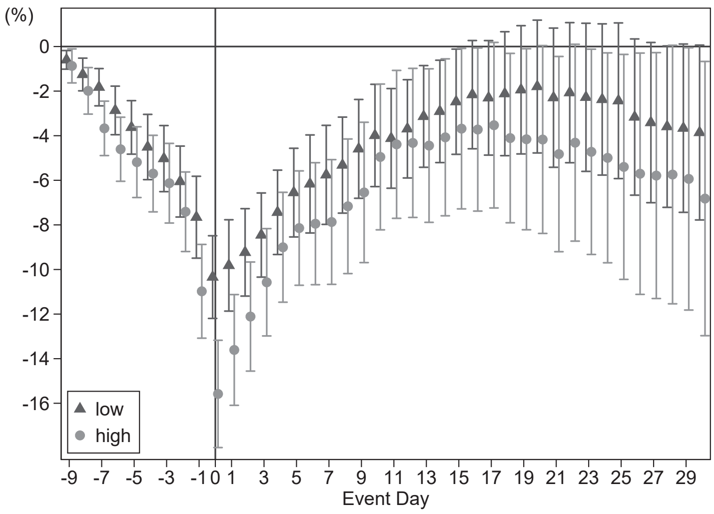
(b) Comparison of PnL between High and Low $N2V$ in Industry-adjusted Return

Figure 7. Cumulative Abnormal Return around Knock-in Event with Various Event Window

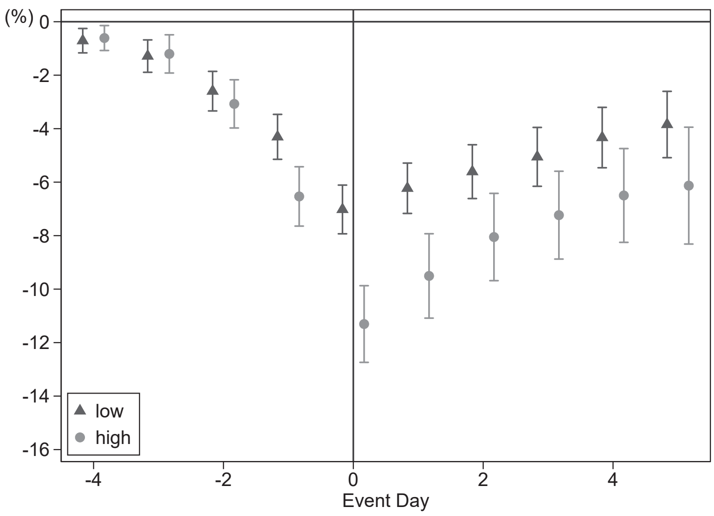
This figure plots the event-time pattern of CAR defined in as follows:

$$CAR_{i,\tau} = \alpha_{I(i)\times M(j)} + \sum_{\tau=T1}^{T2} \beta_\tau \cdot \mathbf{D}_\tau + \gamma X_{i,t(j)} + \varepsilon_{i,\tau},$$

where for a given event j, we regress CAR of underlying stock i of event j, $I(i)$ is the industry of stock i with Korea SIC 2-digit classification, $M(j)$ is the calendar month of the event j, $\mathbf{D}_\tau$ is an indicator variable whose value is 1 only at event day τ; otherwise 0, X is a vector of control variable using the most recent information of firm i known at $t(j)$. $\alpha_{I(i)\times M(j)}$ is Industry × Month fixed effect corresponding to each event. This figure present the point estimates of each β_τ and its 95% confidence interval. We categorize our sample events into three groups using the tercile of $N2V$ and display the point estimates when the events have low $N2V$ (triangle marker) versus high $N2V$ (circle marker). Since the window size of Panel (a) is [-10,+30], $T1$ is -10 and $T2$ is 30. Similarly, for Panel (B), $T1$ is -5 and $T2$ is 5. Sample size of Panel (a) for low $N2V$ and high $N2V$ is 4,920 (120 events × 41 days), respectively. Sample size of Panel (b) for the low $N2V$ ratio is 2,178 (198 events × 11 days) and for the high $N2V$ ratio is 2,167 (197 events × 11 days). In both figures, the CAR in high $N2V$ group statistically lower than CAR in low $N2V$ group. This result support our argument that delta-hedging unwinding forces to draw down its underlying stock price.



