The Impact of Firm and Information Production on the Aftermarket Liquidity of IPO Firms

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ABSTRACT

The Impact of Firm and Information Production on the Aftermarket Liquidity of IPO Firms

Qian Yao

This study investigates the relationship between the aftermarket liquidity and underpricing of IPO firms by examining a sample of U.S. IPOs issued during the period 1996-2011. We first explore the relationship between stock liquidity (e.g., turnover and Amihud illiquidity) and underpricing during a one-year period after the IPO. Our results suggest that underpricing indeed boosts aftermarket liquidity and is thus in line with similar findings in the previous literature. Thus, a possible mechanism is likely to link the initial returns of IPO with lasting higher aftermarket liquidity. In this context, we propose and examine that "information production" hypothesis that IPO firms experience more information revelation to realize a "market appetite" for newly issued shares. Our empirical results demonstrate that analyst coverage, measured by the number of analysts following the IPO, and news reports, measured by the number of news mentioning the IPO firm, are two probable sources for information generation after the IPO. With a higher level of underpricing, IPO companies will certainly attract more analysts and more media coverage. Then, we check the link between information generation after the IPO and liquidity post-listing. Consistent with our expectations, there is a positive and significant relationship between the number of analysts and liquidity, and the number of news and liquidity. Based on this finding, we conclude that more information generation possibly induces attention among institutional investors and the public, which in turn causes higher aftermarket liquidity. Our study indicates that the underpricing of IPO firms serves as a possible compensation for underwriters and potential investors to obtain more analyst coverage and media attention, which is positively related to higher aftermarket liquidity.

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Contents

1. Introduction

Newly issuing firms generally experience underpricing, which is measured by the return of the first trading day closing price over the offer price. Many studies (e.g., Ibbotson, 1975) report positive initial returns for newly issued common stocks worldwide. Aftermarket liquidity is an important factor for new issue firms (see Ibbotson and Ritter, 1995; Amihud et al., 1988, 2000; Holmstrom and Tirole, 1993). In this context, we investigate how the underpricing of initial public offering (IPO) firms influences their aftermarket liquidity.

Using a sample of IPOs listed on the Nasdaq Exchange during the period from 1996 to 2011, we first investigate the relationship between turnover and Amihud illiquidity (as a proxy for aftermarket liquidity) and underpricing during a one-year period after the IPO. In order to examine changes or trends in the impact of underpricing, we divide the one-year post-IPO period into six test windows (the 1 week, 1 month, 3 months, 6 months, 9 months, and 1 year after the IPO). In addition, the regression model includes a set of control variables based on the previous literature, such as underwriter reputation, venture capital dummy, and firm size. The empirical results demonstrate that IPO underpricing has a significant effect on both turnover and Amihud illiquidity in almost all test windows, which is consistent with our hypothesis. Our results suggest that underpricing indeed boosts aftermarket liquidity and is thus in line with similar suggestions in the previous literature.

We start by studying the reasons that suggest a positive relationship between underpricing and liquidity. There are mainly two categories of explanations. One is based on ownership dispersion after the IPO (see Booth and Chua, 1995). The authors argue that underpriced IPO firms reach more and dispersed investors, and that during this process stocks experience high liquidity. The other possible explanation is based on the information momentum effect (see Reese, 1998; Aggarwal, Krigman, and Womack, 2002). They argue that newly issuing firms expect to obtain an information momentum after the IPO via research coverage or investors' interest. In this paper, we assume that IPO companies are concerned about the performance of their shares, such as liquidity, after shares are traded in the secondary market. Thus, these firms are likely to boost aftermarket liquidity actively via analyst coverage and through press exposure. Information generation therefore is viewed as a link between underpricing and aftermarket liquidity. Our tests consist of two steps.

The first step is to explore the relationship between underpricing and information generation after the IPO. We use the number of analysts following an IPO and the number of news mentioning the company's name during a one-year period after the IPO to proxy for information generation. Using ordinary least squares (OLS) regressions, we find that underpricing is positively related to both the number of analysts and the number of news. Consequently, companies are likely to use underpricing as compensation to attract more analysts and more newspaper attention. This finding is consistent with an "information momentum effect" hypothesis.

The second step is to connect the information generation with aftermarket liquidity. Based on our hypothesis, stock turnover should be statistically positively related to both the number of analysts and the number of news reports. The Amihud illiquidity should be negatively associated with those two proxy variables for information generation. We find that continuous information revelation, via professional analysts and news reports, boosts a firm's aftermarket liquidity, which could explain the persistent effect of underpricing on liquidity.

In separate robustness tests, we divide the whole sample into three groups based on the level of underpricing, and the effect on aftermarket liquidity is still holding among the three groups. Furthermore, we check the period of extreme illiquidity caused by the subprime crisis. Excluding IPOs after the year 2007, the positive relationship between underpricing and liquidity is unchanged. Furthermore, we use a two-stage regression method to ensure that any potential endogeneity problems among our information generation variables do not bias our empirical results, and find that, if anything, the impact of information generation on aftermarket liquidity is potentially underestimated.

The remainder of this paper is organized as follows: section 2 reviews the previous studies on this topic. Section 3 proposes three main hypotheses based on the related literature. The data, sample construction, and data description are provided in Section 4. The methodology is introduced in section 5. In section 6, we report our empirical results and provide interpretations. Robustness tests are introduced in section 7. Section 8 provides conclusions and discussion.

2. Literature Review

In this section, we review the related work on this topic, which consists of three parts: the related literature on IPO underpricing, the related literature on the benefits of liquidity, and the link between underpricing and aftermarket liquidity.

2.1 Literature on IPO Underpricing

Researchers have documented underpricing of newly issued companies since the 1970s. Ibbotson (1975) finds that newly issued common stocks offered to the public during the 1960s generated an 11.4 percent initial return. In addition, the initial returns are consistent with aftermarket efficiency. Ibbotson and Ritter (1975) report a 16.8 percent average excess return of IPO stocks relative to the market.

Researchers develop many models and theories to solve the "underpricing mystery." Many earlier studies that research IPO underpricing are based on an information asymmetry assumption. Rock (1986) proposes the "winner's curse" in the new issue market, which is perhaps the most famous theory on underpricing. He argues that there is information asymmetry among external investors, and divides them into two groups: informed investors and non-informed investors. Informed investors may better understand the true value of a company, and will crowd out the non-informed investors if the newly issued stock is a good one. However, if the new public offering is inferior, these informed investors may leave the potential loss to uninformed investors. IPO firms therefore use underpricing to compensate and attract more non-informed investors. Another model based on asymmetric information assumes that companies have better information about the true value and risk of their stock than do investors. Thus, firms going public may underprice their stocks voluntarily to convince potential investors that the firm has a high value; this is called the "signaling theory." Welch (1989) argues that the initial offering price is used as a signal by newly listed firms and that high-quality firms underprice in order to obtain an advantage in a seasoned equity offering. For low-quality firms, imitation costs are sufficiently high and investors may discover this imitation. Thus, underpricing voluntarily can produce another expense to low-quality firms that may reveal their true low value. Benveniste and Spindt (1989) use the auction process, which can reveal the true demand of informed investors to investment bankers to explain underpricing in the IPO market. They argue that underwriters face an unknown demand for newly issued stock from investors. Therefore, by underpricing on the deal, investment bankers reward investors who reveal positive information. Moreover, the amount of "money left on the table" depends on the profit expected from informed investors through hiding the information. Jedageesh, Weinstein, and Welch (1993) develop the "market feedback hypothesis" to explain IPO underpricing, which assumes that some investors are more informed than issuing firms. They argue that managers depend on the aftermarket feedback to understand the true value of companies revealed by informed investors. Additionally, they provide empirical evidence that IPO underpricing is positively associated with the probability of seasoned equity offerings and with the seasoned equity offering proceeds. None of the above theories or models considers the investment bank. However, there may be a principal-agent problem during the flotation. There is insufficient competition in many countries to create a thriving market for underwriters, which is likely to cause a principal-agent problem whereby underwriters benefit from IPOs at the expense of issuing firms. Baron (1982) offers a model based on the information asymmetry between issuing firms and investment bankers. Investment banks have access to better information about the true value of new stocks, and are responsible for advising on and distributing stocks. The optimal decision about the offer price is made by informed investment banks through underpricing new stocks. Information generation after the IPO is another way to explain underpricing. Aggarwal, Krigman, and Womack (2002) present a model in which issuing firms intentionally underprice their stocks in order to gain an information momentum after going public. Consequently, more research coverage revealing information about firms may shift the demand curve upward, generating higher aftermarket prices. Obviously, there is imperfect information among market participants, and issuing new stocks at a discount rate can be viewed as a compensation for one party with superior information.

There are also some theories based on information symmetry in the IPO. Hughes and Thakor (1992) develop a model to explain IPO underpricing. Based on the institutional environment, they propose that in order to avoid legal liability for mis-statements in the IPO prospectus, underwriters and issuing firms are willing to underprice. This intentional underpricing plays an important role during the IPO and serves as an insurance against securities litigation. Undoubtedly, lawsuits after going public are harmful and costly for issuing firms, as well as for underwriters. Loughran and Ritter (2000) use the prospect theory model to explain why issuers are willing to leave money on the table. They argue that issuers are more concerned with the total wealth change in the aftermarket. By measuring the covariance of the underpricing level and total wealth changes, they find that issuing firms view the money on the table as a compensation for investment banks. Thus, underpricing is an indirect cost to issuers, and firms will expect wealth increases in the aftermarket.

Jenkinson and Ljungqvist (2001) review a variety of theories and empirical work on the underpricing phenomenon and reach the conclusion that no single theory can explain this confusing problem.

2. 2 Literature on Stock Liquidity

Liquidity is an important attribute of financial instrument. Stock is considered liquid when it is easy for investors to buy or sell shares without influencing the stock price. Previous literature has taken the stock liquidity risk into the security-pricing model. Amihud and Mendelson (1986) examine the effect of liquidity costs on the asset pricing. They use the bid-ask spread as a proxy for the liquidity costs of stocks, and analyze a model assuming that investors would trade assets with different bid-ask spreads. The finding is that investors require high expected returns for securities with a high spread. More liquid securities usually have lower expected returns, which produces incentives for firms to increase liquidity. Amihud (2002) presents an empirical result on the relationship between expected return and market illiquidity over time. The excess expected return can be viewed as an illiquidity premium for investors, because investors require higher excess return to offset illiquidity cost. Acharya, Pedersen (2005) construct an overlapping generation equilibrium model incorporating liquidity risk. This liquidity-adjusted asset-pricing model not only considers an individual security's expected liquidity cost, but also takes covariance of its own return and liquidity with market return into consideration. They also find that the liquidity-adjusted pricing model is a better fit for the actual stock market. Thus, this model predicts that the expected return required by investors depends on market risk as well as liquidity risk, and provides evidence for the phenomenon of "flight to liquidity." Guerrieri and Shimer (2012) develop a dynamic equilibrium model in the assets market affected by adverse selection due to asymmetric information. They find that severe information asymmetry can lead liquidity costs to go up in the assets market.

