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Price Shocks, News Disclosures, and Asymmetric Drifts*

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ABSTRACT

Motivated by investor disagreement and corporate disclosure literatures, we examine how stock price shocks affect future stock returns. We find that both large short-term price drops and hikes are followed by negative abnormal returns over the subsequent year, consistent with the conjecture that price shocks are useful indicators of inter-temporal spikes in investor disagreement and investor opinion converges gradually. The asymmetric drifts, return continuation for negative price shocks versus return reversal for positive ones, are in sharp contrast to the general findings of symmetric drifts in corporate event studies. Moreover, price shocks associated with public news events are followed by significantly weaker downward drifts, suggesting that news disclosures mitigate disagreement-induced overpricing. Examining the dynamics of a disagreement proxy during and after price shocks, we provide further evidence for the disagreement hypothesis. The economic significance of the price shock effect is illustrated with a revised momentum strategy that generates an annualized abnormal return of 16.92 percent.

Keywords: Price shocks, disclosure, disagreement, drift, stock return

I. INTRODUCTION

Large stock price movements are visible and often attention grabbing. The occurrence of extreme stock price shocks in the absence of public announcement of firm specific news is particularly puzzling. The cause of these shocks is uncertain. Private information, liquidity shocks, and manipulation can all generate the shocks. The existence of noise traders (Black 1986) and different interpretations of price signals can effectively prevent investors from quickly reaching consensus after price shocks.

We take advantage of this natural yet novel setting to test investor disagreement theory (Miller 1977; Harrison and Kreps 1978; Kim and Verrecchia 1994; Hong and Stein 2007). Specifically, we conjecture that due to the uncertainty concerning their causes, extreme price shocks are useful indicators of inter-temporal spikes in investor disagreement,[1] and that investor disagreement declines gradually over a post-shock period. The disagreement literature predicts that in the presence of short-sale constraints, opinion divergence generates a bubble component in asset prices. Therefore, the post-shock convergence is expected to lead to downward drifts in stock prices following both positive and negative price shocks, as illustrated in Diagrams A and B of Figure 1. In addition, as news disclosures help reduce information uncertainty (Berkman, Dimitrov, Jain, Koch, and Tice 2009),[2] we expect that the magnitude of the spikes in investor disagreement is smaller for extreme price shocks with accompanying news events than for those without. As a result, the post-shock downward drifts in stock prices are weaker for the shocks with accompanying news events, as depicted in Diagrams C and D of Figure 1.

Figure 1 about here

[1]Temporarily increased investor disagreement can also be a potential cause of extreme price shocks. Therefore, extreme price shocks are not necessarily the cause of increased investor disagreement, but they are useful to identify and isolate periods of acute opinion divergence. We thank the editor for pointing this out.

[2]Some studies suggest that public news events can increase disagreement in the short run (Kandel and Pearson 1995; Bamber, Barron, and Stober 1997; Hong and Stein 2007), while other studies reach the opposite conclusion (Berkman et al. 2009). The argument that news disclosures reduce information asymmetry and opinion divergence in the long run is consistent with the ultimate purpose of accounting disclosures.

The main finding of our study is that price shocks are followed by significant and long-lasting abnormal returns. The drifts that our tests uncover are asymmetric — return continuation following extreme negative price shocks and return reversal following extreme positive shocks. This finding is in sharp contrast to most results in the event study literature. Moreover, we find that price shocks with news disclosures, compared to those without accompanying news, are followed by weaker downward drifts. This evidence suggests that reduction of information uncertainty weakens disagreement-induced overpricing.

We provide direct evidence that investor disagreement increases when extreme price shocks occur and gradually decreases in the post-shock period. Specifically, we examine the pattern of time-variation in a disagreement proxy based on Garfinkel and Sokobin (2006). Consistent with our conjecture, we find that the disagreement proxy increases at extreme price shocks, and gradually decreases over the 240-trading-day period following the shocks. In addition, we show that the decrease in the disagreement proxy is associated with negative abnormal stock returns, supporting the hypothesis that opinion convergence leads to downward drifts in stock prices.

We present evidence that the post-shock asymmetric drifts are more salient among stocks with strong short-sale constraints. We use mutual fund breadth and institutional ownership to proxy for short-sale constraints, and find that the post-shock asymmetric drifts are stronger among stocks with low mutual fund breadth or low institutional ownership. This result is consistent with the assumption of disagreement models that short-sale constraints are an essential condition for generating an asset bubble.

We also examine the related issue of whether the post-shock opinion convergence and the associated return drifts are caused by news, especially significant bad news, occurring in the post-shock period. Test results are consistent with the post-shock news events not being the main driver for the opinion convergence. This evidence also suggests that the argument that stock prices reflect expectations of future bad news when investors interpret no disclosures as withholding negative information (Dye 1985; Diamond and Verrecchia 1987; Lev and Penman 1990) cannot explain the price shock effects.

Jiang, Lee, and Zhang (2005) and Zhang (2006) document a relation between information uncertainty (IU) and cross-sectional stock returns. Our study of price shocks is related to but different from this information uncertainty literature. Both Jiang et al. (2005) and Zhang (2006) use firm characteristics to proxy for the information uncertainty environment. In contrast, we focus on the dynamics of investor disagreement. Using cross-sectional regressions, we show that the price shock effects are robust to controlling for IU proxies, and that the price shock effects exist in both high-IU and low-IU stocks. In addition, in the momentum setting, we find that the return pattern based on price shocks differs from the patterns documented in Jiang et al. (2005) and Zhang (2006).

We investigate other potential explanations for the asymmetric drifts but do not find supportive evidence. Our results show that the asymmetric drifts are not a manifestation of post-earnings announcement drifts (Ball and Brown 1968), illiquidity (Amihud 2002), liquidity shocks (Bali, Peng, Shen, and Tang 2013), speculative preferences of retail investors (Kumar 2009; Bali, Cakici, and Whitelaw 2011), information risk (Brown, Harlow, and Tinic 1988, 1993), or idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang 2006, 2009; Bali, Scherbina, and Tang 2010).

Our study contributes to the accounting and finance literature in several ways. First, our focus on no-news price shocks is novel, and the results are surprising. The literature started by Ball and Brown (1968) and Beaver (1968) has been focusing on firms experiencing certain types of explicit public news disclosures, even though Cutler, Poterba, and Summers (1989) and Roll (1988) show that a large portion of the variance of the aggregate stock market return cannot be explained by public news on fundamentals. Recently, Ball and Shivakumar (2008) show that only five to nine percent of total information incorporated in stock prices over a year is associated with quarterly earnings announcements. Why do researchers ignore no-news price shocks in cross-sectional studies over such a long time period? It is likely due to an implicit hypothesis that no-news shocks have no clear informational content and represent noise to investors. From this perspective, such shocks have no implications for future returns, and therefore are unimportant. Thus, a novel contribution of our paper is that we show that no-news price shocks *are* important because they are followed by significant and long-lasting negative abnormal returns.

Second, our study contributes to the disagreement literature. No-news price shocks are easily observable but apparently ambiguous signals. The uncertainty associated with these shocks leads us to hypothesize that such shocks offer a good opportunity to capture changes in disagreement, and thus provides a good setting for testing the investor disagreement theory. The asymmetric drift pattern that we find following price shocks provides empirical support for the disagreement theory, in sharp contrast to the general findings of symmetric drifts in corporate event studies. We also offer direct evidence on opinion divergence at price shocks and opinion convergence thereafter by examining the dynamics of a disagreement proxy, which is rarely shown in the existing literature.

Third, our study suggests that the effects of price shocks and news disclosures should be treated differently, i.e., we should control for the price shock effects when examining the role of disclosures. Tests of disclosure effects in the literature are unconditional, not differentiating between these two effects. In our study, we compare price shocks with and without accompanying news events. Such a conditional test design enables us to check news-generated effects while controlling for price-shock-generated effects. This approach differentiates our study from other tests in the literatures on corporate disclosures and opinion divergence, including Kandel and Pearson (1995), Garfinkel and Sokobin (2006), and Bali, Scherbina, and Tang (2010). We find evidence that news events mitigate disagreement effects, which is otherwise difficult to demonstrate. The evidence is consistent with the role of disclosures in reducing information asymmetry (Diamond and Verrecchia 1991) and the ultimate objective of corporate disclosures. At the same time, our study is complementary to other studies aiming to separate the effects of fundamental news and investor recognition, such as Richardson, Sloan, and You (2012).

Finally, the asymmetric drift pattern is significant in terms of its economic magnitude. In the momentum setting, the profitability of the regular momentum strategy is enhanced by modifying the winner portfolio to include only winner stocks without extreme price shocks and modifying the loser portfolio to include only loser stocks that have no-news price shocks. We show that the difference in the monthly Fama-French three-factor alphas between the modified winner and loser portfolios is equivalent to an annualized abnormal return of 16.92 percent. This result suggests that the pattern of asymmetric drifts uncovered by our study generates interesting implications for portfolio and trading strategies.

Section II reviews the related literature. Section III describes how the test sample is constructed, discusses our predictions and main methodology, and presents summary statistics of our sample. Section IV presents the shock effects, evidence of disagreement, and the economic significance of the asymmetric drifts. Section V explores other potential explanations, and Section VI concludes.

II. RELATED LITERATURE

No-news price shocks are quite common. Cutler et al. (1989) show that nearly half of the return variance of the aggregate stock market cannot be explained by public news on fundamentals, and Roll (1988) makes the same point. A tantalizing question generated from these studies is whether large price shocks without accompanying disclosures about fundamentals are important for investors. In other words, do such shocks have implications for future stock returns? Existing studies provide no clear answers. Considering that price shocks reflect uncertainty on firm valuation and opinion divergence, we frame our research questions in terms of the disagreement and disclosure literature in accounting and finance.

Following the seminal work of Miller (1977) and Harrison and Kreps (1978), there has been a growing literature on investor disagreement (Harris and Raviv 1993; Kim and Verrecchia 1994; Chen, Hong, and Stein 2002; Scheinkman and Xiong 2003; Banerjee, Kaniel, and Kremer 2009). The main prediction of Miller's model is that prices reflect an optimistic bias when differences of opinion exist and pessimistic investors cannot take adequate short positions. Harrison and Kreps (1978) extend Miller's static model to a dynamic setting. They show that in the presence of short-sale constraints and different prior beliefs among investors, the stock price exceeds the fundamental value by the value of a resale option, which is positive on average. Tirole (1982), Milgrom and Stokey (1982), and Diamond and Verrecchia (1987) show that the resale options suggested by Harrison and Kreps do not arise in asset prices in models with asymmetric information but identical priors, even if short-sale constraints are imposed. Thus, a key condition for a price bubble is that heterogeneous priors exist. As long as investors agree to disagree and there are short-sale constraints, the resale option has positive value on average. This line of literature implies that when investor opinion converges, stock prices drift downward.