(a) Knock-in Effect on CAR by N2V Group (-10,+30)



(b) Knock-in Effect on CAR by N2V Group (-5,+5)

Table I. Data Description

Panel (a) illustrates the process of sample selection. During our sample period, from 2006 to 2017, we have 38,035 of publicly and privately placed structured equity derivatives notes issuance. After confirming data availability and filtering out notes by criteria: at least one underlying asset as a stock, notes with knock-in barrier, and the notes experience the knock-in event, the final sample contains 8,174. Lastly, when the multiple knock-in events are associated with any identical stocks, we aggregate these events and treat them as one knock-in event on the underlying, converting data structure to event-day × stock level information. Our final sample is 1,302 unique knock-in event days. Panel (b) describes the trend of the notes and the market characteristics by year. The table shows total number of notes, total number of stocks, and total notional size of structured notes newly issued (regardless of whether they are knocked-in or not during the corresponding event year) in the same year. Similarly, we add columns for those of notes that experience knock-in events in the corresponding year. At last, we augment the table by annual return and volatility of the benchmark market index (KOSPI).

(a) Sample Creation

Filter	Sample Size	No. of Stock
Initial Sample: ELS contracts between 1/2006 - 12/2017	38,035	141
Excluding contracts (foreign underlying stocks, non-downside knock-in barrier contracts, missing barrier and issue amount contracts)	21,273	
	16,736	122
Excluding contracts with un-knock-in event	8,562	
Final Sample: ELS contracts with knock-in event	8,174	90
Final Sample: ELS knock-in event days (Merge the ELS contracts at the knock-in event day)	1,301	90

(b) Trend of ELS Contracts and Market Index

	Issuance			Knock-In			Market(KOSPI)	
Year	N.Obs (1 unit)	Amount (bil. KRW)	Stock (1 unit)	N.Obs (1 unit)	Amount (bil. KRW)	Stock (1 unit)	RET(6M) (%)	VOL(6M) (%)
2006	237	1,544	43	.	.	.	4.9	18.1
2007	882	5,808	62	16	83	4	32.3	22.7
2008	1,228	5,736	61	1,604	9,342	65	-40.7	38.6
2009	1,456	2,900	55	14	19	3	49.7	24.7
2010	2,551	3,878	73	25	27	6	21.9	15.0
2011	3,231	4,105	78	2,152	3,028	59	-10.7	26.0
2012	3,339	3,307	72	386	481	27	9.4	15.3
2013	2,106	1,630	79	756	832	28	0.7	12.2
2014	796	377	59	1,915	1,784	28	-4.8	10.0
2015	135	54	38	1,186	814	29	2.4	12.6
2016	139	135	27	109	53	11	3.1	12.1
2017	636	499	52	11	3	3	21.9	9.1
Total	16,736	29,974	122	8,174	16,466	90	.	.

Table II. Summary Statistics

This table reports the summary statistics of selected variables. *N2V*, *Proximity*, and *R2V* are calculated by each definition in Equation (1), (8), and (11), respectively. Size is the logarithm of book value of equity. Book-to-market is book value of asset / market value of equity. RVol is annualized volatility using 1-month return of stock.