Other studies connect the stock liquidity with some other benefits for companies, such as capital cost and company governance. Amihud and Mendelson (1988) develop a theory that claims that there is a trade-off between liquidity benefits and costs. Increasing liquidity of stocks leads to lower opportunity cost of capital for firms. Hence, we can observe many corporate financial policies and institutional arrangements used to improve liquidity, which also imposes costs on firms. Holmstrom and Tirole (1993) investigate the role of the stock market in monitoring executive behaviors. The ownership structure influences the market value of monitoring activities through its effect on market liquidity. With more liquidity, traders buying or selling stocks actively, informed investors are more likely to benefit from their private information. Ibbotson and Ritter (1995) find that when firms go public, liquidity is an important consideration for them, since a higher level of liquidity is related to lower transaction costs. Investors may view the higher liquidity level of stocks as sufficient information disclosure to the public, and will be optimistic about the future stock price. Hence, firms with liquid stocks face favorable transaction costs of future financing.

Previous studies provide ample evidence on the relationship between a higher expected return of security and higher illiquidity. In addition, there is a link between liquidity and many other aspects of a firm, including monitoring activities, anti-takeover, and information revelation. Based on these findings, aftermarket liquidity is certainly an important consideration when firms go public.

2.3 Literature on the Relationship between IPO Underpricing and Aftermarket Liquidity

Previous literature studying the link between underpricing of new listed firms and liquidity finds consistent conclusion. Most empirical evidence supports that aftermarket liquidity is positively related to the underpricing. However, a few studies find a negative relationship.

A variety of literature finds a positive relationship between underpricing of IPOs with aftermarket liquidity. Miller and Reilly (1987) use a sample of over 500 IPOs occurring during the period of 1982 to 1983, and find a positive relationship between the aftermarket trading volumes, representing the market liquidity, and underpricing level. Schultz and Zaman (1994) document that the trading volume of fully priced IPOs remains consistently below than that of underpriced IPOs for the first day of trading. For underpriced IPOs, 17 percent of stocks issued are traded within the first ten minutes of opening. This number, however, is 10 percent for fully priced IPOs. Nevertheless, the studies above overlook potential reasons behind this relationship. Booth and Chua (1995) argue that issuing firms are willing to realize dispersion ownership after flotation, which in turn improves aftermarket liquidity. Dispersed ownership, usually realized through oversubscription, requires that potential investors produce more information about companies. Thus, the underpricing of an IPO can be viewed as compensation for those informed investors. Increased liquidity is likely an incentive for firms to underprice. Most studies follow the theory from Booth and Chua (1995) to explore the relationship between underpricing and liquidity based on ownership dispersion. Pham, Kalev, and Steen (2003) investigate the underpricing level and aftermarket liquidity of IPOs in the Australian market. They find significant evidence that liquidity is a partial but important benefit of underpricing of an IPO. Furthermore, they connect the underpricing level with aftermarket liquidity based on ownership dispersion. Higher underpricing is related to broader investors, which favors the aftermarket liquidity. Li, Zheng, and Melancon (2005) find empirical results indicating a positive relationship between turnover ratio, measuring the aftermarket liquidity, and initial returns. Furthermore, they find that owners' retention rate is positively related to the aftermarket turnover ratio. Thus, we possibly view retention rate as a quality indication, improving the liquidity of stocks. Gajewski and Gresse (2006) examine the relationship between IPO underpricing and post-listing liquidity under the hypothesis that change of ownership structure in new listed companies has effects on liquidity. They demonstrate a positive correlation between post-listing liquidity and underpricing. However, they fail to prove if it is influenced by ownership dispersion. Furthermore, the level of underpricing is negatively related to information asymmetry, which suggests that firms use underpricing to encourage potential investors to produce public information. Zheng and Li (2008) check a sample of newly Nasdaq listed firms and find that underpricing has effects on secondary market liquidity. In addition, underpricing is positively correlated with the number of non-block institutional shareholders but negatively correlated with the changes in the total number of shareholder.

Other studies focusing on the relationship between aftermarket liquidity and underpricing are based on information revelation or underwriters' participation. Reese (1998) finds that in the first two trading days, newly issued stocks with underpricing experience higher trading volume than IPOs without underpricing. This trading volume difference is significant and lasts up to three years after the issue date. Furthermore, he argues that the interest of investors may be a plausible explanation for this phenomenon. Popescu and Xu (2011) explore the link between co-managers and post-listing liquidity. The principal finding is that with higher numbers of co-managers, adverse selection costs and the probability of informed trading are lower. Furthermore, revision of offer price, underwriting rank, and analyst recommendation are beneficial for improvement in aftermarket liquidity.

Most of the above studies find a positive link between underpricing and aftermarket liquidity. However, they find different mechanisms to explain the reason behind this relationship. One hypothesis links underpricing with liquidity via ownership dispersion (see Pham, Kalev, and Steen, 2003; Zheng and Li, 2008; Gajewski and Gresse, 2006). Another theoretical interpretation of empirical evidence is based on information production, such as the interest of investors (see Reese, 1998; Aggarwal, Krigman, and Womack, 2002; Popescu and Xu, 2011).

In contrast, not many researchers offer empirical evidence supporting the negative relationship between IPO underpricing and post-listing liquidity. Ellul and Pagano (2006) assume that since asymmetric information exists among participants in the IPO process, investors expect less liquidity. Thus, severe asymmetric information will lead to higher level underpricing, causing higher illiquidity. The data from British IPOs supports this hypothesis.

3. Testable Hypotheses

3.1 Hypothesis about Aftermarket Liquidity and Underpricing

Based on previous studies, high liquidity can be viewed as compensation for IPO underpricing (see Booth and Chua, 1995). Firms going public are certainly eager to improve their stock liquidity. Liquid stocks are related to lower future financing costs, effective management monitoring, and better firm performance, benefits explored by previous researchers (see Amihud, 2002; Holmstrom and Tirole, 1993; Ibbotson and Ritter, 1995). We thus propose Hypothesis 1 as follows:

Hypothesis 1: The aftermarket liquidity of newly issued stocks is positively related to the underpricing level.

3.2 Hypothesis about Information Revelation after the IPO and Liquidity

Most empirical evidence supports the theory that the underpricing of IPO boosts its aftermarket liquidity (except for Ellul and Pagano, 2006). There are two theories exploring the reasons behind this positive effect. One explanation that is examined, and even proved, by some researchers is based on the ownership dispersion of issuing firms. Booth and Chua (1995) demonstrate that underpricing is used to promote ownership dispersion, which in turn boosts aftermarket liquidity. Pham, Kalev, and Steen (2003) and Zheng and Li (2008) provide empirical evidence from various developed stock markets for this explanation. When issuing new stocks, companies possibly attempt reaching more shareholders, and prevent block-holders from forming. With dispersed shareholders, who are possibly non-informed investors, the liquidity of firms would be improved. This possible explanation has been sufficiently studied.

The other hypothesis aiming to explain the positive relationship between underpricing and liquidity links the initial return of IPO firms with information generation. Undoubtedly, new issuing companies are associated with information asymmetry (see Rock, 1986; Welch, 1989; Benveniste and Spindt, 1989; Aggarwal, Krigman, and Womack, 2002). In order to understand the demand of potential investors and to attract more investors, IPO firms probably depend on analyst coverage to induce investor interest (see Aggarwal, Krigman, and Womack, 2002). Furthermore, public interest for an IPO can be motivated when more analysts follow the IPO, which is also related to liquid performance (see Reese, 1998).

In this paper, we explore the relationship between the underpricing of IPO firms and aftermarket liquidity and how information generation, such as analyst coverage, affects liquidity. More information can be produced after stocks are traded in a secondary market and used to motivate market interest. Thus, companies are willing to accept a lower price than "true value" as their issue prices to compensate analysts and investors who are engaged in information production. Roulstone (2003) finds that analyst following has a positive effect on liquidity. Granger causality tests show that characteristics of analyst coverage lead to market liquidity.

Based on the argument above, we propose the following testable hypotheses.

Hypothesis 2: The underpricing of issuing firms attracts information production from potential investors, and increases analyst coverage and news reports.

Hypothesis 3: Information generated after the initial public offering contributes to the higher levels of aftermarket liquidity.

4. Data Collection and Sample

4.1 Data Collection

The data used in this study comes from five sources. Firstly, we collect IPO data from the Securities Data Corporation (SDC). Since the microstructure literature demonstrate that the liquidity characteristics on the Nasdaq Exchange are quite different from those on the NYSE and AMEX (see Zheng and Li, 2008), we only cover IPOs listed on the Nasdaq Exchange. Our initial sample consists of 8877 records of equity issued during the period from January 1st, 1996 to December 31st, 2011. Then, we apply the following screening criteria.

1) We exclude IPO firms that are financial institutions including closed-end funds and real estate investment trusts, and utility companies based on their business description. This screen reduces the sample to 6,817 IPOs.

2) We exclude American Depository Receipts (ADRs), American Depository Shares (ADS), Shares of Beneficial Interest (SBIs), Units, and Stock Units. This screen reduces the sample to 5,754 IPOs.

3) We exclude IPOs with an offer price below $5. This screen reduces our sample to 5,511 IPOs.

4) We exclude repeated IPOs and inaccurate IPO records. We are concerned and cautious about the quality of IPO data, so we check the IPO list on the Jay Ritter Website (http://bear.warrington.ufl.edu/ritter/), which includes the founding date of each issuing company. This screen reduces our sample to 3,013 IPOs.

Secondly, we obtain the stock returns and trading volume from the Center for Research in Security Prices (CRSP) all for IPOs in our sample. We require each IPO firm to have at least 252 trading days of data available in CRSP. After this screening procedure, there are 1,829 IPOs satisfying our requirements.

Thirdly, we impose the restriction that financial data must be available in the Compustat Database. Only 1,161 IPOs satisfy this requirement.

In addition, we obtain data on co-managers and management fees from the SDC database, and data on underwriter reputation from Jay Ritter Website. This screen reduces our sample to 910 IPOs.

Furthermore, we obtain data on analyst coverage from I/B/E/S database (Institutional Brokers' Estimate System). Specifically, we impose the restriction that brokerage firms should cover each IPO for at least one year after the issuing date. The resultant sample consists of 862 IPOs satisfying this requirement.

Finally, we use the number of news citations for an IPO as a proxy of market interest. This data comes from the Factiva database. For each IPO, we manually collect the number of news during one year following the issue date. If an IPO firm is not mentioned in the news, it is not dropped from our sample, but is assigned a value of zero for its news coverage.

Consequently, our sample contains 862 IPOs for further empirical analysis.

4.2 Descriptive Statistics for Our Sample

(Insert Table 1 here)

Table 1 provides descriptive statistics for our sample. We observe that the level of underpricing, calculated as (closing price at first trading day- offer price)/ offer price-S&P 500 index return, has a mean value of 32.57%, and a median of 14.29%. Compared with the previous literature, the underpricing is somewhat higher than that reported by other researchers. Loughran and Ritter (2002) show that the level of underpricing was 7.4% during the 1980-1989 period and 14.4% in 1990-1998. Since there are only a small number of IPOs after the year 2008 (27 out of 862, accounting for only 3.2% of the whole sample), we combine the IPOs during 2008 to 2011 into one group for our data description in Table 2. Compared with Loughran and Ritter (2002) report a 65% level of underpricing during the period of 1999-2000, the highest level of underpricing in our sample occurs in 1999, with a mean of 73.07%, which is perhaps connected with the dotcom bubble.

