https://doi.org/10.1016/j.jcorpfin.2017.06.013

What do stock price levels tell us about the firms?

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June 17, 2017

Abstract

We hypothesize that high stock price levels impede informed trading on the stocks and reduce price informativeness. This is because uninformed trading is needed to facilitate informed trading, and high stock prices may impose budget constraints on uninformed investors. Indeed, we find, for high-price firms, (i) options to stock trading volume (O/S), an informed trading measure in options market, is higher, (ii) price informativeness about future earnings is lower, and (iii) investment sensitivity to price is lower. We also find these patterns reverse after stock splits, suggesting that firms can use splits to improve informed trading and enhance price informativeness.

JEL classification: G30, G12, G14, G17

Keywords: Stock price level, price informativeness, O/S, future earnings, stock splits

We are grateful to Gurdip Bakshi, Hendrik Bessembinder, Utpal Bhattacharya, Mark Grinblatt, Jiekun Huang, Jingzhi Huang, Neil Pearson, Tie Su, Avanidhar Subrahmanyam, and participants at the Sixth Chulalongkorn Accounting and Finance Symposium, Hong Kong Baptist University, Hong Kong Polytechnic University, Louisiana State University, Shanghai University of Finance and Economics, and University of Hong Kong for helpful comments. Chan acknowledges the financial support from National Science Council, Taiwan (NSC 101-2410-H-004-085). Tse-Chun Lin gratefully acknowledges the research support from the Faculty of Business and Economics and the University of Hong Kong and the Research Grants Council of the Hong Kong SAR government. Any remaining errors are ours.

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1. Introduction

Weld, Benartzi, Michaely, and Thaler (2009) review potential explanations on the phenomenon that the average nominal price for stocks has been largely at $35 since Great Depression. They argue that none of the existing theories including signaling and optimal trading range are able to explain why firms split their stocks to manage their stock price levels. Similarly, Easley, O'Hara, and Saar (2001, p. 25) point out "why a split per se is necessary is unclear… empirical research has documented a wide range of negative effects such as increased volatility, larger proportional spreads, and larger transaction costs following the splits. On balance, it remains a puzzle why companies ever split their shares." The fact that the market reacts positively to split announcements seems to suggest that the benefits of lowering stock price levels to split firms should outweigh the associated negative effects.

Yet, there are many firms that keep their stock prices at relatively high levels, like Berkshire Hathaway-A at $248,440 and Priceline at $1,877 per share.[1] These high-price firms could go for a stock split but choose not to.[2] This raises several intriguing questions: What do stock price levels tell us about the firms? Why do less known firms tend to choose lower stock price levels? If there are some benefits of doing a stock split, why do high-price firms choose not to take it?

The purpose of our study is to shed light on these questions. Based on market microstructure theories that will be discussed in next section, we hypothesize that *high stock price levels impede informed trading on the stocks and reduce price informativeness*. This is because high stock prices may impose budget constraints on uninformed investors and limit their

[1] The prices were observed on May 31, 2017.

[2] Dyl and Elliott (2006) show a substantial variation in the prices of common stocks in U.S. markets due to firms selecting particular price ranges for their shares. In general, they find that firms with better investor recognition, i.e., larger firms and firms with more institutional ownership, tend to have higher stock price levels.

risk sharing capacity, while uninformed trading is needed to facilitate informed trading (Kyle, 1985; Glosten and Milgrom, 1985).[3] When stock prices are less informative, informed traders are more likely to capitalize on the information not yet reflected into stock prices.

We conduct three main tests to provide supportive evidence to our hypothesis. First, the literature has shown that the informed traders tend to use options to exploit the trading opportunities due to the high embedded leverage in options and potential short-sale constraints in stock.[4] Hence, our hypothesis predicts that when their stock prices are less informative, the options of higher-price stocks would be more attractive to traders, causing the relative trading of options over stock (i.e., O/S ratio in Roll, Schwartz, and Subrahmanyam's (2010)) to increase with stock price levels.

Our hypothesis also predicts that, controlling for the determinants identified by Roll et al. (2010), O/S should be positively related to the stock price level and this positive relation should be stronger for firms that have more difficulty to attract small investors, who are more likely to be uninformed. To proxy for the ease in attracting small investors, we use dollar ownership per shareholder, i.e., market value of equity divided by the number of shareholders. If a firm can easily attract small investors, it would have many small investors as shareholders and the dollar ownership per shareholder would be relatively small.

The second test utilizes the future earnings response coefficient (FERC) from the return-earnings model to measure the informativeness of current stock prices for future earnings (e.g.,

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[3] High stock price levels may discourage uninformed individual traders from participating in trading the stocks because, facing budget constraints, they may not be able to buy a few round lots of high-price stocks. Even if they can buy odd lots of high-price stocks, they may not be able to diversify their portfolios. This suggests that high stock price levels may limit uninformed individual investors' risk sharing capacity.

[4] There is growing evidence of the informational role of option trading in price discovery process (e.g., Skinner, 1990; Amin and Lee 1997; Jin, Livnat, and Zhang, 2012; Chakravarty, Gulen, and Mayhew, 2004). While a high stock price level may discourage uninformed trading and reduce the stock market depth, it should not affect the options market depth because, due to the nature of leverage in options, the option price is usually a fraction of the underlying stock price and hence uninformed trading in the options market should not be affected by the high stock price level.

Collins, Kothari, Shanken and Sloan, 1994; Lundholm and Myers, 2002; Gelb and Zarowin, 2002). Presumably, stock prices would be more informative if there is more informed trading or if stock returns contain more firm-specific information. FERC would capture the intuition that more informative stock prices contain more information about future earnings. If our hypothesis holds, we would expect a lower FERC for high-price stocks.

The last test of our hypothesis is to examine whether managers of high-price firms learn less from the stock market as the prices contain less information. Prior studies suggest that price informativeness improves resource allocations and is valuable to firms (e.g., Khanna, Slezak, and Bradley, 1994; Subrahmanyam and Titman, 2001; Chen, Goldstein, and Jiang, 2007). Hence, when stock prices are more informative and contain information that managers otherwise would not know, their real decisions should be more influenced by stock prices. Specifically, we test whether corporate investment sensitivity to stock price is inversely related to stock price levels.

Using Fama-Macbeth regression analysis on a comprehensive sample of 5,527 firms with listed options from 1996 to 2016, we find that O/S is positively related to stock price levels after controlling for other known determinants of O/S. Our findings indicate that, holding other things constant, high stock price levels have drawbacks to attract both uninformed and informed trading to the stocks, and stock price levels matter in price informativeness and in where informed traders choose to trade. In addition, our subsample analysis shows a non-linear relation between O/S and stock price, which is primarily driven by firms with stock prices in the top quartile. We also find that the high price effect on O/S is stronger for firms that have more difficulty in attracting small investors to provide liquidity in the stock market.

We further show that price informativeness about future earnings is inversely related to stock price levels. In particular, while stock returns in a given year are positively related to future earnings in the next three years, the relations are weaker for high-price firms as revealed by the interaction of Ln(Price) and future earnings being significantly negative in the regressions. Moreover, our subsample analysis indicates that stock price informativeness is significantly lower for high-price firms without listed options compared to comparable firms (that have similar stock price, size, and book-to-market ratio) with listed options. The results provide supportive evidence that stock prices are less informative for higher-price stocks due to a drop of informed trading on the stocks.

Finally, we find that corporate investment sensitivity to stock price is lower for firms with higher stock price levels. The evidence suggests that when making investment decisions, managers of higher-price firms put less weight on their stock prices. One implication of this finding is that when firms need less feedback from stock prices, they keep their stock prices at higher levels, which also allow them to avoid the negative effects of lowering stock price levels that Easley et al. (2001) mention. Since high-price firms rely less on the inputs from the market, we conjecture that their managers perhaps rely more on "their own ideas" in running their firms.

If our hypothesis that high stock price levels impede informed trading on the stocks is valid, a stock split, which has been shown to attract more uninformed trading to the stock, should be able to lessen the constraints on informed trading and enhance price informativeness.[5] Thus, stock splits allow us to further test our hypothesis by examining changes in price informativeness following split-induced changes in stock price levels.

To do so, we collect 1,836 stock splits undertaken by firms with listed options during the period 1996-2016. Indeed, the average O/S of the split firms gradually increases during the pre-split 12 months, reaches the peak in the month immediately before the split announcement, and

[5] For example, Schultz (2000) shows a significant increase in small trades following the splits. Also, Easley, O'Hara and Saar (2001) document more uninformed trades— and more informed trades as well—after stock splits.

then declines significantly after the ex-date of the split. We further show that changes in O/S from before to after stock splits are positively related to the corresponding changes in stock price levels, and this effect is more pronounced for firms that had more difficulty to attract small investors before stock splits. The results are largely consistent with our hypothesis that the pre-split high stock price levels make split firms' options more appealing to informed traders, and as stock splits attract more uninformed trading to improve informed trading on the stock, informed traders find the equity market an attractive trading venue again.

One may argue that if some traders are merely aware of the forthcoming split events, which on average receive positive market reactions, they could still profit by trading options regardless of reasons behind splits.[6] To address this concern and to better understand the information content of pre-split O/S, we link pre-split O/S to split announcement returns and post-split firm performance. Our empirical results show that the higher the pre-split O/S, the higher the split announcement returns.[7] Also, firms with higher pre-split O/S are associated with larger earnings surprises over the first four quarters after stock splits. These results are consistent with the notion that pre-split O/S reflects informed traders' preference of options over stock. The results also suggest that the informed have information about the firms' future prospects and that they are not merely reacting to forthcoming split announcements.

The fact that the information content of pre-split O/S was not fully impounded into stock price until the firms announce to undertake stock splits suggests that the price discovery function in the equity market was impaired by high stock price levels prior to stock splits and there is a need to improve informed trading. By lowering stock price levels to attract more liquidity trading,

[6] In fact, if traders in the options market are merely aware of the occurrence of split events, we would only observe a high O/S ratio before stock split but no positive correlation between pre-split O/S and the split announcement CAR.

[7] A related paper by Gharghori, Maberly, and Nguyen (2017) examines the expectations of option traders on future stock return and volatility changes due to splits, but finds that the pre-split implied volatility spread and skew do not predict the split announcement returns.

stock splits could improve informed trading on the stocks and restore the price discovery function. We find that post-split stock prices are indeed more informative about future earnings than pre-split stock prices. The results provide supportive evidence to our hypothesis that nominal stock price level has a real effect on the price informativeness.

The remainder of the paper is organized as follows. Section 2 reviews the literature and develops our hypothesis. Section 3 describes the data and provides summary statistics. Section 4 discusses empirical results for our hypothesis. Section 5 presents additional tests using the setting of stock splits. Section 6 offers our concluding remarks.

2. Literature review and hypothesis development

2.1. The literature on nominal stock prices

A firm's stock price level to a large extent reflects how it "cuts its pie." For example, given a $1 billion dollar firm, its stock price level could be $200 a share if the firm has 5 million shares outstanding or $20 if its outstanding shares are increased to 50 million. Do stock price levels matter? If they do, where do they matter? A large body of literature has examined these issues. Weld, Benartzi, Michaely, and Thaler (2009) point out that "It is surprising that firms actively maintained constant nominal price for their shares while general prices in the economy went up more than tenfold." What could motivate managers to do stock splits to keep their firms' stock prices constant in nominal terms? Recently, Baker, Greenwood, and Wurgler (2009) propose a catering theory of nominal stock prices, which predicts that when investors place higher valuations on low-price firms, managers respond by supplying shares at lower price levels, and vice versa. While firms may have catering incentives, it is possible that when investors place higher valuations on low-price firms, low prices increase individual investors' risk sharing capacity, which allows low-price firms to take more risky projects and, as we will discuss below, make their stock prices more informative. At which time, firms are also more likely to split their stocks to capture the benefits of enlarging investors' risk sharing capacity.

Nevertheless, none of the existing studies have explored the possibility that high stock price levels may create problems for informed trading and make stock prices less informative. The reason we suspect such problems could arise is that market microstructure theories have suggested that informed trading is a key element of the price discovery function of the market and that uninformed trading is needed to facilitate informed trading (Kyle, 1985; Glosten and Milgrom, 1985). As Admati and Pfleiderer (1988) point out, informed traders tend to camouflage their trades among uninformed trades. If high stock price levels create barriers for uninformed investors to enter the market because of budget constraints and limited risk sharing capacity, they could have negative impacts on informed trading as well.