	Mean	St.Dev	25th Pct.	Median	75th Pct.	N
N2V	0.10	0.19	0.01	0.03	0.10	1,301
Proximity	0.72	0.93	0.04	0.52	1.18	1,234
R2V	0.24	0.43	0.06	0.06	0.29	1,031
Size	23.82	1.13	23.05	23.6	24.38	1,296
Book-to-Market	1.23	0.81	0.74	1.05	1.54	1,296
Avg. 1-month ret	-8.02	9.55	-13.66	-7.79	-2.05	1,301
Avg. 6-month index ret	-3.79	11.43	-7.58	-1.75	3.58	1,301
RVol	42.42	24.91	25.18	36.13	53.19	1,301

Table III. Impact of Knock-in Event on Cumulative Abnormal Return

This table shows the result of regress CAR on $N2V$:

$$CAR_{i,t(j)} = \alpha_{I(i)\times M(j)} + \beta N2V_j + \gamma X_{i,t(j)} + \varepsilon_j,$$

where for a given event j, we regress CAR of underlying stock $i = i(j)$ of the event at the event day $t(j)$ on $N2V$ of the same event. $I(i)$ is the industry of stock i with Korea SIC 2-digit classification, $M(j)$ is the calendar month of the event j, X is a vector of control variable using the most recent information of firm i known at $t(j)$. $\alpha_{I(i)\times M(j)}$ is Industry × Month fixed effect corresponding to each event. Across these specifications, the coefficient β are consistently negative and highly significant. Upon a knock-in event, there is a substantial price pressure on the underlying stock via hedging related liquidation. Quantitatively, 1 standard deviation increase of $N2V$ corresponds to 59 basis points of more negative CAR. The price dislocation is more severe when the firm is smaller as measured by natural log of book value of asset. Also, a higher degree of negative abnormal return is associated with a higher level of return volatility of the affected stock. These patterns are consistent with Duffee (1995) who provides evidence that stock return is negatively correlated with its volatility, and also shows that this relation is strongest among small firms. The t-statistics with standard errors clustered at the event level are reported below the coefficients. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively.

Dependant: Cumulative Abnormal Return	(1)	(2)	(3)	(4)	(5)
N2V	-0.029**	-0.030**	-0.030**	-0.030**	-0.031**
	(-2.09)	(-2.29)	(-2.05)	(-2.07)	(-2.22)
Size		0.018***			0.017***
		(3.27)			(3.22)
Book-to-Market		0.004			0.004
		(0.65)			(0.79)
Avg. 1-month ret			-0.043	-0.033	-0.058
			(-1.06)	(-0.69)	(-1.21)
RVol			-0.129***	-0.129***	-0.127***
			(-3.96)	(-3.90)	(-3.90)
Avg. 6-month index ret				-0.040	-0.007
				(-0.39)	(-0.06)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	1,301	1,296	1,301	1,301	1,296
R-squared	0.422	0.437	0.444	0.444	0.459

Table IV. Controlled Distribution Comparison

This table reports the result of controlled distribution comparison. For event p,

$$\mu_p^{'} = \alpha_{i(p)\times M(p)} + \beta \cdot \mathbf{I}_{2,p} + \gamma X_{i,p} + \varepsilon_p.$$

where $\mu_p^{'}$ is the difference between sample mean and mean by MLE within the same event p. $\mathbf{I}_{2,p}$ is indicator function, equal to 1 when actual mean is estimated in Stage II. Stage I is the omitted category. $\alpha_{i(p)\times M(p)}$ is the firm × Month fixed effect corresponding to each event, and Stage I is the omitted category. Similarly, we execute regression on standard deviation as follows:

$$\sigma_p^{'} = \alpha_{i(p)\times M(p)} + \beta \cdot \mathbf{I}_{2,p} + \gamma X_{i,p} + \varepsilon_p.$$

where $\sigma_p^{'}$ is the difference between sample standard deviation and standard deviation by MLE within the same event p. The t-statistics with standard errors clustered at the firm level are reported below the coefficients. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively.