(Insert Table 2 here)

There is a “clustering phenomenon” for the IPO market, meaning that a year with many new issues is more likely followed by another year with many IPOs. In our sample, the number of IPOs peaks during the period 1996 to 2000. After the year 2000, the number of IPOs for each year is relatively small. The mean age for companies is 12.24 years, and the market value of firms, measured by the product of the closing price on the first trading day and shares outstanding, has a mean value of 484.98 million dollars, with a median of 250.22 million dollars. On average, 4.95 million shares are offered for the whole sample. The number of analysts during one year after the IPO has a mean of 3.24, and a median of 3 for all companies. For the number of news items after the IPO, the mean for the whole sample is 281.33, with more news for IPOs during 2007-2011, which is possibly caused by the fast development of the web media.

(Insert Table 3 here)

Table 3 shows the correlation coefficients between our independent variables. Most of the correlation coefficients are relatively low with absolute values 0.40. Thus, there is only a slight possibility that our regression results are distorted by the potential multi-colinerarity. There are just two correlation coefficients greater than 0.5. The first is the coefficient between the number of analysts and the number of news reports. The correlation coefficient of 0.575 is not surprising, because both are proxy variables measuring the information generation after the IPO. In fact, these high correlation coefficients support our choice of proxies. Furthermore, the stock volatility during two different aftermarket periods is both highly and positively correlated, which is also not surprising.

5. Measurements and Methodology

5.1 IPO Underpricing

In this paper, underpricing level of IPO is measured as the percentage change of the first trading day close price to the issue price, which is adjusted with the S&P 500 index daily return:

Underpricing = $(\frac{P_1 - P_0}{P_0} - \ Return_{sp500})$*100

Where P_1 is the close price in the first trading day, P_0 is the issue price of an IPO, and $Return_{sp500}$ is the daily return of S&P 500 Index at the issue day.

This method to calculate the underpricing is a conventional measurement (see Reese. 1998; Bradley. D., 2009; Zheng and Li, 2008).

5.2 Aftermarket Liquidity Measurement

Since we mainly focus on the liquidity performance for IPOs, we need to measure the liquidity over a post-listing period. In this paper, turnover and Amihud illiquidity (2002) are the two main measurements of liquidity level. We just cover one-year period after the firms go public.

Turnover is measured as the ratio of daily trading volume over shares outstanding as follows:

$Daily\ Turnover_{i,j}$=$Trading\ Volume_{i,j}$ / $Shares\ Outsatading_{i,j}$*100

Where i denotes the IPO_i, and j denotes the jth trading day post-listing.

Though turnover is a conventional proxy for liquidity (see Roll 1981; Amihud and Mendelson 1986; Reese 1998; Pham K. et al 2003; Zheng et al.2008), it ignores the impact of trading activity on the stock price, which is an important factor for liquidity.

The second proxy for liquidity is the Amihud illiquidity (2002).

Daily Amihud $\text{Illiquidity}_{i,j}$= $\left|Return_{i,j}\right|$ / Daily Volume in $\text{Dollars}_{i,j}$ =

$\left|Return_{i,j}\right|$ / ($Trading\ Volume_{i,j}$*$Close\ Price_{i,j}$)*10^6

Daily Amihud illiquidity is scaled by 10^6. Amihud illiquidity (2002) considers the price changes associated with trading volume. If stock is liquid, this ratio should be small, due to little price change associated with per volume in dollar.

Since there are six test windows, we calculate the average turnover ratio and Amihud illiquidity over different periods (1 week, 1 month, 3 months, 6 months, 9 months, and 1 year after the IPO, respectively).

5.3 Analyst Coverage and Newspaper Citations

To measure the analyst coverage for an IPO, we follow previous literature (see Hong. H, Lim.T, and Stein. J, 2000; Cliff and Denis, 2004) and use the number of analysts following the IPO as the proxy for analyst coverage, From the I/B/E/S database, we acquire the number of analysts over one year after going public for each IPO.

Following Reese (1998), we use the number of news items citing the IPO firms as a proxy for press interest. With more news mentioning the IPO firm, this firm is more likely to be exposed to the public, including potential investors and analysts. Klibanoff, and Wizman (1998) offered the empirical evidence that the relative salience of news plays an important role in the reaction of investors to an event or company, which links the newspaper citation with the investors' interest.

In order to measure the number of news sources citing the IPO company, we search the company name manually in the Factiva Database and count the number of news items during the year after the issue date. For a majority of companies in our sample, the newspaper press is from the US.

In this paper, we use the analyst coverage and newspaper citations as the proxy for information generation after IPO.

5.4. Other Variables

To test our hypothesis using OLS method, we include some control variables in the regression models. Here we introduce some control variables and the reason why they are incorporated in the regression equations.

Stock price volatility is a control variable for aftermarket liquidity. Zheng and Li (2008) find that volatility is significantly positively related to the trading volume after going public.

Domowitz and Wang (1994) demonstrate that price volatility is greater, the bid-ask spread is smaller, and trading volume is greater in market. Hence, stock volatility may be a factor having impact on liquidity. Volatility is measured as the close-to-close volatility, which is the standard deviation of the daily return over corresponding trading days.

Venture capital is an important source of capital for new and growing companies. Filed and Hanka (2001) find that when lockup period expires, there is a permanent negative abnormal return with a significant increase in average trading volume. At the same time, venture capitalists sell stocks more aggressively than do other insiders. Bradley and Bradford (2001) find empirical evidence that lockup period expirations for IPOs are, on average, associated with significant and negative abnormal returns, and that losses are concentrated in firms with venture capital backing. As a result, we put the venture capital as a control variable on the right hand of the equation.

Plentiful previous literature focusing on the IPO take the underwriter reputation as control variable, since the underwriter plays a key role in the IPO process (see Zheng and Li 2008; Ellul and Pagano, 2004). Thus, we take Jay Ritter's updated Carter-Manaster (1990) underwriter ranking as control variable, which is a conventional proxy to measure underwriter reputation. This measure ranges from 9.000 (best quality underwriter) to 1.000 (worst quality underwriter).

Cheolwoo Lee (2012) finds empirical evidence to support that the gross spread (uniformly clustered at 7%) is used to compensate the underwriter for analyst coverage after IPO. Cliff and Denis (2004) argue that underpricing and gross spread are two main compensation sources for analyst coverage but failed to prove that gross spread has significant influence. Following previous literature, we also include the gross spread of the IPO in the regression to control the analyst coverage.

5.5 Empirical Research Design

The empirical research in this paper incorporates three stages, which mainly examine Hypothesis 1 to Hypothesis 3. First, we study the relationship between the IPO underpricing and aftermarket liquidity. The following stage is to explore how the underpricing is associated with the information generation, measured by analyst coverage and newspaper citation. Finally, the relationship between aftermarket liquidity and information production of IPOs is examined.

5.5.1 The First Phase of Our Empirical Study

To test the Hypothesis 1.1, the regression specification is as follows:

$$\text{Liquidity Measurement} = \mathrm{b}_0 + b_1 Underpricing + b_i \sum_{i=2}^{n} CV_i \tag{1}$$

In regression model (1), liquidity measurement consists of the average turnover and average Amihud illiquidity calculated by daily observations. Underpricing is measured as the percentage change of first trading day close price to the issue price, adjusted by S&P 500 market index return.

CV_i is the set of control variables for the aftermarket liquidity. In the regression model (1), control variable set includes stock volatility measured by the standard deviation of daily return; underwriter reputation measured by Jay Ritter's updated Carter-Manaster (1990) underwriter rankings; firm size measured by natural logarithm on total asset; high-technology which is a dummy variable, taking 1 if the IPO firm is high-tech group (SICs 2833, 2834, 2835, 2836, 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7377, 7378, 7379), and otherwise equals 0; venture-capital backed which is a dummy variable, taking 1 for IPO backed by venture capital, otherwise taking 0; sale ratio in the IPO, measured by the ratio of number of shares offered in IPO divided by shares outstanding after IPO, reflecting the allocation during the IPO. Some studies find a positive relationship between trading volumes and float ratio (see Zheng and Li, 2008).

This regression model explores the relationship between liquidity of IPOs with underpricing. We have access to one year of aftermarket liquidity data, thus we divide the year into six test windows to reflect possible changes in aftermarket liquidity: first trading week (1^{st} trading day to 5^{th} trading day); first trading month (6^{th} trading day to 21^{st} trading day); three months after IPO (6^{th} trading day to 63^{rd} trading day); six months after IPO (6^{th} trading day to 126^{th} trading day); nine months after IPO (6^{th} trading day to 189^{th} trading day); and one year after IPO (6^{th} trading day to 252^{nd} trading day). We only include the first trading week in the first test window as newly issued stocks are actively traded during several trading days to reach a "fair value" which is accepted by the public. Consequently, we separate the first trading week into an individual test window. Ellise, Michaely, and O'Hara (2000) report that the lead underwriter is always the dominant market maker during the three months after IPO. Such price stabilization for some unsuccessful IPOs lasts for three months after first trading day. Other previous literature find that price support of underwriters and lockup period expiration (see Filed and Hanka, 2001; Bradley and Bradford, 2001) of IPOs affect the market liquidity. Lockup period usually lasts for 180 calendar days (for most IPOs) or 270 calendar days (for a smaller quantity of IPOs) after the issue date. We therefore include 6 months and 9 months as test windows.

Regression model (1) focuses on the link between IPO underpricing and liquidity, but pays no attention to the reasoning behind that relationship. To test Hypothesis 2 and 3, we estimate four following regression models using OLS method.

5.5.2 The Second Phase of Our Empirical Study

To test Hypothesis 2, the following regression models are estimated:

$$\text{Analyst Coverage} = \mathrm{b}_0 + b_1 Underpricing + b_2 Number\ of\ Lead\ and\ Co\ Managers + b_3 Venture\ Capital\ Backed + b_4 Firm\ Size + b_5 Number\ of\ IPOs + b_6 Gross\ Spread \quad (2)$$

$$\text{News Report} = \mathrm{b}_0 + b_1 Underpricing + b_2 Number\ of\ Lead\ and\ Co\ Managers + b_3 Venture\ Capital\ Backed + b_4 Firm\ Size + b_5 Number\ of\ IPOs + b_6 Web\ News\ Popular \quad (3)$$

In regression model (2), analyst coverage is measured as the number of analysts following the IPO during the first year. The dependent variable in regression model (3) is the news report, which is measured as the number of news items mentioning the company's name over one year from the IPO. The data comes from Factiva Database. The percentage of first trading day closing price to offer price adjusted by market index return is the proxy for underpricing. The other four control variables included in both equation (2) and (3) are number of lead and co- managers for the IPO (Cliff and Denis 2004 find positive relation between analyst coverage and number of co-managers, since lead and co-manager are often involved in the aftermarket support through offering stock analysis and buy-recommendation); venture-capital backed dummy which equals 1 if the IPO is backed by venture capital, and equals 0 otherwise; firm size measured by the natural logarithm on total assets of the company; number of IPOs during the year the firm goes public (see Cliff and Denis 2004).