2.2. The literature on budget constraints and uninformed/informed trading

Several studies have discussed the budget constraint issue for risk sharing. For example, Amihud, Mendelson, and Uno (1999) show that when companies in Japan reduce their stock's minimum trading unit, i.e., the number of shares in a round lot, to better facilitate trading by small investors, the number of their individual shareholders significantly increases. Similarly, Fernando, Krishnamurthy, and Spindt (1999) analyze mutual fund share splits and find that, relative to non-splitting matched funds, split funds experience significant increases in net assets and shareholders. Moreover, Schultz (2000) shows a significant increase in small trades following the splits; and Easley, O'Hara, and Saar (2001) document more uninformed trades (and more informed trades as well) after stock splits. The evidence from these studies suggest that small individual investors have limited risk sharing capacity and are likely subject to budget constraints. Consequently, they could be excluded from participating in trading stocks with high price levels. When informed traders cannot effectively camouflage their trades among uninformed trades in the equity market, their private information would not be efficiently impounded into stock prices; and the informational role of stock price could diminish.

When stock price becomes less informative, informed traders may find listed options an attractive vehicle for profiting from their private information. Because of the nature of implicit leverage in options, option prices are usually fractions of the underlying stock price. The relatively low prices of options could attract speculative trading and hedging trading as well. Easley, O'Hara, and Srinivas (1998) measure the depth of the stock market or the options market by the number of uninformed traders in each market, and suggest that decreasing the depth of the stock market could result in more informed traders using options.[8] Thus, if high stock price levels unfavorably affect uninformed trading and reduce the depth of the stock market, we should see that more informed traders migrate their trades to the options market.

2.3. The hypothesis on nominal stock price level and price informativeness

Based on the previous literature review and discussions, our main hypothesis is that *high stock price levels impede informed trading on the stocks and reduce price informativeness*.

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[8] Using O/S, Roll et al. (2010) track where investors prefer to trade, the options market or the equity market. The advantages of options are their implicit leverage and usefulness for hedging positions in the underlying stock or other options. However, the liquidity in each market is also a very important factor. Indeed, they find that options delta and trading costs, along with institutional holdings, analyst following, and analyst forecast dispersion are important determinants of O/S. They also provide evidence on the stock return predictability of O/S and the occurrence of more informed trading in options prior to earnings announcements. This return predictability of O/S is further explored in recent research (e.g., Johnson and So, 2012; Chan, Ge and Lin, 2015; Ge, Lin, and Pearson, 2016). Similarly, Cao, Chen, and Griffin (2005) document that options volume is related to takeover announcement returns of target firms and provide evidence that informed traders make trades prior to takeover announcements. These findings are consistent with Pan and Poteshman (2006), who show that put/call ratios reflect fluctuations in informed trading in the options market and are good predictors of future stock returns.

Empirically, since informed trading with private information in each market is not easily observable, we propose three tests to examine our hypothesis. First, we use the O/S ratio, a measure of informed trading in options market proposed by Roll, Schwartz, and Subrahmanyam (2010), to test whether stock price level is related to the informed trading in the options market. Our working assumption is that hedging and speculative trading, the two main motivations for trading options, are relatively stable, and that the fluctuation in O/S is largely attributable to changes in trading motivated by information. Roll et al. (2010) have identified a set of important determinants of O/S, including the costs of trading, the size of the firm, the available degree of leverage in options, institutional holdings, and proxies for the availability of private information and the diversity of opinions.

Our hypothesis predicts that there would be more informed trading in options relative to the underlying stock when the stock price level is higher, and that the effect of stock price level on the relative informed trading should be larger for firms that have more difficulty in attracting small investors. Thus, the first test of our hypothesis also extends Roll et al. (2010) by proposing that, in addition to the O/S determinants they identify, stock price levels and the interaction between stock price levels and dollar ownership per shareholder, which is a proxy for the ease in attracting small investors, are also important determinants of O/S.

The second test of our hypothesis relies on the FERC proposed by Collins, Kothari, Shanken and Sloan (1994) and Lundholm and Myers (2002). Specifically, following Lundholm and Myers (2002), we define price informativeness as the association between current stock returns and future earnings. Our hypothesis predicts that stock returns of high-price firms are less informative about their future earnings.

Finally, prior studies have suggested that price informativeness is valuable, allowing firms to improve resource allocations. If keeping stock prices at relatively low levels leads to higher price informativeness as our hypothesis suggests, firms may put the higher price informativeness into good use. Conversely, firms that keep their stock prices at higher levels may rely less on information from stock prices in making investment decisions. For instance, when managers have "their own ideas" of how to manage and lead the firms, they can rely less on the inputs from the market. The tradeoff is that, by not lowering stock price levels to improve price informativeness, high-price firms can also avoid the negative effect of higher return volatility and higher proportional bid-ask spread associated with lowering stock price levels. Hence, our last test of the hypothesis is to examine whether corporate investment sensitivity to stock price is inversely related to stock price levels.

2.4. Stock splits and improving informed trading

Our hypothesis proposes an inverse relationship between price informativeness and stock price levels. If this relationship is robust, we expect that decreases in stock price levels should result in higher price informativeness. Stock splits are an effective mechanism to allow firms to adjust their price levels lower, attract more uninformed trading, and thus improve price informativeness. Accordingly, stock splits provide an interesting setting to further test the inverse relationship between price informativeness and stock price levels. Therefore, we use stock splits as an event study to highlight the relationship between changes in stock price levels and changes in price informativeness.

Moreover, for managers that need price informativeness to help guide their firms, improving price informativeness could be a compelling factor in stock split decisions. Hence, for firms whose high stock price levels hinder uninformed traders to enter the market, managers can use stock splits to attract more uninformed traders to improve informed trading and enhance informational efficiency of stock prices. Meanwhile, despite more uninformed traders are attracted to split firms, stock splits could make price more informative simply because informed traders have more incentives to collect information when there are more uninformed traders in the market (Holmstrom and Tirole, 1993).

Accordingly, we expect that, for splitting firms with listed options, O/S would rise before stock splits since pre-split high stock price levels reduce price informativeness, which makes listed options more appealing to informed traders. If the increase in O/S reflects the increased preference of informed traders as we argue, then pre-split O/S would be informative about split firms' future prospects. Furthermore, O/S should decline after stock splits because as stock splits lower stock price levels and attract more uninformed trading, they should result in more informed trading on the stocks as well. Thus, based on the behavior of O/S surrounding the stock split event, we test whether high stock price levels impede informed trading on the stocks prior to stock splits and whether splitting the stocks improves stock price informativeness.

3. Data and summary statistics

Our sample construction begins with all firms with listed options from OptionMetrics database during the period from Jan 1, 1996 to Apr 30, 2016. We require firms to be listed on the NYSE, AMEX and Nasdaq with ordinary common shares (i.e., CRSP share code 10 or 11). We further require firms to have non-missing values for the variables in our empirical tests. After this filtering process, our comprehensive sample of options consists of 7,322,980 firm-day observations for 5,527 firms during the period 1996-2016.

We also collect firms that made announcements of stock splits with a split factor of at least 0.25 during 1996 to 2016 from the CRSP.[9] We require split firms to be covered by OptionMetrics and to have options trading volume data available before and after stock splits. Our split sample consists of 1,836 splits over the period of 1996-2016.

Following Roll et al. (2010), we use the natural logarithm of two measures: the ratio of the total trading volume of options in the options market to the corresponding trading volume of the underlying stock in the stock market on a given trading day for each firm—O/S based on daily share volume and $O/S based on daily dollar volume.[10] Roll et al. (2010) show that O/S is higher around earnings announcements and O/S prior to earnings announcements is significantly related to the absolute earnings announcement returns. They thus argue that O/S fairly represents informed trading on listed options, relative to the underlying stock.

Roll et al. (2010) show that the determinants of O/S include firm size, options spreads, implied volatility, options deltas, number of analysts following the firm, analysts' earnings forecast dispersion, and institutional holdings. In addition to these known O/S determinants, we consider two key variables to test our hypothesis, namely, *Ln(Price)*, the log stock price level, and the interaction between *Ln(Price)* and *Xsmall*, where *Xsmall* is a dummy variable equal to one if the dollar ownership per shareholder is greater than the yearly cross-sectional median, and zero otherwise. We assume that firms with *Xsmall*=1 have more difficulty in attracting small investors than those with *Xsmall*=0.

[TABLE 1 ABOUT HERE]

In Table 1, Panel A reports summary statistics of the variables based on the pooled 7,322,980 daily observations. The mean of Ln(O/S) is −3.411 and its standard deviation is 1.681,

[9] We exclude stock splits with split factors less than 0.25 and drop all stock dividends to be consistent with prior research (e.g., Ikenberry, Rankine, and Stice, 1996; Ikenberry and Ramnath, 2002).

[10] Given the fact that each options contract is for 100 shares of the underlying stock, we compute the O/S as the ratio of total options trading volume multiplied by 100 to stock trading volume. We also adjust trading volume for firms listed on Nasdaq according to Gao and Ritter (2010).

while the same statistics of Ln($O/S) are −6.266 and 1.884, respectively. The mean of Ln(Price) is 3.219, while the highest stock price level is $1470 and the lowest is $0.067. This wide stock price range should give us sufficient power to test whether price informativeness and O/S are related to stock price levels.[11]

Panel B reports summary statistics of the variables for the split sample. The pre-split stock price, averaged over days *t*−22 to *t*−3 before the split announcement date *t*, ranges from $10.344 to $748. The average value of pre-split Ln(Price) is 4.123, which is much higher than that in the comprehensive sample reported in Panel A. Consistent with the literature, our sample split firms on average enjoy 2.8% abnormal returns (i.e., excess returns over the CRSP value-weighted market index returns) during the five days surrounding the split announcement date *t*. These firms are generally growth firms with low book-to-market ratios that have experienced enormous price run-up (96.4%) prior to the split announcements. The average Ln(O/S) and Ln($O/S) are −2.409 and −5.224, respectively.

Panel C presents the average Pearson correlations between the main variables for the comprehensive sample of 7,322,980 observations. For each of the 5,116 trading days over the period 1996-2016, correlations are calculated across firms and then the daily correlations are averaged across all trading days. The two measures Ln(O/S) and Ln($O/S) are highly correlated with an average coefficient of 0.911. Ln(O/S) are positively correlated with Ln(Price) and the interaction term Ln(Price) × Xsmall.

4. Stock price levels, price informativeness and investment sensitivity

In this section, we first examine the relation between O/S and stock price levels. We then

[11] Firms with extremely low stock prices are usually in financial distress, and their stock returns are subject to large influences of bid-ask bouncing. As a robustness check, in unreported results, we find our test results are virtually the same when stocks with daily average price levels below $5 are removed from our sample.

investigate the relation between price informativeness and stock price levels. Finally, we explore how investment sensitivity changes with stock price levels.

4.1. The relationship between O/S and stock price levels

Our hypothesis predicts that high stock price level may impede informed trading on the stock and reduce price informativeness. To test this hypothesis, we use the comprehensive sample of 7,322,980 firm-day observations. Based on Roll et al. (2010), we perform the following Fama-Macbeth regressions for each of 5,116 trading days over the period 1996-2016:

$$Ln(O/S)_{i,t} \text{ or } Ln(\$O/S)_{i,t} = \beta_0 + \beta_1 \mathrm{Ln(Price)}_{i,t} + \delta' X + Industry\ FE + \varepsilon_{i,t}, \tag{1}$$

$$Ln(O/S)_{i,t} \text{ or } Ln(\$O/S)_{i,t} = \beta_0 + \beta_1 \mathrm{Ln(Price)}_{i,t} + \beta_2 \mathrm{Ln(Price)} \times \mathrm{Xsmall}_{i,t} + \beta_3 \mathrm{Xsmall}_{i,t} + \delta' X + Industry\ FE + \varepsilon_{i,t}, \tag{2}$$

in which the dependent variable is Ln(O/S) or Ln($O/S) of firm *i* at day *t*. The vector *X* includes firm-specific control variables: firm size, implied volatility, options deltas, options spreads, number of analysts following the firm, analysts' earnings forecast dispersion, and institutional ownership. All these variables are defined in Appendix. In addition, we control for Fama-French 48 industry fixed effects.

