Liquidation Cascade and Hedging Front-Running: Evidence from the Structured Equity Product Market*

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ABSTRACT

We show that structured equity derivatives could cause a significant price dislocation of the underlying stock caused by an abrupt delta-hedging triggered by a predefined event in the payoff. Moreover, one event causes another: the cascade of event-driven liquidation amplifies the magnitude of the market impact. We find that a single liquidation event is associated with about -4% return on the event day. The non-informational price shock increases, in turn, the probability of a subsequent event by 15.7%. Given the negative price pressure, traders try to liquidate ahead of each other, exacerbating the degree of price dislocation. Our results reveal the chain-reaction mechanism and (mis)coordination device in complex derivatives markets that could provoke a substantial stock-price deviations.

Keywords: Delta-Hedging, Strategic Liquidation, Structured Equity Product, 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 is computed on the assumption that the derivatives themselves do not affect the prices of underlying assets. It has been widely documented, however, that this is not the case in vanilla option markets.[1] The exogeneity assumption is more broadly violated in the case of over-the-counter (OTC) exotic derivatives. Using structured equity products (SEPs), a package of complex options that are marketed aggressively to retail investors, Henderson, Pearson and Wang (2020a) show that issuers have an incentive to inflate the initial fixing of their contracts. They argue that the way that fixings are determined imposes a significant manipulative incentive. In this paper, we explore another contractual feature of SEPs: how a particular payoff can trigger a price dislocation in the context of strategic complementarity among issuers regarding their issuance and hedging.

For this task, we explore SEPs issued in Korea from 2006 through 2017. Several unique features of this market make it an ideal laboratory in which to study the asset-price implications of SEPs. First, the Korean SEP market is exceptionally big relative to its cash equity markets when compared with corresponding markets in other developed economies.[2] Second, Korean SEPs share a largely homogeneous payoff structure based on a particular feature that triggers a sudden liquidity demand via delta-hedging.[3] Lastly, the issuance of SEPs in Korean market is driven predominantly by retail investors' attention. Shin (2018), using the U.S. data, documents that a successful placement of an SEP with a high coupon rate causes those investors to demand more products with the same underlying asset and contract terms. To match the demand, financial intermediaries aggressively market the high-yield complex products to retail investors while maximizing their profits (Celerier and Vallee, 2017; Egan, 2019). Such behaviors originated from both retail investors and issuers cause Korean SEPs on a particular underlying stock to be issued intensively over a short period, forming an issuance wave.

These peculiarities of the market allow us to answer the following questions directly. When a large number of SEPs with the homogeneous payoff structure share an underlying asset,

[1] Ni, Pearson and Poteshman (2005) and Golez and Jackwerth (2012) find that option hedging has a substantial impact on the underlying stock price near the option maturity. Ni, Pearson, Poteshman and White (2018) further argue that hedging amplifies the underlying volatility over the entire lifetime of options, not only the expiration dates.

[2] The SRP Global Structured Product Database shows that, as of 2019, the outstanding notional amount of SEPs in the Korean market is about 242 billion dollars. This accounts for 16% of the total market capitalization, whereas the corresponding ratio for the U.S. is 2% and for the European market it is 6%.

[3] According to the SRP Global Structured Product Database, as of 2019 15.7% of SEPs with the knock-in feature are issued in Korea, which makes Korea unarguably the largest country in terms of the outstanding balance per total market capitalization and the second-largest country in terms of the issue volume during 2019, behind only the U.S. This particular SEP type accounts for 69.4% of the outstanding balance in the Korean SEP market.

would this circumstance exacerbate the price dislocation? Would one delta-hedging event lead to another, causing a sequential price impact? As an SEP issuer conducts a delta-hedge, would her execution behavior differ when the hedge can affect herself versus her competitors? Relatedly, would she act differently if she could foresee the competitors' trading strategy? We believe that answering all these questions is essential for understanding how complex derivatives could damage financial stability, given the mechanisms related to supply and demand of these products (Celerier and Vallee, 2017; Egan, 2019; Shin, 2018). To the best of our knowledge, ours is the first study to document the dynamic aspects of price dislocation as well as the game-theoretic behavior of SEP issuers that could contribute to systematic market disruption.

The structure of the SEPs we study involves a swap of two exotic options.[4] The issuer sells a binary call option whose payoff corresponds to the conditional coupon of the SEP to investors in exchange for a knock-in (KI) barrier put option.[5] Issuers compete on the coupon because it determines the attractiveness of the investment product to retail investors (Celerier and Vallee, 2017). Therefore, if two SEPs on the same stock are issued at a similar time, the barrier levels of their puts are also likely to be similar.[6] When the barrier is breached, the knock-in put suddenly becomes a vanilla put, dramatically shrinking the delta position. Consequently, the knock-in event forces hedgers (issuers) to dump a large quantity of the underlying stock.

Given the homogeneity of payoffs, multiple knock-in events tend to occur simultaneously: when an SEP's knock-in barrier is breached, other SEPs on the same underlying asset are likely to 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 a 'V'-shaped pattern in the abnormal return whose kink point coincides precisely with the timing of the knock-in events. The pattern also indicates that the price does not revert back immediately. It is not surprising to observe a series of negative returns prior to knock-in events because, by definition, those events occur

[4] About 80% of SEPs in Korea have payoffs that can be decomposed in a similar fashion.

[5] The put option typically has an at-the-money (ATM) strike and, therefore, a binary call with a higher payoff has to be exchanged for a KI put option with a higher barrier. In practice, the net swap value is not zero because it includes issuers' upfront margins.

[6] On the day when the most notes were issued in our sample, 179 SEPs were issued on 49 underlying stocks. To compare barriers on the same underlying asset, there must be two or more contracts on one issuance day. Requiring this reduces the number of SEPs issued to 160 and underlying stocks to 30. This means that, on average, issuance is clustered with five contracts per underlying asset. Comparison of barrier levels shows that the percentage of SEPs with a barrier difference that is less than or equal to 5% is 73%, the barrier difference that is less than or equal to 10% is 79%, and the barrier difference that is less than or equal to 20% is 92%.

as a result of the negative returns. However, without the hedging-induced price impact, the stock price would not necessarily correspond to a local minimum or a kink point at the exact time of any knock-in events.

To formally distinguish the hedging-related price impact from a change in firm fundamental, we construct a proxy variable: the ratio of the outstanding notional value of SEPs to the underlying stock's trading volume *at issuance*. We denote this variable as the 'notional-to-volume' ($N2V$) ratio. This ratio would be correlated with the hedging intensity because the dollar amount of the position to be neutralized is proportional to the notional value. The ratio is, however, arguably uncorrelated to the firm fundamental change around the events because this ratio is predetermined at the issuance of SEPs. Given that it takes on average 15 months from the time of issuance for a knock-in to occur, it is unlikely that this ratio is correlated with changes in firm fundamental, particularly at the time of knock-in event.

Our results indicate that knock-in events are associated with an abnormal return of about -7% at the time of the events when the $N2V$ ratio falls into the lowest tercile. However, when the $N2V$ ratio falls into the highest tercile, knock-in events impose an additional -2% of price dislocation on the event day. This result is robust to unobserved heterogeneity regarding event time, industry, and their interaction, confirming that the hedging activities prompt a sudden and significant price dislocation. We also observe that the price impact does not disappear immediately. Focusing on a set of events that occur apart from each other by more than our event window, we show that such a price impact lasts at least longer than two weeks.[7]

Since multiple SEPs on a common underlying asset with largely homogeneous payoffs are contemporaneously issued, we find that one knock-in triggers another, producing a chain reaction. This result has an important implication for market destabilization. When a predetermined trading strategy exists (e.g. a stop-loss policy or a 5% Value-at-Risk (VaR) rule) and it applies to a large portion of traders, an uncoordinated policy-driven execution can cause an undesirable market-wide impact via the chain reaction mechanism.[8]

[7]There is a trade-off in setting the event window. A wide event window that 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 a long enough post-recovery process.

[8]An intraday event in the E-mini S&P 500 futures market known as the 'Flash Crash' occurred on May 6, 2010. According to the CFTC-SEC (2010) report, the Flash Crash was initiated by a large number of fundamental traders who executed a program to sell E-Mini contracts to hedge their existing cash equity positions. This collective transaction drove futures prices down by approximately 3% in less than four minutes, from 2:41 p.m. to 2:44 p.m. The price impact in the futures market quickly spilled over to the underlying stock market. Even after the rapid recovery of the E-Mini, a prevailing stop-loss order triggered another crash, creating a systematic market disruption.

Given the negative price impact upon a knock-in, the trader of a current event may exhibit varying execution behaviors, depending on her own position as well as those of the third parties' that are subject to future knock-ins. Suppose that she has a large hedging position on another SEP whose knock-in event is highly probable. If she is concerned that the current event would lead to unfavorable market condition for unwinding the remaining position upon a subsequent knock-in, she may execute the current position in a way that minimizes the market impact. On the other hand, she may wish to have an additional knock-in as it would make her a put-option holder. In this case, she would conduct aggressive liquidation to impose a heavier price pressure. Moreover, the third parties' positions also matter. If she expects competitors to liquidate their hedging positions imminently, it would affect the way she liquidates hers.

We first show that, upon a knock-in event, the outstanding notional amount of *un-triggered* SEPs contributes to the price dislocation. We normalize the remaining notional amount by trading volume of the underlying asset as in $N2V$, constructing a 'remaining-to-volume' ($R2V$) ratio. Exploiting the fact that barriers of the remaining SEPs are distinct, we show that the notional amount subject to the most imminent knock-in imposes the largest price shock. The impact of $R2V$ is significant even after controlling for $N2V$, showing an additional channel other than the one associated with the current event.

To further distinguish the various incentives related to $R2V$, we separate $R2V$ into the portion of SEPs issued by the same institution of the current knock-in ($R2V_{in}$) and the remaining SEPs ($R2V_{ex}$). Our results show that the degree of price dislocation is more severe with a higher $R2V_{ex}$ but insignificantly related to $R2V_{in}$. This finding indicates that the trader of the current event neither smooths out the execution process nor imposes excessive price pressure beyond the degree associated with the current event. However, she appears to aggressively unwind her position when her competitors are likely to liquidate a substantial portion sometime soon.

This behavior is consistent with the 'rat race' mechanism documented in another context (Brunnermeier and Oehmke, 2013). When a trader expects a negative price shock initiated by someone else, she has an incentive to go in front of the line and pre-execute her position. Such aggressive liquidation aggravates the price pressure and prompts future knock-ins via the chain reaction. Such game-theoretic behavior is more probable when information on other traders' positions is readily available. On April 25, 2013, the Korea Stock Depository (KSD) introduced a system in which a user can easily access SEP issuance records.We utilize this information shock and find that the price impact via $R2V_{ex}$ is most prominent after this service is implemented, supporting the 'rat race' explanation.

We contribute to research investigating the possibility of price dislocation of stocks that underlie OTC derivatives. Prior studies demonstrate that issuers of OTC derivatives affect the prices of underlying stocks for reasons related to hedge rebalancing and stock-price manipulation (Ahn, Choi, Kim and Liu, 2010; Henderson, Pearson and Wang, 2015; Ni *et al.*, 2018; Henderson *et al.*, 2020a).[9] We explore the knock-in events of SEPs and find consistent evidence that OTC derivatives cause a substantial impact on prices and stock market volatility. To exploit non-informational liquidity demand triggered by knock-in events is particularly advantageous as such events provoke dramatic changes in the delta position.

Our paper is also related to research that documents a potential risk in predetermined trading strategies. For instance, a negative price shock can trigger a portfolio insurance program that liquidates the asset, potentially generating a vicious cycle (Gennotte and Leland, 1990; Easley and O'Hara, 1991; Jacklin, Kleidon and Pfeiderer, 1992). Osler (2005) argues that a stop-loss order provokes a cascade of negative price shocks in the currency market. Theoretically, Huang and Wang (2009) provide insight into our results by showing that an endogenous liquidity shock without a fundamental reason could crash the market. In this context, we find empirical evidence that the predetermined barrier associated with OTC derivatives prompts sudden liquidity demand, destabilizing the underlying stock market.

Our findings provide policy implications for market regulation and information transparency. In particular, we find it problematic that issuers competitively issue homogeneous SEPs on specific underlying stocks within a short time window. Although each issuing institution imposes a risk budget on the issuance, such a budget must depend on competitors' activities. We show that, in spite of the likely individual limit, the collective issue quantity can be excessive, necessitating a coordination device or a regulation. Also, our finding that traders jump ahead of each other suggests that enhancing market transparency does not benefit market stabilization.

Relatedly, our paper speaks to discussions related to the dark side of financial innovation. Existing studies have focused on financial intermediaries exploiting uninformed retail investors (Henderson and Pearson, 2011; Vokata, 2018). The room for investor exploitation with a complex product such as SEPs incentivizes intermediaries to generate issuance wave which is highly correlated with a measure of investor sentiment (Henderson, Pearson and Wang, 2020b). We complement these arguments by showing that financial innovation can impair market stability, especially when the issuance wave interacts with issuers' own trading

[9] Ni *et al.* (2018) focus on expiration dates, Ahn *et al.* (2010) examine redemption or maturity dates, while Henderson *et al.* (2015) focus on pricing (issuance) dates or determination (redemption) dates, and Henderson *et al.* (2020a) investigate issuance dates.

to manage the complex risk.

The rest of the paper is organized as follows. In Section 1, we describe our data in detail. In Section 2, we provide empirical evidence that hedging-induced liquidity demand dislocates underlying stock prices. In Section 3, we discuss the chain reaction of knock-in events such that the contemporaneous event increases the future knock-in probability. In Section 4, we examine the strategic behavior of delta-neutralizing traders. In Section 5, we conduct several robustness tests. Section 6 concludes.

1. Data Description

1.1. Overview of structured equity product (SEP) market

The Korean SEP market has experienced rapid growth over time. As shown in Panel (a) in Figure 1, the annual average growth in issue volume was 23% from 2003 through 2017 [10]. Also, as of 2017, the outstanding notional amount of SEPs was 73 billion U.S. dollar-equivalent, accounting for almost 4.9% of total equity market capitalization.