In regression model (2), gross spread is the control variable, which does not appear in regression model (3). The gross spread is the other source of compensation to an underwriter for analyst coverage (see Cliff and Denis, 2004; Lee. C., 2012). In regression model (3), the dummy of whether the web news is popular is a dummy variable for the development of the medium, taking 1 if the IPO occurs after 2007, otherwise taking 0. After 2007, news sources include "web news" for most of the IPOs in our sample; thus, this control variable is used to measure the fast development of news press and web media during later years. In addition, we check our sample by adding a time dummy for the period of 2003-2006, which is after the dotcom bubble, but there is no significant result.

These two regression equations are used to examine whether the underpricing of IPOs is a source of compensation for aftermarket analyst coverage.

5.5.3 The Third Phase of Our Empirical Study

Testable Hypothesis 3 is examined by the following regression equations:

$$\text{Liquidity Measurement} = \mathrm{b}_0 + b_1 Analyst\ Coverage + b_i \sum_{i=2}^{n} CV_i \tag{4}$$

$$\text{Liquidity Measurement} = \mathrm{b}_0 + b_1 News\ Report + b_i \sum_{i=2}^{n} CV_i \tag{5}$$

These two regression models are used to explore the relationship between aftermarket liquidity and information generation of IPOs. Liquidity measurement consists of turnover and Amihud illiquidity. Liquidity and information revelation are measured and calculated for one year after IPO; therefore, we use two test windows (6 months and 1 year after the IPO) to estimate the regression equations. Turnover and Amihud illiquidity are calculated by averaging daily observations (except for the first five trading days because of extremely high trading activities) over 6 months after IPO (6^{th} trading day to 126^{th} trading day) and over one year after IPO (6^{th} trading day to 252^{nd} trading day). In regression model (4), the analyst coverage is measured the same as that in regression model (3). News report is the number of news mentioning IPO firm during one year after IPO divided by 1000, so that we are able to avoid too small of coefficients caused by the small number of liquidity measurements.

In regression equation (4) and (5), control variables are similar to equation (1), including stock volatility, measured as the closing price volatility over 6 months and one year after the IPO; underwriter ranking; firm size, measured as the employees at natural logarithm in order to diminish potential colinearity caused by including total asset as control variable; high-technology industry dummy; and sale ratio measured by the ratio of number of shares sold in the IPO over the shares outstanding in the first trading day.

Using these two regression models, we examine Hypothesis 3: whether the information generation, via analyst coverage and newspaper, is linked with the high liquidity. This is also a plausible explanation for plentiful previous studies finding that higher underpricing is related to higher aftermarket liquidity.

6. Empirical Results

6.1 The Relation between Underpricing and Liquidity

(Insert Table 4 here)

We present the empirical result of regression model (1) in Table 4. The relationship between aftermarket liquidity and initial underpricing is analyzed through multivariate regression. Consistent with most previous empirical studies and our hypotheses, the estimation result demonstrates that in Panel A, the underpricing level is positively related to the aftermarket turnover at statistical significance level for all six estimation equations. Form one week after IPO to one year after IPO, companies with higher underpricing are more likely to experience higher turnover, and this effect is statistically significant. The turnover in the several first trading days is always extremely high, since trading activities are excessively active until the price of new issue shares reaches a "reasonable and fair" level. As a result, the coefficient of the underpricing for the first trading week is noticeably greater than other coefficients of underpricing. Panel A indicates that the firm size has a relatively significant and positive effect on the aftermarket turnover, which is also consistent with expectations. For the venture-capital backed IPOs, companies would generally experience lower turnover, which is, however, statistically insignificant. In accordance with previous studies (see Pham K. et al., 2003; and Xiaofan Zheng et al., 2008), the stock volatility, which is positively related with aftermarket turnover. Extremely actively traded stock is associated with higher volatility, since more non-informed investors are involved in trading activities, causing stock price to change sharply. All the positive coefficients of the high-technology dummy are significantly different from zero (except for 1 month after IPO), indicating both that there is a difference among industries, and that the public may be more interested in trading hi-tech stocks. Though most coefficients of underwriter reputation are positive (except for 1 month after IPO), they are all insignificant. The boosting effect of a high quality underwriter is weak. Sale ratio is positively associated with aftermarket turnover at 0.01 significance level, which is in agreement with previous literature findings. Thus, firms allocating a higher percentage of shares outstanding to the public probably experience higher aftermarket turnover.

In Panel B of Table 4, we find that Amihud illiquidity is statistically negatively related with the underpricing of IPOs for all test windows. In addition, the coefficient of underpricing for the first trading week is excessively small in magnitude, since new stocks are relatively liquid. Underwriter reputation has significantly negative impact on the Amihud illiquidity (except for 6 months after IPO), meaning that a high quality underwriter may improve liquidity of new issues via price support or analyst coverage. Firm size is negatively related with Amihud illiquidity at a conventionally significant level. Most coefficients of the high-technology dummy are negative but the effect is not sufficiently strong to show a statistical significance. Stock volatility has a reversed effect on the Amihud illiquidity for different periods, which conflicts with regression results in Panel A. A possible explanation is that the relationship between Amihud illiquidity and volatility experiences a reverse for IPO firms, so more research is needed to confirm it. Previous literature (see Ellul A. et al., 2003; Pham K. et al., 2003; Xiaofan Zheng et al., 2008) all reports a positive relationship between volatility and effective spread, which measures the trading cost. The effect of venture capital on the aftermarket Amihud illiquidity is mixed and insignificant. Thus, we do not find a significant effect of venture capital on the aftermarket liquidity based on Table 1.

Regarding Hypothesis 1, results of regression model (1) for six different trading periods provide positive empirical evidence. Aftermarket liquidity is significantly related to the underpricing, which is consistent with most previous empirical studies. Moreover, the effect of underpricing on the aftermarket liquidity lasts at least one year after IPO, which is a relatively persistent impact. Thus, there is possibly a link boosting the liquidity via IPO underpricing. The next section explores the link between underpricing and liquidity.

6.2 The Result for Hypothesis 2

(Insert Table 5 here)

Table 5 presents the empirical result regarding the relationship between information production after the IPO and underpricing. In the left column, underpricing is positive with the analyst coverage during one year after IPO at a 0.01 significance level, which is consistent with our expectation. Thus, we fail to reject Hypothesis 2 that IPO companies are likely to underprice their shares voluntarily in order to compensate underwriters to achieve more analyst coverage. Table 5 also indicates that a larger number of lead and co-managers is positively associated with more analysts following IPOs, which is in accordance with previous studies (see Cliff and Denis, 2004). IPOs that are venture capital backed and of a larger size are followed by more analysts, with positive coefficients at 0.01 significance level respectively. Coefficient of gross spread is positive and also statistically significant, indicating that gross spread is another main source for underwriters to provide analyst coverage. Significantly, the negative coefficients of number of IPOs are in accord with our expectations. Since more IPOs at the same period could induce competition within analyst and investor communities, an individual IPO is less likely to attract analysis or coverage by newspapers.

In the right column of Table 5, we find that underpricing has a positive and significant effect on the number of news items during one year after IPO, supporting the Hypothesis

2. The dummy variable measuring whether web news is popular, which is designed to differentiate the effect of recent media development, is positively related to number of news, with a t value of 4.06. All other control variables, including number of lead and co-managers, venture capital backed, firm size and number of IPOs, are statistically significant with the number of news. This estimation result also supports Hypothesis 2.

Based on Table 5, we fail to reject Hypothesis 2, indicating that underpricing of IPOs is linked with more information revelation post-listing. IPO firms therefore are likely to underprice their shares to attract more attention from newspapers and compensate underwriters and co-managers who offer price stabilization and analyst coverage service. This is the first stage to examine the possible explanation regarding the positive link between underpricing and aftermarket liquidity.

6.3 The Result for Hypothesis 3

(Insert Table 6 here)

Table 6 reports the estimation result of regression model (4). When the dependent variable is stock turnover, the coefficient of number of analysts is positive at a 0.01 significance level for both periods. Thus, IPOs followed by more analysts are connected with higher aftermarket liquidity, measured by turnover, which is consistent with Hypothesis 3. Stock volatility and float ratio are all positively related to turnover at a conventionally significant level. Furthermore, firms within the high-technology industry generally experience a higher aftermarket turnover. The impact of underwriter ranking on turnover is negative but insignificant. The coefficient of firm size for six-month period is positive, and for one-year period is negative, but they are all insignificant. Overall, the impact of analyst coverage on the turnover is positive and significant.

When the liquidity measurement is the Amihud illiquidity, the analyst coverage, measured by number of analysts, significantly reduces the illiquidity of shares of IPO firms. Coefficients for the number of analysts are negative and statistically significant for both periods (six-month period and one-year period). The quality of the underwriter has a positive effect on the liquidity, which is similar to regression model (1). Larger companies or firms belonging to high-technology industries are more likely to experience lower illiquidity. Similarly, the coefficient of stock volatility experiences a reverse from negative to significantly positive. The coefficient of sale ratio is positive, but is not significant.

Based on Table 6, we find that analyst coverage after IPO significantly improve the aftermarket liquidity, which supports Hypothesis 3.

(Insert Table 7 here)

Table 7 demonstrates the empirical result of regression model (5). When turnover is aftermarket liquidity, we find that the number of news reports is positive related to the aftermarket turnover at 0.01 significance level. Consequently, more information generation boosts the aftermarket liquidity, verifying Hypothesis 3. Stock volatility, firm size, and high-technology dummy are all significantly and positively related to the turnover, consistent with the estimation result of regression model (1). Sale ratio of the IPO still has positive effect on the turnover. Underwriter reputation shows negative but insignificant effect on turnover. When the dependent variable is Amihud illiquidity, the coefficient for the number of news items for newly issued firms is negative and statistically different from zero. Underwriter reputation, firm size, and high-technology industry all have a significant effect on reducing Amihud illiquidity.

Table 6 and Table 7 show that information production following the IPO has a positive influence on the aftermarket liquidity. This empirical evidence supports Hypothesis 3, the link between decrease in information asymmetry and increase in liquidity. Furthermore, the benefit of more liquidity is probably connected with future seasoned equity offerings, or takeover activities. Jegadeesh, Weinstein, and Welch (1993) find a positive relation between the underpricing of an IPO and the probability and size of subsequent seasoned equity offerings. In addition, Celikyurt, Sevilir, and Shivdasani (2010) find that IPO firms' acquisition activity is fueled by the initial capital raised in the IPO and that IPO firms play a bigger role in the M&A process by participating as acquirer than they do as targets.

