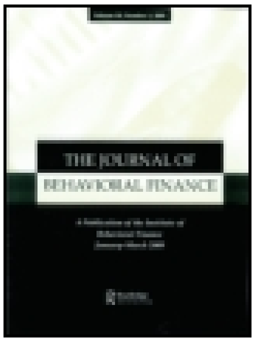

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Crossing of Psychological Price Levels: The Price Dynamics and Interaction between S&P500 Index and Index Futures

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ABSTRACT
The authors provide fresh evidence on the nonfundamental-driven price dynamics and interaction between index and index futures by examining the price movements of the S&P500 index and index futures surrounding the crossing of the 00 psychological barriers and 52-week highs and lows. In contrast to the extant evidence that futures leads in fundamental-driven price movements, the authors show the dominance of the crossing in the index in continuing the price trend after the crossing. Even when synchronized crossings occur, the index rises more than the index futures during upward crossings, whereas the index futures falls more than the index during downward crossings. While volatility is significantly reduced before upward crossings, but not for downward crossings, it is significantly higher during the crossing, and significantly lower after the crossings in both markets. These findings have clear practical implications for index arbitrageurs, investors, and regulators.

KEYWORDS
Psychological barriers; 52-week highs and lows; Spillover effect; Lead-lag relationship; Index arbitrage

Introduction

For over 2 decades, voluminous studies have examined the linkage, especially the lead–lag relationship, between stock indexes and their associated futures contracts. Overwhelmingly, the evidence indicates that futures markets lead indexes in price movements.[1] Accounting for market microstructure and other factors,[2] most studies attribute this evidence to the price discovery role prominently played by the index futures. Almost unanimously, they argue that index futures leads in reflecting information about the firm-specific or market-wide valuation factors. The sheer number of these studies speaks volumes about the importance of the topic, reflecting clearly the widespread academic interest in understanding the price movements between 2 intimately related markets driven by fundamentals. For practitioners, especially arbitrageurs, the lead by futures in price discovery suggests that futures prices contain useful information about subsequent cash prices beyond what is already embedded in the current cash price. Consequently, as demonstrated by Mackinlay and Ramaswamy [1988] and Chung [1989], profitable arbitrage opportunities conceivably exist and can be exploited.

Meanwhile, many market participants and academics have also come to the realization that nonfundamental and psychological factors can move the market. As pointed out succinctly by Shiller [2003], "markets contain quite substantial noise, so substantial that it dominates the movements in the aggregate market." Yet, despite their dominance in swaying the market, little has been done in mainstream academic studies to examine how these factors drive the market and, more interestingly, affect the interaction between 2 related markets. To fill this void, we examine the price dynamics surrounding the crossing of psychological price levels that end in hundreds (hereafter, 00 barriers) and the 52-week highs and lows in the S&P 500 index and futures, focusing, at the same time, on the interaction between the 2 markets.

Having long been in the collective consciousness of all traders, speculators, and investors, these price levels, fittingly called "emotional price levels," constitute the support and resistance levels in technical analysis.[3] The occasional moves of the price above the resistance or below the support levels have been claimed by technical analysts to reveal the constant battle between bulls and bears. By examining the price dynamics surrounding the crossing of these price levels, we therefore provide evidence and contribute to the literature on the price movements in the market that are driven by human emotions and behavior of fear, greed, and herd instinct. Similar to the studies on the excess volatility in the 1980s (e.g., Campbell and Shiller [1988], West [1988]) that conclude changes in prices oftentimes occur for no fundamental reason, the evidence suggests that investors take

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psychological price levels into their buy and sell decisions. The fact that these absolute levels of an index, which are an arbitrarily scaled artificial construct, affect the decisions of investors above and beyond what the fundamental valuation factors do apparently contradicts the rationality assumption underlying the classical market efficiency theory. It validates the tenets of behavioral finance that psychology influences investors' decision making. Not only on their portfolios, this influence also transpires into the mean and volatility effects on the market returns.

For traders and technical analysts, a mean effect at the crossings has a bearing on the efficacy of 2 popular trading strategies as price approaches these support and resistance levels. One strategy is to buy (sell) when an upward (downward) crossing occurs. Obviously, this momentum-based strategy believes an upward (downward) trend will continue if an upward (downward) breakout occurs. The other strategy, in sharp contrast, calls for selling when an upward crossing occurs on the assumption that price will reverse, and buying when a downward breach occurs in anticipation of a value play. A finding of, say, no continuation of the trend after the crossing would render the former a futile endeavor or suggest that its profitable execution needs to be swifter than the daily window we examine. The opposite is true for a finding of a continuation of the trend after the crossing. Similarly, the volatility effect, mainly an escalated volatility, during the crossing has 2 opposite trading implications for the issue of portfolio rebalancing. While investors who are apt at market timing may want to switch out of the stock market into riskless securities around the psychological price levels, small investors might be better off doing their rebalancing outside of these price levels to avoid being whipsawed.[4]

By contrasting the magnitude and volatility of price movements between upward and downward crossings, we further provide empirical evidence that psychological factors, not just fundamentals, help explain the long-recognized phenomenon that all types of markets tend to decline much faster than they rise. Some argue that the evolution of humans has to do with this phenomenon. In the face of constrained available resources, so goes the argument, our ancestors' survival depended much more on keeping what they had than getting something new. As a result, people generally feel twice as much pain with losses than equal-sized gains (Hastie and Dawes [2010]). The prospect theory of Kahneman and Tversky [1979] validates this behavior trait of people experiencing a more emotional impact from losses than gains.

To focus on the interaction between the index and futures, we further examine both markets simultaneously. This examination provides us with evidence to contrast with that from looking at each market separately. More importantly, given the intimate link between the 2 markets, it affords us an opportunity to evaluate the psychology-driven lead–lag relationship between index and futures, and contrast it with that driven by fundamentals. To do so, we examine the spillover effect from one market to the other. We contrast the effect for crossings that occur solely in one market with that for crossings that take place in both markets simultaneously. Ex ante, it is not clear whether the evidence of futures leading index holds for the crossing of psychological price levels. It is possible that the reverse of index leading futures is true or one market leads in upward crossings while the other leads in downward crossings. Undeniably, these additional findings further enhance our understanding of the market and add nuances to the trading implications (e.g., whether to take a long position in the index or in futures) when implementing arbitrage strategies discussed previously.

The potential market impacts from the crossings are likely to create opportunities for speculation. The resulting consequences, as well as those from index arbitrage activities, on the aggregate market should concern regulators. Although the continued and pervasive evidence of the existence of psychological price levels suggests that such profit exploitation may not be strong enough for arbitrageurs to exploit away, it is prudent for regulators nevertheless to observe if there are market participants who have sufficient market power, enjoy low transaction costs, or are capable of influencing or nudging the price around these price levels.

The results show that prior to the crossings, there is a mean effect of a rising price trend in upward crossings and falling price trend in downward crossings. Notably, the magnitude of the decline is much greater than the rise. On the day of the crossing, we find evidence that the index rises more than the futures for upward crossings, but the index futures falls more than the index for downward crossings. After the crossing, there is evidence of a continuing rise in price for upward crossings but partial reversal of the downward price trend for downward crossings. Contributing to these contrasting postcrossing price movements are 2 opposite spillover effects of solo crossings—crossings that occur in one market without a simultaneous crossing in the other market. For the index, the effect of the solo upward (downward) crossings is an increase (decrease) in price that spills over and leads to an increase (decrease) in index futures. In sharp contrast, for the index futures, while solo upward crossings see no postcrossing impact, solo downward crossings result in an increase, not decrease, in price that also spills over to push the index upwards. In addition to these mean and spillover effects on returns, we find that the volatility in both the index and index futures falls before upward crossings, but no significant change occurs before downward crossings. Not surprisingly, volatility rises significantly during the crossing. It then, however, subsides after the crossing.

The remainder of the article is organized as follows: in the second section we review the literature, in the third section we discuss the data and methodology, in the fourth section we present the results, and in the fifth section we conclude the article.

Literature review

Lead–lag relationships between stock index and index futures

The literature on the lead–lag relationships between stock index and index futures dates back to the late 1980s. Finnerty and Park [1987] investigated the Major Market Index and Maxi Major Market Index. They found a strong relationship between index futures price changes and subsequent spot index price changes. Ng [1987] applied the Haugh-Pierce test for Granger causality on the daily S&P 500 index and futures prices and found evidence that futures prices Granger cause spot prices, but not the other way around. Kawaller, Koch, and Koch [1987] examined the intraday price relationship between S&P 500 index and futures. Their results suggest that futures price movements consistently lead index movements by 20–45 minutes while movements in the index rarely affect futures beyond 1 minute. While nonsynchronous trading of the component stocks has been suspected to contribute to this finding, Harris [1989] specifically tackled this trading issue and still founds that futures price strongly leads the cash index. Stoll and Whaley [1990] also find that S&P 500 and MM index futures returns tend to lead stock market returns by about 4 minutes, on average, but occasionally as long as 10 minutes or more, even after stock index returns have been purged of infrequent trading effects.

While these studies suggest index futures lead in price discovery and argue that new information disseminates in the futures before the stock market, Stoll and Whaley [1990] showed that the effect is not completely unidirectional, with lagged stock index returns having a mild positive predictive effect on futures returns. Chan [1992] and Tse and Chan [2009] also reported evidence of index leading index futures. Chan [1992] further found that on days of macroeconomic new releases the evidence of futures leading the index is stronger and index leading the futures weaker. Frino et al. [2000] similarly demonstrated this and suggested that investors with better market wide information prefer to trade in index futures. On the other hand, they showed that around the announcement of firm-specific news, the lead of the index strengthens, suggesting that investors are more likely to trade the individual stocks.

Another line of research on the price discovery function of futures versus cash markets examines the lead–lag relationship of volatility between the two. To name just a few, Chin et al. [1991] conducted such an examination on the S&P 500 index and Major Market Index, arguing that it is the volatility of price, not simply the returns, that is related to the rate of information flow to the market. Their results suggest price innovations in either the index or futures may be able to predict the future volatility in the other market.

Psychological price levels

In contrast to the large volume of studies that examine the lead–lag relationship between index and index futures based on price movements that are fundamental driven, the equivalent examination of price movements driven by nonfundamental factors is rare. Among these nonfundamental factors that are the focus of this study is psychological price levels, and chief among these price levels are the so-called psychological barriers. Defined as specific levels—such as multiples of 10, 100, and 1,000 (henceforth, 0, 00, and 000 barriers)—in market indexes or prices of assets that attract significant attention, especially in financial media. They constitute one major form of the support and resistance levels that are used extensively by technical analysis devotees in analyzing price trends. Treating round numbers such as 10, 20, 35, 50, 100, and 1,000 as support and resistance levels, these technical analysts believe these levels often represent the major psychological turning points at which many traders will make buy or sell decisions.

Reflecting the interest among practitioners, academics have examined the existence of psychological barriers in various asset classes such as equity, bond, and gold over the past 20 years.[5] Based on the test results that reject the null hypothesis of a uniform distribution for these barriers, earlier studies conclude that the barriers exist. Invoking Benford's [1938] "law of anomalous numbers" that the digits in arbitrarily scaled random numbers are not uniformly distributed, De Ceuster et al. [1998] challenged the validity of this test and show that it is hard to prove without any doubts the existence of psychological barriers in either Dow Jones Industrial Average (DJIA) or 2 other major indexes, Financial Times Stock Exchange 100 Index (FTSE 100) and Nikkei Stock Average 225 (Nikkei 225). The evidence in Ley and Varian [1994] of a mean effect in returns heralds the subsequent studies that examine the behavior associated with returns to complement the price-level uniformity tests. Employing a model based on the GARCH model of Glosten, Jagannathan, and Runkle [1993] (hereafter GJR), Cyree et al. [1999] found evidence of changes in the conditional means and variances in DJIA, S&P 500, TSE 300 (Toronto), CAC 40 (Paris), Hang Seng (Hong Kong), Nikkei 225, and the Financial Times UK Actuaries Index, consistent with the existence of psychological barriers.

On the theoretical front, Westerhoff [2003] is the only published article, as far as we know, that specifically addressed psychological barriers. Based on the finding of anchoring and heuristic in Tversky and Kahneman [1974] and the claim by Shiller [2000] that market participants may use the nearest round number as a proxy for the fundamental value, Westerhoff developed a behavioral exchange rate model in which psychological barriers emerge naturally.