Compared with the SEP markets in other countries, the Korean market exhibits an exceptional concentration on one payoff type. Using the SRP Global Structured Product Database, in Panel (b) of Figure 1 we can see the share of outstanding balances across markets for SEPs whose payoffs feature a specific 'knock-in' barrier.[11] As shown in Panel (a) of Table I, the open interest is uniformly distributed across the U.S., European, and Asian market. However, Korea accounts for a predominant portion in Asia, making it the largest single country in terms of open interest relative to stock market capitalization (16% of the open interest in the world). Although the U.S. has the largest outstanding volume in terms of the absolute amount, (108 billion dollars in the U.S. versus 64 billion dollars in Korea), Korea has the highest proportion relative to the size of the underlying stock market (0.3% in the U.S. versus 4.3% in Korea).

[Insert Figure 1 and Table I here.]

It is interesting to observe that the growth steepens after the 2008 financial crisis (23.1% versus 19.4% in the pre-crisis period), during the low-interest-rate regime (Korea's benchmark rate on average is 2.1% in the post-crisis period versus 4.3% in the pre-crisis period).

[10]This figure uses issuance data from 2003 while our sample starts from 2006. Although the data from 2003 through 2005 has sufficient information for the aggregate pattern, it lacks specific payoff information, and consequently, we exclude this portion from the main sample.

[11]This type of payoff is classified as 'protected tracker' or 'reverse convertible' in SRP Global Structured Product Database.

Investors have been attracted by higher yields offered by those investment products. Although they are derivatives contracts, the products are marketed as a kind of fixed-income securities. As is the case with a typical bond, here investors initially invest the par value of the note in exchange for future payoffs (the 'coupon' and the 'principal') at maturity. The maturity payoff of SEPs depends, however, on the underlying asset's performance and the payoff structure of an individual SEP. These products are noticeably popular among retail investors.[12]

1.2. Data construction

Given the non-transparent nature of OTC derivatives contracts, we exploit several information sources to construct a comprehensive data set on SEP issuance. We start from a commercial data provider called FnGuide that provides the notes' issuance histories. For each issuance, we hand-collect contractual details such as knock-in barrier levels and maturities from individual prospectus filed with the Korea Security Depository (KSD) and Financial Supervisory Services (FSS). The collected information includes 38,035 SEPs in total on a basket of stocks, both publicly and privately issued during 2006 and 2017.

Panel (b) of Table I illustrates the sample construction process. We use the following filters to construct the final sample for our study. First, we restrict our focus to SEPs whose underlying assets contain a domestic stock. SEPs are typically written on a basket of underlying assets that could be individual stocks as well as equity indices; we exclude SEPs if they are underlain by a basket of indices only. Furthermore, we require SEPs to have the 'knock-in' feature in the payoff because we treat knock-in events as instruments that trigger extreme delta-hedging activities. The resulting data set contains 16,736 unique SEPs, associating these with 122 unique underlying stocks.

In our sample, usually, an SEP is written on a basket of individual stocks. In this case, the worst performer triggers the knock-in event. For our purposes, this worst performer is recognized as the affected stock by the knock-in event. Therefore, we identify 8,174 unique knock-in events (or unique SEPs that experience knock-in events), covering 90 unique stocks. When a stock triggers multiple knock-in events on the same day, we aggregate those events. This process converts our data structure to the stock $\times$ day-of-event level. Consequently, the transformed data contain 1,296 unique observations (stock $\times$ event days) on 492 unique days-of-event. On average, two or three stocks are affected per day.

[12]According to a 2018 report from Korea Financial Supervisory Services, retail investors hold 47% of the SEP (known in practice as Equity Linked Securities; ELS) and 76% of the marketing channel is comprised by bank trusts, 12% by financial institutions, and 10% by funds.

Panel (c) of Table I presents the time trend for SEP issuance and knock-in events. The issuance column of the table includes the total number of SEPs, the aggregated notional amount, and the unique number of underlying stocks by year of issuance. Column 'Knock-In' presents the comparable quantities, conditioned on the assumption that the knock-in event has been triggered in the corresponding year.

1.3. Issuance herding and knock-in crowding

Since SEPs are largely marketed to retail investors, the choices of underlying stocks are significantly influenced by investor attention. Once a product with an attractive payoff (typically a higher coupon rate) is initially issued, it draws investors' attention and leads them to demand that more SEPs with the equivalent terms be issued. This behavior creates the pattern of issuance herding: over a short period of time, a disproportionately large number of SEPs on a particular underlying stock are being issued. Given a set of underlying stocks, the competition makes the coupon rates of SEPs similar across issuers. To keep the coupon rate competitive, the knock-in barriers of the SEPs tend to be largely identical to each other.

In practice, no issuer can supply the SEPs indefinitely because issuing these notes is equivalent to writing option contracts, and each issuer is bound by its risk budget. Therefore, each issuer typically issues SEPs up to the maximum amount allowed. In aggregate, however, this mechanism can still create excessive issuance concentration at a certain time.

Panel (a) and Panel (b) in Figure 2 visualize this pattern. We select the top five stocks from our sample (for a total 90 stocks) based on the total number of SEPs whose barriers are breached during our sample period, and place them along the vertical axis (ranging from the biggest stock to the fifth-biggest stock). Circle size represents the notional size (Panel (a)) or the number (Panel (b)) of newly issued notes corresponding to each stock in each month on the horizontal axis.

In the absence of issuance herding, we would expect these circles to be equal in size and spread proportionally across the time period. However, the figure shows the contrary: we observe that larger circles are concentrated in specific times but are asynchronous for different stocks, illustrating issuance herding.

As a result of the issuance herding among nearly identical SEPs, the knock-in events are also concentrated during certain periods, which we call 'knock-in crowding'. Panel (c) and Panel (d) in Figure 2 display this pattern. We match the same firms with those from panel (a). The sizes of circles (the amount or the number of SEPs subject to knock-in events) are largely concentrated in a certain month.

[Insert Figure 2 here.]

1.4. Event window selection criteria

To analyze the dynamic price impact around each knock-in event, we use the performance of the corresponding stock for five days before and after the event day (i.e. for a total of 11 days). Unlike other studies that analyze synchronous events, in our study events could overlap with each other because SEPs of the same underlying assets may experience the knock-in event on different days. Therefore, for a given stock, we select non-overlapping events where each event is unique during the event window.

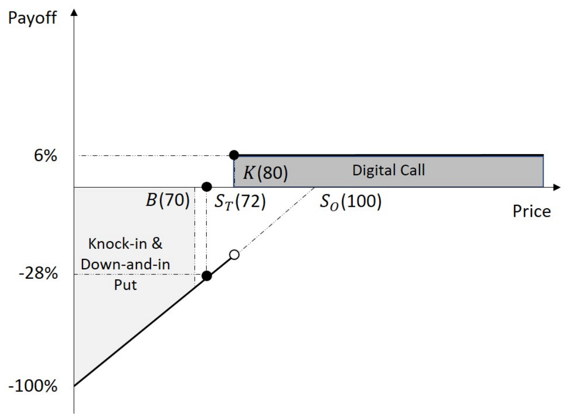
The selection of the window involves a trade-off between the sample size of the non-overlapping events and the number of post-event observations. For example, choosing the narrowest possible window (i.e. a 1-day window) would give us the largest samples because the fewest events would overlap each other. Doing so would, however, fail to provide any post-event information. On the other hand, choosing a wide window (e.g. a 6-month window) would allow us to observe the post-event dynamics, at the cost of having samples that are large enough to meet such a strict condition. In this trade-off, we choose an 11-day window to study the dynamic effects around the event, while a 1-day window when analyzing the event day only is sufficient. As a robustness check, we present the results with alternative windows to ensure that the dynamic results are not sensitive to window size.

2. Price Impacts of Knock-In Events

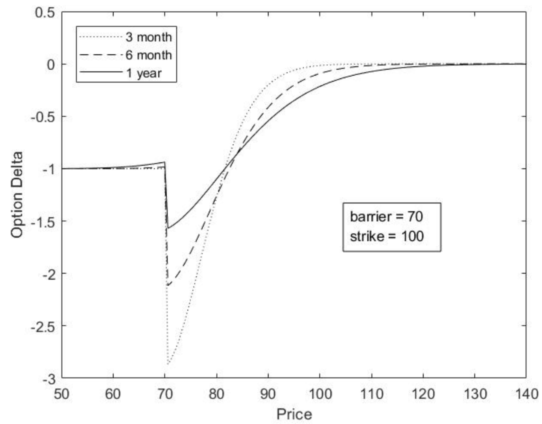
2.1. Structured equity products

The advantage we have for studying how open interest influences the stock market relies on the fact that payoff structures across SEPs are largely homogeneous. Typically, SEPs are composed of multiple underlying assets. For a given set of underlying assets, an investor in an SEP buys a Bermudan style digital call option that can be exercised only on a set of dates (observation dates). The investor finances this position by selling a knock-in barrier put option on the same underlying set to the issuer. This transaction forms a swap of the digital call and the knock-in put, with the complication that the swap is path-dependent: if the digital call is in the money on any observation dates (redemption events), the entire structure is cancelled. Once the redemption event occurs, the investor receives a 'coupon' corresponding to the digital call payoff. The issuer packages this swap in note form by

Illustration 1. Payoff Structure and Delta Variation of SEPs with Knock-In Barrier



(a) Simplified Payoff



(b) Delta of Knock-In Put

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 payout. The coupon and the barrier level involve a trade-off. To earn a higher coupon the investor also has to accept a higher barrier, making the entire structure riskier.[13]

We simplify the payoff by assuming that there is only one observation date, as illustrated in Panel (a) of Illustration 1. The horizontal axis indicates the price of the underlying stock at maturity (the only observation date). For this illustration, we assume that the stock price at inception (S_0) is 100, the digital call strike (K) is 80% of S_0 (80) with payout of 6%, and the knock-in barrier (B) is 70% of S_0 (70). This means that the investor receives 6% of the coupon if the underlying stock ends up higher than 80 (redemption event). If the redemption event does not occur, the investor may experience a loss because she short-sells the put. Because it is a barrier option, however, the put option becomes active only when the knock-in barrier is breached during the life of the option (the knock-in event). There is no loss to the investor as long as the stock price stays above the barrier throughout the time period even if redemption did not occur.

The knock-in event causes a sudden change in the payoff. Suppose that the minimum stock price during the lifetime of the option was 71 (knock-in event did not happen). If the stock

[13] Because 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 investors (Cha, 2017), issuers compete along the dimension of the coupon rate. If two SEPs on the same underlying assets are issued at the same time, it is likely that their barrier levels are close to each other, because coupons cannot be very different as they determine the success of the placement.

price at maturity (S_T) is 72, the investor would not receive the coupon but also would incur no loss. If the minimum price was 70 (knock-in event happened), however, she would lose 28% (=(100-72)/100) in spite of the same stock price at maturity (72). This dramatic payoff change also heavily alters the risk profile of the derivatives upon the knock-in event.

Panel (b) of the Illustration 1 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. The delta-hedging issuer needs to build a long position on the stock to neutralize the negative delta of the put. Prior to the knock-in event, the hedging position can be substantially large because of the huge negative delta. When knocked-in, however, the put option becomes a vanilla one, bounding its delta above at -1. The delta-neutralizing issuer is then left with an excessive stock position. As a result, the issuer is forced to liquidate it immediately.

2.2. Measuring the price impact of knock-in events

We first test whether aforementioned hedging-driven liquidation imposes price pressure, causing the stock price to dislocate from the fundamental value. The biggest challenge is to distinguish price changes caused by the hedging-driven liquidation from the change in fundamental value. The knock-in event is likely to be triggered when the fundamental value also decreases. Our set up provides us with a particular advantage to address this challenge: the fundamental value does not necessarily differ much in the neighbourhood of the barrier level. Therefore, should there be any price dislocation, its magnitude would be most pronounced precisely at the moment of the knock-in event.

We next construct a variable that is associated with liquidation intensity but is unlikely to be correlated with changes in the firm fundamental value. The dollar value of the delta is positively correlated with the size of the SEPs. Given issuance clustering (see Panels (a) and (b) of Figure 2) and the homogeneity of the payoffs, the knock-in events would also cluster (see Panels (c) and (d) of Figure 2). For this reason, there often exist multiple knock-ins from separate SEPs on the same underlying asset at the same time. Using this fact, we define the following 'notional-to-volume' or '$N2V$' measure.

We aggregate the notional amount of a set of SEPs ks whose knock-in barrier is touched by their underlying stock i on day t.[14] We then divide the aggregated notional amount by the

[14] Often, such SEPs have multiple underlying stocks. In this case, contractually, the knock-in event is deemed to occur when *any* of those stocks touches the barrier. In other words, the event is triggered by the *worst* performer of the underlying basket.

average trading volume of stock i. Formally,

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

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

We aggregate across multiple SEPs on the same knock-in day t as stock i triggers the event, so the observation unit for $N2V$ naturally becomes event j, pinning down the affected stock $i(j)$ at the knock-in event time $t(j)$.[15] Therefore, for the sake of notational simplicity, we rewrite (1) as follows:

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

According to Equation (1), $N2V$ is predetermined at the time of SEP issuance, which is long before the knock-in event day t.[16] In Table II, we present summary statistics of all measures and control variables used in this test, including $N2V$. The mean of $N2V$ is about 0.10, which generally implies that when a knock-in event occurs, the notional amount of all SEPs whose knock-in barriers are touched corresponds to about 10% of the average trading volume of associated underlying stocks.

[Insert Table II here.]

The aggregation across SEPs also reflects the fact that multiple knock-ins often occur simultaneously. It is reasonable to expect that a higher $N2V$ is associated with greater price pressure on related underlying stock. There is no obvious reason, though, 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 the OTC derivatives market changes firm fundamental values or that investors invest more on a firm whose fundamental value is expected to drop. One may argue that issuers can benefit by selling SEPs on overpriced stocks and leaving the position unhedged. If this is the case, however, knock-in events would not incur any changes in issuers' position and therefore we should not observe any price

[15] When SEP k has a basket of underlying stocks, the affected stock $i(j)$ in our analysis is the worst performer of the basket that triggers the knock-in event j, making the mapping of $j \mapsto i$ unique.