By estimating regression model (2) (3) (4) (5) and interpreting results, we find empirical evidence for a reasonable and compelling explanation for a positive relationship between underpricing and liquidity of shares. Probably, IPO companies voluntarily underprice their new issues as a compensation for underwriters and a method to attract attention of media, in order to have access to more analyst coverage and newspaper attention, which stimulates their shares to become liquid after they are traded at a secondary market.

7. Robustness Tests

In this section, a further robustness test is designed and implemented to check whether there is difference of aftermarket liquidity among different groups of IPOs and whether outliers of liquidity measurements bias empirical results. Finally, two-stage linear regression analysis is conducted to check for an endogenous problem of analyst coverage and news report.

7.1 Hot, Moderate, and Cold IPOs

This section is dedicated to testing whether the relationship between underpricing and aftermarket liquidity is significantly different among IPOs based on their level of underpricing. We divide the whole sample into three groups of IPOs according to the underpricing level: Hot IPO Group (underpricing level greater than 26%), Moderate IPO Group (underpricing level ranging from 3.7% to 26%), and Cold IPO Group (underpricing smaller than 3.7%). For each group of IPOs, the average turnover and Amihud illiquidity are calculated (the first trading week is excluded because of extremely high liquidity level). In order to avoid the significant influence of some events on liquidity and to smooth varying liquidity, we calculate the weekly average turnover and Amihud illiquidity over five continuous trading days. For example, the first trading week turnover is calculated by averaging the first five trading days' daily turnovers, and so on. Consequently, for each IPO, 252 trading days are divided into 52 trading weeks. We obtained average liquidity measurement for each IPO group.

(Insert Figure 1 here)

(Insert Figure 2 here)

Figure 1 demonstrates the average weekly turnover for three groups of IPOs. The hot IPOs, showed by the black solid line, experience the highest aftermarket turnover for all 52 trading weeks. Cold IPOs have the lowest turnover for around 37 trading weeks. However, on average, the difference between the hot IPOs and the moderate IPOs is relatively larger than that between moderate IPOs and cold IPOs. Figure 2 shows the average weekly Amihud illiquidity for three sub-samples of IPOs. We find that hot IPOs have the lowest Amihud illiquidity for nearly all of 52 trading weeks, and that the fluctuation of Amihud illiquidity for hot IPOs is smoother relative to moderate and cold IPOs. For cold IPOs, Amihud illiquidity is the highest for around 45 out of 52 trading weeks, and there is an obvious rising trend as the trading weeks increase. Amihud illiquidity of moderate IPOs generally lies between hot IPOs and cold IPOs. Thus, the hot IPOs with a higher level of underpricing are more likely to connect with higher turnover and lower Amihud illiquidity, which further reinforces empirical evidence for regression model (1).

(Insert Table 8 here)

Next, we compare the mean difference and median difference between each two groups to examine whether there is significant difference between aftermarket liquidity, the results of which are reported in Table 8. For the aftermarket turnover, the mean of the hot IPO is 1.3913, which is statistically greater than cold IPOs with a mean of 0.7549 and moderate IPOs with a mean of 0.8718. However, the difference between moderate IPOs and cold IPOs is insignificant. The median differences between each group are all statistically significant. When comparing the Amihud illiquidity, hot IPOs have a mean value of 0.09714, which is significantly lower than that of moderate IPOs with a mean of 0.40181 and that of cold IPOs with a mean of 0.7657. The highest mean of Amihud illiquidity is for cold IPOs, which is also significantly higher than that of moderate IPOs. The differences of median between any two groups are all statistically different from zero. Based on these findings, we conclude that there is a significant difference of aftermarket liquidity among hot, moderate, and cold IPOs, measured by the level of underpricing. These findings also support the prior study by Das, Guo, and Zhang (2006) who examine the effect of hot versus cold IPO market periods on aftermarket liquidity, and by Helwege and Liang (2004) who explore different definitions of hot and cold IPO periods.

7.2 The Extreme Illiquidity Period of Stock Market

(Insert Table 9 here)

Undoubtedly, the financial crisis of 2008 has a great influence on market liquidity. The huge influence of the financial crisis of 2008 possibly distorts the empirical result of regression model (1), since the whole stock market experienced a strong liquidity dry up and a panic. In order to check whether the outliers cause the OLS results in the illiquidity period, we exclude IPOs after the year 2007 and re-run the regression model (1) for a sample from the shortened period. For brevity, we just report the regression result for three test windows: 1 month after IPO; 6 months after IPO; and finally, 1 year after IPO. Table 9 demonstrates the estimation results for IPOs before the financial crisis of 2008. Positive and statistically significant coefficients of underpricing still hold for three test windows and other coefficients are generally unchanged when liquidity is measured by turnover ratio. When the dependent variable is Amihud illiquidity, in all three estimation equations, the coefficient of underpricing is negative and statistically significant to at the 0.01 significance level. Other findings on control variables are predominantly consistent with those on the whole sample. Consequently, the outliers do not drive the positive relationship between underpricing and aftermarket liquidity during the illiquidity period.

Furthermore, we divide the whole into two groups using a dummy variable: one group including IPOs before the year 2007, the other including IPOs after 2007, and then re-run regression model (1). The financial crisis dummy allows us to check directly whether the subprime crisis has influence on the liquidity for IPOs. However, the financial crisis dummy is positive and statistically significant only for the 1-week and 1-month test windows when the dependent variable is Turnover, and the dummy is negative and significant only for the 1-year test window when the dependent variable is Amihud illiquidity. We conclude that there is a weak relationship between financial crisis and aftermarket liquidity. However, since there are only 77 IPOs occurring after 2007, this conclusion is relatively weak.

7.3 Endogeneity of Our Information Generation Variables

There is a potential bias for the empirical results of regression model (4) and (5). It could be argued that the analyst coverage and news stories suffers from a potential problem of endogeneity. For example, some companies employ underwriters with a high reputation and employ more co-managers to produce more information via analysts and newspaper attention. This potential endogeneity of information generation variables possibly distorts our empirical results. In order to correct this potential bias, we design and employ two-stage regression to re-run regression model (4) and (5).

First, we construct a regression model for estimating the analyst coverage and number of news reports. The choice of variables on the right hand of the equation is motivated by previous literature and the empirical results of regression model (2) and (3). For the number of analysts after IPO, instrument variables include underpricing level; number of lead and co-managers; venture-capital backed dummy; firm size measured by the natural logarithm on total assets; gross spread of IPO. For the number of news items during one year after IPO, instrument variables are generally similar to those of analysts' number equation, except that we replace the gross spread of IPO with the web news popular dummy. Furthermore, the fitted value from the two models above is used as an independent variable in the second stage estimation. The dependent variables are turnover and Amihud illiquidity in the second stage regression model. Variables on the right hand of the equation include the fitted value from the first stage estimation and the same set of exogenous variables in regression model (4) and (5). In this way, the problem of endogeneity for analyst coverage and newspaper story can be checked and even be corrected. For brevity, we report the empirical results of regression equations for only one test window (one year after the IPO).

(Insert Table 10 here)

Table 10 shows the estimation results of both the OLS and two-stage regression for regression model (4) and (5). Comparing the coefficient at Column (1) and (2), we find the coefficient for the number of analysts increases from 0.141 to 0.174, and is still statistically significant. In Column (3) and (4), the coefficient for the number of news reports distinctly increases from 1.17 to 1.36. Through Columns (5) to (8), the impact of analyst coverage and newspaper items on the aftermarket liquidity becomes larger after we control for the potential endogeneity, which is indicated by the increasing coefficients for the number of analysts and the number of news reports. However, the significance of firm size measured by logarithm on employees is lost for estimation equations at Column (4) and (6), though the signs of those two coefficients are unchanged. Based on these empirical results, we find that the information generation after IPO may suffer from an endogeneity problem and that the impact of information generation on aftermarket liquidity is underestimated. The two-stage regression method to some degree corrects the estimation coefficients of proxy variable for information revelation. This section therefore provides further empirical evidence that is in line with the conclusion of Section 6.3.

8. Discussion and Conclusions

In this paper, we use a sample of U.S. IPOs issued during the period 1996-2011 to explore the relationship between aftermarket liquidity and underpricing. We find empirical evidence of a significant positive relation between these variables. Following previous IPO studies, we first check how underpricing is associated with the liquidity post-listing. One of a variety of explanations for IPO underpricing is that newly issuing firms voluntarily accept the underpricing of their new shares to compensate underwriters and potential investors to provide higher liquidity and more demand after the IPO. By checking the relationship between underpricing and aftermarket liquidity, we find that IPOs with more underpricing are more likely to experience higher aftermarket liquidity, measured by stock turnover and Amihud illiquidity, which supports previous studies. The choice of control variables in our regression models follows the prior literature. Most of the control variables have significant coefficients and expected signs, except for the fact that venture capital shows no significant influence on the liquidity of IPOs. Furthermore, we find that the positive impact of underpricing lasts for at least one year after the issue, i.e. it is relatively persistent. Thus, there is a possible mechanism that links the initial returns of IPO with long-term higher aftermarket liquidity.

Secondly, we use OLS regressions to explore possible explanations for the positive relationship between IPO underpricing and liquidity. A vast body of literature on IPO underpricing explores the information asymmetry among market participants. Under the hypothesis that IPO companies experience higher information revelation to realize a "market appetite" for newly issued shares, we find that analyst coverage, measured by the number of analysts following the IPO, and newspaper attention, measured by the number of news referring to the IPO firm are two probable sources for information generation after the IPO. Our regression model explores whether a firms's underpricing level can explain some part of the change in the number of analysts and the number of news. If so, underpricing could be viewed as compensation of underwriters who are providing analyst coverage.

Finally, we examine the link between information generation after the IPO and liquidity post-listing. Consistent with our expectation, there is a significant and positive relationship between the number of analysts and liquidity, and the number of news stories and liquidity. Based on these findings, we conclude that more information generation possibly induces attention among institutional investors and the public, which in turn causes higher aftermarket liquidity.

Robustness tests show that our empirical results still hold for different groups of IPOs based on the level of underpricing, and that the results are not driven by IPOs during the extreme illiquidity period. Finally, we control for the potential endogeneity of information generation using a two-stage regression method. The results indicate that the impact of analyst coverage and newspaper attention can be possibly underestimated.

Overall, our empirical results support Hypotheses 1, 2 and 3, suggesting that underpricing of IPO firms may serve as a possible entice for underwriters and potential investors to have access to more analyst coverage and media attention, which is positively related to higher aftermarket liquidity. Because the effect of underpricing on liquidity seems relatively persistent, the information production connects the underpricing and benefits of companies post-listing. IPO companies enjoying good liquidity are more likely to be involved in SEOs and acquisition activities as acquirers, leaving a lot of work for further research.