Other than the trailing digits in prices and index levels, 52-week highs and lows are price levels that equally, if not more frequently, attract the attention of market participants. They are reported and mentioned in financial media along with the daily price movements and prominently referred to when traders and technical analysts discuss support and resistance levels. Despite this prominence, they are examined only in few studies. George and Hwang [2004] focused on the predictability of 52-week highs and showed that it dominates and improves the forecasting power of past returns, both individual stock and industry returns, for future returns. In the context of how past price extremes influence investors' trading decisions, Huddart, Lang, and Yetman [2008] examined the effects, as reflected in volume and price patterns, around the 52-week highs and lows of individual stocks. They find that volume is significantly higher when stock prices cross either highs or lows. The increase in volume is more pronounced the longer the time because the stock price last reached the highs or lows, the smaller the firm, the higher the individuals investors interest in the stock, and the greater the ambiguity regarding valuation. Instead of alternative explanations such as hedging or replication of look-back options, they argue that the results are more consistent with the effects of bounded rationality and suggest that the likely explanation for the increase in volume is the effect of increased investor attention. Driesseny, Lin, and Van Hemertx [2011] analyzed the volatility of stocks and the implied volatility of options on stocks before and during the crossing of 52-week highs and lows. They found that implied volatilities and stock betas fall when approaching highs and lows and volatilities increase after the crossings. Finally, Li and Yu [2012] showed that nearness to the DJIA 52-week high positively predicts future aggregate market returns. They further demonstrated that the 52-week high contains information about future market returns beyond what is captured by traditional macroeconomic factors.

Data and methodology

Data

The data used in this study are the daily values of S&P 500 index and prices of the index futures over the period from January 3, 2000, to April 20, 2013. In constructing the series of the futures price, we use the nearest monthly contracts with a time to maturity longer than 1 week. The motivation for examining the S&P 500 is partly due to the primary role it plays as a leading most popular stock market index, which eliminates the possibility of not being able to detect price barriers due to the obscureness of some indexes, such as the Wilshire 5000 examined by Donaldson and Kim [1993].

To determine the crossing of 0 barriers and 00 barriers, we adopt the following procedures: for any given date t, if the closing price is above (below) the barrier and the closing prices of the preceding 3 trading days are below (above) the barrier, an upward (downward) crossing of the barrier is identified.

For 52-week highs and lows, we use 250 trading days as the equivalent to 52 weeks and follow the following steps to identify when the crossings occur:

Step 1: Determine the local peaks/troughs for any date t based on the highest/lowest price in the 10-day window around t (i.e., 5 trading days on either side of t).

Step 2: Determine the 52-week highs/lows based on the maximum/minimum of the local peaks/troughs during the preceding 250 trading days.

Step 3: Identify the crossing of the 52-week highs (lows) from below (above) for any given date t based on whether the closing price on t is above (below) and the closing price on $t - 1$ is below (above) the 52-week highs (lows).

Methodology

Barrier tests

To examine the existence of psychological barriers for the multiples of 10s and 100s, we test the uniform distribution tests of the M-values as having been done since Donaldson [1990]. Following Burke [2001] and Aggarwal and Lucey [2007], we perform 2 tests, the point test and range test. For the latter, the focus is on the ranges of prices plus or minus X the exact tens and hundreds. We specifically use an X of 5 and 10, which mean we examine the ranges of prices between 95 and 105 and between 90 and 110, respectively. If psychological barriers exist, we expect to see relatively fewer occurrences of the exact tens and hundreds and the value with the corresponding plus-minus ranges. We further perform 2 regression tests, the barrier proximity and barrier hump, introduced in Donaldson and Kim [1993]. We omit the discussion of these tests and refer readers to the previously cited articles for the details.

Effects of psychological barriers on returns and volatility: GJR-GARCH modeling

In examining the effect of the crossing of psychological barriers on the returns and volatility of the index and futures, we first perform the examination for each market separately without accounting for the interaction between the 2 markets. This also allows us to compare with previous studies on the existence of psychological barriers such as Cyree et al. [1999]. As shown in Model 1 below, we use an AR(2) for the mean equation and a GJR-GARCH variance equation to model the returns. Widely used, the GJR-GARCH model captures the well-documented leverage effect of negative shocks at time $t - 1$ having a stronger impact on the variance at time t than positive shocks (Black [1976]).[6]

Model 1:

$$r_{s,t} = C + b_1 r_{s,t-1} + b_2 r_{s,t-2} + \varepsilon_t \tag{1}$$

where $r_{s,t}$ is the return on the index on day t, $\varepsilon_t \sim N(0, h_t^2)$ and

$$h_t^2 = c + a_1 \varepsilon_{t-1}^2 + a_2 h_{t-1}^2 + a_3 \varepsilon_{t-1}^2 I_t(\varepsilon_{t-1} < 0).$$

where $I_t(\varepsilon_{t\text{-}1} < 0)$ is an indicator with a value of 1 if $\varepsilon_{t\text{-}1} <$ 0 and 0 otherwise.

To model the returns on the index futures, $r_{f,t}$, we replaced r_{st} with $r_{f,t}$ in Equation 1, and similarly in Equations 2–4 discussed subsequently.

To examine the effect of the crossings of psychological barriers on the returns, we use Models 2 and 3. In Model 2, we add 2 indicator variables, $B_t^{1\sim3}(\uparrow)$ and $B_t^{1\sim3}(\downarrow)$, in the mean equation to capture changes, if any, in returns in the 3-day window before an upward crossing and downward crossing, respectively. We also use $A_t^{1\sim3}(\uparrow)$ and $A_t^{1\sim3}(\downarrow)$, for any possible changes in returns in the 3-day window after an upward and downward crossing, respectively. Each of these 4 indicator variables takes on a value of 1 if day t is within the respective 3-day window. For example, $B_t^{1\sim3}(\uparrow)$ takes on a value of 1 if day t is 1 of the 3 days before an upward crossing, otherwise it has a value of 0. By the definition of a crossing that occurs on day t, we know that the price goes up on that day for an upward crossing and goes down for a downward crossing; therefore, there is no need for an indicator variable on day t in the mean equation. However, along with the previous 4 indicators for before and after crossing, it is necessary to include 2 additional indicator variables, $I_t(\uparrow)$ and $I_t(\downarrow)$, in the variance equation to pick up the changes in volatility during the day of the crossings, which is of most interest in this study. Given that no existing studies have examined whether any lingering effects exist beyond the immediate days after the crossing, it is not clear that we can rule out their existence. Considering the well-documented findings of post–earnings announcement drift (see Bernard and Thomas [1989], [1990]) that suggests market reaction to information release can last even for months, it behooves us to explore such a possibility for nonfundamental-driven crossings of psychological price levels. Consequently, we extend the postcrossing examination to about 1 month by including 12 indicator variables in the mean equation in Model 3, including $A_t^{4\sim6}(\uparrow)$, $A_t^{7\sim9}(\uparrow)$, $A_t^{10\sim12}(\uparrow)$, $A_t^{13\sim15}(\uparrow)$, $A_t^{16\sim18}(\uparrow)$, and $A_t^{19\sim21}(\uparrow)$ for upward crossings and $A_t^{4\sim6}(\downarrow)$, $A_t^{7\sim9}(\downarrow)$, $A_t^{10\sim12}(\downarrow)$, $A_t^{13\sim15}(\downarrow)$, $A_t^{16\sim18}(\downarrow)$, $A_t^{19\sim21}(\downarrow)$ for downward crossings for 6 of the 3-day windows of days 4–6, 7–9, 10–12, 13–15, 16–18, and 19–21. For the sake of parsimony and given that the main interest in volatility is the days immediately around the crossing and, we do not include any of these additional indicators in the variance equation.

Model 2:

$$r_{s,t} = C + b_1 r_{s,t-1} + b_2 r_{s,t-2} + b_3 B_t^{1\sim3}(\uparrow) + b_4 A_t^{1\sim3}(\uparrow) + b_5 B_t^{1\sim3}(\downarrow) + b_6 A_t^{1\sim3}(\downarrow) + \varepsilon_t \tag{2}$$

where $\varepsilon_t \sim N(0, h_t^2)$ and

$$\begin{aligned} h_t^2 &= c + a_1 \varepsilon_{t-1}^2 + a_2 h_{t-1}^2 + a_3 \varepsilon_{t-1}^2 I_t(e_{t-1} < 0) \\ &+ a_4 B_t^{1\sim3}(\uparrow) + a_5 I_t(\uparrow) + a_6 A_t^{1\sim3}(\uparrow) \\ &+ a_7 B_t^{1\sim3}(\downarrow) + a_8 I_t(\downarrow) + a_9 A_t^{1\sim3}(\downarrow). \end{aligned}$$

Model 3:

$$r_{s,t} = C + b_1 r_{s,t-1} + b_2 r_{s,t-2} + b_3 B_t^{1\sim3}(\uparrow) + b_4 A_t^{1\sim3}(\uparrow)$$

$$+ b_5 A_t^{4\sim6}(\uparrow) + b_6 A_t^{7\sim9}(\uparrow) + b_7 A_t^{10\sim12}(\uparrow)$$

$$+ b_8 A_t^{13\sim15}(\uparrow) + b_9 A_t^{16\sim18}(\uparrow) + b_{10} A_t^{19\sim21}(\uparrow)$$

$$+ b_{11} B_t^{1\sim3}(\downarrow) + b_{12} A_t^{1\sim3}(\downarrow) + b_{13} A_t^{4\sim6}(\downarrow)$$

$$+ b_{14} A_t^{7\sim9}(\downarrow) + b_{15} A_t^{10\sim12}(\downarrow) + b_{16} A_t^{13\sim15}(\downarrow)$$

$$+ b_{17} A_t^{16\sim18}(\downarrow) + b_{18} A_t^{19\sim21}(\downarrow) + \varepsilon_t \quad (3)$$

where $\varepsilon_t \sim N(0, h_t^2)$ and

$$h_t^2 = c + a_1 \varepsilon_{t-1}^2 + a_2 h_{t-1}^2 + a_3 \varepsilon_{t-1}^2 I_t(\varepsilon_{t-1} < 0)$$

$$+ a_4 B_t^{1\sim3}(\uparrow) + a_5 I_t(\uparrow) + a_6 A_t^{1\sim3}(\uparrow)$$

$$+ a_7 B_t^{1\sim3}(\downarrow) + a_8 I_t(\downarrow) + a_9 A_t^{1\sim3}(\downarrow).$$

Effects of psychological barriers on returns and volatility: Vector error correction modeling

Similar to the studies on the lead–lag relationship between index and index futures, we examine the interaction between the 2 markets. Specifically, we investigate the spillover effects between the index and index futures by examining whether the crossing of barriers in the index has any impact on the index futures and, vice versa, the crossing in the index futures has any impact on the index. As the S&P500 index and index futures have been shown to contain a unit root (Tsay [2010]), we first verify and account for unit roots then proceed to test for any cointegration relationship between the 2 returns series. Based on the results that the 2 returns are indeed integrated, suggesting a vector error correction model (VECM) as shown in the following model is the most appropriate approach to use to examine the relationship between the 2 markets.