The disclosure literature on disagreement is centered on earnings announcements. There are several theoretical studies with mixed predictions. Kandel and Pearson (1995) build a model in which agents use different likelihood functions to interpret the public announcements. Kim and Verrecchia (1994, 1997) construct models in which agents have different information processing abilities so that some of the agents can process the announcements into private or informed judgement, creating opinion divergence. These theoretical analyses predict that earnings announcements increase disagreement. In the Kim and Verrecchia (1991) model, however, investors are diversely informed and differ in the precision of their private prior information; earnings announcements may then remove the informational disadvantage of some investors, producing a decrease in opinion divergence. Similarly, Diamond and Verrecchia (1991) emphasize the role of earnings announcements in reducing information uncertainty and asymmetry, which should mitigate opinion divergence.

Empirical research on investor disagreement associated with corporate disclosure is also inconclusive. On the one hand, there is evidence that corporate disclosures increase disagreement in the short term. For example, there are studies showing that trading volume, stock return volatility, and dispersion in analyst earnings forecasts increase around earnings announcements (Beaver 1968; Ziebart 1990; Bamber and Cheon 1995; Barron 1995; Bamber et al. 1997; Hong and Stein 2007), suggesting that earnings announcements increase disagreement in the short term. Rogers, Skinner, and Van Buskirk (2009) show that management earnings forecasts generate higher short-term volatility. On the other hand, many studies conclude the opposite in the long term. For example, Brown and Han (1992) show that analyst forecast dispersion declines after earnings announcements. Berkman et al. (2009) suggest that earnings announcements reduce opinion divergence because managers make conscious efforts to communicate information to the market. In general, the argument that corporate public disclosures reduce information uncertainty in the long run is consistent with the intended purpose of accounting disclosures.

To empirically study investor disagreement, a key issue is to come up with proxies for disagreement. Trading volume, stock return volatility, and analyst earnings forecast dispersion are some of the common measures used in the literature (Beaver 1968; Ziebart 1990; Bamber and Cheon 1995; Barron 1995; Bamber et al. 1997; Hong and Stein 2007). Garfinkel and Sokobin (2006) propose measures of opinion divergence based on unexplained trading volume, and Garfinkel (2009) finds that these measures are the best ones when using proprietary limit order and market order data to evaluate the validity of various disagreement proxies. We extend the measure of Garfinkel and Sokobin (2006), specifically taking into account the information effect of news disclosures as detailed in Section IV.

Our investigation of price shocks is related to studies on the effect of information uncertainty. Built on the behavioral finance literature, Jiang et al. (2005) finds that firms operating in a higher information uncertainty environment earn lower future returns. The finding is consistent with theoretical predictions that high information uncertainty exacerbates investor overconfidence and limits rational arbitrage. Zhang (2006) makes a similar argument on the role of information uncertainty, predicting that greater information uncertainty should produce relatively higher expected returns following good news and relatively lower expected returns following bad news. Both Jiang et al. (2005) and Zhang (2006) use relatively stable firm characteristics to proxy for the information uncertainty environment. In contrast, we focus on the dynamic process of opinion divergence and document that disagreement increases when price shocks occur and decreases gradually afterwards. We provide evidence that the price shock effects go beyond the variations explained by the information uncertainty measures, and that the shock effects exist among both low- and high-information-uncertainty firms. We also show that in the momentum setting, the price shocks and information uncertainty effects lead to clearly different drift patterns.

Intuitively, stock returns after large price shocks may be related to activities of retail investors. The role of retail trading has received considerable attention in recent years (Barber and Odean 2008; Kumar 2009). In a related study, Bali et al. (2011) argue that retail investors prefer lottery-like stocks, i.e., stocks that experience large positive shocks. They find that stocks with extreme positive price changes in the ranking month have significantly negative returns in the subsequent month. The lottery explanation is that retail investors prefer lottery-like stocks, and their post-shock purchases inflate the prices of the stocks and generate the negative returns over the subsequent month. Their motivation and focus clearly differ from ours, as we pursue a disagreement explanation of price shocks and study effects of news disclosures. While we also find negative returns following positive shocks, we show that the drift goes far beyond one month as reported in Bali et al. (2011). In addition, we do not find evidence of strong buying activities of retail investors after these shocks, which is inconsistent with the explanation based on the retail investors' preference for lottery-like stocks.

III. DATA AND METHODOLOGY

Sample Construction and Methodology

Our sample contains all ordinary common shares traded on NYSE, AMEX, and NASDAQ, those with share code = 10 or 11 and exchange code = 1, 2, or 3, during the period January 1980 to December 2006. To guard against microstructure effects associated with the small-cap and low-priced stocks, at the beginning of each month we rank stocks into deciles based on the market capitalization, excluding stocks in the smallest market capitalization decile and those with prices lower than $5. Our sample contains 15,846 securities and 1,165,769 stock-month observations in the sample period. The number of stocks ranges from 1,649 in July 1982 to 5,465 in October 1997.

We obtain daily stock returns from the CRSP stock database and define price shocks as the maximum and minimum three-day abnormal returns over a calendar month. For a given stock in a given month, we examine the stock's 21 or 22 trading days in rolling three-day blocks for both the largest and smallest three-day abnormal returns relative to the value-weighted CRSP market portfolio.[3] The largest (smallest) three-day abnormal return is called the positive (negative) price shock of the stock in that month, denoted as r_{shock^+} (r_{shock^-}). At the end of each month, stocks are sorted into deciles cross-sectionally based on the positive and negative price shocks separately. Stocks in decile 1 (decile 10) of negative (positive) price shocks are defined as stocks with extreme negative (positive) price shocks, which are the focus of our study. There are 199,836 stock-months with extreme positive or negative price shocks in the sample.

To construct our sample of news events, we first collect dates of a number of firm-specific news events from various data sources, including earnings announcements from Standard and Poor's Compustat, dividends from CRSP, analyst recommendations from IBES, analyst revisions on annual earnings and management forecasts from First Call, conference calls from BestCalls.com, and M&A and SEO from SDC. Next, we augment our set of news events by including news dates obtained from Capital IQ and Factiva. Capital IQ contains most company news after 2000, and for the period from 1980 to 2000, we obtain headline news dates through Factiva search following the approach described in Cohen, Malloy, and Pomorski (2012). Redundant news events in which the same event is reported by multiple data sources are deleted. If a news event occurs in the window from three days before to three days after a price shock, i.e., [-5, +3] with day 0 being the last day of the shock window, the shock is classified as a shock with accompanying news. Otherwise, it is a shock without accompanying news. Of the 199,836 stock-months with

[3]We choose the market-adjusted price shock because it is a simple signal that investors can easily observe without further analysis, such as building up the size portfolios or calculating the B/M ratio or momentum. We believe that such a simple signal is more likely to attract investor attention and generates opinion divergence. However, our results are robust to the shocks constructed using the equal-weighted 5×5×5 size-B/M-momentum benchmark portfolios. We follow the standard event study window using three trading days. However, our results are robust to price shocks defined on alternative windows, such as one-day or five-day windows.

extreme price shocks, 99,624 are associated with a news event.

Extreme price shocks reflect large jumps in opinion divergence. Based on investor disagreement theories, assuming both the existence of heterogeneous priors and the presence of short-sale constraints, our first prediction is that a jump in opinion divergence at extreme positive or negative price shocks gives rise to negative abnormal returns over a subsequent period when investor opinion converges gradually. That is, we expect asymmetric abnormal return drifts, consisting of a negative shock followed by a a negative drift and a positive shock also followed by a negative drift as in Diagrams A and B in Figure 1. Our second prediction is based on the informational role of disclosure events. We predict that the negative drifts following price shocks without news events are stronger than price shocks with news disclosures as in Diagrams C and D of Figure 1. The second prediction follows from the hypothesis that conditional on large price changes, corporate disclosures help reduce information uncertainty and thus reduce investor opinion divergence.

We adopt an event study approach to test these predictions. We examine daily abnormal returns for stocks with extreme price shocks from the day following the price shock up to one year later. In addition, we construct a proxy for opinion divergence that extends the measure of Garfinkel and Sokobin (2006) based on daily trading volume as detailed in Section IV. We examine the dynamics of the divergence proxy as well as its link to stock returns to provide direct evidence of the opinion divergence in the shock window, the divergence-reducing effect of news disclosure, and the opinion convergence in the post-shock period.

Price Shock Characteristics

Table 1 presents characteristics of the decile groups constructed from sorting on either negative or positive price shocks. Each decile group is further divided into news and no-news groups. Panels A1 and A2 (B1 and B2) are for the decile groups generated by sorting on the negative (positive) price shocks. The listed variables include firm size, book-to-market ratio, 12-month cumulative return before the ranking month (return 12), ranking month return (return t), and negative/positive price shocks (r_{shock^-}/r_{shock^+}). The first three variables, used as control variables in the cross-sectional regressions, correspond to the three known effects of the cross-section of stock returns: the size effect, the value effect, and the Jegadeesh-Titman momentum effect. For each of these variables, we first obtain the cross-sectional mean in a given month and then report the time-series average of the mean. The average number of stocks in each decile group is shown at the bottom of each panel.

Table 1 about here

Table 1 shows that most of the characteristics display significant variation across the deciles, and the patterns are similar for both stocks with and without news events and for sorting based on negative and positive price shocks. It can be seen that stocks with larger price shocks are smaller in size, have lower book-to-market ratios, and have higher pre-ranking 12-month returns. As expected, stocks with larger negative price shocks tend to have lower ranking month returns, and stocks with larger positive price shocks tend to have higher ranking month returns. Comparing news and no-news groups, we find that the news groups are larger in size but smaller in book-to-market ratio and pre-ranking 12-month return. However, the magnitude of price shocks is similar. Finally, Table 1 shows that at least 50 percent of the extreme price shocks, i.e., those in decile 1 on negative price shocks and decile 10 on positive price shocks, cannot be attributed to news events. Decile 1 on negative price shocks, on average, has 184 shocks without news events compared with 175 shocks with news events. For decile 10 on positive price shocks, the numbers are 194 and 166, respectively.

IV. EMPIRICAL RESULTS

Asymmetric Post-Shock Drifts

This subsection presents findings about how extreme price shocks and news events affect future stock returns. We focus on stocks with extreme price shocks, i.e., decile 1 sorted on negative price shocks and decile 10 sorted on positive price shocks. We calculate cumulative abnormal returns (CAR) relative to the equal-weighted 5×5×5 size-B/M-momentum benchmark portfolios in various windows around price shocks. Average CAR is obtained for each ranking month.[4] Cross-month averages are reported in Table 2 with the left panel presenting results for stocks with extreme negative price shocks and the right panel presenting results for stocks with extreme positive price shocks.

Table 2 about here

Rows 3 and 4 for window $[1, 240]$ of Table 2 show that long-term downward drift occurs following both negative and positive extreme price shocks. Over the period of 240 trading days after price shock, the average CAR for stocks with extreme negative and positive shocks are −5.0 percent and −10.6 percent respectively, and both are statistically significant. When dividing the groups into news and no-news sub-groups, the downward drift is stronger for the no-news sub-groups. Extreme negative shocks without accompanying news events are followed by a mean CAR of −5.7 percent, while the mean CAR for shocks with news events is −4.1 percent. The difference has a robust t-value of 2.42. For stock with extreme positive shocks, the mean CAR values over the 240-day window for the news and no-news groups are −7.5 percent and −13.2 percent, respectively. The difference between these values of 5.7 percent is statistically significant. These results are consistent with the argument that price shocks reflect increase in opinion divergence which declines gradually over a post-shock period, and that news events mitigate the disagreement-induced overpricing.