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Appendix: Definition of variables and data sources

Variable	Data Sources	Definition and Description
Underpricing	SDC, CRSP	IPO underpricing, calculated as: (Closing Price on the 1st trading day-Offer Price) / Offer Price-S&P 500 index return
Underwriter Reputation	Jay Ritter's Website	Ranging from 1 (worst) to 9 (best) scale for underwriter ranking
VC-Backed Dummy	SDC	Venture capital backed dummy: 1 if the IPO is backed by venture capital, and 0 otherwise
Log Assets	Compustat	Natural log of firm's total assets
Hi-Tech Dummy	SDC	High-Tech Dummy: 1 if the IPO firm is High Technology firm (Firms with the following SIC codes are identified as high-tech firms: 2833, 2834, 2835, 2836, 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7377, 7378, 7379)
Volatility	CRSP	Standard deviation of daily returns
Sale ratio	SDC, CRSP	Shares offered in issue divided by shares outstanding following the IPO
Number of Managers	SDC	Number of co-managers (including lead managers)
Number of IPOs	SDC	Number of IPOs during the year in which the issuer goes public
Gross Spread	SDC	Gross underwriter spread, in dollars
Web News Popular Dummy	Factiva	Web News Popular Dummy: 1 if the IPOs occurs after 2007 (network media becomes popular), and 0 otherwise
Log Employees	Compustat	Natural log of the number of employees
Number of Analysts	I/B/E/S	Number of analysts following IPO during one year after issue day
Number of News	Factiva	Number of news reports referring the name of the issuer during the first year after issue day
Turnover	CRSP	Turnover ratio calculated as: Trading volume/Shares outstanding
Amihud Illiquidity	CRSP	Amihud illiquidity measure calculated as: (Absolute daily return)/(trading volume*closing price)

Table 1: Descriptive IPO statistics for the whole sample

The sample consists of 862 IPO firms listed on the Nasdaq Exchange during the period 1996 to 2011. The data are collected from SDC database, CRSP database, Compustat database, I/B/E/S database, Factiva database, and Jay Ritter's IPO website (http://bear.warrington.ufl.edu/ritter/). Offer price is defined as the offer price per share of IPO. Closing Price is defined as the closing price at the first trading day. Underpricing is measured by (Closing Price– Offer Price)/Offer Price*100-S&P 500 index return. Shares offered is defined as the number of shares offered at IPO. Sale ratio is defined as the ratio of shares sold in IPO divided by the number of shares following the IPO. Gross spread is defined as the expense of IPO firm on the gross spread. Age is the age of firm in the number of years at the time of IPO. Total assets is measured by the total assets at the end of fiscal year before IPO. Employees is defined as the number of employees at IPO's firm. Market value is calculated as the product of the number of shares outstanding and closing price on the first trading day. Number of analysts is defined as the number of analysts following the IPO firms during one year after IPO. Number of news is measured by the number of news referring firm's name during one year after IPO. Turnover is defined as average daily turnover, calculated by the daily trading volume divided by corresponding shares outstanding. Amihud illiquidity is measured by average daily Amihud illiquidity, calculated by $|Daily\ Return|$/(Trading Volume* Closing Price)*10^6. Volatility is defined as the standard deviation of daily closing return.

Statistics	N	Mean	Median	Min	Max	Standard Deviation
Offer Price ($)	862	13.1773	13.0000	5.0000	65.0000	4.7247
Closing Price ($)	862	18.4868	14.5000	0.2500	172.0000	14.7483
Underpricing (%)	862	32.5660	14.2900	-98.5300	525.0000	60.9676
Shares Offered (in thousands)	862	4950.33	4000.00	1000.00	85300.00	4454.41
Sale Ratio (%)	862	31.2347	27.5909	0.0775	148.1265	19.0883
Gross Spread (in million $)	862	0.9151	0.8780	0.3250	3.4130	0.3118
Age (in years)	862	12.2401	7.0000	0.5000	159.0000	15.7092
Total Assets (million $)	862	197.6009	83.0790	0.0250	44024.7800	1517.0730
Employees (in thousands)	862	0.7308	0.2550	0.0090	21.3790	1.5939
Market Value (in million $)	862	484.9794	250.2205	19.0480	10754.9900	874.9206
Number of Analysts	862	3.2413	3.0000	1.0000	18.0000	1.4426
Number of News Reports	862	281.3341	202.0000	11.0000	3856.0000	298.7912
Turnover (%) (6 months after the IPO)	862	0.8401	0.5965	0.0486	9.7098	0.9008
Amihud Illiquidity (6 months after the IPO)	862	0.2609	0.0531	0.0003	13.1752	0.7936
Volatility (%) (6 months after the IPO)	862	5.3649	4.8070	1.4497	15.1203	2.3733
Turnover (%) (1 year after the IPO)	862	0.8755	0.6341	0.0682	7.2390	0.8129
Amihud Illiquidity (1 year after the IPO)	862	0.4024	0.0622	0.0002	16.4580	1.1822
Volatility (1year after the IPO)	862	5.4146	4.9196	1.3977	18.7948	2.2636

Table 2: Descriptive statistics of initial public offerings grouped by year

The sample consists of 862 IPO firms listed on the Nasdaq Exchange during the period 1996 to 2011. The data are collected from SDC database, CRSP database, Compustat database, I/B/E/S database, Factiva database, and Jay Ritter's IPO website (http://bear.warrington.ufl.edu/ritter/). The last row includes the data of IPOs from 2008 to 2011. Medians are reported in parentheses. Underpricing is measured by (Closing Price– Offer Price)/Offer Price*100-S&P 500 index return. Shares offered is defined as the number of shares offered at IPO. Sale ratio is defined as the ratio of shares sold in IPO divided by the number of shares following the IPO. Gross spread is defined as the expense of IPO firm on the gross spread. Age is the age of firm in the number of years at the time of IPO. Total assets is measured by the total assets at the end of fiscal year before IPO. Employees is defined as the number of employees at IPO's firm. Market value is calculated as the product of the number of shares outstanding and closing price on the first trading day. Number of analysts is defined as the number of analysts following the IPO firms during one year after IPO. Number of news reports is measured by the number of news referring firm's name during one year after IPO. Turnover is defined as average daily turnover, calculated by the daily trading volume divided by corresponding shares outstanding. Amihud illiquidity is measured by average daily Amihud Illiquidity, calculated by $|Daily\ Return|$/(Trading Volume* Closing Price)*10^6. Volatility is defined as the standard deviation of daily closing return.

Year (N)	Underpricing (%)	Shares Filed (in thousands)	Sale Ratio (%)	Gross Spread (in million $)	Age (in years)	Total Assets (in million $)	Employees (in thousands)	Market Value (in million $)	Number of Analysts	Number of News Reports	Turnover (%) (1 year after the IPO)	Amihud Illiquidity (1 year after the IPO)	Volatility (%) (1 year after the IPO)
1996	18.11	2995.08	36.41	0.86	11.00	73.10	0.60	195.08	2.38	140.70	0.65	0.79	4.68
(176)	(9.30)	(2600.00)	(32.03)	(0.84)	(7.00)	(45.02)	(0.19)	(118.44)	(2.00)	(103.00)	(0.55)	(0.23)	(4.71)
1997	15.98	3243.30	34.19	0.83	15.26	86.62	0.78	217.78	2.50	(159.77)	0.71	0.63	4.53
(120)	(10.12)	(2700.00)	(33.66)	(0.77)	(10.00)	(49.90)	(0.26)	(104.56)	(2.00)	(104.50)	(0.57)	(0.17)	(4.49)
1998	36.99	3387.83	35.23	0.90	12.00	102.55	0.73	246.60	2.71	303.55	1.25	0.38	5.94
(56)	(13.27)	(3000.00)	(29.69)	(0.89)	(7.50)	(68.88)	(0.32)	(195.11)	(3.00)	(184.00)	(0.63)	(0.12)	(5.70)
1999	73.07	4485.22	26.01	1.00	8.16	484.27	0.53	823.03	3.39	395.91	1.47	0.14	7.49
(127)	(44.25)	(4000.00)	(22.77)	(0.98)	(5.00)	(87.19)	(0.26)	(372.18)	(3.00)	(325.00)	(1.27)	(0.02)	(7.52)
2000	62.68	5238.47	22.12	1.00	9.21	163.57	0.51	943.37	3.34	250.79	0.81	0.29	8.09
(131)	(36.73)	(4750.00)	(19.03)	(0.98)	(6.00)	(106.24)	(0.25)	(457.64)	(3.00)	(232.00)	(0.64)	(0.09)	(8.14)
2001	22.65	7344.79	21.83	0.93	12.43	191.79	1.02	752.79	3.43	299.29	0.87	0.05	5.40
(7)	(23.44)	(7000.00)	(21.05)	(0.84)	(5.00)	(83.32)	(0.33)	(366.94)	(3.00)	(206.00)	(0.55)	(0.03)	(4.82)
2002	5.62	7383.37	30.24	0.92	16.08	254.20	2.13	369.89	5.50	272.08	0.61	0.10	3.91
(12)	(1.32)	(5198.00)	(28.67)	(0.91)	(9.50)	(96.92)	(0.84)	(280.39)	(4.00)	(272.00)	(0.51)	(0.03)	(3.64)
2003	16.07	6945.88	30.80	0.96	16.06	175.06	0.86	440.33	3.56	357.81	0.82	0.04	3.48
(16)	(16.02)	(5000.00)	(27.92)	(0.98)	(7.00)	(124.14)	(0.21)	(327.44)	(3.50)	(387.50)	(0.59)	(0.03)	(3.33)
2004	12.37	6617.72	32.11	0.79	14.81	165.25	1.12	320.57	3.59	298.05	0.70	0.20	3.59
(59)	(4.70)	(5500.00)	(28.85)	(0.84)	(8.00)	(89.62)	(0.18)	(222.54)	(4.00)	(287.00)	(0.52)	(0.04)	(3.40)
2005	13.94	5820.12	41.26	0.95	16.40	207.37	1.14	310.96	3.73	334.25	0.72	0.22	3.05
(40)	(14.21)	(5083.36)	(30.88)	(0.91)	(10.00)	(106.40)	(0.55)	(270.75)	(4.00)	(316.50)	(0.51)	(0.03)	(3.06)
2006	13.26	7566.02	30.56	0.89	15.07	227.77	0.92	441.71	4.27	365.85	0.99	0.09	3.67
(41)	(9.70)	(6599.49)	(27.67)	(0.84)	(10.00)	(135.56)	(0.29)	(335.89)	(4.00)	(317.00)	(0.74)	(0.01)	(3.09)
2007	14.16	8505.06	29.29	1.01	15.48	266.34	0.70	613.26	4.66	437.22	0.66	0.53	4.58
(49)	(7.60)	(6875.00)	(26.08)	(0.98)	(8.00)	(155.34)	(0.27)	(409.76)	(4.00)	(399.00)	(0.58)	(0.04)	(4.48)
2008-2011	13.48	10900.00	35.87	0.87	15.22	387.90	0.88	695.94	5.15	723.78	0.82	0.04	3.81
(27)	(3.85)	(7000.00)	(30.34)	(0.91)	(9.00)	(141.30)	(0.42)	(380.02)	(4.00)	(504.00)	(0.56)	(0.03)	(3.85)

Table 3: Correlation matrix of variables

This table demonstrates the correlation coefficients between independent variables. The sample consists of 862 IPO firms listed on the Nasdaq Exchange during the period 1996 to 2011. The data are collected from SDC database, CRSP database, Compustat database, I/B/E/S database, Factiva database, and Jay Ritter's IPO website (http://bear.warrington.ufl.edu/ritter/). Underpricing is measured by (Closing Price– Offer Price)/Offer Price*100-S&P 500 index return. Underwriter Reputation is measured by the ay Ritter's updated Carter-Manaster (1990) underwriter rankings, ranging from 1 (worst) to 9 (best). Gross spread is defined as the expense of IPO firm on the gross spread. Age is the age of firm in the number of years at the time of IPO. Total asset is measured by the total assets at the end of fiscal year before IPO. Employees is defined as the number of employees at IPO's firm. Market value is calculated as the product of the number of shares outstanding and closing price on the first trading day. Sale ratio is defined as the ratio of shares sold in IPO divided by the number of shares following the IPO. Number of analysts is defined as the number of analysts following the IPO firms during one year after IPO. Number of news report is measured by the number of news referring firm's name during one year after IPO. Volatility is defined as the standard deviation of daily closing return.