Model 4:

$$\begin{bmatrix} r_{s,t} \\ r_{f,t} \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \end{bmatrix} + \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \text{Coint.—Eq.} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

$$\times \begin{bmatrix} r_{s,t-1} \\ r_{f,t-1} \end{bmatrix} + \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix} \begin{bmatrix} r_{s,t-2} \\ r_{f,t-2} \end{bmatrix}$$

$$+ \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix} \begin{bmatrix} B_t^{1\sim3}(\uparrow) \\ B_t^{1\sim3}(\downarrow) \end{bmatrix} + \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \end{bmatrix}$$

$$\times \begin{bmatrix} A_t^{1\sim3}(\uparrow,\uparrow) \\ A_t^{1\sim3}(\uparrow,0) \\ A_t^{1\sim3}(0,\uparrow) \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \end{bmatrix}$$

$$\times \begin{bmatrix} A_t^{1\sim3}(\downarrow,\downarrow) \\ A_t^{1\sim3}(\downarrow,0) \\ A_t^{1\sim3}(0,\downarrow) \end{bmatrix} + \varepsilon_t \quad (4)$$

As shown, in addition to 2 of its own lag returns, in the model the index returns are also linked to 2 lag returns of index futures. Surrounding the crossing of barriers, we add 2 indicator variables for the 3-day window, $B_t^{1\sim3}(\uparrow)$ and $B_t^{1\sim3}(\downarrow)$, to capture the effects of crossing on the index returns before the crossing. Additionally, 6 indicator variables, including $A_t(\uparrow,\uparrow)$, $A_t(\uparrow,0)$, and $A_t(0,\uparrow)$ for upward crossings and $A_t(\downarrow,\downarrow)$, $A_t(\downarrow,0)$, and $A_t(0,\downarrow)$ for downward crossings, are used to allow us to investigate the effect of crossing during the 3-day period after the crossing. Despite being intimately related, crossing of barriers may not occur in both markets simultaneously. Therefore we need these 6 indicators to represent the 6 possible combinations of the states of crossings in both markets as follows: $A_t(\uparrow,\uparrow)$ or $A_t(\downarrow,\downarrow)$ for synchronized upward or downward crossing when an upward or downward crossing occurs simultaneously in both market, $A_t(\uparrow,0)$ or $A_t(\downarrow,0)$ for a solo upward or downward crossing that happens only in the index, and $A_t(0,\uparrow)$ or $A_t(0,\downarrow)$ for a solo upward or downward crossing that takes place only in the index futures.

Results

Basic statistics

As reported in Table 1, during the sample period, both the S&P 500 index and index futures have average daily returns close to 0, positive kurtosis, and negative skewness. Consistent with the well-documented evidence on daily returns of most financial assets, both returns are definitely not normally distributed, as indicated by the

Table 1. Summary statistics of daily returns on S&P500 index and index futures.

	Index Returns	Index Futures Returns
Observations	3,325	3,325
Mean	0.0000	0.0000
Std. Dev.	0.0134	0.0135
Kurtosis	7.4433	9.4743
Skewness	−0.1624	−0.0135
Minimum	−0.0947	−0.1040
Maximum	0.1095	0.1319
Jarque-Bera	7,664	12,394
p Value	0.0000	0.0000

Note. Sample period: 1/3/2000 to 4/2/2013. Returns on day $t = \ln P_t - \ln P_{t-1}$, where P_t is the value of the index or index futures on day t.

Jarque-Bera test statistics, which are statistically significant at a level better than 1%.

Crossings of psychological price levels

During the sample period, the S&P 500 index hovers between 600 and 1600 and touches 1000 only once, resulting in only 1 price barrier that ends in 000. Therefore, we consider only psychological barriers of the last and last 2 digits of the index values and index futures prices that end in 0 and 00 (hereafter, 0 barriers and 00 barriers). The results from the standard chi-square test[7] (Donaldson [1990], Koedijk and Stork [1994]) support the existence of both the 0 barriers and 00 barriers, while the results from the regression tests[8] introduced in Donaldson and Kim [1993] suggested only the 00 barriers exist. In view of these results (available upon request) we only examine the 00 barriers along with the 52-week highs and lows. Before looking at the main results regarding the effects of barrier crossings, let's look at the frequency of barriers crossing reported in panel A of Table 2. We see that for the 00 barriers, there are 118 (3.55%) downward crossings, 97 (2.92%) upward crossings, and 3,110 (93.52%) no crossings for the S&P 500 index. The corresponding numbers for the index futures are 118 (3.55%) downward crossings, 94 (2.83%) upward crossings, and 3,113 (93.62%) no crossings. There are, therefore, fewer upward crossings for the index futures. For the 52-week highs and lows, there are 29 (0.87%) upward crossings, 62 (1.86%) downward crossings, and 3,234 (97.26%) no crossings for the index and 20 (0.68%) downward crossings, 53 (1.59%) upward crossings, and 3,252 (97.80%) no crossings. Again, the index futures experiences fewer crossings, and in this case, in both downward and upward directions.

We also tabulate the joint frequency distribution of barrier crossings in the index and index futures and report the results in panel B of Table 2. Looking at the crossings of barriers in the index, we see that among the 118 downward crossings in the index, 94 (79.66%) have a synchronized crossing simultaneously in the index futures and the remaining 24 (20.34%) are not accompanied by a crossing in the futures. Among the 3,110 days when no crossings occur in the index, there are 24 (0.77%) downward and 28 (0.90%) upward crossings in the index futures. Among the 97 downward crossings of the index, 31 (31.96%) see no crossings while 66 (68.04) have a simultaneous crossing in the index futures. The fact that the downward crossings of the 00 barriers are accompanied with simultaneous crossings in the index future 79.66% of the time and upward crossing 68.04% of the time, respectively, indicates that in crossing the 00 barriers both markets are clearly not always in sync. This evidence regarding out of synchrony in crossing is even stronger for the crossings of the 52-week highs and lows. As shown, with notably fewer crossings, there are 29 downward and 62 upward crossings in the index and 20 downward and 53 upward crossings in the index futures. The percentage of index crossings accompanied by a simultaneous crossing in the index futures is only 51.72% for the 52-week lows and 51.61% for the 52-week highs.

Effects of barriers crossing on the index and index futures: GJR-GARCH results

Results from the GJR-GARCH modeling are reported in Table 3 for 00 barriers and Table 4 for 52-week highs and lows. Looking first at the mean equation in Table 3, we see that in Model 1 the lag-1 returns of the index and both the first 2 lag returns of the index futures are statistically significant, indicating the AR(2) specification is required to adequately model the returns. Moving on to Model 2, we notice that $B_t^{1\sim3}(\uparrow)$ has a coefficient of 0.0011, which is statistically significant at the 5% level, and $B_t^{1\sim3}(\downarrow)$ has a coefficient of −0.0022 significant at the 1% level, indicating that 3 days prior to an upward (downward) crossing of barriers, the index value is rising (falling). The existence of this mean effect prior to barrier crossings for the S&P 500 index is to be expected, considering the index should be rising (falling) first before it has an upward (downward) crossing. What's interesting to note is that the coefficient for $B_t^{1\sim3}(\downarrow)$ is twice that for $B_t^{1\sim3}(\uparrow)$, indicating the magnitude of the fall in value before the crossings is much greater than that of the rise in value. Indeed, based on the test results reported we see that the hypothesis that the magnitude of the coefficient for $B_t^{1\sim3}(\downarrow)$ less than or equal to that for $B_t^{1\sim3}(\uparrow)$ is rejected at the 10% level. This evidence of a disparity in the size of the movements between upward and downward crossings leads us to suspect there might

Table 2. Frequency and synchronicity of barrier crossings for S&P 500 index and index futures.

Panel A: Frequency of crossings

	Downward Crossing	No Crossing	Upward Crossing	Total
00 Barriers				
Index	118 (3.55%)	3,110 (93.53%)	97 (2.92%)	3,325
Index futures	118 (3.55%)	3,113 (93.62%)	94 (2.83%)	3,325
52-Week Highs and Lows				
Index	29 (0.87%)	3,234 (97.26%)	62 (1.86%)	3,325
Index futures	20 (0.60%)	3,252 (97.80%)	53 (1.59%)	3,325

Panel B: Synchronicity of crossings

		S&P 500 Future			
		$I_t(\cdot,\downarrow)$	$I_t(\cdot, 0)$	$I_t(\cdot,\uparrow)$	Total
00 Barriers					
S&P 500 Index	$I_t(\downarrow, \cdot)$	94	24	0	118
		(79.66%)	(20.34%)	(0.00%)	(100%)
	$I_t(0, \cdot)$	24	3058	28	3110
		(0.77%)	(98.33%)	(0.90%)	(100%)
	$I_t(\uparrow, \cdot)$	0	31	66	97
		(0.00%)	(31.96%)	(68.04%)	(100%)
	Total	118	3,113	94	3,325
52-Week High and Low					
S&P 500 Index	$I_t(\downarrow, \cdot)$	15	14	0	29
		(51.72%)	(48.28%)	(0.00%)	(100%)
	$I_t(0, \cdot)$	5	3208	21	3234
		(0.15%)	(99.20%)	(0.65%)	(100%)
	$I_t(\uparrow, \cdot)$	0	30	32	62
		(0.00%)	(48.39%)	(51.61%)	(100%)
	Total	20	3,252	53	3,325

Note. Sample period: 1/3/2000 to 4/2/2013; 3,325 observations.
I_t(p,q) indicates that index is in state of crossing p and index futures q, where p and q can be ↑, ↓, or 0, indicating, respectively, an upward crossing, downward crossing, or no crossing. I_t(p, ·) (I_t(·, q)) is the "marginal" indicator variable that indicates the state of crossing for the index (index futures), p (q), while ignoring the state of the crossing for the index futures (index).

also be difference in the magnitude of the postcrossing price movements if the nonfundamental-driven barrier crossings are purely psychological so that after the emotions die down the market movements will revert back to be fundamental driven, resulting in the total impact over the same length of time be the same for both upward and downward crossings.

This seems to be the case for the index as we look at the coefficients for the postcrossings indicators. We see in Model 2 that $A_t^{1\sim3}(\uparrow)$ is positive with a value of 0.0012, which is statistically significant at the 5% level, indicating the upward momentum continues after the crossings. On the other hand, we notice that while the coefficient for $A_t^{1\sim3}(\downarrow)$ is −0.0005, it is not statistically significant. To verify our speculation, we take the sum of the coefficients for $B_t^{1\sim3}(\uparrow)$ and $A_t^{1\sim3}(\uparrow)$ to arrive at a total of 0.0023, which is about the same as the magnitude of the coefficient for $B_t^{1\sim3}(\downarrow)$, which is –0.0022, suggesting the postcrossing continuing rise for upward crossings makes up for the smaller movements before the crossings, resulting in a total impact with about the same magnitude by the end of 3 days after the crossings. Looking at Model 2 for the index futures, we see that, similar to the index, the coefficient for $B_t^{1\sim3}(\downarrow)$, –0.0026, is greater in magnitude than that for $B_t^{1\sim3}(\uparrow)$, 0.0011, indicating the magnitude of the fall in value before the crossings is much greater than that of the rise in value. Based on the test results reported, the hypothesis of $B_t^{1\sim3}(\downarrow) \leq B_t^{1\sim3}(\uparrow)$ is similarly rejected at the 10% level. However, neither $A_t^{1\sim3}(\uparrow)$ nor $A_t^{1\sim3}(\downarrow)$ is statistically significant. Therefore, the total effect of downward crossings remains greater in magnitude than that of upward crossings.

To see whether there are further significant movements beyond the 3-day window we look at the results for Model 3. Notice that for the index the coefficient estimates for the same variables that are in Model 2 remain about the same, suggesting the robustness of the results for Model 2. Among the additional terms that capture price movements in the later windows, we see $A_t^{10\sim12}(\uparrow)$ has a significant coefficient of 0.0012, indicating a continuing upward price trend 2 weeks after upward crossings. On the other hand, for downward crossings, we notice that $A_t^{4\sim6}(\downarrow)$ has a positive 0.001 coefficient that is significant at the 5% level, indicating, instead of moving further downward, there is a reversal, albeit partial, of the price movements after downward crossings.

The result of a further rise after upward crossings in the index, however, does not happen for the index futures, as none of the additional 6 variables in Model 3

Table 3. GJR-GARCH results for 00 barriers.