Dependant: $\mu^{'}$	(1)	(2)	(3)	(4)	(5)
Stage II	-0.188***	-0.397***	-0.097	-0.232***	-0.408***
	(-2.97)	(-5.31)	(-1.25)	(-2.91)	(-5.65)
Book-to-Market		4.823***			4.266***
		(6.37)			(5.73)
RVol			1.497***	0.921	0.280
			(2.63)	(1.59)	(0.50)
Avg. 6-month index ret				-6.588***	-2.212**
				(-6.46)	(-2.07)
Firm FE x Time FE	Y	Y	Y	Y	Y
N.Obs	13,508	13,508	13,507	13,507	13,507
R-squared	0.398	0.652	0.601	0.621	0.654

Dependant: $\sigma^{'}$	(1)	(2)	(3)	(4)	(5)
Stage II	0.846***	0.803***	0.791***	0.776***	0.779***
	(9.99)	(7.68)	(9.76)	(9.78)	(8.29)
Book-to-Market		0.675			-0.113
		(0.88)			(-0.09)
Avg. 1-month ret			-1.004*	-0.712	-0.771
			(-1.89)	(-1.10)	(-1.17)
Avg. 6-month index ret				-1.460	-1.530
				(-1.10)	(-0.83)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	13,508	13,508	13,508	13,508	13,508
R-squared	0.682	0.683	0.684	0.684	0.684

Table V. Implied Contribution to the Probability of Knock-in Based on N2V

Table shows the result of Probit regression knock-in indicator ($KI_{i,t}$) on $N2V$. For each event j, its corresponding stock $i = i(j)$ and event time $t = t(j)$, we specify Probit model as follows:

$$KI_{i,t} = \Phi\left(\alpha_{I(i)\times M(j)} + \beta N2V_j + \gamma X_{i,t} + \varepsilon_{i,t}\right),$$

where $\Phi(\cdot)$ is the standard normal cumulative density function, $KI_{i,t}$ is defined above, and all other variables' definitions are identical to ones in Equation (4). Across all specifications, it shows that higher $N2V$ increases future knock-in probability. The effect on the future knock-in is not only statistically but also economically significant. Using the specification in Column (5) of the same table, we estimate that one standard deviation increase of $N2V$ increases the future knock-in probability by 6% keeping all other explanatory variables at their mean.The t-statistics with standard errors clustered at the event level are reported below the coefficients. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively.

Dependant: Future KI Indicator	(1)	(2)	(3)	(4)	(5)
N2V	0.639***	0.638**	0.778***	0.859***	0.868***
	(2.58)	(2.56)	(2.87)	(3.06)	(3.07)
Size		0.110***			0.109***
		(2.87)			(2.74)
Book-to-Market		-0.103*			-0.103*
		(-1.94)			(-1.91)
Avg. 1-month ret			0.544	0.434	0.351
			(1.38)	(1.09)	(0.88)
RVol			-0.550***	-0.348*	-0.301
			(-3.59)	(-1.77)	(-1.49)
Avg. 6-month index ret				0.750*	0.877*
				(1.66)	(1.85)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	1,301	1,296	1,301	1,301	1,296
LRChi2	7.65	15.85	23.62	26.17	32.00
ProbChi2	0.022	0.003	0.000	0.000	0.000
Pseudo R-squared	0.006	0.013	0.018	0.020	0.026

Table VI. Implied Contribution to the Probability of Knock-in Based on N2V and Proximity Group (2-Quantile) Interaction

Table shows the result of the categorical Probit regression by 2-quantile of *Proximity*. To address the barrier heterogeneity across clusters, we use the interaction of *N2V* with *Proximity* in the following specification:

$$KI_{i,t} = \Phi\Bigg(\alpha_{I(i)\times M(j)} + \beta_1 N2V_j^{High} + \beta_2 Proximity_j^{High} + \\ \beta_3 N2V_j^{High} \cdot Proximity_j^{High} + \gamma X_{i,t} + \varepsilon_{i,t}\Bigg),$$

where *Proximity* is defined in Equation (8) and definitions of all other variables are identical to the previous equations. The t-statistics with standard errors clustered at the event level are reported below the coefficients. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively.