[TABLE 2 ABOUT HERE]

Table 2 reports the results from Fama-Macbeth regressions. The dependent variables are Ln(O/S) in columns 1-3 and Ln($O/S) in columns 4-6. In models 1 and 4, we replicate Roll et al.'s (2010) analysis on the determinants of O/S. The results are largely consistent with theirs. That is, O/S is positively related to firm size, implied volatility, number of analysts, analyst forecast dispersion, but negatively related to options spread, options delta and institutional ownership.[12] In columns 2 and 5, we estimate equation (1) and find that stock prices are positively associated with O/S. The average coefficients of Ln(Price) are 0.652 (*t*-value=74.36) and 0.374 (*t*-value=46.02), respectively. Columns 3 and 6 estimate equation (2) and show that both Ln(Price) and Ln(Price) × Xsmall are significantly positive. The results are consistent with our hypothesis that high stock price levels make the stocks less attractive to traders, and increase the attractiveness of the options market to the informed. Thus, the evidence illustrates that stock price levels matter in where traders choose to trade.[13] In Internet Appendix Table A1, we also use panel regressions for robustness checks and find consistent results.

Our hypothesis also predicts that the positive effect of stock price on O/S should be more pronounced for those higher price stocks. In Internet Appendix Table A2, we conduct subsample analysis by dividing the comprehensive sample into price quartiles and estimate equation (1) for each subsample. Our result shows a non-linear relation between O/S and stock price. We find that the effect is primarily driven by firms with stock prices in the top quartile.

If a stock is a constituent of an index (like S&P 500), it does not matter much whether the price of the stock is high or low, as many smaller investors trade through mutual funds that track indexes. As robustness checks, we exclude S&P 500 firms or firms with higher institutional holdings (in top quartile or decile), and find that our results are robust to the exclusion of these firms, as shown in Internet Appendix Table A3.

[12] Since analyst coverage produces information, it would affect price informativeness. While Brennan and Hughes (1991) suggest that lowering stock price levels increases trading costs, which induces brokerage houses to do more analyst coverage, Chang, Dasgupta, and Hilary (2006) find that analyst coverage increases with stock price levels. When testing our hypothesis that firms' stock price informativeness is inversely related to their stock price levels, we control for analyst coverage and other relevant firm characteristics, such as firm size and institutional ownership.
[13] One may argue that the odd-lots trading becomes easier due to online trading system, which might mitigate the budget constraint faced by the uninformed traders. However, even though odd lots are more available, that would not help much in market making and facilitating informed trading in the equity market unless informed traders also use odd lots to capitalize on their information frequently.

4.2. The relationship between price informativeness and stock price levels

To conduct the second test of our hypothesis, we follow Lundholm and Myers (2002) whose methodology is largely based on the regression model of Collins et al. (1994). Collins et al. (1994) argue that the more the current return reflects information about future earnings, the higher the future earnings response coefficient (FERC) is expected to be. However, instead of expected future earnings, which are unobservable, their model uses actual future earrings and suggests future returns as an instrumental variable to correct the measurement error and eliminate the bias in estimating future ERC. The rationale is that returns have little autocorrelation, but future returns are correlated with unexpected future earnings changes. While Collins et al. (1994) use earnings changes as explanatory variables, Lundholm and Myers (2002) use the levels of past, current, and future earnings as explanatory variables to allow for a more general form of earnings expectations model.

Based on the model of Lundholm and Myers (2002), we examine the relationship between price informativeness about future earnings and stock price levels using the following regression (subscript *i* to denote the firm is omitted for simplicity):

$$R_t = \beta_0 + \beta_1 X3_t + \beta_2 Ln(Price) \times X3_t + \beta_3 X_{t-1} + \beta_4 X_t + \beta_5 R3_t + \delta' X$$
$$+ Industry\ FE + Year\ FE + \varepsilon_t. \tag{3}$$

In equation (3), R_t is the cumulative return for fiscal year *t*. $X3_t$ is the future earnings, calculated as the sum of earnings for years $t + 1$ through $t + 3$, deflated by the market value of equity at the beginning of fiscal year *t*. X_t is current earnings for fiscal year *t*, deflated by the market value of equity at the beginning of fiscal year t. X_{t-1} is earnings for fiscal year $t-1$, deflated by the market value of equity at the beginning of fiscal year t. Future returns ($R3_t$) are the buy-and-hold returns for the three-year period following the current year (i.e., starting three months after the current fiscal year-end). $Ln(Price)_t$ is the natural logarithm of average share price in fiscal year t. $Asset\ growth_t$ is the growth rate of total assets for fiscal year t. $Ln(MV)_t$ is the natural logarithm of market capitalization (closing price times the number of shares outstanding) at the beginning of fiscal year t. $Ln(Analyst)_t$ is the average number of analysts following in fiscal year t. We include firm size and analyst coverage to control for possible differences in firms' information environment (e.g., Gelb and Zarowin, 2002). As shown in Collins et al. (1994) and Lundholm and Myers (2002), the coefficient on future earnings (FERC, β_1) is predicted to be positive, the coefficients on past earnings (β_3) and future returns (β_5) are predicted to be negative, and the ERC (β_4) is predicted to be positive. As our hypothesis suggests that higher stock prices contain less information about future earnings, we expect a negative coefficient (β_2) on the interaction term $Ln(Price) \times X3_t$.

[TABLE 3 ABOUT HERE]

In Table 3, Panel A reports the panel regression results using all the Compustat firms with non-missing values of the variables used in equation (3) during the period 1996-2013. Column 1 does not add control variables, column 2 does not include the interaction term and Ln(Price), and column 3 estimates equation (3). The results show that stock returns in a given year are positively related to future earnings in the next three years. In particular, the estimated FERC is 0.126 (*t*-value=4.57) in column 3. But more importantly, the interaction of Ln(Price) and future earnings is significantly negative, with an estimated coefficient of −0.019 (*t*-value=−3.47). The result confirms that price informativeness about future earnings is inversely related to stock price levels.

We also conduct a subsample analysis, comparing option firms with comparable non-option firms. Specifically, each sample firm with listed options is matched with a control firm without listed options, with the closest stock price (*Price*), market value (*MV*), and book-to-market (*B/M*) in fiscal year $t-1$. The values of the three variables *Price*, *MV*, and *B/M* of a potential control firm are required to be within 15%, 20%, and 20% range of the option firm's values, respectively. We calculate the differences of these three variables between option firms and non-option firms, and rank each of the differences, then calculate the total ranking, and finally only keep the control firm with the closest differences (lowest ranking). *Price* is the average stock price in fiscal year $t-1$. *MV* is the market value (closing price times the number of shares outstanding) at fiscal year $t-1$ end. *B/M* is the book-to-market ratio in fiscal year $t-1$. As shown in Panel A of Internet Appendix Table A4, the mean differences of these three variables between option firms and control firms in the fiscal year $t-1$ are statistically insignificant.

In Panel B of Table 3, columns 1-2 and columns 3-4 reports the results for sample option firms and matched non-option firms, respectively.[14] Columns 1 and 3 show that the FERC is 0.218 (*t*-value=5.07) for the option firms, and 0.109 (*t*-value=3.94) for comparable non-option firms. The difference between these two FERCs is −0.109 (*t*-value=−2.13), as shown in the bottom of Panel B. In addition, the coefficients of $Ln(Price) \times X3_t$ are −0.003 (*t*-value=−0.47) in column 2 and −0.018 (*t*-value=−3.58) in column 4, and the difference between these two coefficients is also significantly negative. The results provide evidence that stock price informativeness is lower for firms without listed options compared to other comparable firms with listed options, especially for those higher-price stocks. Thus, stock prices are less informative for high-price stocks due to a drop of informed trading on the stocks, which is consistent with our hypothesis.

[14] In some cases, one non-option firm is matched to more than one sample option firms. In our analysis, we drop the duplicated observations for the matched non-option firms.

As shown in column 2, we still observe a negative relation between stock price and price informativeness for firms with listed options, even though options trading has the potential to incorporate the information as well. A possible reason is that the trading in options market may not be able to fully incorporate the information of informed traders. Moreover, the information incorporated in options trading may take some time to be transmitted to stock market. For example, Xing, Zhang, and Zhao (2010) show that the options implied volatility skew can predict stock returns up to 20 weeks. Their result suggests that the information segmentation between options market and stock market is not trivial.

Given the results, we expect that firms that have significant price run-ups would be interested in reducing the unfavorable effects of high stock price levels on price informativeness. In section 5, we will present evidence that firms indeed use stock splits to accomplish the task.

4.3. The relationship between investment sensitivity and stock price levels

The literature argues that managers learn from market information to make investment decisions (Dow and Gorton, 1997; Subrahmanyam and Titman, 1999). Chen, Goldstein, and Jiang (2007) empirically test this notion and show that the investment sensitivity increases when price is more informative. Since we have demonstrated that stock price levels negatively affect price informativeness, in this subsection, we further test whether corporate investment sensitivity to stock price is inversely related to stock price levels.

Following Chen et al. (2007) and Roll et al. (2009), we examine corporate investment sensitivity using the following panel regression:

$$I_t = \beta_0 + \beta_1\, Ln(Price) \times Tobin's\ Q_{t-1} + \beta_2\, Tobin's\ Q_{t-1} + \beta_3\, Ln(Price)_{t-1} + \delta' X + Industry\ FE + Year\ FE + \varepsilon_t. \quad (4)$$

I_t is the corporate investment in fiscal year t, defined as the sum of capital expenditures and R&D expenses scaled by beginning-of-year book value of total asset. *Tobin's Q* $_{t-1}$ is calculated as the market value of equity plus book value of assets minus the book value of equity, scaled by book assets, all measured at the end of fiscal year $t-1$. $Ln(Price)_{t-1}$ is the natural logarithm of average stock price in fiscal year $t-1$. We add the interaction term *Ln(Price)* × *Tobin's Q* to test whether the investment sensitivity is dependent on the stock price levels. We use two measures of options trading volume, total options trading volume and total dollar options trading volume in fiscal year $t-1$, respectively, to control for the effect that options trading activity has a positive impact on investment sensitivity (Roll et al. (2009)).

[TABLE 4 ABOUT HERE]

In Table 4, column 1 shows the result by estimating equation (4) for the full sample from Compustat over the period 1996-2015, and columns 2-4 report the results for firms with listed options. The coefficients of the interaction term are significantly negative. This result is consistent with our hypothesis that corporate investment sensitivity to stock price is negatively related to stock price levels. The coefficients of other variables are generally consistent with the literature: positive on *Tobin's Q*, interaction of total options trading and *Tobin's Q*, and cash flows. Thus, the evidence in Table 4 confirms our conjecture that stock price levels could somehow tell us the styles of corporate investment decisions.

5. Stock splits and improving informed trading

To further test our hypothesis, in this section, we examine whether stock splits would be able to improve informed trading and enhance informational efficiency of stock prices. We use a sample of split firms with listed options and explore how stock splits affect stock price informativeness, options trading relative to stock, and the information content of O/S.

5.1. Split firms' O/S and stock price levels

We first conduct similar regressions as in equations (1) and (2) for the split sample, and find consistent results as the comprehensive sample. As shown in Internet Appendix Table A5, both pre-split Ln(O/S) and Ln($O/S) are positively related to pre-split Ln(Price) and pre-split Ln(Price)×Xsmall. The results suggest that pre-split high stock price levels lead traders to trade options more relative to the underlying stocks and that the effect of high stock price levels on O/S is larger for split firms that do not attract many small investors. Thus, in light of Easley et al.'s (1998) multimarket sequential trade model, the findings suggest that high stock price levels reduce the depth of the stock market prior to stock splits, resulting in more traders using options.

To better observe the changes in O/S before and after stock splits, we match each split firm with a comparable non-split firm, with the closest pre-split market value (*MV*) and book-to-market (*B/M*). We require the values of the two variables *MV* and *B/M* of a potential control firm to be within 20% range of the split firm's values. We calculate the differences of the two variables between split and non-split firms, and rank each of the two differences. After calculating the total ranking, we keep the non-split firm with the closest differences (lowest ranking). *MV* is the market value at month $t-1$ end before split announcement. *B/M* is measured at fiscal year $t-1$ end before split. As shown in Panel B of Internet Appendix Table A4, the mean differences of pre-split *MV* and *B/M* between split and non-split firms are statistically insignificant.