	Index						Index Futures					
	Model 1		Model 2		Model 3[a]		Model 1		Model 2		Model 3[b]	
	Coefficient	*p* Value	Coefficient	*p* Value	Coefficient	*p* Value	Coefficient	*p* Value	Coefficient	*p* Value	Coefficient	*p* Value
Mean Equation												
C	0.0001	0.681	0.0004***	0.009	0.0002	0.241	0.0001	0.515	0.0005***	0.003	0.0003	0.130
$r_{s,t-1}$	−0.0537***	0.006	−0.0807***	0.000	−0.0839***	0.000	−0.0470**	0.015	−0.0710***	0.000	−0.0736***	0.000
$r_{s,t-2}$	−0.0251	0.152	−0.0549***	0.001	−0.0568***	0.001	−0.0313*	0.068	−0.0547***	0.001	−0.0572***	0.001
$B_t^{1\sim3}(\uparrow)$			0.0011**	0.042	0.0010**	0.050			0.0011**	0.043	0.0011**	0.040
$A_t^{1\sim3}(\uparrow)$			0.0012**	0.037	0.0011*	0.063			0.0004	0.490	0.0004	0.551
$A_t^{4\sim6}(\uparrow)$					0.0002	0.642					−0.0001	0.898
$A_t^{7\sim9}(\uparrow)$					0.0004	0.403					0.0007	0.163
$A_t^{10\sim12}(\uparrow)$					0.0012**	0.018					0.0009	0.105
$A_t^{13\sim15}(\uparrow)$					0.0002	0.636					0.0002	0.686
$A_t^{16\sim18}(\uparrow)$					0.0000	0.992					−0.0003	0.530
$A_t^{19\sim21}(\uparrow)$					−0.0006	0.181					−0.0004	0.375
$B_t^{1\sim3}(\downarrow)$			−0.0022***	0.000	−0.0023***	0.000			−0.0026***	0.000	−0.0027***	0.000
$A_t^{1\sim3}(\downarrow)$			−0.0005	0.401	−0.0005	0.371			−0.0003	0.708	−0.0003	0.641
$A_t^{4\sim6}(\downarrow)$					0.0010**	0.045					0.0009*	0.084
$A_t^{7\sim9}(\downarrow)$					0.0005	0.343					0.0007	0.127
$A_t^{10\sim12}(\downarrow)$					−0.0006	0.190					−0.0005	0.374
$A_t^{13\sim15}(\downarrow)$					0.0007	0.181					0.0011*	0.054
$A_t^{16\sim18}(\downarrow)$					−0.0004	0.433					−0.0005	0.401
$A_t^{19\sim21}(\downarrow)$					−0.0002	0.620					−0.0005	0.334
Variance Equation (%)												
C	0.0002***	0.000	0.0002***	0.000	0.0002***	0.000	0.0002***	0.000	0.0001***	0.000	0.0001***	0.000
ε_{t-1}^2	−2.3600***	0.000	−1.6100***	0.006	−1.7700***	0.002	−1.9300***	0.002	−1.2900**	0.035	−1.5600***	0.009
$\varepsilon_{t-1}^2 I_t(\varepsilon_{t-1} < 0)$	15.6000***	0.000	12.7000***	0.000	12.8000***	0.000	16.7000***	0.000	12.8000***	0.000	13.2000***	0.000
h_{t-1}^2	93.2000***	0.000	93.3000***	0.000	93.4000***	0.000	92.0000***	0.000	92.7000***	0.000	92.8000***	0.000
$B_t^{1\sim3}(\uparrow)$			−0.0007***	0.000	−0.0007***	0.000			−0.0006***	0.000	−0.0007***	0.000
$I_t(\uparrow)$			0.0060***	0.000	0.0060***	0.000			0.0068***	0.000	0.0068***	0.000
$A_t^{1\sim3}(\uparrow)$			−0.0018***	0.000	−0.0019***	0.000			−0.0019***	0.000	−0.0019***	0.000
$B_t^{1\sim3}(\downarrow)$			0.0001	0.627	0.0001	0.456			0	0.928	−0.0001	0.526
$I_t(\downarrow)$			0.0169***	0.000	0.0166***	0.000			0.0203***	0.000	0.0207***	0.000
$A_t^{1\sim3}(\downarrow)$			−0.0051***	0.000	−0.0052***	0.000			−0.0059***	0.000	−0.0062***	0.000
Adj. R^2	0.79		1.48		1.45		0.79		1.45		1.37	

[a]Based on the results from the Wald test, Model 2 strongly outperforms Model 1 (*F* statistics = 12.5848, *p* value = 0.0000) and Model 3 slightly outperforms Model 2 (*F* statistics = 1.6581, *p* value = 0.0696).
[b]Based on the results from the Wald test, Model 2 strongly outperforms Model 1 (*F* statistics = 16.8632, *p* value = 0.0000) and Model 3 slightly outperforms Model 2 (*F* statistics = 1.7601, *p* value = 0.0491).
Significance level: *10%, **5%, ***1%.

are statistical significant. In contrast, for the downward crossings, in addition to a significantly positive coefficient of 0.009 for $A_t^{4\sim6}(\downarrow)$, similar to the significant positive coefficient for the S&P 500 index, the coefficient for $A_t^{13\sim15}(\downarrow)$ is a statistically significant 0.0011. Although both are positive, their sum however is only 0.002, smaller than the magnitude of the coefficient of for $B_t^{1\sim3}(\downarrow)$, –0.0027. Therefore, similar to the index, there is a reversal, again, only partial, of the price movement after downward crossings.

For variance, looking at the variance equation specification in Model 1, we notice ε_{t-1}^2, $\varepsilon_{t-1}^2 I_t(\boldsymbol{\varepsilon}_{t\text{-}1} < 0)$, and h_{t-1}^2 are all statistically significant. Along with the fact that they remain the same in sign and similar in magnitude in Models 2 and 3 after additional terms are added, this result indicates the appropriateness of the GJR-GARCH (1,1) specification for the variance equation. Moving on to the effect of the crossings as shown in Model 2, $B_t^{1\sim3}(\uparrow)$ has a coefficient of –0.007, $I_t(\uparrow)$, 0.0060, and $A_t^{1\sim3}(\uparrow)$, –0.0018, all statistically significant at the 1% level. This indicates volatility drops significantly before an upward barrier crossing, rises significantly during the crossing, and drops significantly after upward crossings. For downward crossings, we see that while $B_t^{1\sim3}(\downarrow)$ has a positive coefficient of 0.001, it is not statistically significant. Similar to upward crossings, $I_t(\downarrow)$ has a positive coefficient of 0.0169 and $A_t^{1\sim3}(\downarrow)$ negative coefficient of –0.0051, both are significant at the 1% level. Comparing the upward with downward crossings, it is clear that the market behaves similarly except that downward crossings are not preceded by a subdued market.

The results for the index futures are similar. Notice that the coefficients for $B_t^{1\sim3}(\uparrow)$ is –0.006, for $I_t(\uparrow)$, 0.0068, and for $A_t^{1\sim3}(\uparrow)$, –0.0019, all statistically significant at the 1% level, This similarly indicate a significant drop in volatility before an upward crossing, significant rise in volatility during the crossing, and significant drop in volatility after upward crossings. For downward

Table 4. GJR-GARCH results for 52-week high and low.

	Index						Index Futures					
	Model 1		Model 2		Model 3[a]		Model 1		Model 2		Model 3[b]	
	Coefficient	*p* Value	Coefficient	*p* Value	Coefficient	*p* Value	Coefficient	*p* Value	Coefficient	*p* Value	Coefficient	*p* Value
Mean Equation												
C	0.0001	0.681	−0.0001	0.627	−0.0001	0.633	0.0001	0.515	0	0.775	0.0001	0.666
$r_{s,t-1}$	−0.0537***	0.006	−0.0652***	0.001	−0.0668***	0.001	−0.0470**	0.015	−0.0573***	0.003	−0.0620***	0.002
$r_{s,t-2}$	−0.0251	0.152	−0.0337*	0.059	−0.0344*	0.055	−0.0313*	0.068	−0.0372**	0.032	−0.0384**	0.028
$B_t^{1\sim3}(\uparrow)$			0.0014***	0.002	0.0014***	0.004			0.0018***	0.000	0.0017***	0.001
$A_t^{1\sim3}(\uparrow)$			0.0002	0.753	0.0002	0.745			0.0001	0.922	0.0002	0.793
$A_t^{4\sim6}(\uparrow)$					−0.0001	0.866					−0.0007	0.165
$A_t^{7\sim9}(\uparrow)$					−0.0001	0.828					−0.0003	0.536
$A_t^{10\sim12}(\uparrow)$					0	0.977					−0.0004	0.513
$A_t^{13\sim15}(\uparrow)$					0.0005	0.340					0.0009*	0.083
$A_t^{16\sim18}(\uparrow)$					−0.0002	0.711					−0.0014**	0.012
$A_t^{19\sim21}(\uparrow)$					0	0.990					0.0002	0.788
$B_t^{1\sim3}(\downarrow)$			−0.0048*	0.080	−0.0049*	0.072			−0.0044*	0.094	−0.0046*	0.098
$A_t^{1\sim3}(\downarrow)$			0.0004	0.908	0.0003	0.924			0.0021	0.491	0.002	0.526
$A_t^{4\sim6}(\downarrow)$					−0.0005	0.896					−0.0038	0.306
$A_t^{7\sim9}(\downarrow)$					−0.0008	0.783					0.001	0.720
$A_t^{10\sim12}(\downarrow)$					0.0037	0.183					0.0022	0.421
$A_t^{13\sim15}(\downarrow)$					−0.0046*	0.069					−0.0033	0.282
$A_t^{16\sim18}(\downarrow)$					0.0044*	0.098					0.0056**	0.035
$A_t^{19\sim21}(\downarrow)$					−0.0008	0.731					−0.0001	0.968
Variance Equation (%)												
C	0.0002***	0.000	0.0002***	0.000	0.0002***	0.000	0.0002***	0.000	0.0002***	0.000	0.0002***	0.000
ε_{t-1}^2	−2.3600***	0.000	−2.0800***	0.000	−2.0400***	0.000	−1.9300***	0.002	−1.6800***	0.008	−1.6200**	0.015
$\varepsilon_{t-1}^2 I_t(\varepsilon_{t-1} < 0)$	15.6000***	0.000	14.1000***	0.000	14.2000***	0.000	16.7000***	0.000	14.5000***	0.000	14.8000***	0.000
h_{t-1}^2	93.2000***	0.000	93.3000***	0.000	93.2000***	0.000	92.0000***	0.000	92.6000***	0.000	92.2000***	0.000
$B_t^{1\sim3}(\uparrow)$			−0.0007***	0.000	−0.0007***	0.000			−0.0008***	0.000	−0.0008***	0.000
$I_t(\uparrow)$			0.0040***	0.000	0.0040***	0.000			0.0041***	0.000	0.0041**	0.000
$A_t^{1\sim3}(\uparrow)$			−0.0006**	0.026	−0.0007**	0.030			−0.0006**	0.025	−0.0005**	0.038
$B_t^{1\sim3}(\downarrow)$			−0.0006	0.881	−0.0005	0.886			−0.0015	0.599	−0.001	0.698
$I_t(\downarrow)$			0.0465*	0.059	0.0471*	0.052			0.0530*	0.078	0.0533*	0.067
$A_t^{1\sim3}(\downarrow)$			−0.0103	0.134	−0.0106	0.118			−0.0108	0.228	−0.0115	0.194
Adj. R^2	0.79		1.12		0.96		0.73		1.1		1.38	

[a]Based on the results from the Wald test, Model 2 strongly outperforms Model 1 (F statistics = 3.3987, p value = 0.0088) and Model 3 slightly outperforms Model 2 (F statistics = 1.6581, p value = 0.0696).
[b]Based on the results from the Wald test, Model 2 strongly outperforms Model 1 (F statistics = 4.2760, p value = 0.0019) and Model 3 slightly outperforms Model 2 (F statistics = 1.5226, p value = 0.1084).
Significance level: *10%, **5%, ***1%.

crossings, while $B_t^{1\sim3}(\downarrow)$ has a statistically insignificant 0.0000, the coefficient for $I_t(\downarrow)$ is a significant 0.0203 and for $A_t^{1\sim3}(\downarrow)$ a significant −0.0059, suggesting there is a significant rise in volatility during the crossing but a significant drop after the crossing. Moving on to Model 3, we see the coefficient estimates remain effectively the same as those in Model 2, suggesting the robustness of the results in Model 2.

Overall, the results from the crossings of 00 barriers indicate the existence of upward price movements before the upward crossings and a downward trend before the downward crossings, with the magnitude of the downward crossings greater than that of the upward crossings. While there is evidence of continuing upward trend for the S&P 500 index, but not the index futures, after upward crossings, there is evidence of partial reversal of the downward movement after downward crossings for both the index and index futures. In addition to these mean effects, volatility rises significantly before upward crossings, but not downward crossings, in both markets. During the crossing, both upward and downward, volatility climbs significantly. Finally, after the crossing, volatility drops off in both upward and downward crossings.