Dependant: Future KI Indicator	(1)	(2)	(3)	(4)	(5)
N2V^{High}	0.040	0.054	0.039	0.041	0.056
	(0.35)	(0.46)	(0.34)	(0.36)	(0.48)
Proximity^{High}	-0.151	-0.126	-0.080	-0.080	-0.044
	(-1.35)	(-1.11)	(-0.64)	(-0.65)	(-0.35)
$\text{N2V}^{High} \times \text{Proximity}^{High}$	0.386**	0.360**	0.390**	0.396**	0.370**
	(2.38)	(2.20)	(2.41)	(2.44)	(2.26)
Size		0.032			0.040
		(0.79)			(0.96)
Book-to-Market		-0.083			-0.090
		(-1.50)			(-1.63)
Avg. 1-month ret			0.132	0.108	0.045
			(0.31)	(0.25)	(0.10)
RVol			-0.277	-0.225	-0.258
			(-1.40)	(-0.95)	(-1.08)
Avg. 6-month index ret				0.214	0.225
				(0.44)	(0.44)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	1,234	1,229	1,234	1,234	1,229
LRChi2	14.91	17.35	17.29	17.88	20.78
ProbChi2	0.005	0.008	0.008	0.013	0.014
Pseudo R-squared	0.011	0.013	0.013	0.013	0.015

Table VII. Expectation Effect

In this table, we examine whether the knock-in expectation has any effect on the current price. As in Equation (5), we regress CAR of underlying stock $i = i(j)$ at day $t(j)$ corresponding to event j on $R2V_{i,t(j)}$:

$$CAR_{i,t(j)} = \alpha_{I(i)\times M(j)} + \beta R2V_j + \gamma X_{i,t(j)} + \varepsilon_j,$$

where all other variable definitions are identical to ones in Equation (5). Our coefficient of interest is β as it would indicate if the expectation for the future events is priced in. The t-statistics with standard errors clustered at the event level are reported below the coefficients. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively.

Dependant: Cumulative Abnormal Return	(1)	(2)	(3)	(4)	(5)
R2V	0.006	0.003	0.009	0.009	0.006
	(0.79)	(0.38)	(1.06)	(1.11)	(0.76)
Size		0.018***			0.017***
		(3.23)			(3.21)
Book-to-Market		0.003			0.003
		(0.51)			(0.58)
Avg. 1-month ret			-0.061	-0.049	-0.071
			(-1.49)	(-1.04)	(-1.52)
RVol			-0.130***	-0.129***	-0.127***
			(-3.97)	(-3.91)	(-3.89)
Avg. 6-month index ret				-0.052	-0.015
				(-0.50)	(-0.14)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	1,301	1,296	1,301	1,301	1,296
R-squared	0.419	0.434	0.442	0.442	0.455

Table VIII. Expectation Effect and Liquidity Effect

In this table, we conduct decomposition of the price dislocation into a portion due to the contemporaneous liquidity demand and a portion corresponding to investors' rational expectation that takes imminent negative shock in the consideration. For this task, we simultaneously include the measure of contemporaneous effect ($N2V$) and future effect ($R2V$) of knock-in events as below:

$$CAR_{i,t(j)} = \alpha_{I(i)\times M(j)} + \beta_1 N2V_j + \beta_2 R2V_j + \gamma X_{i,t(j)} + \varepsilon_j.$$

$R2V$ is defined in Equation (11) and all other variable definitions are identical to previous equations (e.g., Equation (12)). Comparison of β_1 and β_2 would show the relative importance of two different causes for the negative price impact. Table shows that the $N2V$ effect exists but $R2V$ effect is not. The t-statistics with standard errors clustered at the event level are reported below the coefficients. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively.