[FIGURE 1 ABOUT HERE]

If high stock price levels induce more trading on options over stock, then pre-split price run-ups should lead to an increasing trend in O/S prior to stock splits. Figure 1 clearly shows such a trend for split firms starting 12 months prior to split announcements—the average O/S rises from around 0.106 in month $t-12$ to about 0.140 in month $t-1$ before split announcements. While comparable non-split firms, matched by firm size and B/M, also exhibit a slightly upward trend in O/S, the pre-split increases in the average O/S of split firms are much more substantial and visible. The figure also shows that the average O/S of split firms declines remarkably after stock splits and stabilizes at the level similar as comparable non-split firms. For the matched firms, we do not observe any significant changes in their average O/S during the post-split period, suggesting that the declines in the average O/S of split firms are likely associated with lower stock price levels induced by stock splits.

To confirm our conjecture, Table 5 reports the results of regressing changes in O/S from before to after the stock splits on changes in stock price levels, controlling for changes in the O/S determinants identified by Roll et al. (2010). Indeed, the results show that changes in O/S surrounding the split event are significantly related to changes in stock price levels induced by stock splits, and that the effect of lowering stock prices on changes in O/S is stronger for split firms that had more difficulty to attract small investors before stock splits.

[TABLE 5 ABOUT HERE]

In sum, the evidence suggests that stock price levels matter in where informed traders choose to trade. The lower post-split O/S implies that, by lowering stock price levels to attract more uninformed trading to the stocks, stock splits also make the stocks more attractive to informed traders.

5.2. The information content of pre-split O/S

To show the information content of pre-split O/S, Table 6 reports the results of regressing the five-day split announcement returns on pre-split Ln(O/S), the natural logarithm of average O/S over days $t-22$ to $t-3$, and a set of control variables, including firm size, B/M, pre-split run-up, pre-split stock price level, the split factor, and changes in stock liquidity. To control for potential liquidity improvement on the stocks associated with stock splits, we use changes in Amihud's (2002) illiquidity measure and share turnover around stock splits.[15] We find that the pre-split Ln(O/S) is significantly positive. The result indicates that the higher the pre-split O/S, the higher the split announcement returns, suggesting that pre-split O/S is very informative.

[TABLE 6 ABOUT HERE]

This finding has two implications. First, it implies that the rise in pre-split O/S reflects more informed trading in the options over the stocks. Second, split firms with more pre-split O/S benefit more from announcing a stock split. These two implications build on the notion that when pre-split high stock price level discourages uninformed trading on a stock, it constrains informed trading on the stock and weakens the stock's price discovery function as well. The weakened price discovery on the stock market is evident by the increasing options trading activities, whose information content is not fully reflected in pre-split stock prices. Furthermore, the more the informed trading on the stock is constrained prior to the stock split, the higher the benefit to the split firm.

To show that the pre-split increases in trading options over stocks do not merely reflect that informed traders anticipate the upcoming stock split announcements, Table 7 shows that pre-split O/S can also predict earnings surprises for the first four quarters after the stock splits. Since

[15] We try different windows to measure changes in liquidity, such as one year before and one year after the split announcement date, or one year before and one year after the effective date of splits. The results are similar.

the earnings surprises are based on I/B/E/S reported analyst forecasts and actual earnings, the regression results suggest that options traders prior to stock splits are informed about future earnings surprises.

[TABLE 7 ABOUT HERE]

In sum, our evidence suggests that informed traders seem to know split firms' future prospects before stock splits and that the better the future prospects, the more they trade listed options over the stocks prior to stock splits. The finding that the informed know in advance casts doubts on the validity of the signaling hypothesis that managers use stock splits to signal their firms' future prospects. Rather, the evidence is consistent with our hypothesis that high stock price levels impede informed trading on the stocks and make listed options more appealing to the informed prior to stock splits.

5.3. Post-split stock price informativeness about future earnings

Finally, we examine changes in the price informativeness associated with stock splits and test whether post-split stock prices contain more information about future earnings. Specifically, we estimate equation (3) for the two years before and after splits separately. Table 8 reports the results of price informativeness before splits in columns 1-2 and after splits in columns 3-4. The result shows that the FERC, i.e., the coefficient on future earnings changes, increases from 0.371 (*t*-value=6.64) in column 1 to 0.726 (*t*-value=12.31) in column 3. Similarly, the coefficient on the interaction term Ln(Price) × $X3_t$ also increases after stock splits. The differences in these coefficients are statistically significant, as reported in the bottom rows. Thus, the increase in stock price informativeness associated with stock splits is relatively large and significant. The results are consistent with our hypothesis that stock splits make stock price more informative.

[TABLE 8 ABOUT HERE]

The finding is striking at first glance because the common impression in the literature is that, by lowering stock price levels, stock splits attract more small and uninformed traders, who seem likely to create more noises in stock prices rather than making stock prices more informative. However, the evidence is consistent with our conjecture that stocks attract more uninformed trading to improve informed trading after stock splits.[16]

6. Conclusion

In this paper, we address the questions of why stock price levels matter and why firms undertake stock splits to lower their stock price levels. Specifically, we propose that since uninformed trading is needed for market making, and high stock price levels may impose budget constraints on uninformed traders (who have limited risk sharing capacity) to enter the market, informed trading on the stocks could be impeded by high stock price levels. Consequently, high stock price levels could reduce price informativeness.

We conduct three main tests to provide supportive evidence to our hypothesis. First, we find that O/S, the relative trading of options over stock, increases with stock price levels, and this effect is more pronounced for firms that have more difficulty to attract small investors. Second, we show that stock price informativeness about future earnings is lower for firms with higher stock price levels. Third, we find that corporate investment sensitivity to stock price is inversely related to stock price levels. The results from these three tests are all consistent with our hypothesis that nominal price level is inversely related to the informativeness of stocks. These findings also suggest that there are drawbacks associated with high stock price levels.

[16] Our result is also consistent with the information production theory of stock split in Brennan and Hughes (1991) and Chemmanur, Hu, and Huang (2015), who argue that information production increases after stock splits and hence may lead to more informed trading.

To carry out further tests on our hypothesis, we analyze a sample of split firms. We find that the average O/S rises considerably prior to stock splits and the pre-split rise in O/S reflects an increase in informed trading in the options market because pre-split O/S can predicts split firms' future performance. After stock splits, O/S falls and stock price becomes more informative about future earnings. In sum, the evidence indicates that firms can use stock splits to improve informed trading.

While we have discussed the benefits of lowering stock price levels, a caveat is in order. Dewing (1934) note that "When the stock of a corporation is quoted below $10 per share, there is an implied suggestion that the credit of the corporation is low." Thus, to avoid the low-credit image, firms may not adjust their stock prices too low.

Another issue we have no answer is: Why have firms managed their stock price levels close to $35 since the Great Depression as Weld et al. (2009) point out? Our study suggests that improving price informativeness is a benefit of lowering stock price levels. We leave for future research to see whether the $35 price level is the optimal result of the tradeoff between the benefits and the costs of lowering stock price levels.

Appendix. Variable Definitions

Variable	Definition
Table 1 (Panels A and C) and Table 2 (comprehensive sample)	
Ln(O/S)	The natural logarithm of the ratio of total options trading volume to the corresponding stock trading volume at day *t*. Given the fact that each options contract is for 100 shares of the underlying stock, we compute the O/S as the ratio of total options trading volume multiplied by 100 to stock trading volume. We also adjust trading volume for firms listed on Nasdaq according to Gao and Ritter (2010).
Ln($O/S)	The natural logarithm of the ratio of dollar options trading volume (end-of-day quote midpoint times trading volume) to the corresponding dollar stock trading volume (midpoint times trading volume) at day *t*.
Ln(Price)	The natural logarithm of stock price at day *t*.
Xsmall	A dummy equal to 1 if dollar ownership per shareholder in fiscal year $t-1$, defined as the market value divided by the number of common/ordinary shareholders from Compustat, is greater than the yearly cross-sectional median.
Size	The natural logarithm of the book value of total assets (*at*, in million U.S dollars) from Compustat.
Implied volatility	The average (weighted by options trading volume) implied volatility for all options traded on day *t* from OptionMetrics.
Delta	The average (weighted by options trading volume) delta (put deltas are reversed in sign) for all options traded on day t. The delta of the option indicates the change in option premium with respect to a $1.00 change in the price of the underlying stock.
Spread	The average (weighted by options trading volume) bid-ask spread divided by the midpoint for all options traded on day t.
Ln(Analysts)	The number of analysts who provide earnings forecasts for the next fiscal year from I/B/E/S in month $t-1$.
Analysts dispersion	The standard deviation across earnings forecasts in month $t-1$.
Institution ownership	The total shares held by institutions divided by shares outstanding from Thomson Reuters in quarter $t-1$.
Table 1 (Panel B) and Table 6 (split sample)	
Ln(O/S)	The natural logarithm of the average ratio of total options trading volume to the corresponding stock trading volume from day $t-22$ to $t-3$ relative to the stock split announcement date *t*.
Ln($O/S)	The natural logarithm of the average ratio of total dollar options trading volume to the corresponding stock trading volume from day $t-22$ to $t-3$ relative to the stock split announcement date *t*.
Ln(Price)	The natural logarithm of the average stock price from day $t-22$ to $t-3$.
Xsmall	A dummy equal to 1 if dollar ownership per shareholder, defined as the market value divided by the number of common/ordinary shareholders from Compustat, is greater than the cross-sectional median in the pre-split fiscal year.
Size	The natural logarithm of pre-split total assets (*at*) measured at quarter $t-1$.
Implied volatility	The average daily implied volatility from day $t-22$ to $t-3$ relative to the split announcement date *t*.
Delta	The average daily delta from day $t-22$ to $t-3$ relative to the split announcement date *t*.
Spread	The average daily spread from day $t-22$ to $t-3$ relative to the split announcement date *t*.
Split factor	The factor to adjust prices (*facpr*) from CRSP.
CAR	The five-day (−2,+2) stock returns around split announcements, subtracting the CRSP value-weighted index returns.
Run-up	The pre-split 11-month stock return cumulative from month $t-12$ to day $t-23$ before splits.
B/M	The pre-split book-to-market ratio, defined as book value of equity divided by market value of equity. Book equity is the book value of assets (*at*) minus total liabilities (*lt*) plus balance sheet deferred taxes and investment tax credit (*txditc*, if available), minus the book value of preferred stock. Depending on availability, we use redemption (*pstkrv*), liquidation (*pstkl*), or par value (*pstk*) (in that order) for the book value of preferred stock. Market equity equals common shares outstanding times stock price, *prcc_f*×*csho*.

Change in turnover	Turnover is stock trading volume divided by shares outstanding. Pre-split turnover is estimated over days *t*−22 to *t*−3 before the split announcement date, and post-split turnover is estimated over days *t*+3 to *t*+22 after the effective date. Change in turnover is the difference between pre- and post-split values.
Change in ILLIQ	ILLIQ is Amihud's (2002) illiquidity measure defined as the average ratio of the daily absolute return to its dollar trading volume. Pre-split ILLIQ is estimated over days *t*−22 to *t*−3 before the split announcement date, and post-split ILLIQ is estimated over days *t*+3 to *t*+22 after the effective date. Change in ILLIQ is the difference between pre- and post-split values, and multiplied by 1,000,000.