[16] Average time gap between issuance date and knock-in event day is over 1 year (15 month). The trading volume around knock-in events may be a consequence of hedging position liquidation. In an unreported result, we find that the trading volume increases significantly around events. Such an endogeneity discourages using the volume around knock-in, and it can be circumvented by using the volume at the issue date of event-experiencing-notes.

impact upon knock-in events.

It is possible, however, that $N2V$ is correlated with future economic conditions. In particular, retail investors may chase the past stock return. A stock that had recently generated a high return may draw investor attention and drive a large SEP issuance. When such issue-timing occurs near the peak of the economic cycle, multiple SEPs will be simultaneously knocked-in (resulting in high $N2V$) during a subsequent downturn. In this case, a high $N2V$ may coincide with a more negative return because of the issuance timing. To circumvent this concern, we use $N2V$ with an interactive industry fixed effect and event calendar time fixed effect that controls for the industry-wide economic condition.

2.3. Empirical design

As a first step, we examine the pattern of underlying stock price movements around knock-in events. To this end, we use the event window that ranges from 5 trading days prior to and 5 trading days after a knock-in event. To focus on stock-specific price movements, we use standard market-adjusted cumulative abnormal returns (CARs) following Ritter (1991) and MacKinlay (1997). Specifically, for event j that occurs at $t(j)$, the CAR of affected stock $i(j)$ on event day $\tau \in [-5, +5]$ is calculated in the following way:

$$CAR_{j,\tau} = \sum_{q=-5}^{\tau} \Big\{ R_{i(j),t(j)+q} - R_{m,t(j)+q} \Big\}, \tag{3}$$

where $R_{i,t}$ is the return on stock i on day t, $R_{m,t}$ is the return on the market index (KOSPI Composite) on day t, $i(j)$ is the affected stock at event j, and $t(j)$ is the event day of j. The reference point of the CAR is 5 days prior to the event day ($t-5$), which corresponds to the inception point of the event window.

To show the event-time-variation price pattern, we use the following specification. For event j that occurs at $t = t(j)$, we regress the CAR of affected underlying stock $i = i(j)$ on event-day-dummy variables $\mathbf{D}$:

$$CAR_{j,\tau} = \alpha_{I(i)\times M(t)} + \sum_{\tau=-5}^{5} \beta_\tau \cdot \mathbf{D}_\tau + \gamma X_{i,t-10} + \varepsilon_{j,\tau}, \tag{4}$$

where $I(i)$ is the industry of stock i as per the Korea SIC 2-digit classification, $M(t)$ is the calendar month of day t, $\mathbf{D}_\tau$ is an indicator variable whose value is 1 only on event day τ and 0 otherwise, and X is a vector of control variables using the most recent information on firm i known at $t-10$. We lag the control variable to avoid an endogenous event-driven correlation between the control variable and the outcome variable. Specifically, we use 10-day lag because events are distanced from each other by more than 10 days in our non-overlapping sample. Although we adjust for the market return via CAR, economic conditions across industries at the event time may vary. To control for industry-wide variation, we use Industry × Month fixed effects $\alpha_{I(i)\times M(t)}$ that correspond to each event. Therefore, our results are robust to heterogeneity in industry-specific economic conditions or unobservable expectations around the event time. Our coefficients of interest are β_τ ($\tau = \{-5, ..., +5\}$). The estimated dynamics of the abnormal return would suggest whether a knock-in event imposes a price dislocation.

More formally, we use $N2V$ in Equation (2) to distinguish the effects of unwinding from changes in firm fundamentals. For event j, we regress the CAR of affected underlying stock $i = i(j)$ on the event day $t = t(j)$ on $N2V$ of the same event j:

$$CAR_j = \alpha_{I(i)\times M(t)} + \beta N2V_j + \gamma X_{i,t-10} + \varepsilon_j. \tag{5}$$

Other variable definitions are identical to those used in Equation (2) and Equation (4). The coefficient β in Equation (5) would differentiate the CAR on stock i on the *event day* across the variation by predetermined $N2V$. As a higher $N2V$ corresponds to higher hedging intensity, a negative β would provide strong evidence that hedging causes price dislocations while alleviating the concern that the abnormal return is a consequence of unobserved changes in firm fundamentals that happen to coincide with knock-in events.

2.4. Dynamic price impact

The results reported in Panel (a) of Figure 3 illustrate the dynamics of CAR as defined in Equation (3). Using Equation (4), we plot the point estimates of each β_τ and its 90% confidence interval. The knock-in events are asynchronous. To clearly investigate the dynamics around an event, we use the non-overlapping sample in this analysis. In this subset, we allow only one event to exist in the 11-day window to avoid convolution from event overlap. The 11-day (5 days before and 5 days after) window is chosen under the consideration of the trade-off between the sample size and pre/post-event observations. Consequently, the total sample size for Panel (a) is 3,300 (300 unique events × 11 days). We note that, on the knock-in day (the vertical line), the CAR becomes noticeably negative at 8 percent on average. This magnitude is both economically and statistically very significant. We first observe that the CAR is already negative prior to the event. This result may simply reflect the fact that a knock-in event occurs *as a result of* the negative return. It is also possible that the issuer foresees the knock-in and begins unwinding the position in advance. Such a pre-hedging activity may contribute to the declining CAR pattern. On the other hand, the negative CAR pattern flips over immediately after the knock-in.

This notable 'V' shape yields an implication regarding the source of the negative CAR prior to the knock-in. The negative CAR itself cannot sufficiently imply dislocation from the fundamental value resulting from the hedging activity. If the negative CAR peaks precisely at the moment of the knock-in event and CAR recovers immediately after, however, it is likely that the event-driven liquidation induces substantial price dislocation.

[Insert Figure 3 here.]

In Table III, we present the results derived from Equation (5). This analysis uses all samples because we estimate the price impact only on the event day and therefore there are no overlapping events. Since our events occur at different times and with different stocks, our outcome variables are subject to time-series as well as cross-sectional heterogeneity. To address the potentially confounding effects that this might cause, we include five specifications of control variables such as firm-specific variables (size and book-to-market) as well as past market information (past returns, the volatility of the affected stock and market returns) in addition to industry-time fixed effects. Across these specifications, the coefficient βs are consistently negative and highly significant. Upon a knock-in event, there is substantial price pressure on the underlying stock via hedging-driven liquidation. Quantitatively, a one-standard-deviation increase in $N2V$ corresponds to a 70 basis points more negative CAR.[17]

[Insert Table III here.]

These results also imply that, when knock-in events are clustered in time, the downward price pressure will be severe. If multiple SEPs are knocked-in on the same day, many aggregate shares would need to be liquidated, corresponding to a high $N2V$. Such a large scale unwinding, relative to the stock's intrinsic volume, would result in greater price dislocation. The original source of this amplification channel is that the issuance of SEPs itself was clustered. Although each institution limits its own issue size, the aggregate quantity can be far larger in the absence of a coordination device, partially defeating the purpose of the individual limit.

Several patterns regarding control variables are worth noting. Price dislocation is more severe for small firms, as measured by the natural log of the book value of assets. Also, a higher

[17] The standard deviation of $N2V$ is 0.1946. The estimated coefficient on $N2V$ is -0.036. Therefore, the magnitude of a one-standard-deviation of $N2V$ is about -0.70% (-0.0070=0.1946*(-0.036)).

degree of negative abnormal return is associated with a higher level of return volatility for the affected stock.[18] These patterns are consistent with Duffee (1995), who provides evidence that a stock's return is negatively correlated with its volatility, also suggesting that this relationship is strongest among small firms. During the event period when the affected stock return is likely to be negative, smaller firms with greater volatility earn relatively worse returns.

Finally, we repeat the estimation of the dynamic pattern separately for each subset of the event by $N2V$. We categorize our sample events into two groups using the median of $N2V$. We report the regression result with the subsample in the top and bottom groups in Panel (b) of Figure 3. This figure displays the point estimates of β_τ in Equation (4) when the events belong to the bottom $N2V$ group (the triangle marker) rather than the top $N2V$ group (the circle marker).

Both patterns form a similar 'V' shape. We further note that, on the event day, the CAR from events with high $N2V$ is significantly lower than in the case of low $N2V$. These figures are not statistically different from each other prior to the event, however, suggesting that the $N2V$ measure is not strongly correlated with variations other than the intensity of the immediate hedging. This result further supports our claim that the delta-hedging unwinding is the main driver of the price dislocation upon the knock-in event. In both cases, we observe the direct reversion after the event day. However, given the bigger drop on the event day, it takes longer for high-$N2V$ events to recover from the liquidation shock.

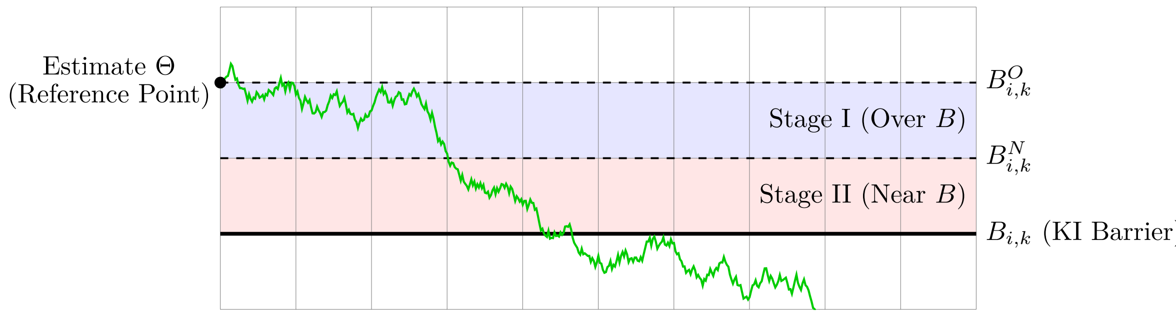
2.5. Parametric analysis of the knock-in barrier

In the previous section, we find that greater hedging intensity leads to more severe price dislocation. In the following analysis, we adopt a parametric approach to test whether price dynamics vary near the barriers. If the hedging activity distorts a stock's price, the existence of the barrier may alter the price dynamics near it. To test this, we divide the price range into two stages: Stage I ('Over') and Stage II ('Near'), based on the SEP barrier level. In Illustration 2, we show a simplified illustration of the stage classification by distance-to-barrier.

Consider an underlying stock i with t-price $S(t)$ and its associated SEP k whose barrier level is B and maturity is T. At reference time t, we set the 'Over' boundary B^O such that probability $\mathbb{P}(B^O \downarrow B^N) = P$. Similarly, we set the 'Near' boundary B^N such that the probabilistic distance to B is identical, i.e. $\mathbb{P}(B^N \downarrow B) = P$. Note that $\mathbb{P}(S(t) \downarrow B)$ is the

[18] Return volatility is annualized volatility using 1-month stock returns.

Illustration 2. Illustration of Stage Classification by Distance-to-Barrier



probability of hitting boundary B from $S(t)$ before the SEP's maturity T, as defined below using the first-passage time (Bielecki and Rutkowski, 2004):

$$\mathbb{P}(S(t) \downarrow B) \equiv \mathbb{P}(s \leq T \mid \mathcal{F}_t) = \Phi\left(\frac{-ln(\frac{S(t)}{B}) - \nu(T-t)}{\sigma\sqrt{T-t}}\right) + e^{-\frac{2\nu}{\sigma^2} ln\left(\frac{S(t)}{B}\right)} \Phi\left(\frac{-ln(\frac{S(t)}{B}) + \nu(T-t)}{\sigma\sqrt{T-t}}\right), \quad (6)$$

where $\Phi(\cdot)$ is the standard normal cumulative density function, the stock price $S(t)$ follows a standard Geometric Brownian Motion with the Wiener process W: $dS(t) = \mu S(t)dt + \sigma S(t)dW(t)$, and B is the barrier of interest. [19] Also, s is the first-passage time, i.e., $s = \inf\{t \geq 0 : S(t) \leq B\}$ and $\nu = \mu - \frac{1}{2}\sigma^2$. The parameter set as $\Theta = \{\mu, \sigma\}$ is estimated via Maximum Likelihood Estimation (MLE) using prior 252-day (12-month) returns at the reference point $S(t) = B^O$.

Specifically, on each day t, we estimate the Θ for stock i that underlies SEP k. With the estimated Θ, we use $P = 90\%$ to define B^O and B^N using Equation (6).[20] We first determine B^N such that it satisfies $\mathbb{P}(B^N \downarrow B) = 90\%$. We then subsequently find B^O to meet the equidistance requirement: $\mathbb{P}(B^O \downarrow B^N) = 90\%$. Next, we compare the current stock price $S(t)$ with B^O, and set t as a reference date if $S(t) = B^O$. We repeat this process for each day during the k contract period. Once a reference date is set, we fix B^O and B^N to define the intervals, as follows:

$$\text{Stage I (Over KI Barrier)}: \quad S_i \in (B^N_{i,k},\ B^O_{i,k}]$$
$$\text{Stage II (Near KI Barrier)}: \quad S_i \in (B_{i,k},\ B^N_{i,k}]$$

[19] $\mathcal{F}_t$ is a filtration within time t, and so represents the information known at time t.
[20] The choice of 90% is arbitrary. However, our results are robust to several reasonable threshold choices.

In Stage I, the stock price level is relatively distant from the knock-in barrier, as it lies between $B^N_{i,k}$ and $B^O_{i,k}$. On the other hand, as the stock price enters Stage II, the knock-in is far more probable. We compare parameters estimated in both stages against those estimated at the reference point. We conjecture that the existence of the knock-in barrier alters the return dynamics of the underlying stock. In this case, we should be able to observe that distortion of the dynamics is most pronounced near the barrier.