Dependant: Cumulative Abnormal Return	(1)	(2)	(3)	(4)	(5)
N2V	-0.031**	-0.031**	-0.033**	-0.033**	-0.033**
	(-2.25)	(-2.40)	(-2.20)	(-2.24)	(-2.34)
R2V	0.008	0.005	0.011	0.011	0.008
	(1.09)	(0.66)	(1.34)	(1.40)	(1.03)
Size		0.017***			0.017***
		(3.19)			(3.13)
Book-to-Market		0.004			0.004
		(0.66)			(0.75)
Avg. 1-month ret			-0.057	-0.043	-0.064
			(-1.39)	(-0.92)	(-1.37)
RVol			-0.131***	-0.130***	-0.128***
			(-3.99)	(-3.93)	(-3.91)
Avg. 6-month index ret				-0.059	-0.021
				(-0.56)	(-0.20)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	1,301	1,296	1,301	1,301	1,296
R-squared	0.423	0.437	0.446	0.446	0.459

Table IX. Robustness Check

Table summarize the nested regression of the main regression with alternative $N2V^a$ and $R2V^a$. The numerator of alternative measures are exactly same with the definition of original $N2V$ and $R2V$. However, the denominator of the measure is changed: date of the trading volume change from issuance date to 11 days before the event day. The definition of alternative measures are as follows: for an underlying stock i, notional amount of a note k, event day t,

$$N2V^a_{i,t} = \frac{\sum_{k \in \mathbf{K}_{i,t}} Amount_k}{Volume_{i,t-11}},$$

$$R2V^a_{i,t} = \frac{\sum_{k \in \mathbf{K}''_{\mathbf{i,t}}} Amount_k}{Volume_{i,t-11}},$$

$Volume_{i,t-11}$ is the 6-month average dollar volume of stock i at the 11 days before the event day. All other variables' definitions are identical to Equation (1) for $N2V^a$ and Equation (11) for $R2V^a$. From first columns to third, the dependent variable is CAR and the variable of last two columns is knock-in indicator, equal to 1 when the event experience the future knock-in. Since the result with the nested regression model, all settings are comparable to the setting of fifth column in each main regression. In general, our results remain qualitatively unchanged with this alternative measure.The t-statistics with standard errors clustered at the event level are reported below the coefficients. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively.

	CAR			KI Indicator	
	(1)	(2)	(3)	(4)	(5)
N2V^a	-0.022***		-0.022***	0.393*	0.201
	(-2.80)		(-2.86)	(1.65)	(0.53)
R2V^a		0.001	0.003		
		(0.09)	(0.36)		
Proximity^{Mid}					-0.073
					(-0.65)
Proximity^{High}					0.208
					(1.42)
$\text{N2V}^a \times \text{Proximity}^{Mid}$					0.402
					(0.74)
$\text{N2V}^a \times \text{Proximity}^{High}$					0.860*
					(1.68)
Size	0.016***	0.018***	0.016***	0.124***	0.057
	(2.96)	(3.27)	(2.95)	(3.11)	(1.34)
Book-to-Market	0.005	0.003	0.005	-0.112**	-0.117**
	(0.90)	(0.60)	(0.85)	(-2.08)	(-2.07)
Avg. 1-month ret	-0.059	-0.066	-0.061	0.373	0.005
	(-1.25)	(-1.40)	(-1.30)	(0.94)	(0.01)
RVol	-0.131***	-0.126***	-0.132***	-0.239	-0.410
	(-4.01)	(-3.88)	(-4.01)	(-1.19)	(-1.61)
Avg. 6-month index ret	-0.008	-0.005	-0.013	0.773	0.339
	(-0.08)	(-0.05)	(-0.12)	(1.63)	(0.66)
Industry	Y	Y	Y	Y	Y
N.Obs	1,296	1,296	1,296	1,296	1,229
Pseudo or R-squared	0.459	0.455	0.459	0.023	0.024