In Rows 5 to 12 for windows $[1, 60]$, $[61, 120]$, $[121, 180]$, and $[181, 240]$, we investigate the persistence of the downward drift by examining the mean CAR in the four 60-day windows after price shocks. In general, we find that the price shock effect and the effect of

[4]We also examine the results based on value-weighted average CAR, and the findings are similar.

the news events are both persistent. In almost every 60-day window, the mean CAR for stocks with positive or negative extreme price shocks is significantly negative. The negative drift for shocks without news events is stronger than that with news events, as shown by the significantly positive news minus no-news difference in the mean CAR values. The only exception is the [1,60] window for extreme negative shocks. The cumulative abnormal returns are significantly positive over this period.

To understand the underlying cause of the positive CAR for stocks with extreme negative shocks in the [1,60] window, we divide the 60-day window into the three 20-day windows of [1,20], [21,40], and [41,60], and examine the mean CAR values in each of the sub-windows. Test results, reported in Rows 13 to 18 of Table 2, suggest that the positive abnormal returns only exist in the first 20-day window after extreme negative price shocks. One potential explanation for this finding is the well known one-month short-term reversal effect. To examine whether the finding is indeed consistent with the short-term reversal, in the last two rows of Table 2 we report mean CAR values over the window [-20,0]. Consistent with the reversal effect, the CAR values over [-20,0] are significantly negative for stocks with extreme negative price shocks. These results suggest that the short-term reversal effect dominates the negative drift due to opinion convergence in the window [1,20], yielding significantly positive mean CAR values. For stocks with extreme positive shocks, mean CAR values over [-20,0] are significantly positive. Both the short-term reversal effect and the opinion convergence induced negative drift contribute to the negative CAR in the window [1,20]. Therefore, the magnitude of CAR is larger in this window than that in other windows.

In sum, results in Table 2 support our predictions as described in Figure 1. Diagrams A and B predict long-lasting negative abnormal returns following extreme negative or extreme positive price shocks. Diagrams C and D predict stronger effects for no-news shocks.

Investor Disagreement

The hypothesis that extreme price shocks reflect increase in opinion divergence is intuitive as discussed by Hong and Stein (2007) and the references they describe. It would be difficult for many investors to immediately assess the precise impact on future cash flows when they observe a large sudden change in stock prices, especially when there is no corporate disclosure associated with the price change. This subsection provides direct evidence of opinion divergence at price shocks and the convergence following price shocks by investigating the variations in a disagreement proxy.

Disagreement Proxy

Our disagreement proxy is *standardized unexpected volume controlled for news events (SUVN)*. We construct the proxy based on trading volume and it extends the SUV measure of Garfinkel and Sokobin (2006), who examine the relation between post-earnings announcement returns and opinion divergence at the earnings announcement date. When constructing the proxy for disagreement, they specifically recognize that the arrival of new information about a stock can lead to increased volume (Holthausen and Verrecchia 1990; Crabbe and Post 1994). Therefore, we must control for both the liquidity effect and the information effect when using trading volume to measure investor disagreement.

The Garfinkel and Sokobin (2006) proxy of opinion divergence, SUV, for stock i on day j is calculated as a standardized prediction error from a univariate model of trading volume on the absolute value of returns:

$$\begin{aligned} SUV_{i,j} &= UV_{i,j}/S_{i,j}, && (1)\\ UV_{i,j} &= Volume_{i,j} - E[Volume_{i,j}], && (2)\\ E[Volume_{i,j}] &= \hat{\alpha}_i + \hat{\beta}_{i,1} \times |r_{i,j}|^+ + \hat{\beta}_{i,2} \times |r_{i,j}|^-, && (3) \end{aligned}$$

where $r_{i,j}$ and $Volume_{i,j}$ are return and the natural log of turnover for stock i on day j, $|r_{i,j}|^+ = \max(0, r_{i,j})$, and $|r_{i,j}|^- = -\min(0, r_{i,j})$. Parameter estimates $\hat{\alpha}_i$, $\hat{\beta}_{i,1}$, $\hat{\beta}_{i,2}$ are obtained from the regression using daily data in an estimation window. $S_{i,j}$ is the standard deviation of the residuals from the regression. The liquidity effect is represented by $\hat{\alpha}_i$, and the information effect in trading volume is captured by $\hat{\beta}_{i,1} \times |r_{i,j}|^+ + \hat{\beta}_{i,2} \times |r_{i,j}|^-$.

Garfinkel and Sokobin (2006) focus on the sample with earnings announcement, so their sample consists only of stocks with accompanying news in the form of earnings announcements. Therefore, the occurrence of news does not contribute to the cross-sectional variation in the information effect, and the information effect is captured by price change as shown in Eq.(3). In contrast, our sample contains price shocks with and without accompanying news. Therefore, in our sample, the occurrence of public news disclosure should naturally influence the information effect in trading volume cross-sectionally. As a result, we construct our disagreement proxy ($SUVN$) by extending Garfinkel and Sokobin's model to control for the effect of news disclosures:

$$\begin{aligned}
SUVN_{i,j} &= UVN_{i,j}/S_{i,j}, && (4)\\
UVN_{i,j} &= Volume_{i,j} - E[Volume_{i,j}], && (5)\\
E[Volume_{i,j}] &= \hat{\alpha}_i + \hat{d}_i \times news_{i,j} + \hat{\beta}_{i,1} \times |r_{i,j}|^{+} + \hat{\gamma}_{i,1} \times |r_{i,j}|^{+} \times news_{i,j} + \\
&\quad \hat{\beta}_{i,2} \times |r_{i,j}|^{-} + \hat{\gamma}_{i,2} \times |r_{i,j}|^{-} \times news_{i,j}, && (6)
\end{aligned}$$

where $news_{i,j}$ is a dummy variable indicating whether a news event occurs for stock i on day j.[5] Our model captures both the direct impact of the occurrence of a news event on the information effect in trading volume and the indirect impact through changing responsiveness of trading volume to price changes. The regression is conducted for each price shock using daily data over $[t-56, t-6]$ where t is the last day of the shock window. In the revised model, the information effect is captured by $\hat{d}_i \times news_{i,j} + \hat{\beta}_{i,1} \times |r_{i,j}|^{+} + \hat{\gamma}_{i,1} \times |r_{i,j}|^{+} \times news_{i,j} + \hat{\beta}_{i,2} \times |r_{i,j}|^{-} + \hat{\gamma}_{i,2} \times |r_{i,j}|^{-} \times news_{i,j}$.

Opinion Divergence at Price Shocks

Panel A of Table 3 examines the correlation between price shocks and the average $SUVN$ over the three-day shock window. If price shocks are associated with increased investor disagreement, we expect a negative (positive) relation between negative (positive) price shocks and $SUVN$. Results in Panel A are consistent with our prediction. The average correlation between $SUVN$ and negative price shock is -0.097 with a t-value of -26.68,

[5] For a given news event, we classify days $[-1, +1]$ relative to the event day as news days.

and that between $SUVN$ and positive price shocks is 0.095 with a t-value of 24.45. We also calculate the correlations for the news and no-news group separately. If news disclosures mitigate investor disagreement, we expect a correlation coefficient with smaller magnitude for the news group relative to the no-news group. The results in Panel A support our prediction. The average correlations of the news and no-news group are -0.096 and -0.109, respectively, for negative price shocks. The difference, 0.012, is statistically significant. For positive price shocks, the average correlations are 0.089 and 0.109 for the news and the no-news group. The difference is again statistically significant.

Table 3 about here

Panel B of Table 3 reports the correlations between $SUVN$ and alternative disagreement proxies used in empirical accounting and finance literatures. ΔTO and SUV are the two unexplained volume based measures of opinion divergence in Garfinkel and Sokobin (2006). Average daily values are obtained for each stock in the shock window. The estimation or control window is $[t-56, t-6]$, where t is the last day of the shock window. ΔDisp is the change in analyst dispersion from the Thomson Reuters statistical period immediately before price shock to the corresponding period following the shock, where the dispersion is the standard deviation of the earnings forecasts divided by the absolute mean value. The forecast target is the first annual earnings after month $m+12$ where m is the shock month.[6] Results in Panel B indicate that $SUVN$ is significantly positively correlated with these alternative disagreement proxies, although the correlation with ΔDisp is smaller. This may reflect the fact that not every stock has analyst following, which indicates a potential selection bias and can change the information environment for a stock (Hong, Lim, and Stein 2000).

Opinion Convergence after Price Shocks

Table 3 provides evidence that investor disagreement increases at price shocks. Table

[6]We thank the referee for suggesting the forecast target which ensures a fixed analyst forecast target over the twelve-month period after each price shock.

4 Panel A reports variations in the disagreement proxy ($SUVN$) for stocks with extreme price shocks, i.e., decile 1 sorted on negative shocks and decile 10 sorted on positive shocks, in the periods following the shocks. For each stock in the extreme shock decile, we calculate the average daily $SUVN$ in the shock window as well as in four 60-day windows following the shock. For each of the post-shock windows, we calculate the change in the average daily $SUVN$ from that of the previous window. To avoid the influence of outliers, we focus on cross-sectional median values for each shock month and report cross-month averages and robust t-values. Row 4 of Panel A, i.e., [-2,0], presents the average daily $SUVN$ in the shock window. The significantly positive estimates confirm the finding in Table 3 that investor disagreement increases at large price shocks. The remainder of the panel shows that changes in disagreement are significantly negative in all of the four periods following price shocks, consistent with the prediction that investor disagreement decreases gradually following the shocks.

Table 4 about here

In addition to $SUVN$, in untabulated results, we also examine post-shock convergence using three alternative disagreement proxies. Results based on measures using unexplained trading volume, i.e., SUV and ΔTO, are similar to those in Panel A of Table 4. There is strong evidence of divergence, indicating greater disagreement among investors, at extreme price shocks and long-term gradual convergence over a 240-day period following price shocks. Results based on change in analyst dispersion (ΔDisp) are generally consistent with our prediction, but relatively weak compared to the results based on unexplained trading volume measures. These weak results may reflect the analyst dispersion issues discussed previously.

Table 4 Panel B examines whether opinion convergence is associated with negative price moves as predicted by the disagreement hypothesis. Specifically, we compute the cross-sectional correlation between changes in investor disagreement and contemporaneous cumulative abnormal stock returns in various windows after price shocks for each shock month. The panel reports cross-month average correlations and robust t-values. Results in Table 4 Panel B support our prediction of a positive correlation between the changes in $SUVN$ and the contemporaneous stock CAR for both negative and positive price shocks. Every 60-day window after positive and negative price shocks is characterized by significantly positive correlations. The correlation in the first 60-day window is smaller than that in the subsequent three windows. The weaker correlation between stock return and opinion convergence may reflect the noise introduced by the short-term reversal effect in this window, as shown in Table 2.