The previous results are similarly reported for 52-week highs and lows reported in Table 4. For both the index and futures the magnitude of the coefficient for upward crossings is notably smaller than that for the downward crossings. The hypothesis that the hypothesis of $B_t^{1\sim3}(\downarrow) \leq B_t^{1\sim3}(\uparrow)$ is rejected for the index, but not for the index futures, at the 10% significance level. After the crossings, we see no significant upward movements in the index. However, beyond the first 3 days after the crossing, for the index futures the coefficient for $A_t^{13\sim15}(\uparrow)$ is a statistically significant 0.0009 and for $A_t^{16\sim18}(\uparrow)$ statistically significant −0.0014, with a sum of −0.0005, which indicates a partial reversal of the upward trend before the crossing. For downward crossings, the index has a statistically significant coefficient of −0.0046 for $A_t^{13\sim15}(\downarrow)$ and a statistically significant 0.0044 for $A_t^{16\sim18}(\downarrow)$, with a sum of –0.0002, indicating a further, albeit small, downward movement. For the Index futures, the statistically significant 0.0056 for $A_t^{16\sim18}(\downarrow)$, which is greater than the –0.0046 for $B_t^{1\sim3}(\downarrow)$ and suggests a complete reversal that offset the price movement before the crossing.

For variance, the results for upward crossings are similar to those in Table 3 for 00 barriers. With a statistically significant decrease in volatility, the market is clearly subdued both before and after the crossings and a statistically significant increase in volatility during the crossing, indicating a volatile market while crossing. For downward crossings, the results are similar to those for 00 barriers in that there is no significant change in volatility before the crossings and significant increase in volatility during the crossing. In contrast, after the crossings, the change in volatility, though negative, is not statistically significant.

Interactions between the index and index futures surrounding the crossing: VECM results

Together, the results from examining each market separately reported in the section titled "Effects of barriers crossing on the index & index futures: GJR-GARCH results" suggest the presence of both mean and variance effects on the returns of the index and index futures around the crossing of 00 barriers and 52-week highs and lows. While the overall evidence is consistent with the literature on the existence of psychological barriers, the inclusion of the index futures in the examination, as opposed to only examining the index as previous studies have done, affords us fresh evidence on the disparity in postcrossing price movements between upward and downward crossings. For upward crossings, we continue to see a rise in the index but partial reversal in the index futures, while for downward crossings, there is an across-the-board partial reversal and in 1 case a complete reversal. With both the index and index futures, we can further examine both markets simultaneously and offer new evidence regarding the interactions between the 2 markets.

Before presenting the results from this further examination, we address the issues of unit roots and cointegration. Based on the literature that both the S&P500 index and index futures contain a unit root (Tsay [2010]), we perform the augmented Dickey-Fuller test. The results (available upon request) indicate that after a first-order differencing, both returns series no longer contain a unit root. Proceeding to test for cointegration, we employ both trace test and maximum-eigenvalue test. The results indicate the existence of 1 cointegration equation at the 5% level. Based on these results, the appropriate model for the relationship between the index and index futures is a VECM as presented in Model 4. In estimating the models, the cointegration equation is estimated separately for the 00 barriers and 52-week highs and lows. For the former, the estimated equation is $\ln(S_{t-1}) - 0.9903 \times \ln(F_{t-1}) - 0.0681$ and for the 52-week highs and lows, it is $\ln(S_{t-1}) - 0.9906 \times \ln(F_{t-1}) - 0.0656$. These equations are applied to their respective models to arrive at the estimates for the remaining variables.

As reported in Table 5, the results for the 00 barriers show that the for the index, the coefficients for the lag-1 index returns, and both lag-1 and lag-2 index futures returns are all statistically significant. These results confirm a definite link between index and index futures. This is true for index futures as well, as indicated by significant coefficients for the lag-2 index return and both lag-1 and lag-2 index futures returns. Once the returns on the other market are included in the equation, we now see that for the index the coefficient for $B_t^{1\sim3}(\uparrow)$ is no longer significant, though still positive, suggesting that the significant run-up evidenced by the statistically significant coefficient for $B_t^{1\sim3}(\uparrow)$ in Tables 3 and 4 may simply reflect the lag returns of the other market that are not included in the model there.

Moving on to the interactions after the crossings, notice that the coefficients for $A_t^{1\sim3}(\uparrow,\uparrow)$ is statistically insignificant, suggesting that when upward crossings occur in both index and index futures there is no further rise after the crossing. In contrast to this lack of further movements after both markets move in sync in crossing the barrier, the solo crossings that occur only in the index are accompanied by further postcrossing movements in both markets. We see that the coefficient for $A_t^{1\sim3}(\uparrow, 0)$ for the index is positive, 0.0031, and for the index futures also positive, 0.0028, both are statistically significant at the 5% and 10% levels, respectively. On the other hand, when the solo crossing occurs only in the index futures, the coefficients for $A_t^{1\sim3}(0,\uparrow)$ for both the index and index futures, though remain positive, are statistically insignificant. These contrasting results suggest that when upward crossing occurs only in the index, the markets continues their upward trend, yet when upward crossing occurs only in the index futures, there is no such a continuing upward trend. This contrasting evidence is also present for the downward crossing, but with a twist. While there is similarly no continuing fall in price when crossings occur in both index and index futures, as indicated by the statistically insignificant coefficient for $A_t^{1\sim3}(\downarrow,\downarrow)$, and when crossings occur solely in the index we also see a continuing downward movement in both markets, notably different now is that when downward crossings occur only in the index futures, there is actually a reversal, instead of

Table 5. Vector error correction model results for 00 barriers and 52-week high and low.

	00 Barriers				52-Week High and Low			
	Index		Index Futures		Index		Index Futures	
	Coefficient	*p* Value	Coefficient	*p* Value	Coefficient	*p* Value	Coefficient	*p* Value
Coint. Eq	0.0346	0.573	0.1483**	0.016	0.0369	0.548	0.1478**	0.017
$r_{s,t-1}$	−0.3746***	0.000	0.1114	0.270	−0.3707***	0.000	0.1301	0.200
$r_{s,t-2}$	0.0760	0.421	0.2846***	0.003	0.0650	0.492	0.2861***	0.003
$r_{f,t-1}$	0.2804***	0.005	−0.1906*	0.056	0.2812***	0.005	−0.2072**	0.039
$r_{f,t-2}$	−0.1539*	0.099	−0.3572***	0.000	−0.1410	0.131	−0.3596***	0.000
C	0.0003	0.228	0.0003	0.287	0.0000	0.979	0.0000	0.986
$B_t^{1\sim3}(\uparrow)$	0.0012	0.149	0.0013	0.126	0.0021*	0.052	0.0023**	0.038
$B_t^{1\sim3}(\downarrow)$	−0.0035***	0.000	−0.0034***	0.000	−0.0052***	0.003	−0.0046**	0.010
$A_t^{1\sim3}(\uparrow,\uparrow)$	−0.0006	0.530	−0.0008	0.423	0.0006	0.639	0.0005	0.740
$A_t^{1\sim3}(\uparrow,0)$	0.0031**	0.033	0.0028*	0.056	0.0009	0.566	0.0005	0.772
$A_t^{1\sim3}(0,\uparrow)$	0.0006	0.714	0.0006	0.673	−0.0002	0.914	0.0001	0.977
$A_t^{1\sim3}(\downarrow,\downarrow)$	−0.0004	0.628	−0.0001	0.928	0.0032	0.122	0.0018	0.385
$A_t^{1\sim3}(\downarrow,0)$	−0.0060***	0.000	−0.0064***	0.000	−0.0101***	0.003	−0.0118***	0.001
$A_t^{1\sim3}(0,\downarrow)$	0.0033**	0.048	0.0039**	0.021	0.0028	0.442	0.0034	0.362

Note. Both trace test and max-eigenvalue test indicate cointegrating equation at the 0.05 level and the estimated cointegrating equation is: $\ln(S_{t-1}) - 0.9903 \times \ln(F_{t-1}) - 0.0681$ for the 00 barriers and $\ln(S_{t-1}) - 0.9906 \times \ln(F_{t-1}) - 0.0656$ for the 52-week highs and lows.
Significance level: *10%, **5%, ***1%.

a continuing fall, of the price movement, as indicated by the positive and statistically significant coefficient for $A_t^{1\sim3}(0,\downarrow)$.

For the 52-week high and low, we see similar results of lag-returns on the index and index futures have statistically significant effects on the returns in both markets. We also see that $A_t^{1\sim3}(\uparrow,\uparrow)$ and $A_t^{1\sim3}(\downarrow,\downarrow)$, are both statistically insignificant, indicating that when both markets agree and act in sync in either upward or downward crossing, then no more continuing price trend after the crossing. Similarly, when the crossing occurs only in the index futures, both the coefficients for $A_t^{1\sim3}(0,\uparrow)$ and $A_t^{1\sim3}(0,\downarrow)$, are statistically insignificant. Different from the 00 barriers; however, when upward crossings occur only in the index we see no continuing rise in price movement as indicated by the insignificant coefficient for $A_t^{1\sim3}(\uparrow,0)$. In contrast, as indicated by the significant coefficients for $A_t^{1\sim3}(\downarrow,0)$ of –0.0101 and –0.0108, respectively, for the index and index futures, there is a continuing fall in price in both markets after solo downward crossings in the index.

Overall, Table 5 presents new findings about the spillover effects of the crossings between the markets. Such effects depend clearly on whether the crossing occurs simultaneously or only in 1 market. In the case of synchronized crossings, there is no further upward or downward movement after the crossing. For crossings only in 1 market, it depends on in which market the crossings occur. When they occur only in the index, the price trend continues. On the other hand, when crossings happen solely in the index futures, there is no significant upward movement for upward crossings but prices stop falling for downward crossings.

Nonsynchronicity in barrier crossings between index and index futures

The previous results from VECM modeling are consistent with the evidence in the literature of a linkage between indexes and their associated index futures contracts. However, notably different from the typical finding of futures leading index in revealing information the results indicate the dominance of the index in determining the postcrossing price continuation. Only in crossings that occur solely in the index do we see prices continue to rise in both markets after upward crossings and fall after downward crossings. This price continuation is clearly not present when both markets cross the barrier simultaneously. Moreover, when the crossing occurs only in the index futures, the precrossing momentum actually stopped after the crossing.

In addition to the previous results regarding the direction of price movements before and after the crossings, the inclusion of both the index and index futures further offers us opportunity to compare the relative magnitude of the price movements in the index and index futures during the crossing and contrast between upward and downward crossings. For this, we examine the basis because it is a gauge of the difference between the index and index futures.

In performing this examination, we use the following definition of the basis, BA_t[9]:

$$BA_t = \ln(S_t) - \ln(F_t) \quad (5)$$

where S_t and F_t are the value of the index and index future on day t, respectively.

It is well known that the basis between the spot and futures markets is not zero except on or immediately before the maturity date of the futures. After accounting for the factors behind this fact, we can then see how the crossing of the psychological price levels transpires on the spread. A priori, if the crossing has no impact on the markets, then one would expect to see nothing results in the spread. If this is not the case, it is interesting to examine what happens to each market. Clearly, when a solo barrier crossing happens, the 2 markets diverge regarding the price momentum and such divergence should be reflected in the spread. Even when both markets agree on the price direction and have a synchronized crossing, it is possible that the magnitude of the price momentum can still vary between the 2 markets. Furthermore, one should also entertain the possibility that the 2 markets may behave differently during upward crossings than downward crossings. To investigate these possibilities, we perform regression tests on the basis based on the following model:

$$BA_t = \alpha + \beta \times Time\ to\ Maturity + \gamma_1 BA_{t-1} + \gamma_{21} BA_{t-2} + \delta_1 I_t^{\uparrow,\uparrow} + \delta_2 I_t^{\downarrow,\downarrow} + \delta_3 I_t^{\uparrow,0} + \delta_4 I_t^{\downarrow,0} + \delta_5 I_t^{0,\uparrow} + \delta_6 I_t^{0,\downarrow} \tag{6}$$

where time to maturity and the first 2 orders of the lagged basis are used as control variables, given that time to maturity has been shown to be linked to the basis and AR(2) best represents the dynamics between the basis and its past. The remaining 6 regressors, $I_t^{\uparrow,\uparrow} I_t^{\downarrow,\downarrow}$, $I_t^{\uparrow,0}$, $I_t^{\downarrow,0}$, $I_t^{0,\uparrow}$, and $I_t^{0,\downarrow}$, are variables indicating the occurrence on day t of a synchronized upward crossing, synchronized downward crossing, index-only upward crossing, index-only downward crossing, futures-only upward crossing, and futures-only downward crossing, respectively. The coefficients and test statistics are estimated based on weighted least square regression with the time to maturity as the weight.