If the boundaries that define Stages I and II are static, we may have two returns for completely separate periods in the same stage. Imagine that a stock enters Stage I at t as $S(t) \leq B^O$ and then the next day immediately exits the stage as $S(t+1) > B^O$. If this stock re-enters Stage I, say, a year later, as $S(t+252) \leq B^O$, these two returns assigned in Stage I are one-year apart, and they may reflect different macro or firm-specific conditions. To reduce this noise, we reset the boundaries by a cycle.[21] A cycle c is initiated by entering Stage I and terminated by exiting Stage I. Our earlier illustration, therefore, encompasses two cycles and the boundaries become cycle-specific. This process makes our observation unit also cycle-specific $i-k-c$, as opposed to the observation level used in the previous analyses: stock(i)-contract(k). Also, in this analysis, we include all $i-k$ pairs even if the knock-in events had never occurred. When the stock hits the barrier B, however, the corresponding $i-k$ is never assigned to any cycle and is removed from the subsequent analysis.

When stock i that underlies SEP k touches below the 'Over' boundary or $B^O_{i,k}$, we classify the daily return into either stage g (g=I or II) depending on the location of the stock price in the interval, as long as the returns belong to the same cycle c.

Figure 4 plots the fitted normal distribution for returns in Stage I ('Over') and Stage II ('Near'). The graph represents the mean and volatility distribution of average returns estimated for each $i-k-c$ pair combination from a total of 16,736 contracts. The blue (red) solid line represents the distribution of daily returns that belong to Stage I (II). The blue (red) vertical dotted line represents the location of the sample mean of Stage I (II). This figure shows that Stage II has a lower mean and greater volatility than Stage I, indicating that the stock price gravitates to the barrier as it approaches it. We refer to this phenomenon as the 'magnet effect' of the knock-in barrier.

To analyze the magnet effect formally, we compare these distributions while controlling for firm characteristics or market conditions. For each classification p by which an $i-k-c$ pair touches $B^O_{i,k,c}$,

$$\mu_p = \alpha_{I(p)\times M(p)} + \beta \cdot \mathbf{II}_p + \gamma X_{i(p),t(p)} + \varepsilon_p, \tag{7}$$

[21] In this set-up, the boundaries are c-dependent, i.e. $B^N_{i,k,c}, B^O_{i,k,c}$. For the sake of brevity, we describe the construction process and define the boundaries without the c notation, assuming that only one cycle exists.

where μ_p is the drift term of the return dynamics in classification p. $\mathbf{II}_p$ is an indicator function that equals to 1 when the price falls in Stage II. X is a vector of firm characteristics and $\alpha_{I(p)\times M(p)}$ is the Industry $\times$ Month fixed effect corresponding to each classification. Stage I is the omitted category.

Similarly, we estimate the regression on the standard deviation as follows:

$$\sigma_p = \alpha_{I(p)\times M(p)} + \beta \cdot \mathbf{II}_p + \gamma X_{i(p),t(p)} + \varepsilon_p, \tag{8}$$

where σ_p is the diffusion term of the return dynamics in classification p. Definitions for $\mathbf{II}_p$, X, and $\alpha_{I(p)\times M(p)}$ are identical to those used for Equation (7).

Table IV shows the results of the regression. We find consistently that the parameters estimated in Stage I and Stage II differ from one another. The results reported in Panel (a) show that the drift term in Stage II is significantly smaller than the one in Stage I. The results are robust after controlling for firm characteristics and market conditions as well as unobserved heterogeneity across industries at different times. Specifically, the estimated drift of Stage II is lower by -20 basis points in daily terms compared with what occurs in Stage I. The results reported in Panel (b) indicate that the diffusion term in Stage II is larger than that in Stage I by an economically huge margin: about 40-50 basis points in daily term. Generally, we find a strong support for the magnet effect of the knock-in barrier.

[Insert Figure 4 and Table IV here.]

3. Event Chain Reaction

3.1. Knock-in cascade

The parametric results as well as declining CAR prior to a knock-in event shown in Figure 3 indicate that the stock price gravitates toward the barrier level (magnet effect), shortening the distance to the next adjacent barrier for this mechanism to repeat itself. On the other hand, as a result of competition, contemporaneously issued SEPs on the same underlying assets are likely to have similar knock-in barriers. Given the magnet effect as well as the homogeneity of barrier level, a knock-in event may cause another, creating a cascade of events.

The possibility of multiple issue waves imposes an empirical challenge. The barrier levels are alike within a cluster. However, if there is another wave that occurred at a sufficiently different time, the average barrier levels across two clusters may differ. While the cascading is plausible within a cluster, it is difficult to separate waves and perform within-cluster analysis because they are not separated by clear borders.

To address this problem, we exploit a variable that allows us to select candidate SEPs whose barriers are within a certain proximity. Specifically, for knock-in event j, its corresponding stock $i = i(j)$ and event time $t = t(j)$, we construct the variable as follows:

$$Z_j \equiv Z_{i,t} = \frac{1}{\mathrm{n}[\mathbf{K}'_{i,t}]} \sum_{k \in \mathbf{K}'_{i,t}} \mathbb{P}(s \leq T \mid \mathcal{F}_t)_{i,k,t}, \tag{9}$$

where $\mathbf{K}'_{i,t}$ is a set of outstanding SEPs underlaid by stock i whose barriers have never been touched as of t, $\mathrm{n}[\mathbf{K}'_{i,t}]$ is the number of SEPs in $\mathbf{K}'_{i,t}$, and finally $\mathbb{P}(s \leq T \mid \mathcal{F}_t)_{i,k,t}$ is the probability of hitting the barrier before the SEP's maturity T as defined in Equation (6). Z is therefore the average of this probability across SEPs in $\mathbf{K}'_{i,t}$. A high $Z_j = Z_{i(j),t(j)}$ implies that, on average, outstanding SEPs on stock $i = i(j)$ have barriers close to be touched sometimes subsequent to $t = t(j)$.

3.2. Empirical design

We propose a model to test whether a contemporaneous knock-in event increases the future knock-in probability. To this end, for each event j, we construct an indicator variable $KI_{i,(t+1,t+10)}$ that yields 1 if there is any knock-in on the same underlying $i = i(j)$ in the next 10 days from the event time $t = t(j)$ and 0 otherwise. With this variable, we specify a Probit model using $N2V$ as the measure of hedging activity intensity as follows:

$$KI_{i,(t+1,t+10)} = \Phi\Big(\alpha_{I(i)\times M(t)} + \beta N2V_j + \gamma X_{i,t-10} + \varepsilon_j\Big), \tag{10}$$

where $\Phi(\cdot)$ is the standard normal cumulative density function, $KI_{i,(t+1,t+10)}$ is as defined above, and all other variable definitions are identical to those used in Equation (2) and Equation (4). The coefficient β of the above equation would reveal whether the price shock driven by one event would lead another to occur, underpinning the chain reaction mechanism.

Further, to observe whether such a shock is propagated to other SEPs with barriers close by, we divide total events into terciles of $N2V$ and Z. The SEPs that belong to the top tercile of Z are likely those issued during the same issue wave, and therefore interactions between these two terms allows us to observe the cascading effect within an issue cluster. We propose the following categorical Probit specification:

$$
\begin{aligned}
KI_{i,(t+1,t+10)} =& \Phi\Big(\alpha_{I(i)\times M(t)} + \beta_1 N2V_j^M + \beta_2 N2V_j^H + \beta_3 Z_j^M + \beta_4 Z_j^H + \beta_5 N2V_j^M \cdot Z_j^M \\
& + \beta_6 N2V_j^M \cdot Z_j^H + \beta_7 N2V_j^H \cdot Z_j^M + \beta_8 N2V_j^H \cdot Z_j^H + \gamma X_{i,t-10} + \varepsilon_j\Big),
\end{aligned} \tag{11}
$$

where Z is defined as it is for Equation (9), and $N2V_j^{H,M}$ and $Z_j^{H,M}$ are dummy variables that indicate if i belongs to the top tercile (H) or mid tercile (M) of the respective measure. $N2V_j^L$ and Z_j^L are the omitted category. All other variable definitions are identical to those used in Equation (4). The coefficients of interest are those on the interaction terms (β_{5-8}), as they would reveal the chain reaction mechanism.

3.3. Results of event chain reactions and related discussion

Table V presents the results derived from Equation (10). For ease of interpretation, we report the marginal effect of each variable at the mean with five sets of control variables. The coefficients therefore measure the instantaneous rate of change at the mean of each variable. Across all specifications, our results show that higher $N2V$ of the contemporaneous event increases the probability of knock-in during the following 10 days. We find that event-driven liquidity demand leads other SEPs to knock-in. The effect on future knock-ins is both statistically and economically significant. Using the specification reported in Column (5), we estimate that a one-standard-deviation increase in $N2V$ increases the future knock-in probability by 5.3%, holding all other explanatory variables constant.[22]

[Insert Table V here.]

In Table VI, we report the regression results derived from Equation (11) and further clarify how $N2V$-related effects are propagated to subsequent knock-ins. Our results show that price pressure caused by a current event increases the knock-in probability in a sequential order measured by Z. Neither $N2V$ nor Z alone appears to induce future knock-ins. However, a high $N2V$ (indicated by $N2V^H$) is more likely to lead to subsequent knock-ins of SEPs when their barriers are closer to the barrier of the current event (indicated by Z^H). According to the results reported in Column (5), for example, an event corresponding to the high-Z, high-$N2V$ group is 15.7% more likely to trigger future knock-in than the high-Z, low-$N2V$

[22] The mean of $N2V$ is 0.0995 and the standard deviation is 0.1946. The predicted probability of $N2V$ at the mean level is 0.7284 and the predicted probability at a one-standard-deviation increase above the mean level (0.2941 = 0.0995+0.1946) is 0.7814. Therefore, the marginal effect of a one-standard-deviation increment of $N2V$ at the mean is 5.3% (0.0530=0.7814-0.7284).

group.[23]

These results not only provide additional support for the chain reaction mechanism, but they also further alleviate the concern that $N2V$ correlates with a market condition in a particular way. In the previous analysis of events that are contemporaneous with $N2V$, we address this with Industry × Month fixed effects. As we examine future events, however, Z helps us rule out the possibility of there being a spurious relationship between $N2V$ and future knock-ins. We are concerned in particular that $N2V$ could be larger in the period of negative returns for reasons unrelated to the liquidity demand measured by $N2V$. Then, $N2V$ would be positively correlated with the future knock-ins, but not because of liquidity demand. On the other hand, during the period of negative returns, Z would decrease continuously as more SEPs from the same issue-vintage experience knock-ins and eventually disappear from the subsequent calculation of Z.

To illustrate this point, suppose that there is only one SEP of a specific vintage whose barrier remains untouched. Also suppose that a latent variable orthogonal to liquidity demand drives $N2V$ larger and the underlying asset's return more negative, as we have surmised. Once the SEP is knocked-in, the corresponding Z would become small since it is based entirely on SEPs from another cluster with a substantially lower barrier level. Then, the positive correlation of $N2V$ and the future knock-in probability must be stronger when Z is small.

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

[Insert Table VI here.]

4. Strategic Hedging Activity

4.1. Measures of a future knock-in

In the presence of event-driven price pressure and event cascading, changes in an expected shock can alter hedging behavior upon a knock-in. Also, how a trader executes hedging operation may differ depending on her incentives. In this section, we examine this possibility. To this end, we construct a 'remaining-to-volume,' or '$R2V$' ratio. This variable, like $N2V$,

[23] In the high Z group (Z^H), the predicted probability associated with the high-$N2V$ group is 0.8550, and the predicted probability of low-$N2V$ group is 0.6977. Therefore, the marginal effect of $N2V^H$ on the dependence of the future knock-in probability Z^H is 15.7% (0.1573=0.8550-0.6977).

measures the price impact of a contemporaneous knock-in, except that $R2V$ is related to the price impact of unrealized future knock-ins. Specifically, for underlying stock i and event time t corresponding to event j (i.e., $i = i(j), t = t(j)$), we aggregate the notional amount of SEP k in the relevant set $\mathbf{K}''_{i,t}$, and then normalize it by the average volume of stock i:

$$R2V_j \equiv R2V_{i(j),t(j)} = \frac{\sum_{k \in \mathbf{K''_{i,t}}} Notional_k}{Volume_{i,\bar{t}(\mathbf{K}''_{i,t})}}, \tag{12}$$

where $\mathbf{K}''_{i,t}$ is a set of outstanding SEPs underlaid by stock i whose barriers have never been touched as of t, $Notional_k$ is the notional size of SEP $k \in \mathbf{K}''_{i,t}$ divide by total number of underlying assets, and $Volume_{i,\bar{t}(\mathbf{K}''_{i,t})}$ is the 6-month average dollar volume of stock i as of the earliest issue date among SEPs in $\mathbf{K}''_{i,t}$ denoted by $\bar{t}(\mathbf{K}''_{i,t})$.

From this baseline measure, we construct three additional sub-$R2V$ variables. $R2V^1_j$ uses only SEPs whose distance between their barriers and the barrier associated with event j is the smallest among $\mathbf{K}''_{i,t}$. In other words, $R2V^1$ is based on SEPs whose barriers are immediately below the currently touched barrier (the first immediate barrier). $R2V^2_j$ and $R2V^3_j$ are created in the same way with the second and third immediate barriers, respectively. Given the strict knock-in order among $R2V^1$, $R2V^2$, and $R2V^3$, we conjecture that $R2V^1$ provides the most relevant information while the three ratios may have differential impacts on the hedging behavior.

To study strategic hedging behaviors, we further decompose $R2V^1$ based on issuer identity. Specifically, we split $R2V^1$ into an in-house portion and an external portion. The in-house portion ($R2V^1_{j,in}$) exploits only SEPs issued by the same issuer at event j in the corresponding set $\mathbf{K}''_{i,t}$ with $i = i(j)$ and $t = t(j)$, whereas the external portion ($R2V^1_{j,ex}$) uses the remaining SEPs in the same set whose issuers differ.

4.2. Incentives for strategic execution

Rational delta-hedging traders may have numerous incentives that affect how they execute a transaction triggered by a knock-in event. We first discuss three distinct incentives and explore their testable implications for execution behavior.

1. **Price manipulation:** An issuer of SEP is typically long the down-and-in barrier put option. If the trader is not sufficiently delta-neutralized, she may benefit from a knock-in event because it would activate the barrier option and the trader then becomes a holder of the vanilla put. In this case, if she has a large position with an imminent knock-in (high $R2V^1_{in}$), she may unwind the current hedging in a relatively

more aggressive way to increase the probability of knock-in for her imminent position.