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Table 1
Summary statistics

Panel A reports summary statistics for the comprehensive sample of 7,322,980 firm-day observations during the period 1996-2016. Firms have available data for O/S and control variables. Firms with zero daily options trading volume are excluded. *Ln(O/S)* is the natural logarithm of the ratio of total options trading volume to the corresponding stock trading volume at day *t*. *Ln($O/S)* is the natural logarithm of the ratio of dollar options trading volume (end-of-day quote midpoint times trading volume) to the corresponding dollar stock trading volume (midpoint times trading volume) at day *t*. *Ln(Price)* is the natural logarithm of stock price at day *t*. *Xsmall* is a dummy equal to 1 if dollar ownership per shareholder in fiscal year $t-1$, defined as the market value divided by the number of common/ordinary shareholders from Compustat, is greater than the yearly cross-sectional median. *Ln(Price)* × *Xsmall* is the interaction of *Ln(Price)* with *Xsmall*. *Size* is the natural logarithm of total assets from Compustat. *Implied volatility* is the average implied volatility for all options traded on day *t* from OptionMetrics. *Delta* is the average delta (put deltas are reversed in sign) for all options traded on day *t*. The delta of the option indicates the change in option premium with respect to a $1.00 change in the price of the underlying stock. *Spread* is the average bid-ask spread divided by the midpoint for all options traded on day *t*. For each day, a firm's average *Implied volatility*, *Delta*, and *Spread* are value-weighted by options trading volume. *Ln(Analysts)* is the number of analysts who provide earnings forecasts for the next fiscal year from I/B/E/S in month $t-1$. *Analysts dispersion* is the standard deviation across earnings forecasts in month $t-1$. *Institution ownership* is the total shares held by institutions divided by shares outstanding from Thomson Reuters in quarter $t-1$. Panel B shows the summary statistics for 1,836 stock splits during 1996-2016. All variables are defined in Appendix. In Panel C, for each of 5,116 trading days over the period 1996-2016 for the comprehensive sample, Pearson correlations are calculated for each day and then daily correlations are averaged across all trading days.

Panel A: Summary statistics for the comprehensive sample (7,322,980 observations)

	Mean	Median	Quartile 1	Quartile 3	Std. Dev.	Minimum	Maximum
Ln(O/S)	-3.411	-3.269	-4.494	-2.193	1.681	-12.193	5.100
Ln($O/S)	-6.266	-6.093	-7.442	-4.934	1.884	-17.471	3.629
Ln(Price)	3.219	3.310	2.708	3.805	0.849	-2.708	7.293
Xsmall	0.500	0.776	0.000	1.000	0.500	0.000	1.000
Ln(Price) × Xsmall	1.662	1.190	0.000	3.386	1.757	-2.659	7.293
Size	7.468	7.360	6.076	8.707	1.928	0.178	14.761
Implied volatility	0.487	0.426	0.309	0.600	0.255	0.002	4.874
Delta	0.437	0.424	0.343	0.514	0.145	0.003	1.000
Spread	0.318	0.213	0.135	0.369	0.318	0.003	2.000
Ln(Analysts)	2.168	2.211	1.657	2.708	0.703	0.693	4.025
Analysts dispersion	0.279	0.069	0.033	0.175	1.475	0.000	76.000
Institution ownership	0.680	0.714	0.553	0.846	0.219	0.000	1.000

Panel B: Summary statistics for the split sample (1,836 stock splits)

	Mean	Median	Quartile 1	Quartile 3	Std. Dev.	Minimum	Maximum
Ln(O/S)	-2.409	-2.343	-3.102	-1.672	1.027	-5.932	1.357
Ln($O/S)	-5.224	-5.120	-6.002	-4.355	1.186	-9.222	-2.506
Ln(Price)	4.123	4.128	3.769	4.454	0.489	2.336	6.617
Xsmall	0.503	1.000	0.000	1.000	0.500	0.000	1.000
Ln(Price) × Xsmall	2.118	3.062	0.000	4.217	2.135	0.000	6.617
Size	7.308	7.140	6.000	8.437	1.746	2.901	13.612
Implied volatility	0.462	0.405	0.305	0.572	0.215	0.137	1.450
Delta	0.462	0.459	0.416	0.504	0.069	0.239	0.844
Spread	0.207	0.173	0.133	0.230	0.146	0.025	1.466
Ln(Analysts)	2.322	2.303	1.946	2.773	0.619	0.693	3.932
Analysts dispersion	0.097	0.040	0.020	0.090	0.162	0.000	1.010
Institution ownership	0.670	0.693	0.538	0.832	0.211	0.000	1.000
Split factor	0.903	1.000	0.500	1.000	0.449	0.250	9.000
CAR	0.028	0.019	-0.010	0.058	0.074	-0.261	0.682
Run-up	0.964	0.528	0.275	0.989	1.686	-0.419	36.988
B/M	0.273	0.233	0.133	0.368	0.195	-0.649	1.455

Table 1 *(continued)*

Panel C: Average Pearson correlations across 5,116 trading days for the comprehensive sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Ln(O/S)											
(2) Ln($O/S)	0.911										
(3) Ln(Price)	0.149	-0.061									
(4) Xsmall	0.097	0.089	0.120								
(5) Ln(Price) × Xsmall	0.134	0.082	0.326	0.949							
(6) Size	0.042	-0.084	0.426	-0.086	0.008						
(7) Implied volatility	0.179	0.360	-0.571	0.072	-0.046	-0.533					
(8) Delta	-0.100	0.163	-0.140	-0.027	-0.059	-0.096	0.054				
(9) Spread	-0.198	-0.326	-0.219	-0.063	-0.104	-0.163	0.076	-0.359			
(10) Ln(Analysts)	0.133	0.038	0.382	0.115	0.185	0.564	-0.320	-0.097	-0.199		
(11) Analysts dispersion	0.031	0.075	-0.178	-0.008	-0.042	-0.092	0.172	0.017	0.023	-0.068	
(12) Institution ownership	-0.068	-0.120	0.308	0.126	0.183	0.094	-0.198	-0.041	-0.079	0.198	-0.072

Table 2
Fama-MacBeth regressions of O/S measures on share price

This table shows the results of daily Fama and MacBeth (1973) regressions of O/S measures on share price using the comprehensive sample of 7,322,980 firm-day observations. The following regressions are performed for each of 5,116 trading days over the period 1996-2016:

$Ln(O/S)_{i,t}$ or $Ln(\$O/S)_{i,t} = \beta_0 + \beta_1 \text{Ln(Price)}_{i,t} + \delta' X + Industry\ FE + \varepsilon_{i,t}$,

$Ln(O/S)_{i,t}$ or $Ln(\$O/S)_{i,t} = \beta_0 + \beta_1 \text{Ln(Price)}_{i,t} + \beta_2 \text{Ln(Price)} \times \text{Xsmall}_{i,t} + \beta_3 \text{Xsmall}_{i,t} + \delta' X + Industry\ FE + \varepsilon_{i,t}$.

The dependent variables are *Ln(O/S)* in columns 1-3 and *Ln($O/S)* in columns 4-6. All variables are defined in Appendix. All regressions control for Fama-French 48 industry fixed effects. Numbers in parentheses are *t*-statistics based on Newey-West (1987) adjusted standard errors. The average adjusted R^2 are reported. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Dependent variable	Ln(O/S)			Ln($O/S)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Price)		0.652***	0.606***		0.374***	0.313***
		(74.36)	(66.01)		(46.02)	(35.41)
Ln(Price) × Xsmall			0.086***			0.114***
			(28.44)			(35.25)
Xsmall			-0.236***			-0.316***
			(-23.19)			(-29.51)
Size	0.129***	0.114***	0.116***	0.118***	0.111***	0.113***
	(49.91)	(42.64)	(42.86)	(45.91)	(41.23)	(41.86)
Implied volatility	1.902***	3.076***	3.066***	3.422***	4.141***	4.126***
	(79.40)	(74.02)	(74.10)	(103.30)	(85.74)	(85.70)
Delta	-1.993***	-1.430***	-1.427***	0.683***	1.020***	1.023***
	(-52.15)	(-42.32)	(-42.24)	(19.93)	(34.31)	(34.44)
Spread	-1.219***	-0.886***	-0.887***	-1.844***	-1.657***	-1.657***
	(-68.05)	(-47.30)	(-47.38)	(-130.33)	(-134.22)	(-134.92)
Ln(Analysts)	0.256***	0.148***	0.144***	0.206***	0.145***	0.141***
	(50.95)	(31.09)	(30.87)	(45.54)	(35.48)	(34.99)
Analysts dispersion	0.004***	0.035***	0.035***	0.021***	0.039***	0.038***
	(3.06)	(23.53)	(23.30)	(16.00)	(24.51)	(24.24)
Institutional ownership	-0.624***	-1.028***	-1.034***	-0.801***	-1.022***	-1.032***
	(-51.12)	(-107.75)	(-110.80)	(-62.96)	(-102.64)	(-105.49)
Constant	-4.060***	-6.526***	-6.406***	-8.302***	-9.751***	-9.587***
	(-145.28)	(-109.90)	(-105.31)	(-263.79)	(-165.74)	(-158.40)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,322,980	7,322,980	7,322,980	7,322,980	7,322,980	7,322,980
Average Adjusted R^2	0.212	0.262	0.263	0.326	0.342	0.343

Table 3
Price informativeness and stock price levels

This table shows the price informativeness about future earnings with share price levels based on the model of Lundholm and Myers (2002):

$R_t = \beta_0 + \beta_1 X3_t + \beta_2 Ln(Price) \times X3_t + \beta_3 X_{t-1} + \beta_4 X_t + \beta_5 R3_t + \delta' X + Industry\ FE + Year\ FE + \varepsilon_t$.

R_t is the cumulative return for fiscal year *t*. $X3_t$ is the future earnings, calculated as the sum of earnings for years *t* + 1 through *t* + 3, deflated by the market value of equity at the beginning of fiscal year t. The FERC is the estimated coefficient β_1. X_t is current earnings for fiscal year *t*, deflated by the market value of equity at the beginning of fiscal year *t*. X_{t-1} is earnings for fiscal year *t*−1, deflated by the market value of equity at the beginning of fiscal year *t*. Future returns ($R3_t$) is the buy-and-hold returns for the three-year period following the current year (i.e., starting three months after the current fiscal year-end). *Asset growth*$_t$ is the growth rate of total assets for fiscal year *t*. *Ln(MV)*$_t$ is the natural logarithm of market capitalization (closing price times the number of shares outstanding) at the beginning of fiscal year *t*. *Ln(Price)*$_t$ is the natural logarithm of average share price in fiscal year *t*. *Ln(Analyst)*$_t$ is the average number of analysts following in fiscal year *t*. Panel A reports panel regression results using all the Compustat firms with non-missing data of the variables used in equation (3) during the period 1996-2013. Panel B reports the results for subsample analysis. Each sample firm with listed options is matched with a control firm without listed options, with the closest stock price (*Price*), market value (*MV*), and book-to-market (*B/M*) in fiscal year *t*−1. The values of the three variables *Price*, *MV*, and *B/M* of a potential control firm are required to be within 15%, 20%, and 20% range of the option firm's values, respectively. *Price* is the average stock price in fiscal year *t*−1. *MV* is the market value (closing price times the number of shares outstanding) at fiscal year *t*−1 end. *B/M* is the book-to-market ratio in fiscal year *t*−1. All regressions control for year and Fama-French 48 industry fixed effects. Numbers in parentheses are *t*-statistics based on standard errors clustered by industry and year (Petersen (2009)). ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

Panel A: Full sample 1996-2013

	(1)	(2)	(3)
$X3_t$	0.091***	0.080***	0.126***
	(4.71)	(4.56)	(4.57)
Ln(Price) × $X3_t$			-0.019***
			(-3.47)
X_{t-1}	-0.442***	-0.399***	-0.394***
	(-5.26)	(-5.23)	(-4.97)
X_t	0.155**	0.144**	0.134**
	(1.98)	(2.00)	(2.11)
$R3_t$	-0.054***	-0.053***	-0.051***
	(-3.28)	(-3.30)	(-3.31)
Ln(MV)		-0.072***	-0.142***
		(-3.34)	(-5.03)
Asset growth		0.148***	0.096***
		(4.01)	(3.09)
Ln(Analyst)		0.088***	0.082***
		(3.05)	(3.17)
Ln(Price)			0.204***
			(5.92)
Constant	0.227***	0.534***	0.413***
	(13.50)	(5.37)	(4.21)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	73,092	73,092	73,092
Adjusted R^2	0.201	0.221	0.254

Table 3 (continued)