Impact of Short-Sale Constraints

Short-sale constraints are an important assumption of disagreement models, so this subsection tests whether the post-shock drift pattern varies with the degree of short-sale constraints. Following Chen et al. (2002) and Cen, Lu, and Yang (2013), we use mutual fund holding breadth as a proxy for short-sale constraints. This measure is motivated by the fact that many mutual funds are not allowed to short-sell even if they hold pessimistic views about any stocks. The breadth is defined as the ratio of the number of mutual funds that hold a long position in the stock to the total number of mutual funds for that quarter reported in Thomson Financial Mutual Fund Holdings database. We define the smallest (largest) tercile as the low- (high-) holding-breadth group. In other words, the low-breadth group consists of stocks in the lowest tercile when sorted by the value of their breadth. Based on disagreement models, we expect that the post-shock abnormal return drifts to be more salient among stocks with low breadth, reflecting stronger short-sale constraints.

We focus on stocks with extreme price shocks, i.e., decile 1 sorted on negative price shocks and decile 10 sorted on positive price shocks, and also in the low-breadth or high-breadth group. Among stocks with extreme negative price shocks, on average, 158 (59) are in the low- (high-) breadth group. The numbers for stocks with extreme positive price shocks are 173 and 45 for low- and high-breadth groups, respectively. Table 5 reports the cumulative abnormal returns (CAR) relative to the equal-weighted 5×5×5 size-B/M-momentum benchmark portfolios in various windows around price shocks for the low- and high-breadth groups. The left (right) panel presents results for stocks with extreme negative (positive) price shocks.

Table 5 about here

Rows 3 and 4, i.e., window [1,240], of Table 5, show that the long-term downward drift following extreme price shocks is indeed more significant for stocks in the low-breadth group. Over the period of 240 trading days after price shock, the mean CAR value of the low-breath group is -6.8 percent compared to 0.1 percent for the high-breadth group among stocks with extreme negative price shocks. The difference of -6.9 percent has a robust t-value of -3.69. Among stocks with extreme positive price shocks, over the same period, the mean CAR values of the low- and high-breadth groups are -12.2 percent and -4.0 percent, respectively. The difference of -8.2 percent is also statistically significant (t-value $= -4.02$).

Rows 5 to 12, i.e., windows [1,60], [61,120], [121,180], and [181,240], analyze whether the stronger downward drift for stocks in the low-breadth group is persistent by examining the mean CAR values in the four 60-day windows after price shocks. Test results indicate that in almost every 60-day window and for both extreme negative and extreme positive shocks, the CAR value of the low-breadth group is significantly lower than that of the high-breadth group. The only exception is the $[1, 60]$ window for extreme negative shocks, where the CAR values for both groups are positive, and the difference is not statistically significant. As discussed previously, this phenomenon is most likely due to the well known one-month short-term reversal effect, consistent with the results in the remaining rows of the table.

In sum, Table 5 shows that stocks with stronger short-sale constraints in the form of low breadth are associated with stronger post-shock downward drift, consistent with disagreement models. Motivated by findings of Asquith, Pathak, and Ritter (2005) and Nagel (2005), we also use institutional ownership as an alternative proxy for short-sale constraints. Stocks with low institutional ownership are more expensive to borrow, and therefore tend to have stronger short-sale constraints. We calculate institutional ownership as percentage of shares outstanding owned by institutions as reported in Thomson Financial Institutional Holdings (13F) database. We sort stocks into terciles based on institutional ownership each shock month and classify the lowest (highest) tercile as the low- (high-) institutional-ownership group. Similar to Table 5, untabulated results show that price-shock effects are much stronger among stocks with stronger short-sale constraints in the form of low institutional ownership. For example, over the 240-day period after price shock, CARs of the low- and the high-institutional-ownership groups are −6.8 percent and −2.6 percent respectively among stocks with extreme negative shocks. The difference of −4.2 percent has a robust t-value of −2.94. Among stocks with extreme positive shocks, CARs of the low- and the high-institutional-ownership groups are −12.5 percent and −7.8 percent respectively over the same 240-day window. The difference is statistically significant, with a robust t-value of −3.42.

Post-Shock News Events

We have shown that investor disagreement increases when price shocks occur and the disagreement decreases in the period following price shocks, which leads to a downward drift in stock returns following price shocks. One plausible explanation for the convergence following price shocks is that news events following price shocks help reduce investor disagreement. If this is the case, then we expect the downward drift in stock returns to be concentrated around news events that drive the convergence.

Using Fama-MacBeth cross-sectional regressions, we next examine this possibility but do not find evidence that the opinion divergence at price shocks is resolved by subsequent news events. Instead, the long-term and gradual convergence process documented in this study is consistent with the argument in Giglio and Shue (2013) that the absence of news reports and the passage of time often contain important information, and investors incorporate this information into their valuation gradually.

For each positive and negative price shock, Table 6 decomposes the post-shock one-year cumulative stock return into news-day and no-news-day cumulative returns. We collect the dates of all news events in the one-year period after price shock, and for each news event, following the standard event study window, we classify days [-1, +1] as news days. We classify all remaining days in the one-year period as no-news days.[7] We obtain cumulative news-day return and cumulative no-news-day return separately for a given price shock. The cumulative one-year stock returns in Columns 2 and 3, the news-day returns in Columns 4 and 5, and the no-news-day returns in Columns 6 and 7 are the dependent variables in the cross-sectional regressions in Table 6. We examine the relation between these returns and negative shocks, r_{shock^-}, or positive shocks, r_{shock^+}. We include stock size, book-to-market ratio, and pre-ranking 12-month cumulative stock returns as control variables.

Table 6 about here

Column 2 presents a significantly positive relation between post-shock one-year stock returns and negative price shocks with an estimated coefficient of 0.69 with a robust t-value of 4.99, and Column 3 shows a significantly negative relation between post-shock one-year stock returns and positive price shocks with an estimated coefficient of -0.27 with a robust t-value of -2.25. These results confirm the asymmetric price shock effects identified in Table 2. Results in Columns 4 to 7 suggest that the downward drifts occur mainly in days without news events. The estimated coefficients of r_{shock^-} and r_{shock^+} when no-news-day returns are used as dependent variable in Columns 6 and 7 are 0.59 (t-value of 6.16) and -0.30 (t-value of -3.96), respectively. When news-day returns are the dependant variables in Columns 4 and 5, none of the coefficients are statistically significant and the coefficient

[7] We find that stocks with extreme price shocks, i.e., decile 1 sorted on negative price shocks and decile 10 sorted on positive price shocks, tend to have fewer news days in the following year. A potential explanation for this finding is that many firms in the extreme shock deciles are firms with high information uncertainty, and these firms tend to have fewer news disclosures. In addition, using positive and negative three-day CAR relative to the value-weighted CRSP market portfolio to classify positive and negative news, we find that the occurrence of positive and negative news in the one-year post-shock period is quite evenly divided for stocks with extreme price shocks, suggesting that the negative drifts are unlikely due to a high rate of negative news.

of r_{shock^+} becomes positive. Results in Table 6 indicate that the long-term negative drift following price shocks is unlikely to be driven by post-shock news events. Understanding the exact cause of the slow convergence is an interesting question that we leave for future research.

Finally, results in Table 6 are also inconsistent with the argument that the price shock effects arise because investors interpret no disclosure as management withholding negative information. In such a case, the stock price reflects the expectations of potential bad news (Dye 1985; Diamond and Verrecchia 1987; Lev and Penman 1990). As shown in Table 6, returns around news events in the one-year post-shock period are not significantly related to price shocks, which is inconsistent with the argument that negative information related to future cash flows has been withheld at the time of large price shocks.

Economic Significance in a Momentum Setting

This subsection demonstrates the economic significance of the price shock effects conditional on the well-documented momentum effect (Jegadeesh and Titman 1993). We predict that the extreme price shocks add a negative drift to the return continuation of both the winner and the loser portfolios and that news disclosures weaken the negative drift, as depicted in Figure 2.

Figure 2 about here

We first create momentum portfolios by sorting stocks into deciles based on returns from month $m-12$ to month $m-1$ where m is the ranking month. Column 2 in Table 7 reports the Fama-French (1993) three-factor alphas and the robust t-values for the winner (decile 10) and the loser (decile 1) portfolios.[8] The alpha is 0.03 percent (-0.79 percent) per month for winner (loser) stocks. Consistent with findings in the momentum literature, the alpha of the difference portfolio of 0.82 percent is statistically significant with a robust t-value of 4.38 (untabulated).

[8]Since the portfolio sorts are conditional on momentum, the alphas in Table 7 are based on the Fama-French three-factor model.

$\boxed{\text{Table 7 about here}}$

We divide the winner and loser groups into two sub-groups: those with extreme price shocks in the ranking month and those without. The alpha for the losers with price shocks is −1.14 percent per month, which is significantly lower than that of −0.64 percent for the losers without price shocks, consistent with our predictions as illustrated in Diagram C of Figure 2. The alphas for the winners with and without price shocks are −0.22 percent and 0.15 percent, respectively. The difference portfolio has a significantly negative alpha of −0.37 percent with a robust t-value of −3.54, supporting the conjecture highlighted in Diagram B of Figure 2. These results suggest that price shocks add a significantly negative drift to the return continuation of both the winner and the loser portfolios over the twelve months following the ranking month.

We also expect the alphas of the no-news groups to be significantly lower than those of the news groups, as illustrated in Diagrams D and E of Figure 2. Consistent with our predictions, Table 7 shows that for loser stocks with shocks that are not accompanied by any news events, the alpha is −1.26 percent, significantly lower than that of −0.84 percent for loser stocks with shocks accompanied by news events. The effect of news events is directionally the same for winner stocks with extreme price shocks. The alphas for the news and no-news groups are 0.07 percent and −0.34 percent, respectively, and the alpha of the difference portfolio is 0.41 percent with a robust t-value of 3.60.

In sum, results in Table 7 support our conjecture that the opinion convergence process following extreme price shocks adds a negative price drift to the existing momentum effect, and that news disclosures mitigate such negative drift. We demonstrate the economic significance of these effects by examining the profitability of a revised momentum strategy that buys winner stocks without extreme price shocks and short-sells loser stocks that have no-news price shocks. The revised hedge portfolio generates a three-factor alpha of 1.41 percent ($= 0.15\% - (-1.26\%)$), equivalent to an annualized abnormal return of 16.92 percent, improving the profitability of the regular momentum strategy by 72 percent.

V. OTHER POTENTIAL EXPLANATIONS

Information Uncertainty

Studies in the information uncertainty literature, such as Jiang et al. (2005) and Zhang (2006), document a negative cross-sectional relation between information uncertainty (IU) and stock returns over subsequent months. This subsection provides evidence that the information uncertainty effect and the price shock effect are different. The existing literature tends to treat information uncertainty as a relatively stable firm characteristics. In contrast, price shocks capture the change in disagreement instead of the level of disagreement. The level of disagreement may be closely related to information uncertainty, but the change in disagreement is less likely to be so. Therefore, we expect price shock and information uncertainty to be two different effects.