2. **Execution smoothing:** If a trader at the current event has additional positions to liquidate when subsequent knock-ins occurs with high likelihood (high $R2V^1_{in}$), she may want to avoid the price pressure from the current unwinding. In this case, she would liquidate the portion related to the current event in a smoother way to minimize the market impact.
3. **Liquidation 'rat race':** Suppose a trader needs to unwind a part of her position in response to the current knock-in and sees that other unaffiliated traders have large positions that are subject to imminent knock-ins (high $R2V^1_{ex}$). In this case, beyond the position related to the current event, she may go in front of the line and pre-execute the remaining position before the third-party trader imposes a negative price dislocation. In general, the presence of other parties' positions can induce current delta-hedgers to competitively pre-execute their positions, aggravating the price dislocation. This collective behavior resembles the 'rat race' mechanism that Brunnermeier and Oehmke (2013) analyze.

4.3. Empirical design

We first examine whether expected *future* knock-ins have any effect on the price shock when the *current* event occurs. In the spirit of Equation (5), we regress the CAR of underlying stock $i = i(j)$ on event day $t = t(j)$ upon knock-in event j on the future hedging-intensity measure $R2V_j$:

$$CAR_j = \alpha_{I(i)\times M(t)} + \beta R2V^q_j + \gamma X_{i,t-10} + \varepsilon_j \qquad (q = 1, 2, 3), \tag{13}$$

where $R2V_j$ follows Equation (12) and all other variable are defined as for Equation (4). Our coefficients of interest are β, as they would indicate whether the future knock-ins influence the abnormal return in response to the current event as well as the relative importance depending on the immediacy.

Next, we decompose the contribution to the price dislocation into a portion that is related to the contemporaneous liquidity demand and a portion that is related to the expected future unwinding. For this task, we simultaneously exploit the measures of contemporaneous effects ($N2V$) and future effects ($R2V^1$) of knock-in events as follows:

$$CAR_j = \alpha_{I(i)\times M(t)} + \beta_1 N2V_j + \beta_2 R2V^1_j + \gamma X_{i,t-10} + \varepsilon_j, \tag{14}$$

where $N2V$ and $R2V^1$ are defined as they are for Equations (2) and (12), respectively. Also, the definitions of all other variables are identical to those for Equation (4). Comparing β_1 and β_2 should reveal the relative importance of the two sources of the negative price impact.

Using issuer identity, we further discriminate the effects of future knock-ins when the next immediate position to be liquidated is an in-house position and when it is an external position. Given event j, its underlying stock $i = i(j)$ and event time $t = t(j)$, we use intensity measures of future knock-ins by issuer type:

$$CAR_j = \alpha_{I(i)\times M(t)} + \beta_1 N2V_j + \beta_2 R2V^1_{j,in} + \beta_3 R2V^1_{j,ex} + \gamma X_{i,t-10} + \varepsilon_j. \tag{15}$$

$R2V_{in}$ and $R2V_{ex}$ in Equation (15) are defined as they are for Equation (12) and the description following the equation. Controlling for liquidity demand related to the current event ($N2V$), comparing β_2 and β_3 should show the heterogeneous effects depending on issuer type on the price pressure upon the current event. All other variable definitions are identical to those used in Equation (4).

The external position measure $R2V_{ex}$ is subject to information accessibility. Practically speaking, the opaqueness of OTC derivatives markets makes it difficult for any issuer to discover its competitors' outstanding positions. Under the rat race explanation, the effects of $R2V_{ex}$ would be pronounced when the unwinding trader has an easy way to learn of the unaffiliated traders' outstanding SEPs and their terms. To test this possibility, we exploit an institutional shock to the information accessibility. On April 25, 2013, information on SEP issuance became electronically accessible to market participants. The database was prepared by the Korea Security Depository to enhance market transparency. Previously, such information had to be hand-collected from each institution's issuance report.

To formally test this possibility, we use the following specification. Given event j, for affected stock $i = i(j)$ and at event time $t = t(j)$:

$$\begin{aligned} CAR_j =& \alpha_{I(i)\times M(t)} + \beta_1 N2V_j + \beta_2 R2V^1_j + \beta_3 Ex + \beta_4 Post \\ &+ \beta_5 R2V^1_j \cdot Ex + \beta_6 R2V^1_j \cdot Post + \beta_7 Ex \cdot Post \\ &+ \beta_8 R2V^1_j \cdot Ex \cdot Post + \gamma X_{i,t-10} + \varepsilon_j, \end{aligned} \tag{16}$$

where $N2V$ and $R2V^1$ are defined as they are for Equations (2) and (12). Ex is an indicator variable whose value is 1 if the dominant portion of $R2V^1$ is competitors' and 0 otherwise.[24]

[24]In a simple case, Ex equals 1 when $R2V$ is composed entirely of external positions. In most cases, however, $R2V$ is composed of both in-house and external positions. In this case, we calculate the median of the external portion using these samples, and assign the value of 1 when the external portion is higher than the calculated median.

Post is also an indicator variable that equals to 1 if t is on or after the inception time of the data service (April 25, 2013) and 0 otherwise. All other variable definitions are identical to those for Equation (4). The coefficient on the triple interaction term, β_8, should reveal the differential effects of $R2V$ when it corresponds to mostly external positions and after competitors' information becomes readily available.

4.4. Results and discussion on strategic hedging behavior

Table VII presents estimation results derived from Equation (13). We find strong evidence that the imminent risk of price dislocation is priced in across all $R2V$s; however, the magnitudes of the $R2V$s varies. Specifically, $R2V^1$ as shown in Column (1) has the largest negative coefficient at the 1% significance level. As the degree of immediacy drops ($R2V^2$ and $R2V^3$), both the magnitude and statistical significance decrease. A one-standard-deviation increase of $R2V^1$ corresponds to a 72 basis points more negative CAR.[25] The economic magnitude is comparable to that associated with $N2V$. Our results reveal the pre-execution behavior of investors and indicate that $R2V^1$ is of first-order importance regarding price dislocation.

[Insert Table VII here.]

To compare the price impact of a current knock-in with that of future knock-ins, we estimate Equation (14) and report the results in Table VIII. We find that the economic magnitudes of $R2V^1$ are in line with the results reported in Table VII, even after controlling for liquidity demand the current event stimulates. This result confirms that those channels are independent. A one-standard-deviation increase in $R2V^1$ corresponds to a 61 basis points decrease in CAR, which is almost identical to the 60 basis points decrease that is associated with $N2V$, supporting the conclusion that, in terms of price impact, the expectation of a future knock-in is as important as the intensity of liquidation as a result of the current event.[26]

[Insert Table VIII here.]

We next estimate Equation (15) to reveal traders' strategic hedging behavior in the context of the incentives we have discussed. The results are presented in Table IX. While the magnitude of $N2V$ remains qualitatively unchanged, we find that the coefficients on $R2V^1_{in}$ are negative but not statistically different from zero. These results suggest that traders do not try to

[25]The standard deviation of $R2V^1$ is 0.0542 and the coefficient on $R2V^1$ is -0.132. Therefore, the marginal effect of a one-standard-deviation increment of $R2V^1$ is -0.72% (-0.0072=0.0542*(-0.132)).

[26]Insofar as $N2V$'s standard deviation is 0.1946 and the coefficient is -0.031, the marginal effect of a one-standard-deviation increment in $N2V$ is -0.60% (-0.0060=0.1946*(-0.031)). Since $R2V^1$'s standard deviation is 0.0542 and the coefficient of $R2V^1$ is -0.113, while the marginal effect of a one-standard-deviation increment in $R2V^1$ is -0.61% (-0.0061=0.0542*(-0.113)).

minimize the market impact of the knock-in event even if they have a substantial position to liquidate imminently. Also, we do not find sufficient evidence of price manipulation through traders, conducting overly aggressive executions to trigger future knock-in. Our interpretation of this result is that issuers are largely delta-neutralized and therefore they do not have a particular incentive to trigger a knock-in event: a potential gain from the put is likely to be offset by their hedging positions.

On the other hand, the coefficients on $R2V^1_{ex}$ are consistently negative and highly significant. This result supports the conclusion that a trader employs a preemptive hedging strategy. As she unwinds the position related to the current event (as measured by $N2V$), she appears to jump in front of the line and liquidates excess positions before competitors impose a negative price pressure, exhibiting liquidation 'rat race' behavior (Brunnermeier and Oehmke, 2013). Our findings suggest that such a game-theoretic strategy exacerbates the price dislocation.

[Insert Table IX here.]

Lastly, in Table X we report the estimation results derived from Equation (16). We find that the coefficients on $N2V$ are comparable to previous outcomes. Interestingly, the effect on $R2V^1$ is concentrated when the outstanding notional amount is composed predominantly of external positions *and* traders have easy access to information about outstanding SEPs issued by their competitors ($R2V^1 \times Ex \times Post$). In this case, we estimate a one-standard-deviation change on $R2V^1$ corresponds to a 2.8% decrease in CAR.[27]

This finding further supports the rat race explanation. Allowing traders easy access to competitors' positions induces strategic hedging behavior. Given the previous finding that one knock-in can trigger another, the game-theoretic incentive that unaffiliated traders have to front-run can create a significant market disruption. We find that improving the transparency of the market can sometimes serve as a mis-coordination device.

[Insert Table X here.]

5. Robustness Test

A selection of event windows involves a trade-off between sample size and the observable length of the dynamics. In our main analysis, we select an 11-day window, ranging from 5 days before to 5 days after the event, [-5,+5]. An alternative selection would compose a different sub-sample. To check whether our choice is subject to any particular selection bias

[27] The standard deviation of $R2V^1$ is 0.0542 and the coefficient of $R2V^1 \times Ex \times Post$ is -0.509. Therefore, the magnitude of a one-standard-deviation increment in $R2V^1$ is -2.76% (-0.0276=0.0542*(-0.509)).

that might contribute to the 'V'-shaped pattern, we repeat the dynamic analysis with three alternative event windows: [-3,+3], [-10,+10], and [-15,+15].

On the one hand, in an effort to ensure that we collect non-overlapping events, we reduce our window size to [-3,+3] and increase the numer of events from 300 to 373 at the expense of the event period. In Panel (a) of Figure 5 we plot the point estimates of each β_τ and its 90% confidence interval: for event j, we regress CAR of the affected underlying stock i of event j, i.e. $i(j)$, on event-day-dummy variables $\mathbf{D}$,

$$CAR_{j,\tau} = \alpha_{I(i)\times M(t)} + \sum_{\tau=-T}^{T} \beta_\tau \cdot \mathbf{D}_\tau + \gamma X_{i,t(j)-(2*T)} + \varepsilon_{j,\tau}, \tag{17}$$

where all the settings are identical to those used for in Equation (4) except the period of the window: $T = 3$. Our coefficients of interest are β_τ.

The results depicted in Panel (a) of Figure 5 consistently present a 'V'-shaped price dislocation in the [-3,+3] case. The magnitude of CAR drop on the event day t is about 3%, compared with the drop on the previous day, $t - 1$. It is worth noting that the confidence interval in this case is much tighter than for our earlier results obtained with [-5,+5], confirming that there is no selection bias and having larger samples increases the statistical power.

On the other hand, to check the post-event reversion pattern, we expand the event window to roughly two weeks ([-10,+10]). In Panel (b) of Figure 5 we plot the point estimates β_τ and their 90% confidence intervals as defined for Equation (17), with $T = 10$.

Widening the window means that the total number of non-overlapping events decreases from 300 events to 206 events. The post-event window widens, however, enabling us to observe a recovery pattern. In Panel (b) of the same figure, we find a more explicit 'V'-shaped CAR on the event day, and it recovers about half of the lose in CAR after two weeks. Given the possibility of return momentum or a cyclical trend in firm fundamentals, we do not expect CAR to recover up to the inception level of the event window. For the same reason, it is hard to define the reversion period in the absence of the counterfactual. Based on this figure, however, we confirm that the sharply reduced price impact does not disappear quickly: it takes roughly at least a week to recover.

Finally, we expand our window size to [15,+15] and the number of events drops further, from 206 to 179 events. In Panel (c) of Figure 5 we plot the point estimates β_τ and their 90% confidence intervals as defined for Equation (17), with $T = 15$. This result reiterates the 'V'-shaped pattern and also suggests that the acute price pressure does not resolve within a week. In this section, we test our model through various event windows and confirm that price dislocation caused by a hedging-driven liquidity shock exists regardless of window size.

[Insert Figure 5 here.]

6. Conclusion

In this paper, we document a salient case in which financial innovation can sometimes entail price disruption. In particular, a certain type of SEPs triggers a sudden and dramatic change in the delta position, forcing hedgers to immediately unwind a large position. This event occurs when the stock price breaches a pre-determined boundary. Such 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 ways. When a large number of products with similar triggering conditions have been issued in the market, one event can cause another, creating a cascade of price dislocations. In this case, the impact of a shock can last substantially longer. On the other hand, when a trader can observe her competitors' outstanding positions, she has an incentive to front-run others. This strategic hedging behavior can lead to coordination failure.

We believe that our results imply that issuance coordination is necessary. Practically every financial institution imposes a risk budget by itself. We show, however, that it is not sufficient to keep an aggregated quantity under a desirable level. Also, in the presence of pre-determined execution conditions, we find that a policy that requires other market participants' interest to be revealed does not necessarily enhance market stability.

More broadly, our finding has theoretical implications for options pricing. Our findings suggest that pricing derivatives can be more complex than a typical option-pricing model without a hedging-related price impact implies. This complexity is particularly severe with exotic derivatives. Such options often induce dramatic transactions involving the underlying assets, generating notable price impacts that feed back to the option value. This characteristic exacerbates the complexity of pricing already-complex derivatives.