Panel B: Subsample analysis

	Firms with listed options		Matched firms without listed options	
	(1)	(2)	(3)	(4)
$X3_t$	0.218***	0.227***	0.109***	0.148***
	(5.07)	(3.98)	(3.94)	(3.45)
Ln(Price) × $X3_t$		-0.003		-0.018***
		(-0.47)		(-3.58)
X_{t-1}	-0.936***	-0.960***	-0.569***	-0.572***
	(-5.40)	(-5.93)	(-5.70)	(-6.54)
X_t	0.602***	0.304***	0.479***	0.358***
	(6.40)	(2.89)	(4.04)	(4.11)
$R3_t$	-0.099***	-0.085***	-0.092***	-0.085***
	(-4.40)	(-4.15)	(-5.00)	(-4.96)
Ln(MV)	-0.172***	-0.395***	-0.095***	-0.247***
	(-3.70)	(-4.92)	(-3.52)	(-5.64)
Asset growth	0.165***	0.021	0.124***	0.048
	(2.91)	(0.65)	(3.38)	(1.65)
Ln(Analyst)	0.116***	0.123***	0.009	0.008
	(2.98)	(3.58)	(0.47)	(0.42)
Ln(Price)		0.441***		0.294***
		(4.58)		(7.59)
Constant	0.941***	1.127***	0.360***	0.506***
	(3.90)	(4.39)	(2.66)	(3.19)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	14,165	14,165	8,707	8,707
Adjusted R^2	0.289	0.368	0.237	0.307
Difference in $X3_t$ (3) – (1)	-0.109**			
	(-2.13)			
Difference in Ln(Price) × $X3_t$ (4) – (2)	-0.015*			
	(-1.88)			

Table 4
Investment sensitivity to share price

This table reports investment sensitivity to share price by running the following panel regression of investment:
$I_t = \beta_0 + \beta_1 Ln(Price) \times Tobin's\ Q_{t-1} + \beta_2 Tobin's\ Q_{t-1} + \beta_3 Ln(Price)_{t-1} + \delta' X + Industry\ FE + Year\ FE + \varepsilon_t$.
I_t is the corporate investment in fiscal year *t*, defined as the sum of capital expenditures and R&D expenses scaled by beginning-of-year book value of total asset. *Tobin's Q* $_{t-1}$ is calculated as the market value of equity (price times shares outstanding from CRSP) plus book value of assets minus the book value of equity (Item 6–Item 60), scaled by book assets, all measured at the end of fiscal year $t-1$. *Ln(Price)*$_{t-1}$ is the natural logarithm of average stock price in fiscal year $t-1$. *Ln(Price) × Tobin's Q* is the interaction of *Ln(Price)* with *Tobin's Q* at fiscal year $t-1$. *Ln(Total options trading volume)*$_{t-1}$ is the natural logarithm of total options trading volume in fiscal year $t-1$. Ln(Total dollar options trading volume) $_{t-1}$ is the natural logarithm of total dollar options trading volume in fiscal year $t-1$. Total options trading volume and total dollar options trading volume are in ten thousands. *1/Assets*$_{t-1}$ is the inverse of total assets at the end of fiscal year $t-1$. *Return*$_{t+1}$ is the annual return over the fiscal year t+1. *Cash flow*$_t$ is measured by net income plus depreciation, amortization, and R&D expenses, scaled by beginning-of-year book value of total asset. Column 1 uses the full sample from Compustat over the period 1996-2015. Columns 2-4 use the sample of firms with listed options. All regressions control for year and Fama-French 48 industry fixed effects. Numbers in parentheses are *t*-statistics based on standard errors clustered by industry and year (Petersen (2009)). ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	Full sample	Firms with listed options		
	(1)	(2)	(3)	(4)
Ln(Price) × Tobin's Q	-0.008***	-0.007***	-0.007***	-0.008***
	(-5.25)	(-3.78)	(-3.99)	(-4.38)
Tobin's Q	0.046***	0.041***	0.040***	0.042***
	(7.83)	(5.11)	(5.32)	(5.55)
Ln(Price)	0.002	0.002	0.001	0.002
	(0.75)	(0.74)	(0.40)	(0.42)
1/Assets	0.129*	3.885***	4.154***	4.177***
	(1.82)	(5.43)	(5.86)	(5.98)
Return	-0.003	-0.003	-0.003	-0.003
	(-1.18)	(-0.86)	(-0.85)	(-0.84)
Cash flow	0.054**	0.108***	0.112***	0.114***
	(2.21)	(3.31)	(3.45)	(3.53)
Ln(Total options trading volume) × Tobin's Q			0.001***	
			(2.65)	
Ln(Total options trading volume)			0.001	
			(0.82)	
Ln(Total dollar options trading volume) × Tobin's Q				0.001***
				(3.29)
Ln(Total dollar options trading volume)				0.001
				(0.55)
Constant	-0.030***	-0.030***	-0.026**	-0.026**
	(-5.05)	(-2.90)	(-2.33)	(-2.19)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	104,456	45,253	45,253	45,253
Adjusted R^2	0.413	0.472	0.474	0.475

Table 5
Changes in O/S before and after splits

This table shows the regressions of changes in O/S around splits on changes in price. The dependent variable is change in O/S, expressed in 100%. All the change variables are defined as the difference between the average value in *x* months (*x*=3, 6, 9, 12) after the split effective date and the average pre-split value. The pre-split O/S, $O/S, Price, Spread, Implied volatility, and Delta are based on the average values from day *t*−22 to *t*−3 relative to the split announcement date. Xsmall is a dummy equal to 1 if dollar ownership per shareholder, defined as the market value divided by the number of common/ordinary shareholders from Compustat, is greater than the cross-sectional median in the pre-split fiscal year. Change in assets is divided by 1,000. Numbers in parentheses are t-statistics based on White (1980) heteroskedasticity-adjusted standard errors. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in price	0.085***	0.067***	0.095***	0.071***	0.097***	0.075***	0.104***	0.079***
	(7.42)	(5.38)	(10.20)	(5.14)	(10.18)	(5.40)	(11.08)	(5.43)
Change in price × Xsmall		0.027*		0.038**		0.034*		0.039**
		(1.80)		(2.03)		(1.81)		(2.08)
Xsmall		0.416		0.842		0.698		0.863
		(0.82)		(1.43)		(1.15)		(1.40)
Change in assets	-0.036	-0.037	-0.020	-0.026	-0.022	-0.024	-0.018	-0.021
	(-0.35)	(-0.38)	(-0.30)	(-0.40)	(-0.49)	(-0.54)	(-0.44)	(-0.51)
Change in implied volatility	-0.853	-0.973	-0.182	-0.413	-0.308	-0.471	-1.134	-1.253
	(-0.28)	(-0.32)	(-0.10)	(-0.22)	(-0.15)	(-0.23)	(-0.56)	(-0.62)
Change in delta	-7.364**	-7.500**	-11.127***	-11.226***	-14.238***	-14.187***	-15.684***	-15.553***
	(-2.64)	(-2.75)	(-3.42)	(-3.45)	(-4.10)	(-4.09)	(-4.40)	(-4.37)
Change in spread	-2.606	-2.816	-4.136*	-4.227*	-6.088***	-6.126***	-6.665***	-6.689***
	(-1.38)	(-1.49)	(-1.82)	(-1.87)	(-2.61)	(-2.66)	(-2.81)	(-2.86)
Change in analysts	0.076*	0.079*	0.075	0.080	0.064	0.070	0.050	0.058
	(1.78)	(1.79)	(1.26)	(1.34)	(1.03)	(1.13)	(0.77)	(0.89)
Change in analyst dispersion	-5.682**	-5.616**	-1.883	-1.861	-1.071	-1.123	-0.057	-0.142
	(-2.19)	(-2.11)	(-0.86)	(-0.85)	(-0.52)	(-0.54)	(-0.03)	(-0.07)
Change in institutional ownership	1.144	1.195	0.706	0.821	0.010	0.137	0.063	0.226
	(0.95)	(1.02)	(0.41)	(0.48)	(0.01)	(0.08)	(0.03)	(0.12)
Constant	-0.013	-0.290	-0.063	-0.556	-0.022	-0.455	0.117	-0.414
	(-0.04)	(-0.82)	(-0.19)	(-1.28)	(-0.06)	(-0.98)	(0.34)	(-0.86)
Observations	1,818	1,818	1,812	1,812	1,790	1,790	1,774	1,774
Adjusted R^2	0.072	0.074	0.094	0.096	0.107	0.109	0.125	0.127

Table 6
Regressions of split announcement returns on O/S

This table shows the regressions of split announcement returns on pre-split Ln(O/S). The dependent variable is the five-day (−2,+2) stock returns around split announcements, subtracting the CRSP value-weighted index returns. *Ln(O/S)* is the natural logarithm of the average ratio of total options trading volume to the corresponding stock trading volume from day $t-22$ to $t-3$ relative to the stock split announcement date t. *Size* is the natural logarithm of pre-split total assets from Compustat. *B/M* is the pre-split book-to-market ratio. Ln(*Price)* is the natural logarithm of the average stock price from day $t-22$ to $t-3$. *Run-up* is the pre-split 11-month stock return cumulative from month $t-12$ to day $t-23$ before splits. *Turnover* is stock trading volume divided by shares outstanding. *ILLIQ* is Amihud's (2002) illiquidity measure defined as the average ratio of the daily absolute return to its dollar trading volume. Pre-split turnover and ILLIQ are estimated over days $t-22$ to $t-3$ before the split announcement date, and post-split turnover and ILLIQ are estimated over days $t+3$ to $t+22$ after the effective date. *Change in turnover* and *Change in ILLIQ* are the differences between pre- and post-split values. *Change in ILLIQ* is multiplied by 1,000,000. All regressions control for year fixed effects. Numbers in parentheses are *t*-statistics based on White (1980) heteroskedasticity-adjusted standard errors. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
Ln(O/S)	0.005***	0.004***	0.005***	0.005***	0.005***
	(3.40)	(2.68)	(3.05)	(3.15)	(2.97)
Size			-0.005***	-0.005***	-0.005***
			(-3.77)	(-3.73)	(-4.16)
B/M			-0.001	-0.002	0.001
			(-0.10)	(-0.16)	(0.06)
Run-up			-0.001	-0.001	-0.001
			(-0.55)	(-0.58)	(-0.59)
Ln(Price)			-0.010*	-0.010*	-0.010*
			(-1.83)	(-1.80)	(-1.93)
Split factor			0.010**	0.010**	0.010**
			(2.43)	(2.41)	(2.46)
Change in turnover				0.819*	
				(1.78)	
Change in ILLIQ					-2.773***
					(-4.15)
Constant	0.040***	0.034***	0.109***	0.107***	0.115***
	(8.86)	(2.88)	(4.69)	(4.63)	(4.95)
Year FE	No	Yes	Yes	Yes	Yes
Observations	1,836	1,836	1,836	1,836	1,836
Adjusted R^2	0.005	0.006	0.025	0.028	0.037

Table 7
Regressions of post-split SUE on pre-split O/S

This table shows regressions of post-split standardized unexpected earnings (SUE) on pre-split Ln(O/S) for the first four post-split quarterly earnings announcements. *SUE* is earnings surprise based on I/B/E/S reported analyst forecasts and actual earnings as in Livnat and Mendenhall (2006). The dependent variable is SUE decile rank (10 being the top decile). *Change in earnings* is the difference of earnings between quarter t and quarter $t-1$, divided by earnings in quarter $t-1$. *Accruals* is calculated as the change in non-cash current assets less the change in current liabilities excluding the change in debt included in current liabilities and the change in income taxes payable, minus depreciation and amortization expense. Accruals are scaled by average total assets from the beginning to the end of a quarter. *Ln(O/S)* is the natural logarithm of the average ratio of total options trading volume to the corresponding stock trading volume from day $t-22$ to $t-3$ relative to the stock split announcement date t. All regressions control for year fixed effects. Numbers in parentheses are t-statistics based on White (1980) heteroskedasticity-adjusted standard errors. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	Post-split quarters				
	1st quarter	2nd quarter	3rd quarter	4th quarter	All four quarters
	(1)	(2)	(3)	(4)	(5)
Ln(O/S)	0.169***	0.090*	0.093*	0.090*	0.116***
	(3.87)	(1.84)	(1.87)	(1.75)	(4.81)
Size	-0.116***	-0.148***	-0.059**	-0.039	-0.097***
	(-4.87)	(-5.42)	(-2.14)	(-1.25)	(-7.11)
B/M	1.434***	1.540***	1.577***	1.449***	1.498***
	(5.75)	(5.40)	(5.14)	(3.96)	(10.17)
Change in earnings	-0.005	0.065	-0.026	0.066	0.027
	(-0.05)	(0.71)	(-0.23)	(0.60)	(0.52)
Accruals	0.527	-2.946**	1.419	-2.737**	-1.038
	(0.46)	(-2.39)	(1.09)	(-2.03)	(-1.64)
Constant	6.881***	6.127***	5.494***	5.483***	5.811***
	(12.98)	(11.31)	(23.20)	(8.85)	(17.45)
Year FE	Yes	Yes	No	Yes	Yes
Observations	1,764	1,736	1,703	1,704	6,907
Adjusted R^2	0.036	0.031	0.017	0.018	0.028