We empirically examine whether these are indeed two effects by including common proxies for information uncertainty into cross-sectional regressions with the one-year post-shock cumulative return as the dependent variable. The information uncertainty proxies that we examine include firm age, stock return volatility, and average daily turnover. Jiang et al. (2005) show that the relation between information uncertainty and subsequent stock return is not monotonic. Firms in the highest IU deciles earn sharply lower returns. Therefore, instead of a continuous variable, we include in our regressions a dummy variable indicating whether a stock is in the highest IU decile.[9]

Table 8 about here

Table 8 Panel A confirms that high IU is associated with lower future returns, as shown by the negative coefficients of the IU dummies. However, the IU dummies do not take away the significance of the price shock (r_{shock^-} and r_{shock^+}), suggesting that the information uncertainty, captured by the IU dummies, and the price shock are two separate effects.

[9] Using continuous variables in the regressions lowers the significance of information uncertainty proxies, but does not change the significant effect of price shocks.

Table 8 Panel B includes the interaction terms between the IU dummies and the price shocks in the regressions to examine the price shock effect among stocks with low and high information uncertainty separately. Results in Panel B show that the price shock effect is larger among stocks with high information uncertainty, but the effect is also statistically significant among stocks with low information uncertainty. This finding suggests that as long as there is inter-temporal spike in investor disagreement, as captured by extreme price shocks, we see the price shock effect even among stocks with low level of information uncertainty.

Finally, we notice that the empirical predictions from information uncertainty and price shock effect are different in the momentum setting. Both Jiang et al. (2005) and Zhang (2006) assume that investors tend to be overconfident, which makes investors overweight their private information and underweight public information. Therefore, information contained in public news is gradually incorporated into stock prices, and information uncertainty tends to slow down this price adjustment process. As a result, the information uncertainty hypothesis predicts that the momentum effect is stronger among high-IU firms, and that both winner stocks and loser stocks contribute to the increased momentum profit. That is, high-IU winner (loser) stocks are expected to outperform (underperform) low-IU winner stocks. Using the common proxies for information uncertainty, both Jiang et al. (2005) and Zhang (2006) provide supportive evidence for this prediction. Our price shock effect, in contrast, predicts that in both winner and loser groups, stocks with extreme price shocks are expected to under-perform those without shocks, and results in Table 7 are consistent with this prediction. Therefore, extreme price shocks and information uncertainty have different effects on future stock returns.

Post Earnings Announcement Drifts

Post-earnings-announcement drift (PEAD) is a well known phenomenon documented in the accounting literature (Ball and Brown 1968; Bernard and Thomas 1990). It refers to the tendency of a stock's post-announcement cumulative abnormal return to move in the direction of an earnings surprise. Unlike the price shock effect, the PEAD predicts a symmetric drift pattern. This subsection examines how the PEAD contributes to the price shock effect.

Each quarter, we rank stocks into quintiles based on earnings surprise (UE), which is calculated as the cumulative abnormal return (CAR) relative to the value-weighted CRSP market return over the [-1, +1] window with day 0 being the earnings announcement day. The PEAD predicts stock prices in quintile 1 (5) to drift downward (upward) after earnings announcements. To understand the influence of the PEAD on the price shock effect, we exclude stocks in the lowest (highest) UE quintile based on the most recent UE ranking from decile 1 (decile 10) sorted on negative (positive) price shocks, and examine the cumulative abnormal returns (CAR) of the remaining stocks over the 240-day window after price shocks. Test results are reported in Rows 7 and 8 in Table 9. To facilitate the comparison, we present again in Rows 4 and 5 the mean CAR values for the extreme shock groups as shown in Table 2.

Table 9 about here

Table 9 suggests that after excluding stocks in the extreme UE quintiles, we continue to observe the significantly negative drifts following both extreme negative and positive price shocks. The mean CAR value in the 240-day window for stocks with extreme negative (positive) price shocks is -4.3 percent (-12 percent) with a robust t-value of -4.21 (-9.57). In addition, the mitigating effect of news disclosures also remains. The negative drifts are stronger for stocks with extreme price shock but without news events than those with both. The mean difference in CAR of news minus no-news is 1.7 percent for extreme negative shocks and 5.2 percent for extreme positive shocks. Both are statistically significant.

Comparing the results in Rows 4 and 5 to those in Rows 7 and 8, we are able to infer the effect of PEAD. Stocks with low UE are expected to drift downward. Excluding these stocks from the group with extreme negative price shocks, the post-shock negative drift weakens, and the difference is significant, -0.7 percent with a t-value of -4.03. In contrast, stocks with high UE are followed by an upward drift. The magnitude of the post-shock negative drift becomes larger after excluding the high-UE stocks from the group with extreme positive price shocks. The average difference in CAR is 1.4 percent with a t-value of 8.60. In sum, Table 9 shows that PEAD exists in our sample, but it cannot explain the price shock effect.

Liquidity, Liquidity Shock, and Retail Trading

Stocks with large price shocks tend to be associated with high trading volume, which may reflect high liquidity of the stocks. It is well documented that the level of individual stock illiquidity is positively priced in the cross-section of expected stock returns (Brennan, Chordia, and Subrahmanyam 1998; Amihud 2002). We examine whether the illiquidity can explain the price shock effect using Fama-MacBeth cross-sectional regressions with the post-shock one-year cumulative stock return as the dependent variable. Stock illiquidity is defined, similar to that in Amihud (2002), as the average ratio of the daily absolute return to the dollar trading volume on that day in the month prior to price shocks. Columns 2 and 3 of Table 10 report test results. Consistent with findings from prior studies, post-shock stock returns are positively related to stock illiquidity. However, the illiquidity measure cannot take away the significance of price shocks. After including the illiquidity measure into regressions, the coefficient of negative price shock (r_{shock^-}) is 0.69 with a robust t-value of 5.15, and that of positive price shock (r_{shock^+}) is -0.28 with a robust t-value of -2.29. Therefore, the level of individual stock illiquidity cannot explain the price shock effect.

Table 10 about here

Liquidity tends to vary over time. A recent study by Bali et al. (2013) finds that change in liquidity can predict future stock returns. Specifically, the authors show that negative liquidity shocks lead to negative stock returns up to six months in the future. Following the procedure in Bali et al. (2013), we calculate the liquidity shock as the negative value of the difference between the monthly Amihud-type illiquidity measure and the average monthly illiquidity measure over the previous 12 months, standardized by the standard deviation of the 12 monthly illiquidity measures, and include this liquidity shock measure in our cross-sectional regressions to examine whether the liquidity shock effect can explain the price shock effect. Columns 4 and 5 of Table 10 report test results. The positive coefficients of the liquidity shock measure confirm the findings in Bali et al. (2013). However, the coefficients of price shocks barely change after including the liquidity shock measure. The price shock effects remain significant.

Finally, we investigate whether the price shock effects are due to irrational trading by a subset of investors. Retail investors are found to exhibit a greater propensity to gamble (Kumar 2009). Han and Kumar (2013) find that stocks with a high proportion of retail trading tend to earn lower future returns. Bali et al. (2011) argue that retail investors' preference for lottery-like stocks leads to negative returns following positive price shocks. We examine whether the speculative preferences or heuristic trading of retail investors can explain the drifts subsequent to stock price shocks. Following prior empirical studies, we separate retail trades from institutional trades using the dollar value traded in each transaction obtained from the TAQ and ISSM database. Trades of less than $7,000 are classified as retail trades, and those of greater than $30,000 are classified as institutional trades (De Franco, Lu, and Vasvari 2007).[10] Retail trading proportion (RTP) is defined as the average daily ratio of retail trading volume to the trading volume of both retail and institutional investors on the same day in the month prior to price shocks. The last two columns of Table 10 report the cross-sectional regression results including RTP.[11] Test results show that including RTP does not take away the significance of price shocks, suggesting that RTP cannot capture the cross-sectional return effects of price shocks.

In untabulated tests, we also examine the retail order imbalance after price shocks

[10]The cutoffs for retail and institutional trades vary across different studies. In addition to the $7,000/$30,000 classification, we also check the robustness of our results to two other classifications, 1,000/10,000 shares (Lee 1992) and $5,000/$5,000 (Han and Kumar 2013). Results are similar and not reported for brevity.

[11]In recent years, institutional investors have used algorithmic trading platforms to execute their orders. When large orders are broken into small orders, the retail/institutional trade classification contains significant errors. To mitigate this concern, our sample period stops at year 2000 for tests including RTP.

to shed light on retail investors' post shock trading activities. Buyer- or seller-initiated trades are determined using the Lee and Ready (1991) algorithm. Test results suggest that retail investors are net buyers after large negative shocks and net sellers after large positive shocks. Therefore, it is unlikely that lottery-like preference of retail investors can explain the long-lasting post-shock negative drifts.

Other Robustness Checks

In this subsection, we discuss some other robustness checks that we have conducted but not tabulated for brevity. First, Brown et al. (1988, 1993) develop and test an uncertain information hypothesis (UIH), which predicts that risk averse investors respond to unanticipated price changes by adjusting their risk estimates and expected returns. Under UIH, we should observe positive drifts following both positive and negative price shocks. We replicate the study of Brown et al. (1988) and compare the UIH results with our findings. Like Brown et al. (1988), we document weak positive drifts among the largest 200 stocks in S&P 500. However, among stocks with extreme price shocks, i.e., decile 1 (10) sorted on negative (positive) price shocks, the asymmetric drifts subsume the UIH effect.

Second, we investigate whether some alternative effects documented in prior studies can explain the asymmetric drift pattern following price shocks using cross-sectional regressions similar to those in Table 10. Specifically, we examine the following effects: idiosyncratic volatility (Ang et al. 2006, 2009); changes in idiosyncratic volatility (Bali et al. 2010); spread (Demsetz 1968); delay (Hou and Moskowitz 2005); and skewness (Barberis and Huang 2008). Test results show that none of these effects can account for the asymmetric persistent patterns in returns after positive and negative shocks.

VI. CONCLUSIONS

Motivated by investor disagreement and corporate disclosure literatures, we examine how stock price shocks affect future stock returns. We find that price shocks are followed by significant and long-lasting abnormal returns. The drifts that our tests uncover are asymmetric — return continuation following extreme negative price shocks and return reversal following extreme positive shocks. This finding is in sharp contrast to most results in the event study literature. Moreover, we find that price shocks with news disclosures, compared to those without accompanying news, are followed by weaker downward drifts. This evidence suggests that reduction of information uncertainty as a result of public news disclosures weakens disagreement-induced overpricing. Using an extended disagreement measure of Garfinkel and Sokobin (2006), we examine the dynamics of disagreement around price shocks, and provide direct evidence supporting our conjecture. A number of robustness tests yield results consistent with predictions of disagreement models but inconsistent with other explanations.

The importance of price shocks per se suggests the need to separate disclosure effects from price shock effects. The findings from our conditional tests give rise to an interesting perspective about the role of regulations on corporate disclosures as the empirical results suggest that public disclosures actually improve market efficiency through the reduction of investor disagreement. We acknowledge that our news data set may not be exhaustive, but missing any significant news events would result in price shocks associated with these events being misclassified into the no-news group, which should weaken our results.

Our findings also have useful implications for portfolio management. The revised momentum strategy of buying winner stocks without price shocks and short-selling loser stocks having no-news price shocks would improve the profitability of the simple buying-winner-selling-loser momentum strategy by 72 percent. Our empirical results generally suggest that individuals who chase stocks that have recent large price shocks are likely to suffer substantial losses. In that sense, corporate disclosures effectively mitigate the wealth transfer.