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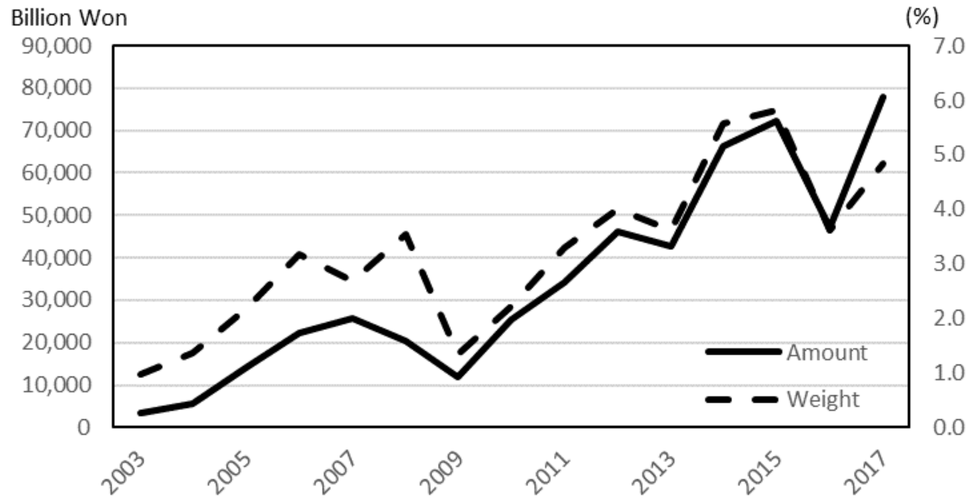
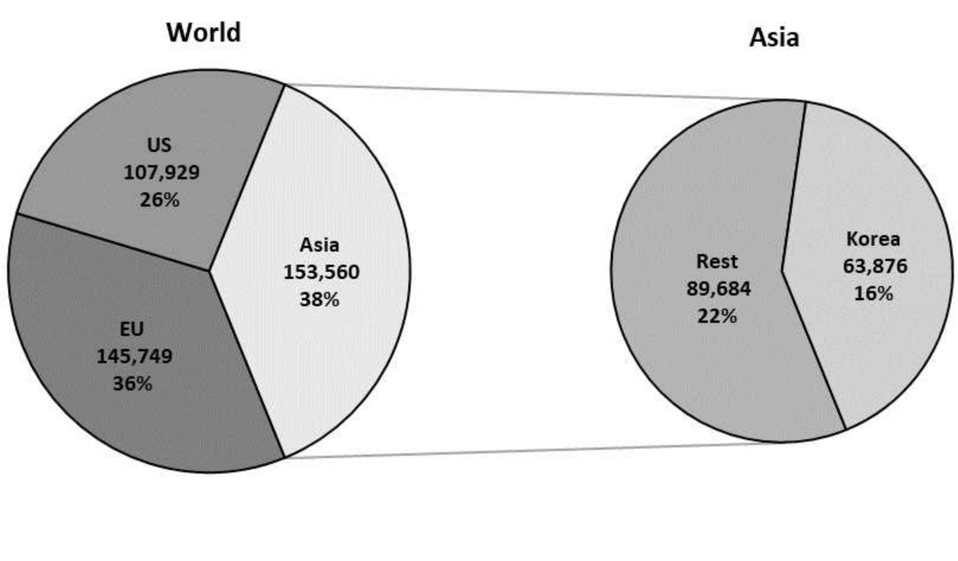
Figure 1. Overview of Structured Equity Products (SEPs) Market

Panel (a) shows the aggregate pattern of SEP issuance in Korea. From 2003 through 2017, the annual average growth rate of the issue volume has been 23 percent. The solid line represents the aggregate issuance amount of SEPs and the dotted line illustrates the portion of the aggregated issuance amount of SEPs of Korean equity market capitalization. The growth steepens after the 2008 Global Financial Crisis (19.4% versus 23.1%), during the low-interest-rate regime (Korea's benchmark rate on average is 2.1% in the post-crisis versus 4.3% in the pre-crisis period). Panel (b) illustrates the share of outstanding balances across markets for SEPs whose payoffs feature a specific 'knock-in' barriers. The pie chart on the left shows the portion of products distributed across the U.S., European, and Asian markets, and the right presents the share of the Korean market.



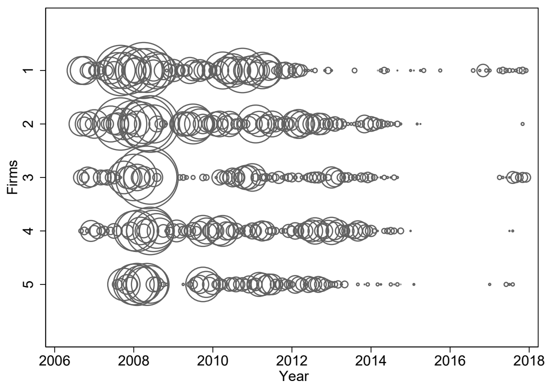
(a) SEPs Issuance in the Korean Market



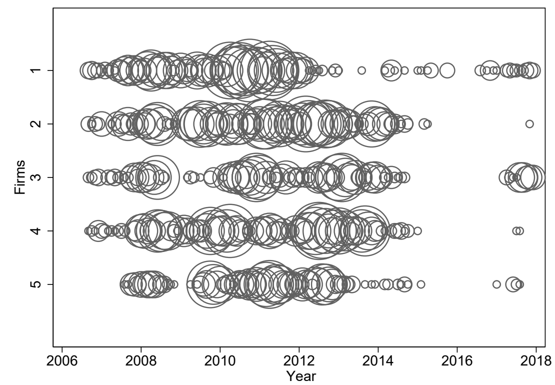
(b) Distribution of 'Knock-In' Type SEPs in the Global Market

Figure 2. Issuance Herding and Knock-in Crowding

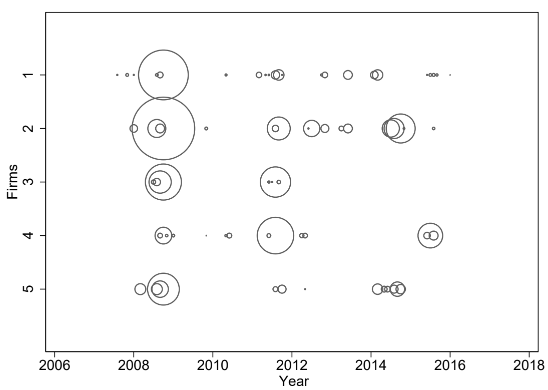
The figure visualizes how issuance and knock-in events are concentrated at a certain time. We select the top 5 stocks from our sample (for a total of 90 stocks) based on the total amount of SEPs whose barriers are breached during our sample period, and place them along the vertical axis (ranging from the biggest stock to the fifth-biggest stock). Circle size on the horizontal axis represents the notional size (Panel (a)) or the number (Panel (b)) of newly issued notes corresponding to each stock in each month on the horizontal axis. Likewise, circle size represents the notional size (Panel (c)) or the number (Panel (d)) of SEPs that are subject to knock-in events. We match the same firms across the panels.



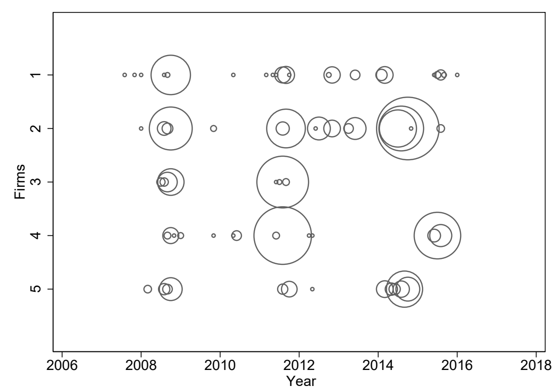
(a) Issuance Herding (Amount)



(b) Issuance Herding (Unit)



(c) Knock-in Crowding (Amount)



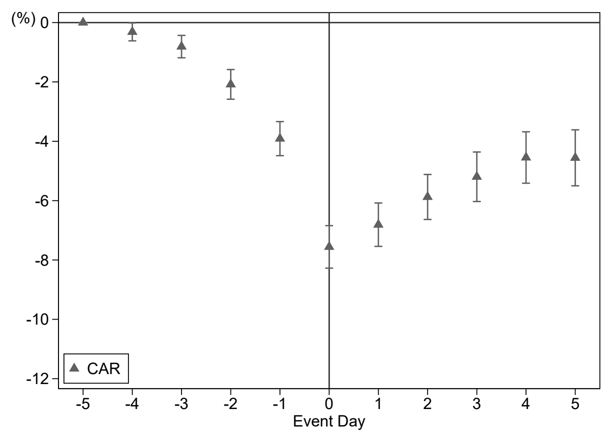
(d) Knock-in Crowding (Unit)

Figure 3. Cumulative Abnormal Return Variations around Knock-in Events [-5,+5]

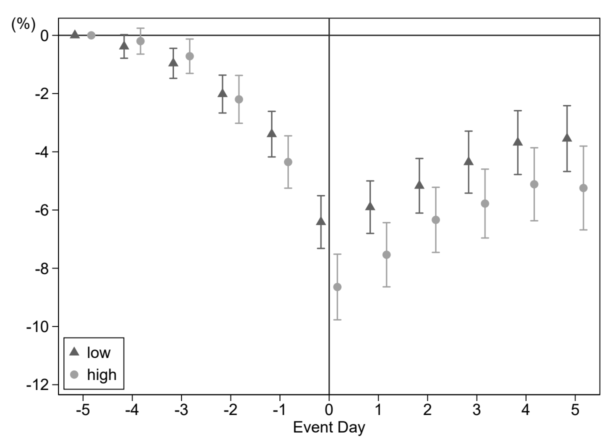
This figure plots the event-time pattern of CARs. For event j that occurs at $t = t(j)$, we regress the CAR of affected underlying stock $i = i(j)$ on event-day-dummy variables $\mathbf{D}$:

$$CAR_{j,\tau} = \alpha_{I(i)\times M(t)} + \sum_{\tau=-5}^{5} \beta_\tau \cdot \mathbf{D}_\tau + \gamma X_{i,t-10} + \varepsilon_{j,\tau},$$

where $I(i)$ is the industry of stock i as per the Korea SIC 2-digit classification, $M(t)$ is the calendar month of day t, $\mathbf{D}_\tau$ is an indicator variable whose value is 1 only one event day τ and 0 otherwise, and X is a vector of control variables using the most recent information on firm i known at $t - 10$. $\alpha_{I(i)\times M(t)}$ is the Industry × Month fixed effects corresponding to each event. The figure presents the point estimates of each β_τ ($\tau = \{-5, ..., 5\}$) and its 90% confidence intervals. Panel (a) shows the average knock-in effect of non-overlapping samples on CAR. Total sample size of Panel (a) is 3,300 (300 events × 11 days). In Panel (b), we categorize our sample events into two groups using the median of $N2V$. Panel (b) displays the point estimates when the events fall into the bottom $N2V$ group (triangle marker) versus the top $N2V$ group (circle marker). Both of the sample size for the bottom $N2V$ and the sample size for the top $N2V$ groups are 1,650 (150 events × 11 days). The knock-in days are plotted by the vertical line and $t - 5$ is an omitted category.



(a) Aggregate Knock-in Effects on CAR



(b) Knock-in Effects on CAR: Top versus Bottom N2V

Figure 4. Comparison of Return Distribution between the Stages

This chart illustrates the fitted normal distribution for returns in Stage I and Stage II. For underlying stock i, its SEP contract k, and cycle c, each stage is defined using each threshold (B^O, B^N, B) through Equation (6). Each $i-k-c$ pair has a return distribution available to estimate the average return in each stage. The graph represents the mean and volatility distributions of average returns estimated for each $i-k-c$ pair combination from a total of 16,741 contracts. The blue (red) solid line represents the distribution of daily returns that belong to Stage I (II). The blue (red) vertical dotted line presents the locations of the sample means of Stage I (II). The x-axis of the graph represents the return in percentages, and the y-axis represents the density of probability.

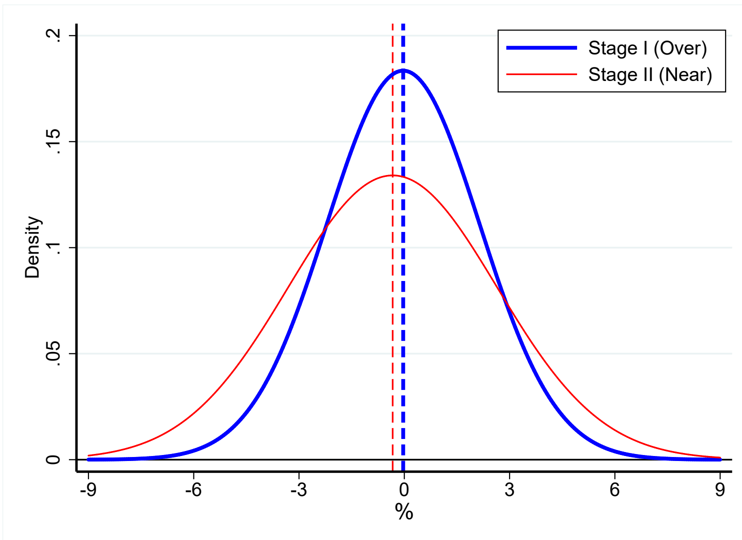
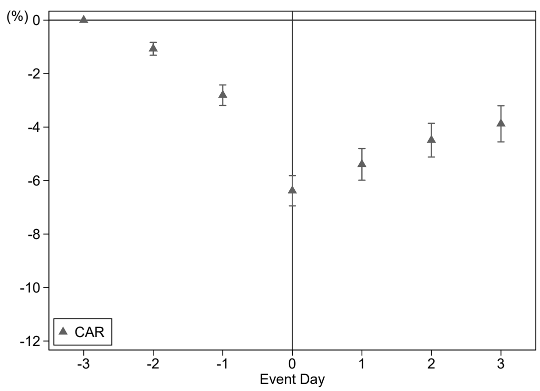


Figure 5. Cumulative Abnormal Return around Knock-in Events with Various Event Windows