Variable	Underpricing (%)	Underwriter Rank	Gross Spread (in million $)	Total Asset (in million $)	Employees (in thousands)	Sale Ratio (%)	Number of Analysts	Number of News Reports	Volatility (%) (6 months after the IPO)	Volatility (%) (1 year after the IPO)
Underpricing (%)	1.0000	0.1430	0.3839	0.0778	-0.0372	-0.1628	0.2407	0.3036	0.3550	0.3283
Underwriter Rank	0.1430	1.0000	0.2649	0.0388	0.0894	-0.1482	0.3238	0.2338	0.0833	0.0571
Gross Spread (in million $)	0.3839	0.2649	1.0000	0.0499	0.1139	-0.1116	0.3246	0.2059	0.0825	0.0447
Total Asset (in million $)	0.0778	0.0388	0.0499	1.0000	0.1082	-0.0014	0.1173	0.1159	0.0490	0.0347
Employees (in thousands)	-0.0372	0.0894	0.1139	0.1082	1.0000	0.0969	0.1168	0.0059	-0.1933	-0.2143
Sale Ratio (%)	-0.1628	-0.1482	-0.1116	-0.0014	0.0969	1.0000	-0.0759	-0.1244	-0.2870	-0.2850
Number of Analysts	0.2407	0.3238	0.3246	0.1173	0.1168	-0.0759	1.0000	0.5754	-0.0017	-0.0138
Number of News Reports	0.3036	0.2338	0.2059	0.1159	0.0059	-0.1244	0.5754	1.0000	0.0774	0.0824
Volatility (%) (6 months after the IPO)	0.3550	0.0833	0.0825	0.0490	-0.1933	-0.2870	-0.0017	0.0774	1.0000	0.8880
Volatility (%) (1 year after the IPO)	0.3283	0.0571	0.0447	0.0347	-0.2143	-0.2850	-0.0138	0.0824	0.8880	1.0000

Table 4: The impact of underpricing on aftermarket liquidity

This table reports the estimates of regressions of aftermarket liquidity on underpricing of IPOs. The sample consists of 862 IPO stocks listed on Nasdaq Exchange from the year of 1996 to 2011. The data are collected from SDC database, CRSP database, Compustat database, I/B/E/S database, Factiva database, and Jay Ritter IPO website. (http://bear.warrington.ufl.edu/ritter/). Dependent variables are turnover and Amihud illiquidity. There are six test windows for each regression model. Underpricing is defined as (Closing Price– Offer Price)/Offer Price*100-S&P 500 index return. Underwriter Reputation is measured by the ay Ritter's updated Carter-Manaster (1990) underwriter rankings. VC-backed is a dummy, which equals 1 for IPOs backed by venture capital and 0 otherwise. Log Asset is natural log total assets of IPO firm. High-Tech is a dummy, which equals 1 for IPOs belonging to High-Technology Industry based on SIC (2833, 2834, 2835, 2836, 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7377, 7378, 7379), and 0 otherwise. Sale Ratio is defined as the ratio of shares sold in IPO divided by the number of shares following the IPO. Volatility is defined as the standard deviation of daily closing return. T-statistics are reported in parentheses. "*", "**", and "***" represent statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Dependent variable= Turnover

Independent Variables	1 Week after IPO	1 Month after IPO	3 Months after IPO	6 Months after IPO	9 Months after IPO	1 Year after IPO
Underpricing	0.026***	0.003**	0.003**	0.003***	0.003***	0.003***
	(4.08)	(2.53)	(2.28)	(2.86)	(3.23)	(3.90)
Underwriter Reputation	0.161	-0.005	0.007	0.004	0.012	0.015
	(1.22)	(-0.18)	(0.41)	(0.24)	(0.83)	(1.03)
VC-Backed Dummy	-0.186	-0.208**	-0.091	-0.067	-0.031	0.009
	(-0.42)	(-2.16)	(-1.21)	(-1.03)	(-0.54)	(0.15)
Log Assets	0.073	0.002	0.039	0.076*	0.094**	0.100***
	(0.39)	(0.07)	(0.99)	(1.83)	(2.57)	(2.92)
High-Tech Dummy	0.901**	0.116	0.141**	0.175***	0.181***	0.181***
	(2.01)	(1.32)	(2.20)	(3.01)	(3.30)	(3.02)
Volatility	0.528***	0.221***	0.189***	0.143***	0.136***	0.113***
	(7.92)	(7.22)	(7.60)	(8.50)	(8.16)	(7.00)
Sale Ratio	0.229***	0.034***	0.030***	0.023***	0.019***	0.016***
	(8.26)	(8.73)	(7.49)	(5.82)	(5.57)	(5.23)
Intercept	-5.270***	-0.946***	-1.345***	-1.199***	-1.173***	-1.029***
	(-3.01)	(-3.29)	(-4.36)	(-3.72)	(-4.11)	(-3.92)
Observations	862	862	862	862	862	862
Adj. R^2	0.495	0.403	0.396	0.349	0.328	0.273

Panel B: Dependent variable= Amihud Illiquidity

Independent Variables	1 Week after IPO	1 Month after IPO	3 Months after IPO	6 Months after IPO	9 Months after IPO	1 Year after IPO
Underpricing	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***	-0.002***
	(-4.77)	(-5.19)	(-3.41)	(-3.23)	(-3.97)	(-3.50)
Underwriter Reputation	-0.004***	-0.015*	-0.028**	-0.057	-0.066*	-0.087*
	(-2.70)	(-1.92)	(-2.06)	(-1.57)	(-1.79)	(-1.95)
VC-Backed Dummy	-0.004	0.015	0.034	-0.010	-0.011	0.007
	(-1.43)	(1.34)	(1.12)	(-0.22)	(-0.22)	(0.11)
Log Assets	-0.009***	-0.024***	-0.088***	-0.123**	-0.147***	-0.192***
	(-3.64)	(-4.58)	(-3.75)	(-2.19)	(-2.63)	(-2.92)
High-Tech Dummy	-0.005	0.007	0.018	-0.038	-0.131*	-0.354***
	(-0.81)	(0.68)	(0.60)	(-0.59)	(-1.81)	(-3.18)
Volatility	0.000	-0.003***	-0.011***	0.006	0.022	0.097***
	(0.96)	(-2.71)	(-3.05)	(0.42)	(1.46)	(3.12)
Sale Ratio	0.000	-0.000*	-0.000	0.001	0.002	0.004
	(0.50)	(-1.79)	(-0.60)	(0.69)	(0.96)	(1.34)
Intercept	0.088***	0.291***	0.822***	1.256***	1.428***	1.607***
	(4.38)	(5.22)	(6.71)	(7.30)	(6.68)	(4.75)
Observations	862	862	862	862	862	862
Adj. R^2	0.046	0.097	0.050	0.065	0.099	0.113

Table 5: The impact of underpricing on analyst coverage and on news reports

This table reports the estimates of regressions of information generation after IPO on underpricing. The sample consists of 862 IPO stocks listed on Nasdaq Exchange from the year of 1996 to 2011. The data are collected from SDC database, CRSP database, Compustat database, I/B/E/S database, Factiva database, and Jay Ritter IPO website. (http://bear.warrington.ufl.edu/ritter/). Dependent variables are the number of analysts following IPO during one year after issue date, and number of news referring firm's name during one year after issue date. Underpricing is defined as (Closing Price–Offer Price)/Offer Price*100-S&P 500 index return. Number of Managers is defined as the sum number of lead manages and co-managers for IPO. VC-backed is a dummy, which equals 1 for IPOs backed by venture capital and 0 otherwise. Log Asset is natural log total assets of IPO firm. Number of IPOs is defined as the number of IPOs occurring at the same year when that firm goes public. Gross spread is defined as the amount of gross spread (million $). Web news popular is a dummy, which equals 1 for IPOs after the year of 2007 and 0 otherwise. T-statistics are reported in parentheses. "*", "**", and "***" represent statistical significance at 10%, 5%, and 1% level, respectively.

Dependent Variable	Number of Analysts	Number of News Reports
Independent Variables		
Underpricing	0.005***	1.361***
	(4.92)	(9.16)
Number of Managers	0.451***	26.105***
	(9.42)	(3.71)
VC-Backed Dummy	0.417***	74.565***
	(3.41)	(4.18)
Log Assets	0.307***	52.799***
	(4.42)	(5.59)
Number of IPOs	-0.007***	-0.908***
	(-5.53)	(-4.63)
Gross Spread	1.038***	
	(4.62)	
Web News Popular Dummy		165.187***
		(4.06)
Intercept	0.527	-38.413
	(1.41)	(-0.71)
Observations	862	862
Adj. R^2	0.354	0.282

Table 6: The impact of analyst coverage on aftermarket liquidity

This table reports the estimates of regressions of aftermarket liquidity on analyst coverage of IPOs. The sample consists of 862 IPO stocks listed on Nasdaq Exchange from the year of 1996 to 2011. The data are collected from SDC database, CRSP database, Compustat database, I/B/E/S database, Factiva database, and Jay Ritter IPO website. (http://bear.warrington.ufl.edu/ritter/). Dependent variables are turnover and Amihud illiquidity. There are two test windows for each regression model (6 months and 1 year after IPO). Number of news is defined as the number of analysts following IPO during one year after issue date. Underwriter Reputation is measured by the ay Ritter's updated Carter-Manaster (1990) underwriter rankings. Log Employees is defined as natural log on number of employees in firm. High-Tech is a dummy, which equals 1 for IPOs belonging to High-Technology Industry based on SIC (2833, 2834, 2835, 2836, 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7377, 7378, 7379), and 0 otherwise. Sale Ratio is defined as the ratio of shares sold in IPO divided by the number of shares following the IPO. Volatility is defined as the standard deviation of daily closing return. T-statistics are reported in parentheses. "*", "**", and "***" represent statistical significance at 10%, 5%, and 1% level, respectively.