While we argue that the evidence is consistent with the predictions of disagreement models, there are caveats that should be noted. First, as emphasized by Fama (1998), it is important to have a unified theory to explain why the same investors under-react in some cases but overreact in others. We do not assume an ad hoc combination of under-reaction and overreaction as an alternative explanation for the asymmetric drifts. We pursue a theory that can simultaneously explain the abnormal return patterns following both negative and positive shocks. Nevertheless, it is difficult to rule out the possibility that the asymmetric drifts are due to a combination of under-reaction and overreaction. Second, we conjecture that extreme price shocks reflect an increase in opinion divergence which decreases over a long term period following price shocks. We verify our conjecture by examining the dynamics of an unexplained volume based disagreement proxy. However, trading-based disagreement proxy may not capture the opinion of investors who have pessimistic views about a stock and currently do not participate in the trading of the stock. Third, we do not find evidence that extreme price shocks are followed by a high degree of bad news, and test results suggest that post-shock news events are not the main driver for opinion convergence. The exact cause of the gradual post-shock opinion convergence is still unclear. One possible explanation is that diligent information search by investors leads to gradual uncertainty resolution. Alternatively, initial investor optimism may fade when patience runs out in the absence of exciting news or a price run-up. Understanding the exact cause of the gradual convergence is an intriguing task that we leave for future research.

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TABLE 1
Price Shock Characteristics

deciles:	1 (low)	2	3	4	5	6	7	8	9	10 (high)
Panel A1. Ranked by Negative Price Shocks, without News										
size	260.3	317.3	398.8	456.1	581.6	670.9	846.1	1021.2	1223.9	1620.2
B/M	0.64	0.68	0.71	0.73	0.75	0.77	0.79	0.80	0.80	0.79
return 12	55.16	39.50	33.22	28.72	25.98	24.39	23.45	22.79	23.23	23.89
return t	−8.83	−2.65	−0.52	0.89	2.01	2.76	3.50	4.19	5.22	8.29
r_{shock^-}	−17.30	−10.97	−8.76	−7.33	−6.25	−5.36	−4.58	−3.85	−3.10	−2.04
avg # of stocks	184	205	209	210	208	208	206	204	202	194
Panel A2. Ranked by Negative Price Shocks, with News										
size	739.4	1080.8	1356.1	1724.7	2180.5	2688.9	3116.2	3731.9	4453.7	5435.0
B/M	0.60	0.64	0.66	0.67	0.69	0.71	0.71	0.72	0.72	0.71
return 12	42.70	35.89	31.46	27.45	24.63	23.36	22.37	20.81	21.02	21.94
return t	−11.52	−3.04	−0.72	0.84	1.84	2.67	3.41	4.17	5.14	8.22
r_{shock^-}	−18.66	−10.99	−8.77	−7.33	−6.24	−5.35	−4.58	−3.84	−3.09	−2.01
avg # of stocks	175	155	151	150	151	152	154	156	158	165
Panel B1. Ranked by Positive Price Shocks, without News										
size	1424.9	1208.9	1046.7	874.8	750.8	637.5	500.8	397.7	303.1	207.2
B/M	0.79	0.79	0.78	0.78	0.76	0.74	0.72	0.71	0.70	0.68
return 12	22.56	22.23	22.72	23.48	25.13	26.86	30.16	33.84	40.00	48.73
return t	−6.16	−3.26	−2.21	−1.42	−0.59	0.26	1.33	2.90	5.44	12.48
r_{shock^+}	1.93	3.10	3.95	4.79	5.72	6.79	8.11	9.88	12.63	20.59
avg # of stocks	201	203	203	202	202	203	202	201	200	194
Panel B2. Ranked by Positive Price Shocks, with News										
size	5367.8	4445.1	3984.3	3375.4	2661.5	2232.2	1759.2	1222.1	903.4	499.3
B/M	0.71	0.72	0.71	0.70	0.69	0.68	0.67	0.66	0.66	0.67
return 12	20.20	20.00	21.01	22.34	24.23	26.00	28.93	32.76	37.23	40.61
return t	−5.64	−2.72	−1.56	−0.63	0.22	1.26	2.42	4.12	6.70	15.24
r_{shock^+}	1.93	3.10	3.95	4.79	5.71	6.78	8.11	9.88	12.63	21.38
avg # of stocks	158	157	157	158	157	157	158	159	160	166

This table reports summary statistics for stocks in various decile groups sorted on either positive (r_{shock^+}) or negative (r_{shock^-}) price shocks. Each decile group is further divided into "news" and "no-news" groups, based on whether a news event occurs in the window from three days before to three days after the shock. *Size* is the market capitalization of the firm measured in millions of dollars. *B/M* is the book-to-market ratio of the firm. *Return t* and *return 12* denote stock return in the shock month t and cumulative stock return over month $t-12$ to $t-1$. *Return t*, *return 12*, and r_{shock^+} and r_{shock^-} are presented in percentage. The reported values of all variables are first averaged across stocks in a given shock month, and then averaged over time. In addition, the average number of stocks in each group is shown at the bottom of each panel. The sample period is from January 1980 to December 2006.

TABLE 2
Post-Shock Drifts

	Extreme Negative Shocks				Extreme Positive Shocks			
window	decile 1	no news	news	difference	decile 10	no news	news	difference
[1, 240]	−0.050	−0.057	−0.041	0.016	−0.106	−0.132	−0.075	0.057
	(−4.69)	(−4.67)	(−4.05)	(2.42)	(−8.77)	(−9.45)	(−6.85)	(8.94)
[1, 60]	0.017	0.021	0.013	−0.007	−0.058	−0.074	−0.043	0.031
	(5.39)	(6.02)	(4.17)	(−2.88)	(−14.93)	(−15.41)	(−12.40)	(9.79)
[61, 120]	−0.025	−0.030	−0.022	0.009	−0.024	−0.029	−0.018	0.011
	(−7.88)	(−8.03)	(−6.98)	(3.26)	(−6.02)	(−6.55)	(−4.52)	(4.83)
[121, 180]	−0.024	−0.029	−0.018	0.011	−0.020	−0.026	−0.011	0.014
	(−6.91)	(−6.50)	(−5.65)	(3.88)	(−5.16)	(−5.77)	(−3.13)	(5.47)
[181, 240]	−0.020	−0.022	−0.017	0.004	−0.017	−0.020	−0.012	0.008
	(−5.47)	(−5.10)	(−4.79)	(1.78)	(−4.07)	(−4.17)	(−3.10)	(3.53)
[1, 20]	0.036	0.043	0.030	−0.013	−0.043	−0.053	−0.033	0.020
	(15.05)	(14.12)	(13.88)	(−7.72)	(−19.12)	(−19.10)	(−16.34)	(12.39)
[21, 40]	−0.009	−0.011	−0.008	0.003	−0.009	−0.013	−0.006	0.007
	(−7.07)	(−6.03)	(−5.74)	(1.63)	(−7.63)	(−8.72)	(−4.52)	(5.00)
[41, 60]	−0.010	−0.011	−0.008	0.002	−0.007	−0.009	−0.005	0.005
	(−6.87)	(−5.20)	(−6.56)	(1.41)	(−5.35)	(−5.56)	(−3.39)	(3.33)
[−20, 0]	−0.149	−0.132	−0.161	−0.028	0.154	0.149	0.161	0.012
	(−17.26)	(−16.15)	(−18.12)	(−8.53)	(21.29)	(20.39)	(21.79)	(5.01)

This table reports the average cumulative abnormal returns (CAR) for stocks with extreme price shocks (i.e., decile 1 of negative shocks and decile 10 of positive shocks) in various windows around the shocks, where day 0 is the last day of the three-day shock window. The benchmarks are the 125 equal-weighted size-B/M-momentum portfolios ($5 \times 5 \times 5$) constructed following Daniel, Grinblatt, Titman, and Wermers (1997). Stocks with price shocks are further divided into "news" and "no-news" subgroups based on whether a news event occurs in the window from three days before to three days after the shock. For each shock month, a mean CAR value is obtained for stocks with the extreme price shocks, the extreme price shocks with news, and the extreme price shocks without news, respectively. Cross-month averages and Newey-West t-values are reported.

TABLE 3
Opinion Divergence at Price Shocks

A. Correlation between price shocks and SUVN

	negative price shocks				positive price shocks			
	full sample	no news	news	difference	full sample	no news	news	difference
SUVN	−0.097	−0.109	−0.096	0.012	0.095	0.109	0.089	−0.020
	(−26.68)	(−30.72)	(−22.79)	(2.91)	(24.45)	(24.20)	(18.61)	(−4.07)

B. Correlation between SUVN and other disagreement proxies

	negative price shocks			positive price shocks		
	SUV	ΔTO	ΔDisp	SUV	ΔTO	ΔDisp
SUVN	0.679	0.317	0.005	0.614	0.282	0.002
	(56.40)	(46.96)	(2.85)	(48.89)	(42.06)	(1.31)

Panel A investigates the correlation between price shocks and investor disagreement. The disagreement proxy, SUVN, extends the SUV measure in Garfinkel and Sokobin (2006) by including a news dummy and the interaction terms between the news dummy and stock returns in the regression. The estimation window is $[t-56, t-6]$, where t is the last day of the three-day shock window. Average daily SUVN is obtained for each stock in the shock window. For each month, cross-sectional correlation is obtained for the full sample, the news sample, and the no-news sample. The correlation difference between the news and no-news sample is also computed. Cross-month average coefficients and the corresponding t-values are reported.

Panel B examines the correlation between SUVN and three alternative proxies for disagreement. ΔDisp is the change in analyst dispersion from the Thomson Reuters statistical period immediately before price shock to the one following the shock. The dispersion is calculated as the standard deviation of earnings forecast divided by the absolute mean value. The forecast target is the first annual earnings after month $m+12$ where m is the shock month. The other two proxies, ΔTO and SUV, are based on unexplained volume, and are constructed following Garfinkel and Sokobin (2006) with estimation (control) period of $[t-56, t-6]$ where t is the last day of the shock window. Average daily values of ΔTO and SUV are obtained for each stock in the three-day shock window. For each shock month, we compute the cross-sectional correlations between SUVN and these alternative proxies. Cross-month average coefficients and the corresponding t-values are reported.

TABLE 4
Post-Shock Opinion Convergence

A. Variation in SUVN among stocks with extreme price shocks

	Extreme negative shocks		Extreme positive shocks	
window	Estimate	t-value	Estimate	t-value
$[-2, 0]$	0.358	(12.87)	0.444	(19.83)
$[1, 60]$	-0.440	(-18.99)	-0.363	(-23.80)
$[61, 120]$	-0.131	(-7.95)	-0.122	(-7.85)
$[121, 180]$	-0.057	(-3.91)	-0.051	(-3.34)
$[181, 240]$	-0.058	(-3.69)	-0.048	(-3.12)

B. Correlation between CAR and change in SUVN

	Negative shocks		Positive shocks	
window	Estimate	t-value	Estimate	t-value
$[1, 60]$	0.026	(11.99)	0.011	(5.84)
$[61, 120]$	0.044	(12.17)	0.041	(9.60)
$[121, 180]$	0.038	(11.35)	0.035	(9.96)
$[181, 240]$	0.036	(11.27)	0.039	(9.86)

Panel A examines variation in investor disagreement around extreme price shocks (i.e., decile 1 of negative shock and decile 10 of positive shock). SUVN is used as proxy for disagreement. Average daily SUVN is obtained in the shock window (i.e., $[-2, 0]$) as well as the four 60-day windows following price shocks for each stock. For each of the 60-day windows, change in daily SUVN relative to the previous window is computed. The median SUVN over $[-2, 0]$ and the median change in daily SUVN are obtained for each shock month. Cross-month averages and the Newey-West t-values are reported in the panel. Panel B reports the cross-sectional correlation between the stock cumulative abnormal returns (CAR) and the contemporaneous change in disagreement in each of the four 60-day windows following price shocks using the full sample. We compute the correlation for each shock month. Cross-month averages and the Newey-West t-values are reported.