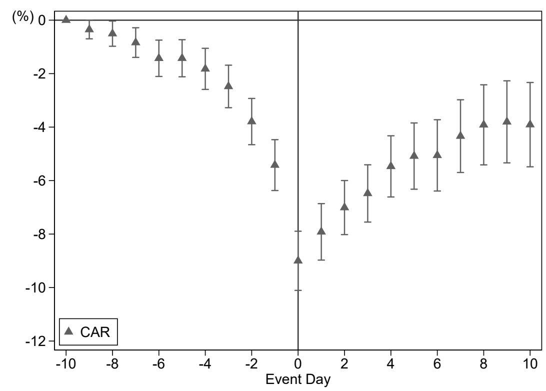
The figure describes the event-time pattern of CARs. For event j that occurs at $t = t(j)$, we regress the CARs of affected underlying stock $i = i(j)$ on event-day-dummy variables $\mathbf{D}$:

$$CAR_{j,\tau} = \alpha_{I(i)\times M(t)} + \sum_{\tau=-T}^{T} \beta_\tau \cdot \mathbf{D}_\tau + \gamma X_{i,t(j)-(2*T)} + \varepsilon_{j,\tau},$$

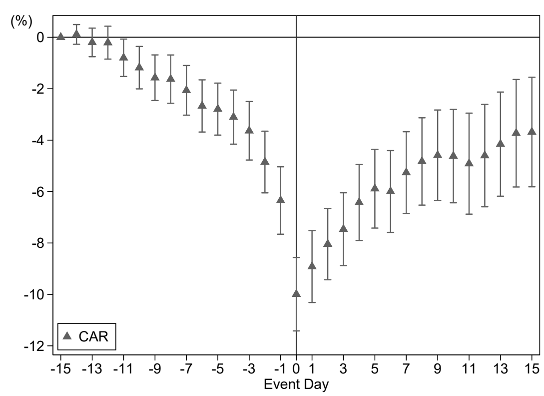
where $I(i)$ is the industry of stock i as per the Korea SIC 2-digit classification, $M(t)$ is the calendar month of day t, $\mathbf{D}_\tau$ is an indicator variable whose value is 1 only on event day τ and 0 otherwise, and X is a vector of control variables using the most recent information on firm i known at $t-(2*T)$. $\alpha_{I(i)\times M(t)}$ is the Industry $\times$ Month fixed effects corresponding to each event. This figure presents the point estimates of each β_τ and its 90% confidence intervals. Since the window size of Panel (a) is [-3,+3], $T = 3$. Similarly, $T = 10$ is set for Panel (b) and $T = 15$ is set for Panel (c). The total sample size for Panel (a) is 2,611 (373 events $\times$ 7 days), for Panel (b) it is 4,326 (206 events $\times$ 21 days), and for Panel (c) it is 5,549 (179 events $\times$ 31 days). The knock-in days are plotted by the vertical lines and $t-T$ is an omitted category.



(a) Aggregate Knock-in Effects on CAR [-3,+3]



(b) Aggregate Knock-in Effects on CAR [-10,+10]



(c) Aggregate Knock-in Effects on CAR [-15,+15]

Table I. Data Description

In Panel (a), the first two rows show the amounts and shares of outstanding balances across markets for structured equity products (SEPs) whose payoffs feature specific ‘knock-in’ barriers in 2019. The following two rows include total stock market capitalization and the ratio of the outstanding balance of SEPs to total stock market capitalization in 2019. Amounts are presented in millions of U.S. Dollars and ratios are in percentages. Panel (b) illustrates the process of sample selection from 2006 through 2017. The results reported in Panel (c) indicate the time trends of SEP issuance and knock-in events. The issuance column of the table includes the total number of SEPs, the aggregate notional amounts, and the unique numbers of underlying stocks by year of issuance. The knock-in column presents the comparable quantities, conditioned on the assumption that the knock-in event has been triggered in the corresponding year.

(a) Distribution of SEPs by Region

	US	EU	Asia	Korea
SEPs (USDm)	107,929	145,749	153,560	63,876
SEPs/Gobal SEPs (%)	26.50%	35.79%	37.71%	15.69%
Exchange ME (USDm)	37,689,256	8,078,749	23,820,189	1,489,611
SEPs/Exchange ME (%)	0.29%	1.80%	0.64%	4.29%

(b) Sample Selection

Filter	Sample Size	No. of Stock
Initial Sample: SEPs between 1/2006 - 12/2017	38,035	141
Excluding SEPs (w/ foreign underlying stocks, non-downside knock-in barrier, missing barrier and issue amount info)	21,273	
Filtered SEPs	16,736	122
Excluding SEPs with un-knock-in event	8,562	
Final Sample: SEPs with knock-in event	8,174	90
Final Sample: SEPs knock-in event days (Aggregate the events when a stock triggers multiple knock-in events on the same day)	1,296	90

(c) Time Trend of SEPs in Korea

	Issuance			Knock-In		
Year	N.Obs (1 unit)	Amount (bil. KRW)	Stock (1 unit)	N.Obs (1 unit)	Amount (bil. KRW)	Stock (1 unit)
2006	237	1,544	43	.	.	.
2007	882	5,808	62	16	83	4
2008	1,228	5,736	61	1,604	9,342	65
2009	1,456	2,900	55	14	19	3
2010	2,551	3,878	73	25	27	6
2011	3,231	4,105	78	2,152	3,028	59
2012	3,339	3,307	72	386	481	27
2013	2,106	1,630	79	756	832	28
2014	796	377	59	1,915	1,784	28
2015	135	54	38	1,186	814	29
2016	139	135	27	109	53	11
2017	636	499	52	11	3	3
Total	16,736	29,974	122	8,174	16,466	90

Table II. Summary Statistics

In this table we report the summary statistics for selected variables. $N2V$ ('notional-to-volume') is associated with the extent of liquidation intensity, where we normalize the notional amounts SEPs related to knock-ins by trading volume of the underlying stocks. Z measures the average future knock-in probability across SEPs on the same underlying stocks of a givien knock-in event. $R2V$ ('remaining-to-volume') is related to the price impact of unrealized future knock-ins, where we normalize the remaining notional amount by trading volume of the underlying asset. From this baseline $R2V$, we construct three sub-$R2V$ variables. $R2V^1$ is based on SEPs whose barriers are immediately below the currently touched barrier (the first immediate barrier). $R2V_j^2$ and $R2V_j^3$ are created in the same way with the second and the third immediate barriers, respectively. We further decompose $R2V^1$ based on issuer identity. Specifically, we split $R2V^1$ into an in-house portion and an external portion. The in-house portion ($R2V_{in}$) indicates only the portion of $R2V$ when an issuer who has knocked-in SEPs still has remaining SEPs under the same underlying stock, whereas the external portion ($R2V_{ex}$) uses the remaining SEPs in the same set whose issuers are different. Detailed functional definitions of $N2V$, Z, and $R2Vs$ are given for Equations (1), (9), and (12), respectively. For $N2V$, Z, and $R2V$, we aggregate the structured note information based on stock level to convert the data structure to event-day $\times$ stock-level information. Size is the logarithm of the book value of asset (values given in thousands). Book-to-market is the book value of equity / the market value of equity. RVol is annualized volatility using 1-month stock return. The sample size for $N2V$, Size, Book-to-market, Average 1-month stock returns, and Average 6-month index returns is 1,296, which is the same as the total sample represented in Table I, while the sample size for Z and $R2Vs$ is 1,229 because we rule out cases in which $R2Vs$ equals zero.

	Mean	St.Dev	25th Pct.	Median	75th Pct.	N
N2V	0.0995	0.1946	0.0096	0.0288	0.1035	1,296
Z	0.7999	0.2138	0.7202	0.8714	0.9662	1,229
$R2V^1$	0.0274	0.0542	0.0039	0.0101	0.0254	1,229
$R2V^1_{in}$	0.0045	0.0215	0.0000	0.0000	0.0017	1,229
$R2V^1_{ex}$	0.0230	0.0484	0.0027	0.0077	0.0202	1,229
$R2V^2$	0.0528	0.0952	0.0107	0.0235	0.0530	1,229
$R2V^2_{in}$	0.0086	0.0311	0.0000	0.0010	0.0057	1,229
$R2V^2_{ex}$	0.0442	0.0842	0.0081	0.0189	0.0443	1,229
$R2V^3$	0.0777	0.1274	0.0186	0.0374	0.0801	1,229
$R2V^3_{in}$	0.0117	0.0350	0.0000	0.0021	0.0096	1,229
$R2V^3_{ex}$	0.0660	0.1152	0.0146	0.0307	0.0694	1,229
Size	23.8154	1.1347	23.0511	23.5989	24.3806	1,296
Book-to-Market	1.2276	0.8107	0.7356	1.0500	1.5361	1,296
Avg. 1-month ret	-0.0801	0.0957	-0.1368	-0.0775	-0.0203	1,296
Avg. 6-month index ret	-0.0381	0.1144	-0.0758	-0.0181	0.0356	1,296
RVol	0.4250	0.2492	0.2521	0.3616	0.5324	1,296

Table III. Impact of Knock-in Events on Cumulative Abnormal Returns

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

$$CAR_j = \alpha_{I(t)\times M(t)} + \beta N2V_j + \gamma X_{i,t-10} + \varepsilon_j,$$

where, for a given event j, we regress the CAR of underlying stock $i = i(j)$ of the event on the event day $t(j)$ on the $N2V$ of the same event. $N2V$ is defined in Table II. $I(i)$ is the industry of stock i as per the Korea SIC 2-digit classification, $M(t)$ is the calendar month of day t, and X is a vector of control variables using the most recent information on firm i known at $t-10$. The definitions of control variables are identical to those given in Table II. $\alpha_{I(i)\times M(t)}$ is the Industry $\times$ Month fixed effects corresponding to each event. 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.

Dependent: CAR	(1)	(2)	(3)	(4)	(5)
N2V	-0.035**	-0.035***	-0.036**	-0.037**	-0.036***
	(-2.53)	(-2.69)	(-2.53)	(-2.56)	(-2.64)
Size		0.018***			0.017***
		(3.28)			(3.23)
Book-to-Market		0.004			0.004
		(0.63)			(0.77)
Avg. 1-month ret			-0.042	-0.031	-0.056
			(-1.02)	(-0.65)	(-1.17)
RVol			-0.130***	-0.129***	-0.128***
			(-4.00)	(-3.94)	(-3.93)
Avg. 6-month index ret				-0.043	-0.010
				(-0.42)	(-0.09)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	1,296	1,296	1,296	1,296	1,296
R-squared	0.423	0.439	0.446	0.446	0.460

Table IV. Comparison of Parameters between the Stages

This table compares the parameters between the two stages. For each classification p in which an $i-k-c$ pair touches $B^{O}_{i,k,c}$,

$$\mu_p = \alpha_{I(p)\times M(p)} + \beta \cdot \mathbf{II}_p + \gamma X_{i(p),t(p)} + \varepsilon_p,$$

where μ_p is the drift term of the return dynamics in classification p. $\mathbf{II}_p$ is an indicator function that equals to 1 when the price falls in Stage II. X is a vector of firm characteristics and $\alpha_{I(p)\times M(p)}$ is the Industry $\times$ Month fixed effect corresponding to each classification. The definitions of control variables are identical to those given in Table II. Stage I is the omitted category. Similarly, we estimate the regression on standard deviations as follows:

$$\sigma_p = \alpha_{I(p)\times M(p)} + \beta \cdot \mathbf{II}_p + \gamma X_{i(p),t(p)} + \varepsilon_p,$$

where σ_p is the diffusion term of the return dynamics in classification p. Definitions for $\mathbf{II}_p$, X, and $\alpha_{I(p)\times M(p)}$ are identical to those used for the previous equation. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively.

(a) Comparison of the drift (μ)

Dependent: μ	(1)	(2)	(3)	(4)	(5)
Stage II	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-4.24)	(-4.50)	(-4.21)	(-4.87)	(-5.21)
Size		0.001			0.001
		(1.36)			(1.55)
Book-to-Market		0.000			0.000
		(0.97)			(0.92)
RVol			0.006*	0.005*	0.005*
			(1.86)	(1.68)	(1.86)
Avg. 6-month index ret				-0.029***	-0.028***
				(-8.77)	(-9.09)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	43,062	43,062	43,062	43,062	43,062
R-squared	0.375	0.377	0.379	0.394	0.396

(b) Comparison of the diffusion (σ)

Dependent: σ	(1)	(2)	(3)	(4)	(5)
Stage II	0.005***	0.005***	0.005***	0.005***	0.004***
	(9.98)	(9.87)	(9.24)	(8.66)	(8.39)
Size		-0.002***			-0.002***
		(-2.90)			(-3.10)
Book-to-Market		0.001*			0.001
		(1.85)			(1.53)
Avg. 1-month ret			-0.013***	-0.012***	-0.012***
			(-4.40)	(-3.90)	(-4.18)
Avg. 6-month index ret				-0.011**	-0.012***
				(-2.17)	(-2.91)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	43,062	43,062	43,062	43,062	43,062
R-squared	0.704	0.710	0.708	0.708	0.714

Table V. Impact of Knock-in Events on Future Knock-in Probability

This table shows results of Probit regressions using $N2V$ as the intensity measure of hedging activity, as follows: for each event j, its corresponding stock $i = i(j)$ and event time $t = t(j)$,

$$KI_{i,(t+1,t+10)} = \Phi\left(\alpha_{I(i)\times M(t)} + \beta N2V_j + \gamma X_{i,t-10} + \varepsilon_j\right),$$

where $\Phi(\cdot)$ is the standard normal cumulative density function, $KI_{i,(t+1,t+10)}$ that yields 1 if there is any knock-in on the same underlying i in the next 10 days from the event time t and 0 otherwise. $I(i)$ is the industry of stock i as per the Korea SIC 2-digit classification, $M(t)$ is the calendar month of day t, and X is a vector of control variables using the most recent information on firm i known at $t-10$. The definitions of control variables are identical to those used for Table II. $\alpha_{I(i)\times M(t)}$ is the Industry $\times$ Month fixed effects corresponding to each event. 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.