Before presenting the regression results, we first look at the time series plot of the spread during the sample period as presented in Figure 1. We notice that the basis hovers between 0.01 and –0.01, but at times deviates beyond this range. The augmented Dickey-Fuller test shows that it is stationary (test statistics is –11.7738 and p value is 0.0000). Moving on to the regression results reported in Table 6, we see that for the 00 barriers, all 6 indicator variables are statistically significant at the conventional levels, indicating a strong relationship between the basis and the crossings of the barriers. The positive coefficient for $I_t^{\uparrow,\uparrow}$ indicates that when synchronized upward crossings occur, the basis increases. As both the index and index futures are rising in this case, the increase in basis means that the index rises more than the index futures. On the other hand, when synchronized downward crossings occur, the positive coefficient for, $I_t^{\downarrow,\downarrow}$ indicates that the basis is also increased. Given that both the index and index futures are falling now, the increase in basis indicates that the index futures falls more than the index. Based on these 2 results, it is clear that the 2 markets react with different magnitude even when they both agree on the direction of the price movement. Proceeding to solo crossings, the positive (negative) coefficient for, $I_t I^{\uparrow,0}$ ($I_t^{\downarrow,0}$) indicates that the basis rises (falls) when upward (downward) crossings occur only in the index, suggesting the index experiences a higher jump (greater fall) in value than the index futures does. Similarly, when upward (downward) crossings occur only in the index futures, the negative (positive) coefficient for $I_t^{0,\uparrow}$ ($I_t^{0,\downarrow}$) indicates the basis increases (falls), suggesting the index futures increases (decreases) more in price than the index futures does. These 2 results for nonsynchronized crossings are to be expected as they demonstrate that the market that crosses the barrier tends to experience a higher jump in value in upward crossings or greater drop in downward crossings than the other market that does not cross the barrier.

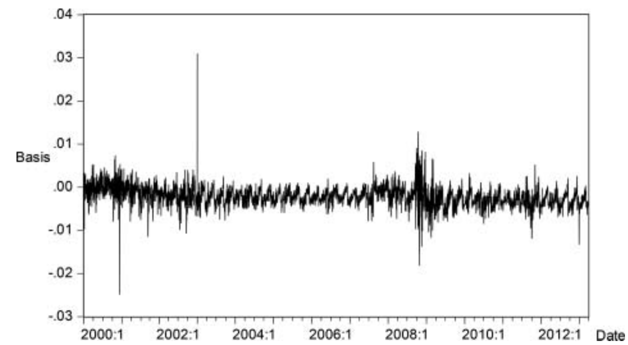

Figure 1. Time series plot of the basis during the sample period.

Table 6. Analysis of the basis.

	00 Barriers		52-Week Highs and Lows	
	Coefficient	p Value	Coefficient	p Value
C	0.0002***	(0.0014)	0.0003***	(0.0000)
Time to Maturity	−0.0030***	(0.0000)	−0.0031***	(0.0000)
AR(1)	0.4504***	(0.0000)	0.4496***	(0.0000)
AR(2)	0.3664***	(0.0000)	0.3641***	(0.0000)
$I^{\uparrow,\uparrow}$	0.0011***	(0.0001)	0.0001	(0.7788)
$I^{\downarrow,\downarrow}$	0.0012***	(0.0000)	0.0001	(0.8879)
$I^{\uparrow,0}$	0.0010**	(0.0170)	0.0009*	(0.0696)
$I^{\downarrow,0}$	−0.0011**	(0.0446)	−0.0013	(0.2201)
$I^{0,\uparrow}$	−0.0012**	(0.0211)	−0.0003	(0.5666)
$I^{0,\downarrow}$	0.0023***	(0.0000)	0.0009	(0.4222)
Adj. R^2 (%)	59.20		58.35	

Note. The estimation is based on weighted least square with time to maturity as the weight.

For the 52-week highs and lows we notice that, in contrast to 00 barriers where all the indicator variables are significant, only $I_t^{\uparrow,0}$ is statistically significant at the 10% level. This lack of significance for the majority of the indicator variables indicates no difference in the price movements during the crossings of 52-week highs and lows between the index and index futures except when an upward crossing occurs only in the index. By examining the basis here, we therefore see that in crossing the 52-week highs and lows, as opposed to the crossings of the 00 barriers, the index and index futures tend to move more evenly between them, even when they do not cross the price levels simultaneously.

Overall, the examination of the spread on the day of crossing yields further insight that pertains specifically to 00 barriers. The index is shown to rise more than the futures when synchronized upward crossings occur but the futures falls more when synchronized downward crossings occur.

Subsample results

The Great Recession in the aftermath of the burst of the subprime real estate bubble in the United States has macroeconomic impacts second only to the Great Depression in the 1930s. Studies such as Malmendier and Nagel [2011] have shown that the experience of the Great Depression has left many investors less willing to take financial risk. Plausibly, the increased aversion to risk can similarly happen to some investors after experiencing the Great Recession. It is therefore necessary to explore whether such a change in investor psyche affects the price dynamics during the crossing of psychological price levels. Additionally, given that we are addressing the issue of investor psychology, the contrast between the irrational exuberance accompanying bull market and the excessive pessimism associated with bear market similarly raises the question of whether the price dynamics of the crossing of psychological price levels vary with the market condition. To provide answers to these 2 questions, we perform subsample examinations for the pre- and postcrisis periods as well as bull and bear markets.

To define the pre- and postcrisis periods, we use the stock market major events as the guide to identify the turning point in the market, considering there is no officially declared beginning and ending dates of the crisis. We use October 10, 2007, the day when both the S&P 500 and DJIA peaked before the major falls started, as the cutoff date. Hence, the precrisis period is from 1/3/2000 to 10/09/2007 and the postcrisis period 10/10/2007 to 4/2/2013. For the identification of bull and bear markets, we similarly rely on the performance of the stock market as a guide and follow the common definition of a bear market as a period in which the S&P 500 falls at least 20% and bull market as one when the S&P rises at least 20%. Based on this criterion, the bear market periods are identified to be the periods of 3/24/2000 to 9/21/2001, 1/5/2002 to 10/9/2002, 10/8/2007 to 11/20/2008, 1/7/2009 to 3/9/2009, and 3/7/2013 to 4/2/2013, and the bull market periods include 1/3/2000 to 3/23/2000, 9/22/2001 to 1/4/2002, 10/10/2002 to 10/7/2007, 11/21/2008 to 1/6/2009, and 3/10/2009 to 3/6/2013. Results from these subsamples yield mostly similar conclusion to what have been reported so far with some subtle subsample differences. To streamline the presentation, we report in Tables 8 and 9, the VECM results and the regression results of the spread, respectively.

Before discussing these subsample results, we first report in Table 7 the frequency of crossings in subsample periods. We see that of the 97 upward crossings of the 00 barriers in the index, 52 occur in the precrisis period while 45 in the postcrisis period. In percentage term, the postcrisis crossings represent 46.4% of the total crossings in the full sample period, suggesting that fewer crossings occur in the postcrisis period. However, if we assume that crossings of the psychological price levels occur in direct proportion to the length of the time period involved and considering that the total of 2,002 days in the postcrisis period constitute only 41.4% of the 4,939 days in the full sample period, there are actually more crossings in the postcrisis period. This is also true for the downward crossings because the 54 downward crossings in the postcrisis period represent 45.8% of all downward crossings. For the index futures, the 55 downward crossings in the postcrisis period represent 46.6% of all downward crossing while the 48 upward crossings 51.1% of all upward crossings. Together, there are actually more crossings, both upward and downward, in the postcrisis period. For the 52-week highs and lows, the postcrisis period experiences 22 (38.6%) upward crossings, which is relatively fewer than the percentage of observations in the postcrisis period. This is similarly true for the index futures because there are relatively fewer, 20 (37%), upward crossings in the postcrisis period. On the other hand, the downward crossings in the postcrisis period in both the index and index futures, 61.9% and 60%, respectively, outnumber the crossings in the precrisis period. Therefore, unlike the 00 barriers, for the 52-week highs and lows there are fewer upward crossings but more downward crossings in the postcrisis period.

For the bull and bear subsamples, the index experiences 74 upward crossings in the bull periods, representing 76.3% of all upward crossings, and is greater than the relative length of the bull periods relative to the full sample period, 72.6%. For the downward crossings, the 71

Table 7. Frequency distribution of crossings for pre- and post-subprime crisis periods and bull and bear markets.

Panel A: Pre- and post-subprime crisis periods

			Index				Index Futures			
			Upward		Downward		Upward		Downward	
	Days	%		%		%		%		%
00-Barriers										
Pre-Crisis	2837	58.6	52	53.6	64	54.2	46	48.9	63	53.4
Post-Crisis	2002	41.4	45	46.4	54	45.8	48	51.1	55	46.6
Total	4839	100	97	100	118	100	94	100	118	100
52-Week Highs and Lows										
Pre-Crisis	2837	58.6	35	61.4	8	38.1	33	62.3	8	40.0
Post-Crisis	2002	41.4	22	38.6	13	61.9	20	37.7	12	60.0
Total	4839	100	57	100	21	100	53	100	20	100

Note. Pre-Subprime Crisis Period: 1/03/2000 to 10/09/2007, 1,947 obs. Post-Subprime Crisis Period: 10/10/2007 to 4/02/2013, 1,378 obs.

Panel B: Bull and bear markets

			Index				Index Futures			
			Upward		Downward		Upward		Downward	
	Days	%		%		%		%		%
Bull	3515	72.6	74	76.3	71	60.2	72	76.6	69	58.5
Bear	1324	27.4	23	23.7	47	39.8	22	23.4	49	41.5
Total	4839	100	97	100	118	100	94	100	118	100
52-Week Highs and Lows										
Bull	3515	72.6	55	96.5	1	4.8	52	98.1	1	5.0
Bear	1324	27.4	2	3.5	20	95.2	1	1.9	19	95.0
Total	4839	100	57	100	21	100	53	100	20	100

Note. Bear market periods: 3/24/2000 to 9/21/2001, 1/5 to 10/9/2002, 10/8/2007 to 11/20/2008, and 1/7 to 3/9/2009, 3/7to 4/2/2013. Bull market periods: 1/3/2000 to 3/23/2000, 9/22/2001 to 1/4/2002, 10/10/2002 to 10/7/2007, 11/21/2008 to 1/6/2009, and 3/10/2009 to 3/6/2013.

crossings in the bull periods constitute 60.2% of all downward crossings, less than 72.6%, the relative length of the bull periods. For the index futures, the bull periods report the similar higher percentage, 76.6%, of upward crossings and lower percentage, 58.5%, of downward crossings. Together, these numbers indicate, not surprisingly, more upward crossings and fewer downward crossings in bull markets and, vice versa, more downward crossings and fewer upward crossings in bear market.

For the 52-week highs and lows, we see the index has a total of 55 (96.5%) upward crossings while only 1 (4.8%) downward crossing in bull markets. For the index futures, the 52 (98.1%) upward crossings and 1 (5.0%) downward crossing similarly show that almost all the upward crossings occur in bull markets while downward crossings take place in bear markets. This phenomenon of both the index and index futures having an extremely high frequency of upward crossings and very infrequent downward crossings in bull markets vividly contrasts with the mirror image in bear markets of very infrequent upward crossings—3.5% and 1.9%, respectively, for the index and index futures, while an overwhelmingly high frequency of downward crossings—95.2% and 95%, respectively. This lopsided subsample characteristic of upward crossings being effectively a bull market phenomenon while downward crossings in fact a bear market event, pose a severe statistical estimation problem and prevent us from performing bull-bear subsample comparison for 52-week highs and lows. Consequently, for the 52-week highs and lows we only examine the pre- versus postcrisis. For the 00 barriers, we include both the pre- versus postcrisis and bull versus bear subsample examinations. The results are reported in Tables 8 and 9.