TABLE 5
Drifts under Low Breadth vs. High Breadth

	Extreme Negative Shocks			Extreme Positive Shocks		
window	low breadth	high breadth	difference	low breadth	high breadth	difference
$[1, 240]$	−0.068	0.001	−0.069	−0.122	−0.040	−0.082
	(−4.80)	(0.12)	(−3.69)	(−7.66)	(−3.25)	(−4.02)
$[1, 60]$	0.015	0.018	−0.004	−0.066	−0.031	−0.035
	(3.86)	(4.59)	(−0.64)	(−12.51)	(−6.91)	(−5.35)
$[61, 120]$	−0.035	−0.005	−0.030	−0.027	−0.009	−0.018
	(−7.39)	(−1.36)	(−4.59)	(−5.52)	(−2.32)	(−2.82)
$[121, 180]$	−0.028	−0.006	−0.022	−0.023	−0.003	−0.020
	(−6.25)	(−1.73)	(−3.85)	(−4.69)	(−0.66)	(−3.17)
$[181, 240]$	−0.024	−0.005	−0.020	−0.020	0.000	−0.020
	(−5.69)	(−1.05)	(−3.37)	(−4.29)	(−0.01)	(−3.24)
$[1, 20]$	0.042	0.026	0.017	−0.050	−0.026	−0.024
	(17.66)	(9.29)	(9.43)	(−15.56)	(−13.65)	(−7.28)
$[21, 40]$	−0.013	−0.003	−0.010	−0.010	−0.003	−0.007
	(−6.71)	(−1.62)	(−3.66)	(−8.03)	(−1.31)	(−3.11)
$[41, 60]$	−0.014	−0.004	−0.010	−0.008	−0.003	−0.005
	(−6.38)	(−2.29)	(−3.65)	(−4.56)	(−1.49)	(−1.91)
$[-20, 0]$	−0.127	−0.169	0.042	0.172	0.132	0.039
	(−15.58)	(−17.55)	(7.32)	(20.09)	(21.11)	(7.91)

This table compares the price shock effects across two subgroups: the one with low breadth vs. the one with high breadth. Stocks are sorted into terciles based on the breadth measure (Chen et al. 2002) each shock month. The lowest (highest) tercile is defined as low- (high-) breadth group. This table focuses on stocks with extreme price shocks (i.e., decile 1 of negative shocks and decile 10 of positive shocks), and reports the mean cumulative abnormal returns (CAR) in various windows around the shocks for those in the low- and the high-breadth groups separately. Day 0 is the last day of the three-day shock window. The benchmarks are the 125 equal-weighted size-B/M-momentum portfolios (5×5×5) constructed following Daniel et al. (1997). For each shock month, a mean CAR value is obtained for stocks with extreme price shocks and in the low-breadth group as well as stocks with extreme price shocks and in the high-breadth group. The difference in CAR between the two groups is calculated each month. Cross-month average and Newey-West t-values are reported.

TABLE 6
Post-Shock Drifts and Post-Shock News Events

	post-shock one-year return		news day returns		no-news day returns	
	negative shocks	positive shocks	negative shocks	positive shocks	negative shocks	positive shocks
intercept	34.82	10.23	2.33	1.21	30.22	8.48
	(4.37)	(1.34)	(1.00)	(0.48)	(4.25)	(1.27)
r_{shock^-}	0.69		0.05		0.59	
	(4.99)		(1.24)		(6.16)	
r_{shock^+}		-0.27		0.03		-0.30
		(-2.25)		(0.89)		(-3.96)
log(size)	-1.09	0.04	0.31	0.20	-1.24	-0.09
	(-2.19)	(0.07)	(1.56)	(0.93)	(-2.92)	(-0.23)
B/M	2.15	3.51	0.49	0.87	1.43	2.38
	(2.24)	(4.03)	(2.05)	(4.09)	(2.02)	(3.46)
return 12	0.04	0.04	0.01	0.01	0.03	0.02
	(4.40)	(3.46)	(2.37)	(2.25)	(3.72)	(2.79)

This table investigates whether the post-shock drift is due to news events after price shocks. We conduct Fama-MacBeth cross-section regressions. We identify all news events in the one-year post-shock period for each price shock, and classify three trading days [-1,0,+1] (where day 0 is the event day) as news days for a given news event. Cumulative one-year return, cumulative news-day return, and cumulative no-news-day return are calculated for each price shock. The dependent variable for Columns 2 and 3 is cumulative one-year return, and that for Columns 4 and 5 (6 and 7) is cumulative news (no-news)-day return. Negative (r_{shock^-}) and positive (r_{shock^+}) price shocks are variables of interest, and are defined as the minimum and maximum three-day abnormal returns over the shock month t. Included as control variables are size, B/M, and return 12, which respectively are the market value, book-to-market ratio, and cumulative 12-month return from month $t-12$ to $t-1$ before the shock month t. The average regression coefficients and the corresponding Newey-West t-values are reported.

TABLE 7
Price Shock Effects in a Momentum Setting

	momentum	stocks with price shocks: all	news	no news	diff	no shocks	shocks - no shocks
losers	−0.79	−1.14	−0.84	−1.26	0.42	−0.64	−0.51
	(−4.56)	(−5.04)	(−3.95)	(−5.04)	(2.86)	(−4.02)	(−4.73)
winners	0.03	−0.22	0.07	−0.34	0.41	0.15	−0.37
	(0.31)	(−1.62)	(0.50)	(−2.50)	(3.60)	(1.68)	(−3.54)

This table examines price shock effects in a momentum setting. At the end of the shock month m, stocks are independently ranked into deciles based on the cumulative return from month m-12 to m-1, the negative price shock, and the positive price shock. Stocks in the highest (lowest) decile based on the cumulative past 12-month return are classified as winners (losers). Equal-weighted portfolios are formed for winners and losers and held for 12 months, following the overlapping construction of Jegadeesh and Titman (1993). The winner and loser groups are further divided into two groups: stocks with price shocks and those without. Stocks in decile 1 (decile 10) ranked on negative (positive) price shocks are classified as stocks with price shocks. The two price shocks groups are classified into news and no-news subgroups, based on whether a news event occurs in the window from three days before to three days after the price shocks. Fama-French three-factor alphas are reported for all portfolios. Newey-West t-values are presented for all alphas.

TABLE 8
Information Uncertainty

A. Information uncertainty

	Age		Return Std.dev.		Turnover	
	negative shocks	positive shocks	negative shocks	positive shocks	negative shocks	positive shocks
intercept	35.05	10.60	35.53	12.72	34.47	9.34
	(4.37)	(1.38)	(4.45)	(1.67)	(4.31)	(1.23)
IU dummy	−1.70	−2.72	−2.74	−7.88	−2.16	−5.89
	(−1.47)	(−2.35)	(−1.33)	(−4.81)	(−1.16)	(−3.98)
r_{shock^-}	0.69		0.65		0.67	
	(4.98)		(5.49)		(5.36)	
r_{shock^+}		−0.26		−0.19		−0.23
		(−2.21)		(−1.78)		(−2.05)
log(size)	−1.11	0.01	−1.16	−0.16	−1.06	0.12
	(−2.20)	(0.03)	(−2.30)	(−0.32)	(−2.11)	(0.25)
B/M	2.10	3.44	2.08	3.28	2.13	3.40
	(2.21)	(3.98)	(2.25)	(3.92)	(2.28)	(4.01)
return 12	0.04	0.04	0.04	0.04	0.05	0.04
	(4.39)	(3.45)	(4.61)	(3.74)	(4.66)	(3.88)

TABLE 8
Information Uncertainty (Continued)

B. Information uncertainty and price shock interactions

	Age		Return Std.dev.		Turnover	
	negative shocks	positive shocks	negative shocks	positive shocks	negative shocks	positive shocks
intercept	34.97	10.57	35.58	12.55	33.99	9.11
	(4.37)	(1.38)	(4.50)	(1.64)	(4.27)	(1.20)
IU dummy	−0.71	−2.04	−2.30	−7.47	0.88	−4.37
	(−0.48)	(−1.60)	(−0.66)	(−2.57)	(0.28)	(−1.82)
r_{shock^-}	0.67		0.65		0.62	
	(4.97)		(4.81)		(4.47)	
$r_{shock^-}\times$IU dummy	0.17		0.04		0.35	
	(1.04)		(0.25)		(2.58)	
r_{shock^+}		−0.25		−0.17		−0.20
		(−2.16)		(−1.38)		(−1.65)
$r_{shock^+}\times$IU dummy		−0.16		−0.06		−0.17
		(−1.53)		(−0.47)		(−1.72)
log(size)	−1.10	0.01	−1.16	−0.15	−1.05	0.12
	(−2.19)	(0.03)	(−2.33)	(−0.31)	(−2.09)	(0.25)
B/M	2.10	3.44	2.07	3.29	2.13	3.41
	(2.21)	(3.97)	(2.28)	(4.00)	(2.29)	(4.04)
return 12	0.04	0.04	0.04	0.04	0.05	0.04
	(4.39)	(3.44)	(4.62)	(3.76)	(4.70)	(3.92)
	0.044	0.044	0.048	0.050	0.047	0.048

This table examines whether the information uncertainty can explain the price shock effect using Fama-MacBeth cross sectional regressions. The dependent variable is the cumulative stock return over the one-year after price shocks. Following Jiang et al. (2005) and Zhang (2006), three proxies of information uncertainty are used: firm age, stock return volatility using daily returns in the month before price shock, and average daily stock turnover in the month before price shock. Each month, stocks are ranked into deciles based on the three proxies of information uncertainty separately. The IU dummy variable is set to one if a stock is in the decile with highest information uncertainty, and zero otherwise. The average regression coefficients and the corresponding Newey-West t-values are reported.