Table 8
Price informativeness before and after splits

This table reports the price informativeness about future earnings around splits by running the following regression based on Lundholm and Myers (2002):

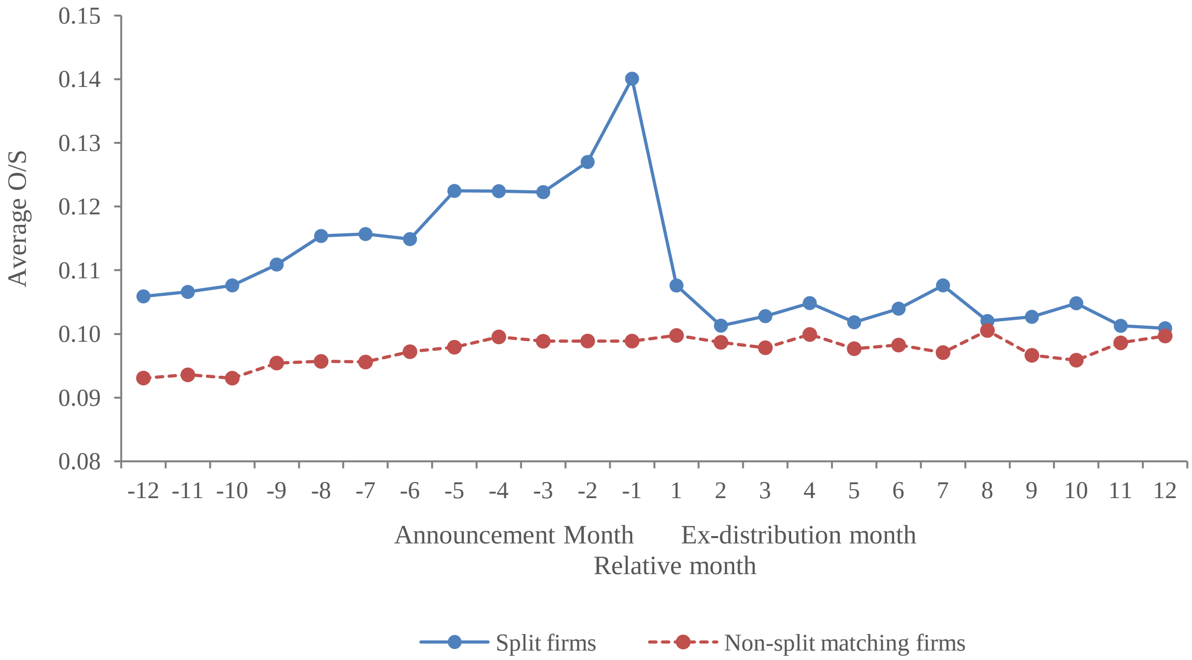
$R_t = \beta_0 + \beta_1 X3_t + \beta_2 Ln(Price) \times X3_t + \beta_3 X_{t-1} + \beta_4 X_t + \beta_5 R3_t + \delta' X + Industry\ FE + Year\ FE + \varepsilon_t$.

The regressions are performed for the two years before splits and two years after splits separately. R_t is the cumulative return for fiscal year *t*. $X3_t$ is the future earnings, calculated as the sum of earnings for years *t*+1 through *t*+3, deflated by the market value of equity at the beginning of fiscal year *t*. The FERC is the estimated coefficient β_1. X_t is current earnings for fiscal year *t*, deflated by the market value of equity at the beginning of fiscal year *t*. X_{t-1} is earnings for fiscal year *t*−1, deflated by the market value of equity at the beginning of fiscal year *t*. *Asset growth*$_t$ is the asset growth rate for fiscal year *t*. *Ln(MV)*$_t$ is the natural logarithm of market capitalization at the beginning of fiscal year *t*. *Ln(Price)*$_t$ is the natural logarithm of average share price in fiscal year *t*. *Ln(Analyst)*$_t$ is the average number of analysts following in fiscal year *t*. All regressions control for year and Fama-French 48 industry fixed effects. Numbers in parentheses are *t*-statistics based on White (1980) heteroskedasticity-adjusted standard errors. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

	2 years before splits		2 years after splits	
	(1)	(2)	(3)	(4)
$X3_t$	0.371***	0.546***	0.726***	0.515***
	(6.64)	(4.65)	(12.31)	(3.35)
Ln(Price) × $X3_t$		-0.061*		0.044
		(-1.82)		(0.96)
X_{t-1}	-2.789***	-2.229***	-0.725***	-0.400*
	(-4.73)	(-6.05)	(-3.08)	(-1.94)
X_t	1.220**	0.812**	0.162	-0.076
	(2.29)	(2.24)	(0.63)	(-0.36)
$R3_t$	-0.145***	-0.104***	-0.189***	-0.151***
	(-12.42)	(-11.72)	(-13.58)	(-12.59)
Ln(MV)	-0.223***	-0.304***	-0.063***	-0.118***
	(-10.68)	(-16.08)	(-6.72)	(-13.22)
Asset growth	0.302***	0.122**	0.030	-0.080***
	(4.13)	(2.43)	(0.84)	(-3.02)
Ln(Analyst)	0.267***	0.221***	0.116***	0.105***
	(6.15)	(6.73)	(4.73)	(5.03)
Ln(Price)		0.557***		0.265***
		(10.29)		(11.16)
Constant	0.352	-1.101***	-0.684***	-1.055***
	(1.10)	(-5.01)	(-5.41)	(-8.95)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,093	3,093	2,716	2,716
Adjusted R^2	0.348	0.408	0.334	0.414
Difference in $X3_t$ (3) – (1)	0.355***			
	(4.37)			
Difference in Ln(Price) × $X3_t$ (4) – (2)	0.105*			
	(1.85)			

Figure 1. Pre-split and post-split O/S of split firms vs. non-split firms

This figure shows the pre-split average O/S from month −12 to −1 relative to the stock split declaration month and the post-split average O/S from month +1 to +12 relative to the ex-distribution month for the split firms and non-split matching firms. Each split firm is matched with a non-split firm, with the closest market value (MV) and book-to-market (B/M) as of split firms. The values of the two variables *MV* and *B/M* of a potential control firm are required to be within 20% range of the split firm's values. We calculate the differences of the two variables between split and non-split firms, and rank each of the two differences. After calculating the total ranking, we keep the non-split firm with the closest differences (lowest ranking). *MV* is the market value at month t−1 end before split announcement. *B/M* is measured at fiscal year t−1 end before split.



Internet Appendix
What do stock price levels tell us about the firms?

Table A1
Panel regressions of O/S measures on share price

This table shows the results of panel regressions of O/S measures on share price using the full sample of 7,322,980 firm-day observations. The dependent variables are *Ln(O/S)* in columns 1-3 and *Ln($O/S)* in columns 4-6. All variables are defined in Appendix. All regressions control for year and Fama-French 48 industry fixed effects. Numbers in parentheses are *t*-statistics based on standard errors clustered by industry and year (Petersen (2009)). ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Dependent variable	Ln(O/S)			Ln($O/S)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Price)		0.583***	0.542***		0.320***	0.262***
		(13.35)	(12.16)		(8.07)	(6.21)
Ln(Price) × Xsmall			0.075***			0.106***
			(3.40)			(4.59)
Xsmall			-0.203***			-0.288***
			(-2.99)			(-4.05)
Size	0.112***	0.088***	0.089***	0.092***	0.078***	0.081***
	(6.74)	(5.62)	(5.64)	(5.83)	(4.97)	(5.07)
Implied volatility	1.445***	2.268***	2.253***	2.831***	3.282***	3.261***
	(11.55)	(12.89)	(12.87)	(19.18)	(16.28)	(16.21)
Delta	-2.192***	-1.688***	-1.686***	0.554***	0.830***	0.833***
	(-12.22)	(-9.90)	(-9.90)	(3.34)	(5.50)	(5.53)
Spread	-1.432***	-1.172***	-1.172***	-1.951***	-1.808***	-1.808***
	(-29.25)	(-15.26)	(-15.23)	(-46.77)	(-39.98)	(-39.94)
Ln(Analysts)	0.234***	0.135***	0.132***	0.182***	0.128***	0.123***
	(7.01)	(4.32)	(4.29)	(6.10)	(4.62)	(4.52)
Analysts dispersion	0.005	0.026***	0.025***	0.017***	0.028***	0.028***
	(1.50)	(7.74)	(7.69)	(5.24)	(7.49)	(7.42)
Institutional ownership	-0.712***	-1.106***	-1.112***	-0.885***	-1.102***	-1.110***
	(-8.56)	(-15.06)	(-15.36)	(-10.75)	(-14.74)	(-15.03)
Constant	-3.990***	-6.068***	-5.962***	-8.208***	-9.348***	-9.199***
	(-18.05)	(-18.52)	(-17.94)	(-36.29)	(-29.38)	(-28.44)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,322,980	7,322,980	7,322,980	7,322,980	7,322,980	7,322,980
Adjusted R^2	0.184	0.231	0.231	0.321	0.332	0.333

Table A2
Subsamples by price quartiles: Fama-MacBeth regressions of O/S measures on share price

This table shows the results of daily Fama and MacBeth (1973) regressions of O/S measures on share price using subsamples. The full sample of 7,322,980 firm-day observations is sorted into quartiles daily based on *Ln(Price)*. The dependent variables are *Ln(O/S)* in the first four columns and *Ln($O/S)* in the other columns. All variables are defined in Appendix. All regressions control for Fama-French 48 industry fixed effects. Numbers in parentheses are *t*-statistics based on Newey-West (1987) adjusted standard errors. *N* is the number of days. The average adjusted R^2 are reported. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	Dependent variable: Ln(O/S)				Dependent variable: Ln($O/S)			
	Ln(Price) quartiles				Ln(Price) quartiles			
	1(Low)	2	3	4(High)	1(Low)	2	3	4(High)
Ln(Price)	0.721***	0.246***	0.648***	1.200***	0.311***	-0.009	0.401***	1.040***
	(63.97)	(15.42)	(40.55)	(93.90)	(30.09)	(-0.60)	(25.63)	(86.22)
Size	0.049***	0.107***	0.172***	0.200***	0.050***	0.108***	0.170***	0.203***
	(16.15)	(30.33)	(37.10)	(52.21)	(15.19)	(31.32)	(39.01)	(52.97)
Implied volatility	1.789***	3.404***	4.368***	4.852***	2.509***	4.517***	5.715***	6.438***
	(59.32)	(69.58)	(68.37)	(65.40)	(73.63)	(77.99)	(75.60)	(72.10)
Delta	-1.411***	-1.584***	-1.352***	-1.201***	0.768***	0.831***	1.223***	1.583***
	(-41.68)	(-41.88)	(-40.11)	(-38.64)	(24.13)	(25.33)	(42.60)	(56.18)
Spread	-0.655***	-0.939***	-1.020***	-1.106***	-1.466***	-1.730***	-1.794***	-1.820***
	(-36.66)	(-44.47)	(-50.48)	(-54.53)	(-118.53)	(-114.54)	(-123.95)	(-115.17)
Ln(Analysts)	0.045***	0.126***	0.208***	0.280***	0.046***	0.119***	0.204***	0.280***
	(8.27)	(22.12)	(32.78)	(47.09)	(9.43)	(22.54)	(35.42)	(48.93)
Analysts dispersion	0.028***	0.094***	0.346***	0.464***	0.029***	0.105***	0.389***	0.505***
	(19.41)	(15.69)	(15.22)	(18.77)	(19.29)	(16.39)	(15.65)	(18.73)
Institutional ownership	-1.266***	-0.993***	-0.692***	-0.786***	-1.289***	-1.013***	-0.680***	-0.749***
	(-110.08)	(-79.63)	(-44.75)	(-53.54)	(-112.25)	(-78.62)	(-42.34)	(-48.38)
Constant	-4.947***	-5.169***	-8.101***	-10.871***	-7.567***	-8.508***	-11.619***	-14.962***
	(-78.82)	(-70.93)	(-89.05)	(-122.66)	(-128.37)	(-119.09)	(-121.52)	(-159.04)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,828,896	1,831,277	1,832,685	1,830,122	1,828,896	1,831,277	1,832,685	1,830,122
Average Adjusted R^2	0.182	0.245	0.277	0.373	0.287	0.344	0.374	0.434