For the VECM results reported in Table 8 we focus on and summarize the coefficients for the indicator variables for the pre- and postcrossing price movements. Compared with the full-sample results, we see among all the coefficients that are statistically significant at the conventional levels their signs remain the same as those of their counterparts in the full sample. This suggests the robustness of the results reported so far. We notice that for the index in both subperiods, $B_t^{1\sim3}(\downarrow)$ is statistically significant. After the crossings, $A_t^{1\sim3}(\uparrow, 0)$ is significant in the precrisis period, but not in the postcrisis period. On the other hand, $A_t^{1\sim3}(\downarrow, 0)$ is significant, but only in the postcrisis period. Finally, $A_t^{1\sim3}(0, \downarrow)$, which is significant in the full sample is no longer significant in both subsamples. One possible reason for the

Table 8. Vector error correction model subsample results: Pre- versus post-subprime crisis.

	Index					Index Futures				
	Full Sample	Precrisis		Post-Crisis		Full Sample	Precrisis		Postcrisis	
	Coefficient	Coefficient	*p* Value	Coefficient	*p* Value	Coefficient	Coefficient	*p* Value	Coefficient	*p* Value
00 Barriers										
$B_t^{1\sim3}(\uparrow)$	0.0012	0.0015	0.1134	0.0011	0.4270	0.0013	0.0021^{**}	0.0352	0.0012	0.3836
$B_t^{1\sim3}(\downarrow)$	-0.0035^{***}	-0.0031^{***}	0.0002	-0.0037^{***}	0.0060	-0.0034^{***}	-0.0031^{***}	0.0004	-0.0031^{**}	0.0211
$A_t^{1\sim3}(\uparrow,\uparrow)$	−0.0006	−0.0014	0.2350	0.0006	0.7165	−0.0008	−0.0012	0.3099	0.0003	0.8449
$A_t^{1\sim3}(\uparrow,0)$	0.0031^{**}	0.0048^{***}	0.0008	−0.0028	0.3681	0.0028^{*}	0.0047^{***}	0.0013	−0.0036	0.2508
$A_t^{1\sim3}(0,\uparrow)$	0.0006	−0.0010	0.5334	0.0027	0.3250	0.0006	−0.0004	0.8108	0.0023	0.3966
$A_t^{1\sim3}(\downarrow,\downarrow)$	−0.0004	−0.0004	0.6929	−0.0004	0.8052	−0.0001	0.0001	0.9286	0.0000	0.9887
$A_t^{1\sim3}(\downarrow,0)$	-0.0060^{***}	0.0003	0.8775	-0.0168^{***}	0.0000	-0.0064^{***}	0.0006	0.7520	-0.0178^{***}	0.0000
$A_t^{1\sim3}(0,\downarrow)$	0.0033^{**}	0.0019	0.3058	0.0038	0.2053	0.0039^{**}	0.0022	0.2497	0.0046	0.1244
52-Week Highs and Lows										
$B_t^{1\sim3}(\uparrow)$	0.0021^{*}	0.0015	0.1858	0.0020^{*}	0.0872	0.0023^{**}	0.0029	0.1631	0.0024	0.2626
$B_t^{1\sim3}(\downarrow)$	-0.0052^{***}	-0.0048^{**}	0.0490	−0.0022	0.3611	-0.0046^{**}	-0.0050^{*}	0.0636	-0.0051^{*}	0.0640
$A_t^{1\sim3}(\uparrow,\uparrow)$	0.0006	0.0007	0.6333	0.0004	0.7825	0.0005	0.0004	0.8837	−0.0001	0.9766
$A_t^{1\sim3}(\uparrow,0)$	0.0009	0.0020	0.3008	0.0013	0.4916	0.0005	−0.0004	0.8981	−0.0004	0.8908
$A_t^{1\sim3}(0,\uparrow)$	−0.0002	−0.0016	0.4075	−0.0013	0.5263	0.0001	0.0012	0.6964	0.0014	0.6646
$A_t^{1\sim3}(\downarrow,\downarrow)$	0.0032	0.0052^{*}	0.0882	0.0043	0.1564	0.0018	0.0017	0.5919	0.0008	0.7838
$A_t^{1\sim3}(\downarrow,0)$	-0.0101^{***}	−0.0010	0.8117	−0.0013	0.7584	-0.0118^{***}	-0.0163^{***}	0.0033	-0.0191^{***}	0.0006
$A_t^{1\sim3}(0,\downarrow)$	0.0028	−0.0055	0.1868	−0.0049	0.2431	0.0034	0.0131^{*}	0.0509	0.0131^{*}	0.0510

Note. Both trace test and max-eigenvalue test indicate cointegrating equation at the 0.05 level and the estimated cointegrating equation for the pre-subprime period is: $\ln(S_{t-1}) - 0.9837 \times \ln(F_{t-1}) - 0.1123$ for the 00 barriers and $\ln(S_{t-1}) - 0.9837 \times \ln(F_{t-1}) - 0.1123$ for the 52-week highs and lows. For the post-subprime period, they are: $\ln(S_{t-1}) - 0.9965 \times \ln(F_{t-1}) - 0.0266$ for the 00 barriers and $\ln(S_{t-1}) - 0.9968 \times \ln(F_{t-1}) - 0.0246$ for the 52-week highs and lows.
Significance level: *10%, **5%, ***1%.

loss of significance of this coefficient has to do with the fact that subsamples obviously have fewer crossings, hence fewer observations for which this variables take on a value of 1, resulting in a loss of statistical power due to relatively larger number of observations having a value of 0.

For the index futures, we see the identical pattern of $B_t^{1\sim3}(\downarrow)$ being significant in both periods, $A_t^{1\sim3}(\uparrow,0)$ significant in the precrisis period, and $A_t^{1\sim3}(\downarrow,0)$ significant in the postcrisis period. Interestingly, we notice that for the index futures $B_t^{1\sim3}(\uparrow)$, which is not significant in the full sample results, is now statistically significant at the 5% level, suggesting upward crossings in the precrisis period are preceded by a significant rise in price. This significant movement is apparently obscured when we combine the 2 subperiods.

For the 52-week highs and lows, we similarly see that the coefficients that are statistically significant have the same sign as those in the full sample. In the index we see $B_t^{1\sim3}(\uparrow)$ is statistically significant in the postcrisis period while $B_t^{1\sim3}(\downarrow)$ is significant in the precrisis period. After the crossings, $A_t^{1\sim3}(\downarrow,\downarrow)$ is now significant in the precrisis period, indicating a significant rise in price, hence a reversal when a downward crossing occurs in both markets. Finally, $A_t^{1\sim3}(\downarrow, 0)$ is no longer significant, possibly due to the reduction of statistical power in subsamples. This loss of significance happens also in the index futures for $B_t^{1\sim3}(\uparrow)$, which is not significant in the subperiods. On the other hand, it is interesting to see that $A_t^{1\sim3}(0,\downarrow)$, which is not significant in the full sample, is now significant in both subsamples.

Looking at bull versus bear results for 00 barriers reported in Table 9, we see the similar results that the signs of the significant coefficients remain the same as those of their counterparts in the full sample, some coefficients—$A_t^{1\sim3}(\uparrow,0)$ and $A_t^{1\sim3}(0,\downarrow)$—lose significance in subsample(s) while other coefficient—$A_t^{1\sim3}(\downarrow,\downarrow)$—is significant in subperiods.

Moving on to the results for the regression of the spread reported in Table 10, we see that for the 00 barriers in the precrisis period, 3 coefficients— $I^{\uparrow,\uparrow}$, $I^{\downarrow,\downarrow}$, and $I^{0,\uparrow}$—are statistically significant. While the smaller sample size may partly explain the results of fewer significant coefficients, the fact that synchronized crossings in both markets, as captured by $I^{\uparrow,\uparrow}$ and $I^{\downarrow,\downarrow}$, are significant suggests that when there is a consensus on the price trend in both markets we see significant price movements and in this case it is the index that experiences a higher rise in value in upward crossings and the index futures that has a greater fall in price in downward crossings. On the other hand, when nonsynchronous crossings occur, the only significant coefficient reported for $I^{0,\uparrow}$ suggests that when the 2 markets don't agree completely, only the upward crossing in the futures has a relatively significant greater increase in price. For the postcrisis period, all coefficients except $I^{0,\uparrow}$ are significant. It is worth pointing out that despite having relative shorter length in time than the precrisis period, the postcrisis period reports more significant coefficients, especially those involving the crossings of the index—$I^{\uparrow,\uparrow}$, $I^{\uparrow,0}$, and $I^{\downarrow,0}$—and among them only one, $I^{\uparrow,\uparrow}$, is significant in the precrisis period. The stronger

Table 9. Vector error correction model subsample results for 00 barriers: Bull versus bear market.

	Index					Index Futures				
	Full Sample	Bull		Bear		Full Sample	Bull		Bear	
	Coefficient	Coefficient	p Value	Coefficient	p Value	Coefficient	Coefficient	p Value	Coefficient	p Value
$B_t^{1\sim3}(\uparrow)$	0.0012	0.0007	0.3729	0.0027	0.2151	0.0013	0.0009	0.2447	0.0037	0.1017
$B_t^{1\sim3}(\downarrow)$	−0.0035***	−0.0021***	0.0083	−0.0041**	0.0135	−0.0034***	−0.0016**	0.0458	−0.0039**	0.0193
$A_t^{1\sim3}(\uparrow,\uparrow)$	−0.0006	−0.0004	0.6823	−0.0027	0.3133	−0.0008	−0.0005	0.6009	−0.0031	0.2529
$A_t^{1\sim3}(\uparrow,0)$	0.0031**	0.0023*	0.0959	0.0036	0.3312	0.0028*	0.0022	0.1096	0.0037	0.3252
$A_t^{1\sim3}(0,\uparrow)$	0.0006	0.0005	0.7457	0.0004	0.9162	0.0006	−0.0003	0.8513	0.0036	0.3895
$A_t^{1\sim3}(\downarrow,\downarrow)$	−0.0004	0.0016*	0.0916	−0.0027	0.1355	−0.0001	0.0016*	0.0900	−0.0018	0.3143
$A_t^{1\sim3}(\downarrow,0)$	−0.0060***	−0.0027*	0.0770	−0.0296***	0.0000	−0.0064***	−0.0024	0.1108	−0.0340***	0.0000
$A_t^{1\sim3}(0,\downarrow)$	0.0033**	0.0032**	0.0433	0.0055	0.2385	0.0039**	0.0032**	0.0415	0.0086*	0.0671

Note. Both trace test and max-eigenvalue test indicate cointegrating equation at the 0.05 level and the estimated cointegrating equation is: $\ln(S_{t-1}) - 0.9896 \times \ln(F_{t-1}) - 0.0708$ for the bear market and $\ln(S_{t-1}) - 0.9849 \times \ln(F_{t-1}) - 0.1068$ for the bull market.
Significance level: *10%, **5%, ***1%.

results suggest that our whole-sample results may be primarily driven by and, hence, reflect the market behavior after the subprime crisis. By the same token, the fact that $I^{0,\uparrow}$ is not significant in the postcrisis period, but, in contrast, significant in the precrisis period suggests that the full sample result for $I^{0,\uparrow}$ mainly reflects this precrisis result. Again, all the significant coefficients in the subsamples have a sign the same as that of their counterparts in

Table 10. Regression analysis of the basis and the barriers: Pre- versus post-subprime crisis and bull versus bear market.