Dependent: Future KI Indicator	(1)	(2)	(3)	(4)	(5)
N2V	0.217***	0.216**	0.260***	0.286***	0.288***
	(2.62)	(2.56)	(2.90)	(3.08)	(3.05)
Size		0.037***			0.036***
		(2.88)			(2.76)
Book-to-Market		-0.034*			-0.033*
		(-1.92)			(-1.88)
Avg. 1-month ret			0.182	0.146	0.118
			(1.39)	(1.10)	(0.89)
RVol			-0.180***	-0.114*	-0.099
			(-3.55)	(-1.74)	(-1.48)
Avg. 6-month index ret				0.245	0.285*
				(1.63)	(1.82)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	1,296	1,296	1,296	1,296	1,296
LRChi2	7.67	15.48	23.41	25.74	31.14
ProbChi2	0.022	0.004	0.000	0.000	0.000
Pseudo R-squared	0.006	0.013	0.017	0.019	0.026

Table VI. Interaction Effect of the Knock-In Intensity and Proximity Contributed to the Future Knock-in Probability

In this table we report the results of Probit regressions using $N2V$ as an indicator of knock-in intensity and Z as the average knock-in probability (proximity). We divided total events into terciles for $N2V$ and Z. We propose the following categorical Probit specification:

$$KI_{i,(t+1,t+10)} = \Phi\Big(\alpha_{I(i)\times M(t)} + \beta_1 N2V_j^M + \beta_2 N2V_j^H + \beta_3 Z_j^M + \beta_4 Z_j^H + \beta_5 N2V_j^M \cdot Z_j^M + \beta_6 N2V_j^M \cdot Z_j^H + \beta_7 N2V_j^H \cdot Z_j^M + \beta_8 N2V_j^H \cdot Z_j^H + \gamma X_{i,t-10} + \varepsilon_j\Big),$$

where Z is defined in Table II. $N2V_j^{H,M}$ and $Z_j^{H,M}$ are dummy variables that indicate if i belongs to the top tercile (H) or the middle tercile (M) of the respective measure. $N2V_j^L$ and Z_j^L are omitted categories. $I(i)$ is the industry of stock i as per the Korea SIC 2-digit classification, $M(t)$ is the calendar month of day t, and X is a vector of control variables using the most recent information on firm i known at $t-10$. The definitions of control variables are identical to those used for Table II. $\alpha_{I(i)\times M(t)}$ is the Industry × Month fixed effects corresponding to each event. 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.

Dependent: Future KI Indicator	(1)	(2)	(3)	(4)	(5)
$N2V^M$	0.064	0.098	0.061	0.062	0.099
	(0.43)	(0.64)	(0.41)	(0.41)	(0.65)
$N2V^H$	-0.242	-0.215	-0.240	-0.234	-0.204
	(-1.38)	(-1.22)	(-1.37)	(-1.34)	(-1.15)
Z^M	-0.055	-0.000	-0.047	-0.044	0.018
	(-0.35)	(-0.00)	(-0.30)	(-0.28)	(0.12)
Z^H	-0.095	-0.012	-0.053	-0.053	0.045
	(-0.58)	(-0.07)	(-0.32)	(-0.32)	(0.26)
$N2V^M \times Z^M$	0.195	0.157	0.206	0.206	0.164
	(0.86)	(0.68)	(0.90)	(0.90)	(0.71)
$N2V^M \times Z^H$	0.128	0.073	0.136	0.138	0.079
	(0.55)	(0.31)	(0.58)	(0.59)	(0.34)
$N2V^H \times Z^M$	0.606**	0.569**	0.633***	0.636***	0.599**
	(2.48)	(2.32)	(2.59)	(2.60)	(2.43)
$N2V^H \times Z^H$	0.759***	0.704***	0.790***	0.804***	0.749***
	(3.08)	(2.83)	(3.21)	(3.25)	(3.00)
Size		0.046			0.055
		(1.08)			(1.26)
Book-to-Market		-0.110*			-0.120**
		(-1.95)			(-2.12)
Avg. 1-month ret			0.170	0.136	0.058
			(0.39)	(0.31)	(0.13)
RVol			-0.300*	-0.224	-0.261
			(-1.70)	(-1.03)	(-1.18)
Avg. 6-month index ret				0.315	0.339
				(0.64)	(0.66)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	1,229	1,229	1,229	1,229	1,229
LRChi2	22.23	26.50	26.10	26.94	31.86
ProbChi2	0.008	0.005	0.006	0.008	0.004
Pseudo R-squared	0.017	0.020	0.019	0.020	0.023

Table VII. Impact of Expected Future Knock-In on Cumulative Abnormal Returns

In this table, we report the results of an analysis in which we examine whether expected *future* knock-ins have any effect on the price shock upon the *current* event. We regress CAR of underlying stock $i = i(j)$ at day $t = t(j)$ upon knock-in event j on the future hedging intensity measure $R2V_j$:

$$CAR_j = \alpha_{I(i)\times M(t)} + \beta R2V_j^q + \gamma X_{i,t-10} + \varepsilon_j \qquad (q = 1, 2, 3),$$

where $R2V_j$ is defined as in Table II. From this baseline $R2V$, we construct three sub-$R2V$ variables. $R2V^1$ is based on SEPs whose barriers are immediately below the currently touched barrier (the first immediate barrier). $R2V_j^2$ and $R2V_j^3$ are created in the same way with the second and the third immediate barriers, respectively. $I(i)$ is the industry of stock i as per the Korea SIC 2-digit classification, $M(t)$ is the calendar month of day t, and X is a vector of control variables using the most recent information on firm i known at $t-10$. The definitions of control variables are identical to Table II. $\alpha_{I(i)\times M(t)}$ is the Industry × Month fixed effects corresponding to each event. 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.

Dependent: CAR	(1)	(2)	(3)
$R2V^1$	-0.132***		
	(-2.72)		
$R2V^2$		-0.053*	
		(-1.95)	
$R2V^3$			-0.043*
			(-1.90)
Size	0.017***	0.018***	0.017***
	(3.70)	(3.76)	(3.69)
Book-to-Market	0.002	0.002	0.002
	(0.30)	(0.38)	(0.43)
Avg. 1-month ret	-0.086*	-0.087*	-0.085*
	(-1.83)	(-1.83)	(-1.80)
RVol	-0.122***	-0.121***	-0.120***
	(-3.84)	(-3.73)	(-3.72)
Avg. 6-month index ret	0.097	0.094	0.098
	(1.00)	(0.97)	(1.00)
Industry FE x Time FE	Y	Y	Y
N.Obs	1,229	1,229	1,229
R-squared	0.481	0.478	0.478

Table VIII. Decomposition of the Impact of Knock-In Events

To obtain the results reported in this table, we decompose the contribution to the price dislocation into a portion related to the contemporaneous liquidity demand and a portion related to expected future unwinding. For this task, we simultaneously exploit measures of contemporaneous effects ($N2V$) and future effects ($R2V^1$) of knock-in events as follows:

$$CAR_j = \alpha_{I(i)\times M(t)} + \beta_1 N2V_j + \beta_2 R2V_j^1 + \gamma X_{i,t-10} + \varepsilon_j.$$

$N2V$ and $R2V^1$ are defined as in Table II. Comparing β_1 and β_2 reveals the relative importance of two sources of the negative price impact. $I(i)$ is the industry of stock i as per the Korea SIC 2-digit classification, $M(t)$ is the calendar month of day t, and X is a vector of control variables using the most recent information on firm i known at $t-10$. The definitions of control variables are identical to those given in Table II. $\alpha_{I(i)\times M(t)}$ is the Industry × Month fixed effects corresponding to each event. 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.

Dependent: CAR	(1)	(2)	(3)	(4)	(5)
N2V	-0.033**	-0.032**	-0.033**	-0.032**	-0.031**
	(-2.26)	(-2.32)	(-2.17)	(-2.13)	(-2.14)
$R2V^1$	-0.113**	-0.085*	-0.137***	-0.139***	-0.113**
	(-2.33)	(-1.67)	(-2.86)	(-2.89)	(-2.24)
Size		0.018***			0.016***
		(3.73)			(3.62)
Book-to-Market		0.001			0.002
		(0.18)			(0.42)
Avg. 1-month ret			-0.048	-0.060	-0.078*
			(-1.14)	(-1.26)	(-1.65)
RVol			-0.129***	-0.129***	-0.123***
			(-3.96)	(-3.98)	(-3.85)
Avg. 6-month index ret				0.049	0.086
				(0.51)	(0.89)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	1,229	1,229	1,229	1,229	1,229
R-squared	0.450	0.464	0.473	0.473	0.485

Table IX. Decomposition of the Impact of Future Knock-Ins and the Liquidity Effect

To obtain the results reported in this table, we distinguish the effects of future knock-ins when the next immediate position to be liquidated is an in-house position from when it is an external position. Given event j, for its underlying stock $i = i(j)$ and at event time $t = t(j)$, we use intensity measures of future knock-ins by issuer type:

$$CAR_j = \alpha_{I(i)\times M(t)} + \beta_1 N2V_j + \beta_2 R2V^1_{j,in} + \beta_3 R2V^1_{j,ex} + \gamma X_{i,t-10} + \varepsilon_j,$$

where $R2V_{in}$ and $R2V_{ex}$ are defined as in Table II. Controlling for the liquidity demand related to the current event ($N2V$), comparing β_2 and β_3 shows the heterogeneous effects depending on issuer type on the price pressure upon the current event. $I(i)$ is the industry of stock i as per the Korea SIC 2-digit classification, $M(t)$ is the calendar month of day t, and X is a vector of control variables using the most recent information on firm i known at $t - 10$. The definitions of control variables are identical to those used for Table II. $\alpha_{I(i)\times M(t)}$ is the Industry × Month fixed effects corresponding to each event. 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.

Dependent: CAR	(1)	(2)	(3)	(4)	(5)
N2V	-0.033**	-0.032**	-0.033**	-0.032**	-0.031**
	(-2.26)	(-2.32)	(-2.17)	(-2.12)	(-2.14)
$R2V^1_{in}$	-0.119	-0.059	-0.120	-0.121	-0.062
	(-1.01)	(-0.53)	(-1.07)	(-1.08)	(-0.58)
$R2V^1_{ex}$	-0.112**	-0.089*	-0.140***	-0.143***	-0.122**
	(-2.22)	(-1.67)	(-2.85)	(-2.86)	(-2.33)
Size		0.018***			0.017***
		(3.73)			(3.62)
Book-to-Market		0.001			0.003
		(0.19)			(0.45)
Avg. 1-month ret			-0.049	-0.060	-0.079*
			(-1.14)	(-1.26)	(-1.66)
RVol			-0.129***	-0.129***	-0.123***
			(-3.96)	(-3.98)	(-3.86)
Avg. 6-month index ret				0.049	0.087
				(0.51)	(0.90)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	1,229	1,229	1,229	1,229	1,229
R-squared	0.449	0.463	0.472	0.472	0.485

Table X. The Impact of Expectation Effects depends on Information Accessibility

In this table, we insert two dummies (*Ex* and *Post*) in the regression to identify the impact of the exterior $R2V$ subjected to information accessibility: given event j, for affected stock $i = i(j)$ and at event time $t = t(j)$,

$$\begin{aligned} CAR_j =& \alpha_{I(i)\times M(t)} + \beta_1 N2V_j + \beta_2 R2V_j^1 + \beta_3 Ex + \beta_4 Post \\ &+ \beta_5 R2V_j^1 \cdot Ex + \beta_6 R2V_j^1 \cdot Post + \beta_7 Ex \cdot Post \\ &+ \beta_8 R2V_j^1 \cdot Ex \cdot Post + \gamma X_{i,t-10} + \varepsilon_j, \end{aligned}$$

where $N2V$ and $R2V^1$ are defined in Table II. Ex is an indicator variable whose value is 1 if the predominant portion of $R2V^1$ is competitors' and 0 otherwise. We calculate the ratio of the external portion to total portion, and assign the value of 1 when the external portion is higher than the median. $Post$ is also an indicator variable that equals to 1 if t is on or after the inception point of the data service (April 25, 2013) and 0 otherwise. $I(i)$ is the industry of stock i as per the Korea SIC 2-digit classification, $M(t)$ is the calendar month of day t, and X is a vector of control variables using the most recent information on firm i known at $t-10$. The definitions of control variables are identical to those given in Table II. $\alpha_{I(i)\times M(t)}$ is the Industry × Month fixed effects corresponding to each event. 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.

Dependent: CAR	(1)	(2)	(3)	(4)	(5)
N2V	-0.030**	-0.030**	-0.031**	-0.030**	-0.029**
	(-2.14)	(-2.19)	(-2.08)	(-2.03)	(-2.03)
$R2V^1$	-0.217**	-0.165	-0.228**	-0.230**	-0.180*
	(-2.00)	(-1.55)	(-2.11)	(-2.14)	(-1.70)
Ex	-0.011	-0.010	-0.010	-0.011	-0.010
	(-1.29)	(-1.20)	(-1.23)	(-1.25)	(-1.19)
Post	0.021	0.031	0.047	0.044	0.048
	(0.80)	(1.30)	(1.26)	(1.22)	(1.52)
$R2V^1$ × Ex	0.149	0.120	0.127	0.128	0.097
	(1.25)	(1.01)	(1.07)	(1.07)	(0.82)
$R2V^1$ × Post	0.267	0.254	0.303	0.304	0.281
	(1.42)	(1.36)	(1.63)	(1.63)	(1.55)
Ex × Post	0.009	0.008	0.009	0.009	0.008
	(0.76)	(0.70)	(0.78)	(0.79)	(0.75)
$R2V^1$ × Ex × Post	-0.497**	-0.519**	-0.501**	-0.500**	-0.509**
	(-2.12)	(-2.27)	(-2.13)	(-2.12)	(-2.22)
Size		0.018***			0.017***
		(3.79)			(3.66)
Book-to-Market		0.001			0.002
		(0.13)			(0.41)
Avg. 1-month ret			-0.043	-0.054	-0.073
			(-1.01)	(-1.13)	(-1.52)
RVol			-0.130***	-0.130***	-0.124***
			(-3.98)	(-3.99)	(-3.87)
Avg. 6-month index ret				0.047	0.084
				(0.49)	(0.86)
Industry FE x Time FE	Y	Y	Y	Y	Y
N.Obs	1,229	1,229	1,229	1,229	1,229
R-squared	0.450	0.464	0.473	0.473	0.485