Table A3
Subsamples by excluding S&P 500 or firms with high institutional holdings: Fama-MacBeth regressions of O/S measures on share price

This table shows the results of daily Fama and MacBeth (1973) regressions of O/S measures on share price using different subsamples. In Panel A, S&P 500 firms are dropped from the full sample of 7,322,980 firm-day observations. In Panel B, firms with intuitional holdings in the top quartile are dropped. In Panel C, firms with intuitional holdings in the top decile are dropped. The dependent variables are *Ln(O/S)* in columns 1-3 and *Ln($O/S)* in columns 4-6. All variables are defined in Appendix. All regressions control for Fama-French 48 industry fixed effects. Numbers in parentheses are *t*-statistics based on Newey-West (1987) adjusted standard errors. *N* is the number of days. The average adjusted R^2 are reported. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Panel A: Excluding S&P 500 firms

Dependent variable	Ln(O/S)			Ln($O/S)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Price)		0.592***	0.549***		0.310***	0.254***
		(63.67)	(61.43)		(36.10)	(29.81)
Ln(Price) × Xsmall			0.077***			0.100***
			(21.29)			(25.44)
Xsmall			-0.186***			-0.248***
			(-16.82)			(-20.45)
Size	-0.036***	-0.039***	-0.039***	-0.046***	-0.047***	-0.047***
	(-16.49)	(-18.71)	(-18.87)	(-21.47)	(-20.69)	(-21.16)
Implied volatility	1.560***	2.575***	2.567***	2.984***	3.556***	3.544***
	(77.79)	(68.89)	(69.51)	(105.66)	(82.26)	(82.78)
Delta	-1.986***	-1.505***	-1.501***	0.652***	0.914***	0.919***
	(-52.91)	(-44.11)	(-43.93)	(18.78)	(29.75)	(29.90)
Spread	-1.104***	-0.810***	-0.808***	-1.736***	-1.586***	-1.584***
	(-61.54)	(-42.88)	(-42.83)	(-120.55)	(-125.37)	(-125.76)
Ln(Analysts)	0.170***	0.080***	0.074***	0.126***	0.081***	0.075***
	(37.63)	(18.55)	(17.67)	(29.24)	(20.83)	(19.43)
Analysts dispersion	0.009***	0.036***	0.036***	0.025***	0.039***	0.039***
	(7.67)	(23.22)	(23.18)	(18.68)	(23.57)	(23.48)
Institutional ownership	-0.431***	-0.818***	-0.822***	-0.646***	-0.834***	-0.839***
	(-38.20)	(-90.01)	(-91.22)	(-53.76)	(-89.90)	(-91.36)
Constant	-2.641***	-4.898***	-4.782***	-6.810***	-8.015***	-7.861***
	(-115.72)	(-95.34)	(-95.65)	(-282.74)	(-166.70)	(-166.59)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,167,817	5,167,817	5,167,817	5,167,817	5,167,817	5,167,817
Average Adjusted R^2	0.166	0.210	0.211	0.306	0.318	0.319

Panel B: Excluding firms with *Institutional ownership* in the top quartile

Dependent variable	Ln(O/S)			Ln($O/S)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Price)		0.615***	0.571***		0.329***	0.269***
		(71.78)	(62.13)		(41.68)	(30.45)
Ln(Price) × Xsmall			0.083***			0.114***
			(24.64)			(31.57)
Xsmall			-0.213***			-0.297***
			(-19.39)			(-25.73)
Size	0.146***	0.128***	0.130***	0.134***	0.126***	0.129***
	(56.49)	(48.99)	(49.13)	(54.06)	(48.95)	(49.59)

Implied volatility	1.752***	2.878***	2.865***	3.269***	3.915***	3.897***
	(77.91)	(71.80)	(71.53)	(103.08)	(83.99)	(83.54)
Delta	-1.953***	-1.418***	-1.416***	0.710***	1.007***	1.009***
	(-54.02)	(-43.58)	(-43.50)	(21.84)	(35.24)	(35.30)
Spread	-1.187***	-0.864***	-0.864***	-1.797***	-1.629***	-1.630***
	(-68.41)	(-46.67)	(-46.69)	(-129.98)	(-132.78)	(-133.15)
Ln(Analysts)	0.229***	0.132***	0.126***	0.179***	0.128***	0.121***
	(47.19)	(27.81)	(27.02)	(39.71)	(30.95)	(29.55)
Analysts dispersion	0.006***	0.038***	0.038***	0.024***	0.041***	0.041***
	(4.24)	(23.62)	(23.47)	(16.45)	(24.48)	(24.32)
Institutional ownership	-0.653***	-0.962***	-0.968***	-0.824***	-0.975***	-0.983***
	(-55.22)	(-95.76)	(-98.59)	(-68.08)	(-93.99)	(-96.92)
Constant	-4.059***	-6.427***	-6.318***	-8.298***	-9.597***	-9.445***
	(-145.20)	(-110.31)	(-104.74)	(-265.01)	(-166.51)	(-157.38)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,492,860	5,492,860	5,492,860	5,492,860	5,492,860	5,492,860
Average Adjusted R^2	0.221	0.268	0.269	0.338	0.351	0.352

Panel C: Excluding firms with *Institutional ownership* in the top decile

Dependent variable	Ln(O/S)			Ln($O/S)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Price)		0.636***	0.592***		0.355***	0.295***
		(74.74)	(66.00)		(45.35)	(34.33)
Ln(Price) × Xsmall			0.083***			0.113***
			(27.44)			(34.55)
Xsmall			-0.222***			-0.304***
			(-21.70)			(-28.46)
Size	0.138***	0.121***	0.123***	0.127***	0.118***	0.121***
	(52.34)	(45.01)	(45.29)	(49.26)	(44.48)	(45.17)
Implied volatility	1.825***	2.981***	2.970***	3.346***	4.036***	4.020***
	(78.87)	(74.11)	(74.03)	(103.98)	(86.07)	(85.84)
Delta	-1.962***	-1.412***	-1.410***	0.709***	1.029***	1.031***
	(-52.69)	(-42.53)	(-42.45)	(21.31)	(35.38)	(35.50)
Spread	-1.195***	-0.867***	-0.867***	-1.813***	-1.634***	-1.635***
	(-68.75)	(-47.09)	(-47.14)	(-132.40)	(-135.20)	(-135.76)
Ln(Analysts)	0.246***	0.144***	0.139***	0.196***	0.141***	0.135***
	(50.05)	(30.55)	(30.19)	(44.03)	(34.56)	(33.80)
Analysts dispersion	0.006***	0.037***	0.037***	0.023***	0.041***	0.040***
	(4.35)	(23.65)	(23.40)	(16.71)	(24.53)	(24.25)
Institutional ownership	-0.711***	-1.073***	-1.080***	-0.892***	-1.083***	-1.093***
	(-58.16)	(-106.34)	(-109.86)	(-71.81)	(-104.11)	(-107.47)
Constant	-4.045***	-6.459***	-6.344***	-8.281***	-9.660***	-9.502***
	(-142.60)	(-110.46)	(-105.59)	(-259.21)	(-166.56)	(-158.67)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,557,634	6,557,634	6,557,634	6,557,634	6,557,634	6,557,634
Average Adjusted R^2	0.216	0.265	0.266	0.332	0.346	0.347

Table A4
Mean differences for matched samples

Panel A reports the mean differences for the three variables *Price*, *MV*, and *B/M* between option firms and non-option firms. Panel B reports the mean differences for the two variables *MV* and *B/M* between split firms and non-split firms. The detailed matching methods are provided in Table 3 and Figure 1, respectively. *N* is the number of observations.

Panel A: Mean differences for the matched sample in Panel B of Table 3

	Firms with options	Firms without options	Difference	t-statistic	p-value	N
Price	15.925	15.829	-0.096	-0.77	0.442	14,165
MV	363.200	352.700	-10.544	-0.99	0.324	14,165
B/M	0.859	0.850	-0.009	-0.20	0.838	14,165

Panel B: The pre-split mean differences for the matched sample in Figure 1

	Split firm	Non-split firm	Difference	t-statistic	p-value	N
MV	10288	9559	-729	-0.75	0.453	1,792
B/M	0.3127	0.3125	0.000	-0.03	0.973	1,792

Table A5
Regressions of pre-split O/S on share price for split firms

This table shows the regressions of pre-split O/S on share price and various control variables for the stock split sample. The dependent variables are *Ln(O/S)* in columns 1-3 and *Ln($O/S)* in columns 4-6. O/S is the average ratio of total options trading volume to the corresponding stock trading volume. $O/S is the average ratio of dollar options trading volume to the corresponding dollar stock trading volume. Ln(O/S) and Ln($O/S) are natural logarithms of ShO/S and $O/S, respectively. Ln(price) is the natural logarithm of average stock price. Spread is the average bid-ask spread divided by the midpoint of all options traded. O/S, $O/S, Price, Spread, Implied volatility, and Delta are based on the average values from day $t-22$ to $t-3$ relative to the split announcement date *t*. Xsmall is a dummy variable which equals 1 if dollar ownership per shareholder, defined as the market value divided by the number of common/ordinary shareholders from Compustat, is greater than the cross-sectional median in the pre-split fiscal year. Size is the natural logarithm of pre-split total assets measured at quarter $t-1$. Analysts is the number of I/B/E/S analysts who provide one-year earnings forecasts. Analysts dispersion is the standard deviation across earnings forecasts. All variables are defined in Appendix. Numbers in parentheses are t-statistics based on White (1980) heteroskedasticity-adjusted standard errors. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

Dependent variable	Ln(O/S)			Ln($O/S)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Price)		0.446***	0.356***		0.332***	0.257***
		(8.24)	(4.82)		(5.79)	(3.90)
Ln(Price) × Xsmall			0.170**			0.143**
			(2.03)			(2.12)
Xsmall			-0.690*			-0.583*
			(-1.96)			(-2.06)
Size	0.039**	-0.005	-0.002	0.045**	0.012	0.014
	(1.99)	(-0.24)	(-0.09)	(2.09)	(0.56)	(0.52)
Implied volatility	1.776***	1.661***	1.649***	3.008***	2.922***	2.913***
	(10.26)	(9.64)	(9.54)	(16.00)	(15.54)	(5.81)
Delta	-3.629***	-3.057***	-3.058***	-0.310	0.116	0.115
	(-9.45)	(-7.87)	(-7.88)	(-0.76)	(0.28)	(0.19)
Spread	-2.813***	-2.493***	-2.485***	-2.940***	-2.701***	-2.695***
	(-13.51)	(-12.07)	(-12.04)	(-13.56)	(-12.42)	(-8.93)
Ln(Analysts)	0.132***	0.091**	0.089**	0.133***	0.102**	0.101**
	(3.28)	(2.31)	(2.23)	(3.10)	(2.41)	(2.38)
Analysts dispersion	0.660***	0.577***	0.582***	0.696***	0.635***	0.639***
	(5.58)	(4.91)	(4.93)	(5.09)	(4.61)	(4.56)
Institutional ownership	-0.485***	-0.555***	-0.539***	-0.463***	-0.515***	-0.501***
	(-4.65)	(-5.42)	(-5.26)	(-4.17)	(-4.68)	(-4.32)
Constant	-0.630	-2.428***	-2.095***	-5.768***	-7.107***	-6.828***
	(-1.60)	(-5.26)	(-4.20)	(-14.48)	(-15.11)	(-11.82)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,836	1,836	1,836	1,836	1,836	1,836
Average Adjusted R^2	0.410	0.433	0.434	0.495	0.504	0.505