Panel A: Pre- versus postcrisis

	Full Sample	Precrisis		Postcrisis	
	Coefficient	Coefficient	p Value	Coefficient	p Value
00-Barriers					
$I^{\uparrow,\uparrow}$	0.0011***	0.0009**	0.0186	0.0008**	0.0182
$I^{\downarrow,\downarrow}$	0.0012***	0.0009***	0.0039	0.0012***	0.0005
$I^{\uparrow,0}$	0.0010**	0.0007	0.1274	0.0022**	0.0133
$I^{\downarrow,0}$	−0.0011**	−0.0008	0.2520	−0.0016*	0.0535
$I^{0,\uparrow}$	−0.0012**	−0.0019***	0.0010	0.0000	0.9820
$I^{0,\downarrow}$	0.0023***	0.0011	0.1117	0.0030***	0.0003
Adj. R^2 (%)	59.20	62.01		23.14	
52-week highs and lows					
$I^{\uparrow,\uparrow}$	0.0001	0.0000	0.0000	0.0007	0.3730
$I^{\downarrow,\downarrow}$	0.0001	0.0020*	0.9154	−0.0017**	0.0364
$I^{\uparrow,0}$	0.0009*	0.0002	0.0621	0.0009	0.1244
$I^{\downarrow,0}$	−0.0013	−0.0011	0.8287	−0.0035*	0.0679
$I^{0,\uparrow}$	−0.0003	−0.0004	0.3395	−0.0003	0.6621
$I^{0,\downarrow}$	0.0009	0.0020*	0.6068	−0.0049*	0.0545
Adj. R^2 (%)	58.35	61.56		21.74	

Panel B: Bull versus bear market: 00 barriers

	Full Sample	Bear Market		Bull Market	
	Coefficient	Coefficient	p Value	Coefficient	p Value
$I^{\uparrow,\uparrow}$	0.0011***	0.0007	0.2493	0.0012***	0.0000
$I^{\downarrow,\downarrow}$	0.0012***	0.0020***	0.0000	0.0007***	0.0043
$I^{\uparrow,0}$	0.0010**	0.0008	0.4265	0.0011**	0.0126
$I^{\downarrow,0}$	−0.0011**	−0.0024	0.2323	−0.0011**	0.0331
$I^{0,\uparrow}$	−0.0012**	−0.0016	0.2979	−0.0013***	0.0097
$I^{0,\downarrow}$	0.0023***	0.0072***	0.0000	0.0009*	0.0769
Adj. R^2 (%)	59.20	49.47		60.87	

Note. The estimation is based on weighted least square with time to maturity as the weight. Pre-Subprime Period: 1/03/2000 to 10/09/2007, 1,947 obs. Post-Subprime Crisis Period: 10/10/2007 to 4/02/2013, 1,378 obs. Bear market: 3/24/2000 to 9/21/2001, 1/5 to 10/9/2002, 10/8/2007 to 11/20/2008, 1/7 to 3/9/2009, and 3/7/2013 to 4/2/2013. Bull market periods: 1/3 to 3/23/2000, 9/22/2001 to 1/4/2002, 10/10/2002 to 10/7/2007, 11/21/2008 to 1/6/2009, and 3/10/2009 to 3/6/2013.
Significance level: *10%, **5%, ***1%.

Table 11. Summary of the VECM results of the effects of barriers on returns.

	GJR GARCH Results					VECM Results			
	00 Barriers		52-Week High and Low			00 Barriers		52-Week High and Low	
	Index	Index Futures	Index	Index Futures		Index	Index Futures	Index	Index Futures
				Upward Crossings					
Before	rise +[a]	rise +	rise +	Rise +	Before			rise +	rise +
After					After	rise	rise		
1∼3	rise				(↑,↑)[b]				
	+				(↑,0)	+	+		
					(0,↑)				
4∼18	rise more +			partial reversal + −					
				Downward Crossings					
Before	fall −	fall −	fall −	fall −	Before	fall −	fall −	fall −	fall −
After					After	fall more	fall more	fall more	fall more
1∼3					(↓,↓)				
					(↓,0)	−	−	−	−
					(0,↓)	+	+	+	+
4∼18	partial reversal +	partial reversal + +	partial reversal − +	full reversal +					

[a]+ (−) indicates a positive and statistically significant coefficient estimate for the indicator variable for the period involved.
[b](p,q) where p (q) = ↑, 0, or ↓ indicates the S&P500 index (index futures) has an upward crossing, no crossing, or downward crossing, respectively.

the full sample, offering another evidence of the robustness of the results.

For the 52-week highs and lows, one immediately notices that while $I^{\uparrow,0}$ is the only 1 indicator variable with a significant coefficient in the full sample results, it is not significant in the results in both subperiods. Instead, we cannot but notice that the coefficients for $I^{\downarrow,\downarrow}$ and $I^{0,\downarrow}$ are statistically significant. More importantly, their sign is positive in the precrisis period but negative in the postcrisis period. Presumably, the opposite signs cancel out each other when both periods are combined in the full sample, resulting in their insignificant coefficient in the full sample. The positive sign in the precrisis period suggests that the magnitude of the fall in the futures is relatively greater than that of the fall in the index. In contrast, in the postcrisis period, the negative sign means that the magnitude of the fall in the index is greater than that of the fall in the index futures. One interpretation of these contrasting results is that in the precrisis period, the index futures dominates in the price drop during a synchronous downward crossing or a solo crossing in the index futures, however, it is the index that dominates in the price drop in the postcrisis period.

For the bull versus bear comparison, our examination of the 00 barriers reported in panel B of Table 10 shows that while only 2 indicator variables, $I^{\downarrow,\downarrow}$ and $I^{0,\downarrow}$ have a coefficient that is significant in bear market, all 6 indicator variables in bull market are statistically significant. One interpretation of these results is that due to the bull market subsample, which has a total of 3,515 observations, outnumbers the bear market subsample, resulting in the full sample reflecting the results of the former.

Overall, while the results from the subsample examinations reported in Table 10 are mostly consistent with the full sample results reported in Table 6, they do reveal some subtle differences. For the 00 barriers, these include the strong results in the post-subprime crisis period and results in bull markets are the same as the full sample results. For the 52-week highs and lows, we see synchronous downward crossings and solo downward crossings in the index futures show opposite signs between pre- and postcrisis subsamples.

Conclusion and discussion

Examining the price dynamics between S&P 500 index and index futures surrounding the crossings of the 00 psychological barriers and 52-week highs and lows, we provide fresh evidence on the price movements between index and index futures that are not driven by fundamental factors. To help summarize these results, we put together in Table 11, the GJR-GARCH results of Model 3 presented in Tables 3 and 4 as well as the VECM results in Tables 5 and 6. As indicated, the crossing of psychological price levels is associated with mean effects that include a buildup of momentum in both markets of rising price before upward crossings and falling price before downward crossings. Comparing the magnitude of the coefficient estimates, we find the fall in price for downward crossings to be greater in magnitude than the increase in price for upward crossings. This is consistent with what many market participants have long observed that markets fall quicker than they rise and that human emotions associated with gain from rising price, and loss from falling markets, are plausibly responsible for this disparity in price movements.

Relatively speaking, we can consider the larger price drop in downward crossings an overreaction and the smaller price increase an underreaction. As the emotions associated with the crossings dissipate, we expect the former to experience a reversal to offset the excessive fall in price while the latter should see a further price increase to compensate for the earlier smaller increase in price. In fact, this appears to be the case. For upward crossings, we see prices continue to rise in the index in the case of 00 price barriers. For downward crossings, we see, instead of continuing to fall, prices rise, resulting in a partial reversal of the falling price trend and, in the case of 52-week lows in the index futures, a full reversal occurs. Pending further investigation before firmer conclusions can be drawn, these findings of a divergence between upward and downward crossings regarding postcrossing price continuation or reversal have implications for trading strategies. While the efficacy of momentum trading is supported in previous studies of fundamental-driven price movements (e.g., Jegadeesh and Titman [1993], [2001]), for psychology-driven price movements such as the crossing of psychological price levels, rigidly following the momentum strategy without distinguishing between upward and downward crossings may not be advisable. While a momentum strategy seems appropriate for upward crossings, the partial reversal of the downward trend after downward crossings suggests that the opposite, a contrarian strategy, is called for in downward crossings.

Including both markets in the VECM model, our examination of the interaction between the 2 markets provides new evidence of the dominance of the index in continuing the price trend of the crossings, contrary to the overwhelming evidence in previous studies of futures leading index in fundamental-driven price movements. Specifically, when a solo crossing occurs only in the index, we find that, in not only the index but also the index futures does price continue to rise after upward crossings and fall after downward crossings. Whereas when a solo downward crossing occurs in the index futures, instead of falling further, the price actually rises. When a synchronized crossing occurs, there is neither a continuation nor a reversal of the price trend. In this case, even though both markets agree on the direction of the price movements, they diverge in the impact of the crossing, with the index rising more than the index futures during upward crossings, whereas the index futures falls more than the index during downward crossings. These differences between the index and futures in magnitude between upward and downward crossings clearly add complexity to the index arbitrage strategy associated with the crossing of psychological price levels. It suggests that arbitrageurs need to take the direction (upward or downward) of the crossings into account when implementing the strategy.

The robustness of the above findings is demonstrated when we examine the subsamples of pre- and post-subprime crisis periods as well as bull and bear markets. Additionally, we find 2 notable variations between the subsamples. First, for the solo-crossings of 00 barriers in the index, we find only in the precrisis period a continuing rise in price after upward crossings while after the crisis a continuing fall in price after downward crossings. We conjecture that a shift in investor sentiment from optimism to pessimism may explain this evidence. Second, for the 52-week highs and lows, we find a positive coefficient for synchronized downward crossings and solo downward crossings in the index futures, but a negative coefficient for synchronized downward crossings and solo downward crossings in both the index and index futures. The former result indicates that for 52-week highs and lows, similar to the previous conclusion for 00 barriers, before the crisis the index futures falls more than the index during downward crossings. However, after the crisis, and only for downward crossings, the index, not the index futures, fall more as well.

Finally, our examination shows that, while volatility is significantly reduced before upward crossings, but not for downward crossings, it is significantly higher during the crossings and significantly lower after the crossings. While volatility is expected to rise on the day of the crossings as the emotions of the crossing take over, the subdued market after downward crossings is different from what we normally observe of higher volatility associated with a declining market. We conjecture that the ephemeral market emotions associated with the crossing of the psychological price levels, as opposed to the longer term secular market condition, may contribute to this different finding.

Our examination of the crossing of psychological price levels can be viewed as an exploratory investigation into the impact of merely one of the many nonfundamental factors that affect the behavior of investors. Clearly, further investigations are required and, hopefully, theoretical models can be developed to explain more fully the large part of price movements, as concluded by Shiller [2003], that cannot be explained by fundamental factors.

Notes

1. Weaker evidence of index leads index futures has also been reported in Stoll and Whaley [1990] and Chan [1992].
2. Such as infrequent or nonsynchronous trading, bid–ask spreads, and short-selling restriction.

3. See "The Psychology of Support and Resistance Zones," by Jean Folger, http://www.investopedia.com/articles/technical/02/061802.asp.
4. As defined in Investopedia (http://www.investopedia.com/terms/w/whipsaw.asp), "Whipsaw is a condition where a security's price heads in one direction, but then is followed quickly by a movement in the opposite direction."
5. For example, equity (Donaldson [1990], Donaldson and Kim [1993], Koedijk and Stork [1994], Ley and Varian [1994], De Ceuster et al. [1998], Cyree et al. [1999]), bond (Burke [2001]), foreign exchange (De Grauwe and Decupere [1992], Westerhoff [2003], Mitchell and Izan [2006]), and gold (Aggarwal and Lucey [2007]).
6. Although the conintegration evidence suggests IGARCH may be an alternative worth considering due to its efficiency. The concern that its restricted assumption of the existence of a unit root in the GARCH process potentially can yield biased estimates as well as efficiency being a moot issue due to our large sample size, we choose not to use IGARCH models. As to other alternative models, Awartani, Corradi and Distaso [2005] show that the symmetric GARCH(1,1) model is inferior to asymmetric GARCH models, among them is GJR GARCH, in predicting the volatility of the S&P 500 index. Brownlees et al. [2011] show that compared with 4 other GARCH models, including EGARCH, the GJR GARCH is often the best forecaster of volatility across asset classes and through calm and storm.
7. Following Burke [2001] and Aggarwal and Lucey [2007], we perform 2 tests, the point test and range test, which examines the ranges of prices ±5 and 10 the exact tens and hundreds.
8. We preform both barrier proximity and barrier hump tests.
9. For econometrical analysis purpose, this definition is differs from the definition used among practitioners in the industry which is just the difference between a future and a spot prices, that is, $Bt = Ft - St$.

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