TABLE 9
Post Earnings Announcement Drifts

Extreme Negative Shocks				Extreme Positive Shocks			
decile 1	no news	news	news - no news	decile 10	no news	news	news - no news
	whole sample				whole sample		
−0.050	−0.057	−0.041	0.016	−0.106	−0.132	−0.075	0.057
(−4.69)	(−4.67)	(−4.05)	(2.42)	(−8.77)	(−9.45)	(−6.85)	(8.94)
	low UE quintile excluded				high UE quintile excluded		
−0.043	−0.049	−0.032	0.017	−0.120	−0.143	−0.090	0.052
(−4.21)	(−4.21)	(−3.28)	(2.62)	(−9.57)	(−9.79)	(−8.03)	(7.60)
	difference				difference		
−0.007	−0.008	−0.009		0.014	0.010	0.015	
(−4.03)	(−2.92)	(−3.73)		(8.60)	(5.42)	(7.23)	

This table examines whether post earnings announcement drifts can explain the price shock effects. Each quarter, stocks are sorted into quintiles based on earnings surprise (UE), which is calculated as the cumulative abnormal return (CAR) relative to the value-weighted CRSP market return over [-1, +1] day of earnings announcement. The two rows for the “whole sample” (i.e., rows 4 and 5) are the same as the first two rows in Table 2, reporting CAR relative to the equal-weighted characteristics based benchmark portfolio for stocks with extreme price shocks over the window [1,240] after the shocks. The next two rows (i.e., rows 7 and 8) are the test results excluding stocks in the lowest (highest) UE quintile, based on the last earnings announcement before price shock, for negative (positive) price shocks. The last two rows show the difference between the whole shock sample and the one excluding the extreme UE quintile. Newey-West t-values are reported in parentheses.

TABLE 10

Liquidity, Liquidity Shock, and Retail Trading

	Liquidity		Liquidity Shock		Retail Trading	
	negative shocks	positive shocks	negative shocks	positive shocks	negative shocks	positive shocks
intercept	33.84	8.04	35.59	9.79	23.02	−9.22
	(3.98)	(1.02)	(4.20)	(1.22)	(2.28)	(−1.06)
illiquidity	0.48	0.48				
	(1.10)	(1.39)				
liq. shock			0.21	0.34		
			(1.46)	(2.49)		
RTP					−0.73	2.08
					(−0.35)	(1.05)
r_{shock^-}	0.69		0.69		0.73	
	(5.15)		(5.13)		(4.85)	
r_{shock^+}		−0.28		−0.27		−0.27
		(−2.29)		(−2.23)		(−1.93)
log(size)	−1.01	0.20	−1.14	0.06	−0.20	1.41
	(−1.87)	(0.39)	(−2.13)	(0.12)	(−0.32)	(2.57)
B/M	1.92	3.40	1.93	3.40	1.03	2.67
	(1.89)	(3.74)	(1.91)	(3.76)	(0.60)	(1.80)
return 12	0.05	0.04	0.05	0.04	0.05	0.05
	(4.41)	(3.54)	(4.29)	(3.34)	(3.35)	(2.84)

This table examines whether liquidity, liquidity shock, or retail trading can explain the price shock effect using Fama-MacBeth cross sectional regressions. The dependent variable is the cumulative stock return over the one-year after price shocks. Stock illiquidity is constructed following Amihud (2002) and liquidity shock is obtained following Bali et al. (2013). *RTP* denotes retail trading proportion. All three measures are constructed using daily data in the month prior to price shock. The average regression coefficients and the corresponding Newey-West t-values are reported in the table. The sample period for the liquidity and the liquidity shock tests are from 1980 to 2006, and that for RTP is from 1983 to 2000.

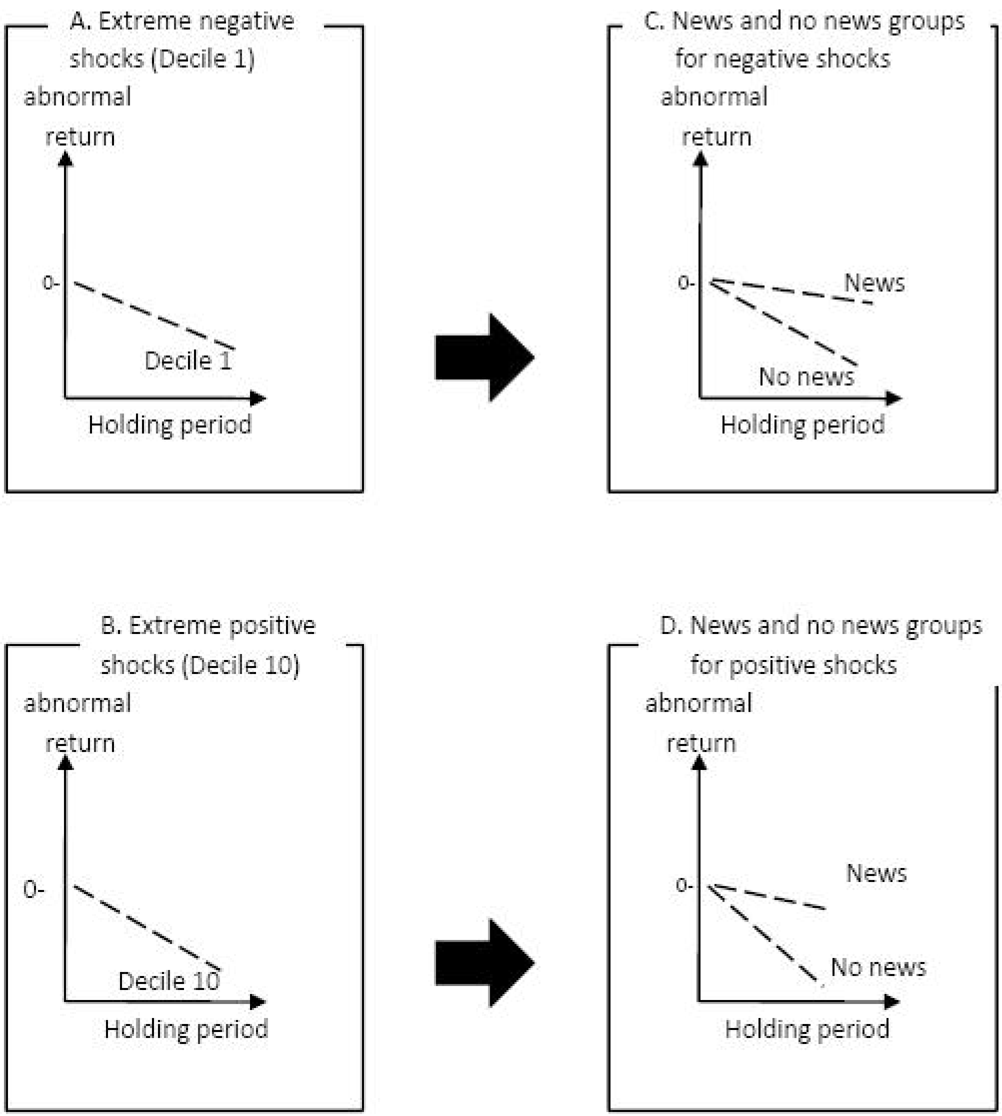

Figure 1: Drifts following extreme price shocks
In Diagram A, stocks are sorted by the minimum three-day abnormal return (i.e., negative price shock). In this case, decile 1 contains stocks with extreme negative price shocks. In Diagram B, stocks are sorted by the maximum three-day abnormal return (i.e., positive price shock). In this case, decile 10 contains stocks with extreme positive shocks. Diagrams C and D show that for both extreme negative and extreme positive shocks, the effects are stronger for no-news shocks.

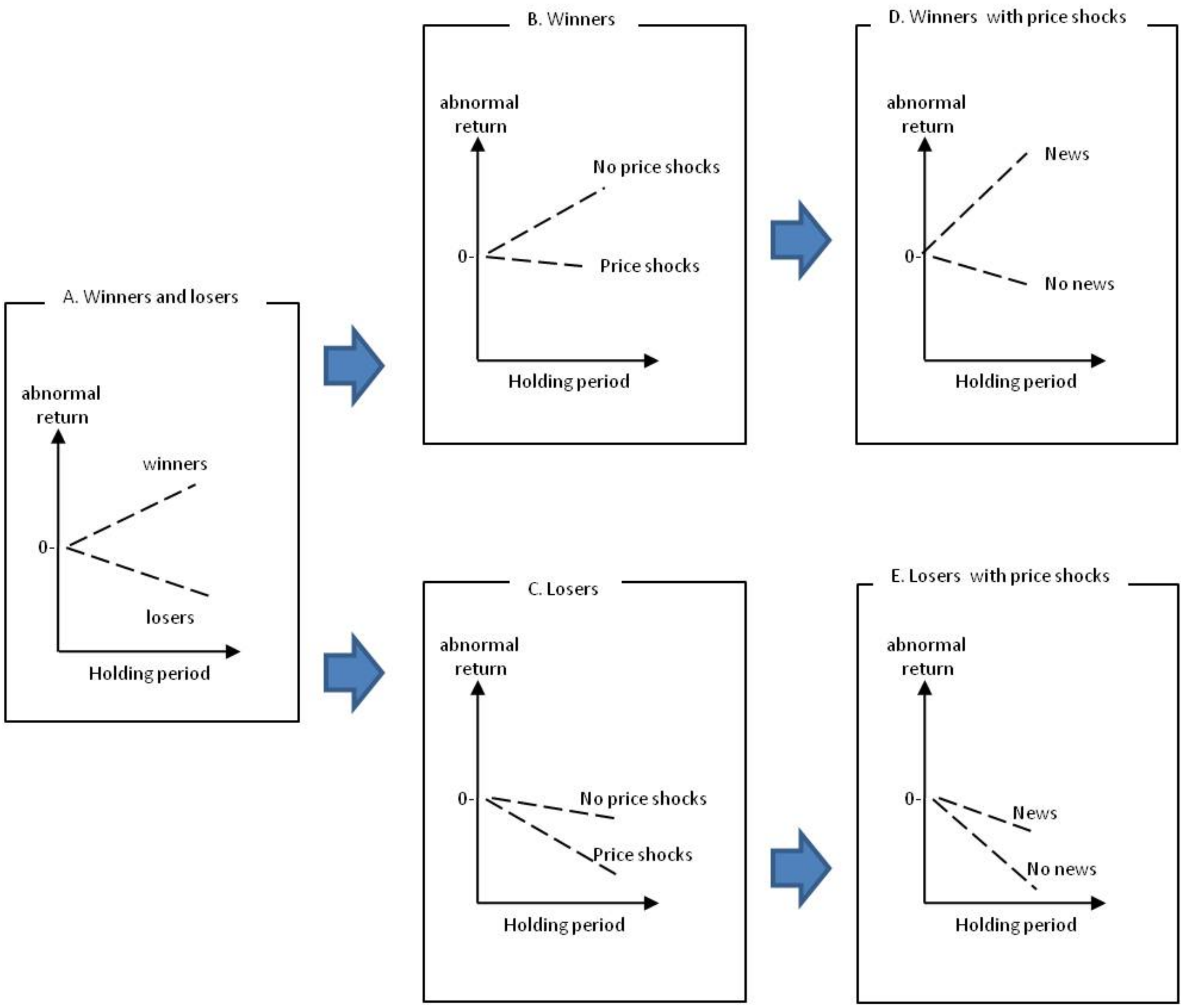

Figure 2: Post-shock drifts in a momentum setting
Within a momentum setup, the figure illustrates disagreement-induced overpricing. The winner stocks are divided into two subsets: those associated with extreme price shocks in the ranking month and those without. The winners with extreme price shocks are further divided, depending on whether the extreme price shock is associated with news (public disclosures). The loser stocks are divided similarly.