Dependent Variable	Turnover		Amihud Illiquidity	
Independent Variables	6 Months after IPO	1 Year after IPO	6 Months after IPO	1 Year after IPO
Number of Analysts	0.110***	0.141***	-0.060***	-0.093***
	(9.22)	(12.51)	(-5.84)	(-6.40)
Underwriter Reputation	-0.017	-0.006	-0.059**	-0.088**
	(-1.13)	(-0.43)	(-2.00)	(-2.25)
Log Employees	0.000	-0.004	-0.048	-0.095**
	(0.00)	(-0.19)	(-1.51)	(-2.09)
High-Tech Dummy	0.075	0.087	-0.008	-0.313***
	(1.21)	(1.50)	(-0.14)	(-2.74)
Volatility	0.158***	0.135***	-0.007	0.076***
	(14.36)	(12.54)	(-0.49)	(2.70)
Sale Ratio	0.021***	0.015***	0.001	0.005
	(15.79)	(11.48)	(1.00)	(1.62)
Intercept	-1.036***	-0.870***	1.227***	1.646***
	(-5.88)	(-5.13)	(7.35)	(5.13)
Observations	862	862	862	862
Adj. R^2	0.351	0.326	0.069	0.114

Table 7: The impact of news reports on aftermarket liquidity

This table reports the estimates of regressions of aftermarket liquidity on news reports of IPOs. The sample consists of 862 IPO stocks listed on Nasdaq Exchange from the year of 1996 to 2011. The data are collected from SDC database, CRSP database, Compustat database, I/B/E/S database, Factiva database, and Jay Ritter IPO website. (http://bear.warrington.ufl.edu/ritter/). Dependent variables are turnover and Amihud illiquidity. There are two test windows for each regression model (6 months and 1 year after IPO). Number of news is defined as number of news referring firm's name during one year after issue date divided by 1000. Underwriter Reputation is measured by the ay Ritter's updated Carter-Manaster (1990) underwriter rankings. Log Employees is defined as natural log on number of employees in firm. High-Tech is a dummy, which equals 1 for IPOs belonging to High-Technology Industry based on SIC (2833, 2834, 2835, 2836, 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7377, 7378, 7379), and 0 otherwise. Sale Ratio is defined as the ratio of shares sold in IPO divided by the number of shares following the IPO. Volatility is defined as the standard deviation of daily closing return. T-statistics are reported in parentheses. "*", "**", and "***" represent statistical significance at 10%, 5%, and 1% level, respectively.

Dependent Variable	Turnover		Amihud Illiquidity	
Independent Variables	6 Months after IPO	1 Year after IPO	6 Months after IPO	1 Year after IPO
Number of News Reports	1.104***	1.172***	-0.244***	-0.377***
	(4.70)	(7.69)	(-4.04)	(-4.14)
Underwriter Reputation	-0.019	-0.001	-0.070**	-0.105***
	(-1.45)	(-0.04)	(-2.27)	(-2.59)
Log Employees	0.026*	0.033**	-0.070**	-0.129***
	(1.66)	(2.13)	(-2.25)	(-2.86)
High-Tech Dummy	0.083*	0.116**	-0.038	-0.360***
	(1.83)	(2.39)	(-0.66)	(-3.09)
Volatility	0.150***	0.125***	-0.004	0.081***
	(10.16)	(9.00)	(-0.26)	(2.84)
Sale Ratio	0.022***	0.015***	0.001	0.005*
	(7.19)	(6.16)	(1.06)	(1.66)
Intercept	-1.030***	-0.878***	1.272***	1.712***
	(-4.78)	(-4.57)	(7.34)	(5.23)
Observations	862	862	862	862
Adj. R^2	0.426	0.385	0.054	0.098

Figure 1: Average Weekly Turnover of IPO stocks

This figure shows the average weekly turnover for hot, moderate, and cold IPOs over the 52 trading weeks (one year) after IPO. The sample consists of 862 IPO stocks listed on Nasdaq Exchange from the year of 1996 to 2011. We divide the IPOs into three groups (hot, moderate, and cold IPOs) according to the level of underpricing. Thus, three groups have approximately the same number of IPOs. The hot IPO group includes 287 IPOs. The moderate IPO group includes 287 IPOs. The cold IPO group includes 288 IPOs. Then, the average weekly turnover is calculated by averaging continuous 5 trading days' daily turnover, measured by trading volume divided by corresponding shares outstanding. Then the averages for each of the three groups of IPOs are calculated for each trading week.

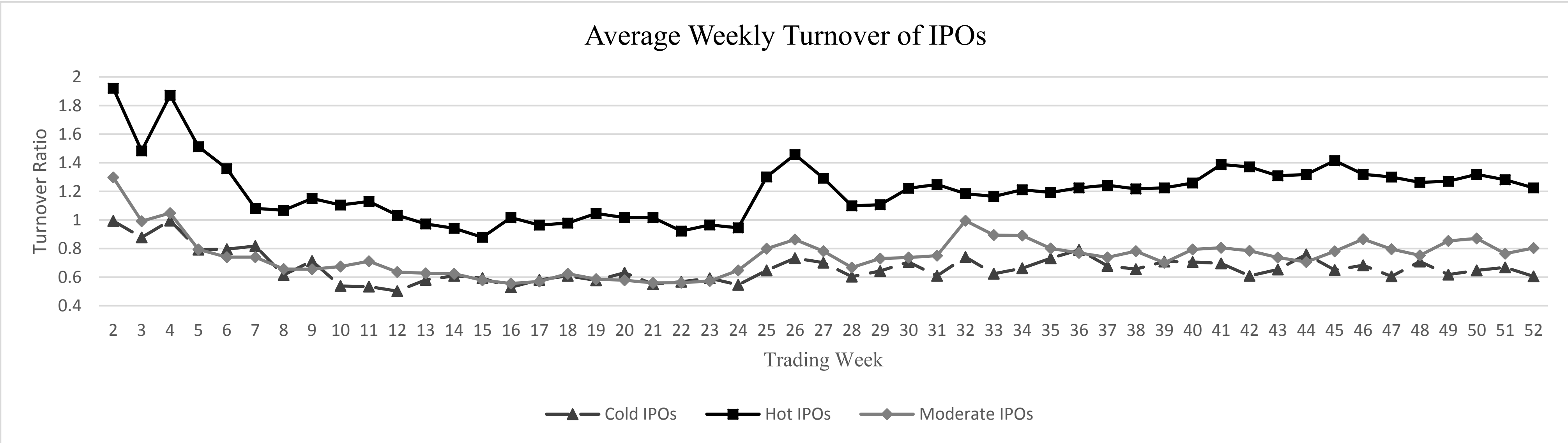

Figure 2: Average Weekly Amihud Illiquidity of IPO stocks

This figure shows the average weekly Amihud illiquidity for hot, moderate, and cold IPOs over the 52 trading weeks (one year) after IPO. The sample consists of 862 IPO stocks listed on Nasdaq Exchange from the year of 1996 to 2011. We divide the IPOs into three groups (hot, moderate, and cold IPOs) according to the level of underpricing. Thus, three groups have approximately the same number of IPOs. The hot IPO group includes 287 IPOs. The moderate IPO group includes 287 IPOs. The cold IPO group includes 288 IPOs. Then, the average weekly Amihud illiquidity is calculated by averaging continuous 5 trading days' daily Amihud Illiquidity measured by $|Daily\ Return|$ divided the product of trading volume and closing price. Then the averages for each of the three groups of IPOs are calculated for each trading week.

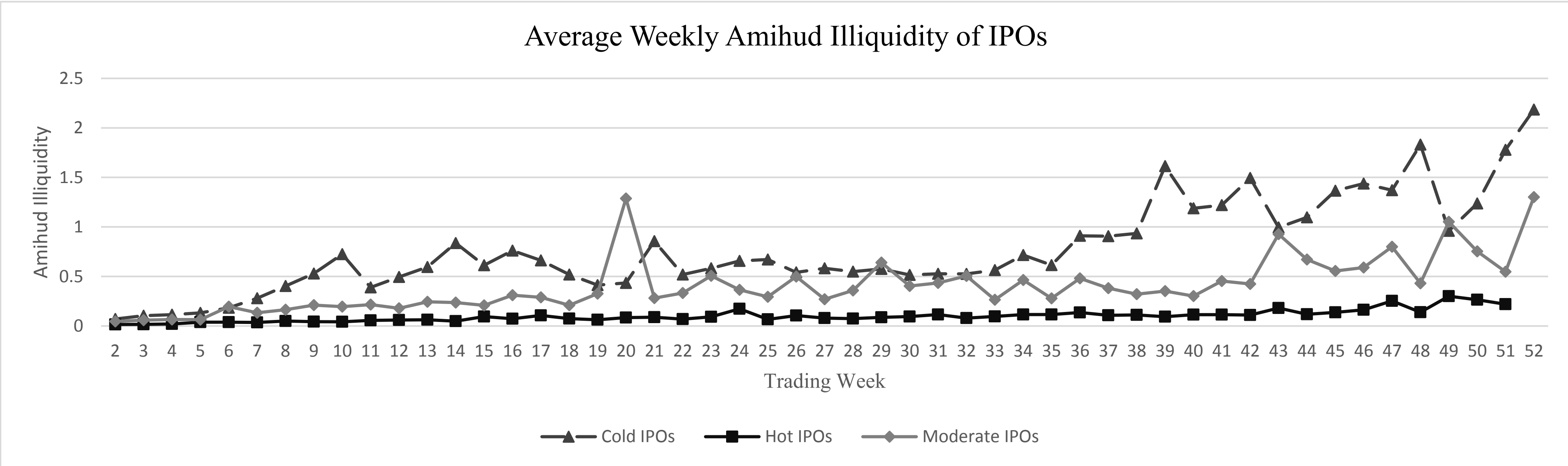

Table 8: The aftermarket liquidity of IPOs

This table presents the aftermarket liquidity of hot, moderate, and cold IPOs over the 52 trading weeks (one year) after IPO. The sample consists of 862 IPO stocks listed on Nasdaq Exchange during the period 1996 to 2011. We divide the IPOs into three groups (hot, moderate, and cold IPOs) according to the level of underpricing. Thus, three groups have approximately the same number of IPOs. The hot IPO group includes 287 IPOs. The moderate IPO group includes 287 IPOs. The cold IPO group includes 288 IPOs. Next, the average weekly turnover is calculated by averaging continuous 5 trading days' daily turnover, measured by trading volume divided by corresponding shares outstanding. The average weekly Amihud illiquidity is calculated by averaging continuous 5 trading days' daily Amihud illiquidity measured by $|Daily\ Return|$ divided the product of trading volume and closing price. Then, the averages for each of the three sub-samples of IPOs are calculated for each trading week. T-test is implemented to examine the difference of means in two sub-samples, and t-statistics are reported in corresponding parentheses. Non-parametric test is implanted to examine the difference of median in two sub-samples, and z-statistics are reported in corresponding parentheses. "*", "**", and "***" represent statistical significance at 10%, 5%, and 1% level, respectively.

Dependent Variable	Statistics	Hot IPOs	Moderate IPOs	Cold IPOs	Hot IPOs - Cold IPOs	Hot IPOs - Moderate IPOs	Moderate IPOs - Cold IPOs
Turnover Ratio	Mean	1.3913	0.8718	0.7549	0.6364***	0.5195**	0.1169
					(3.14)	(2.36)	(0.77)
	Median	1.2229	0.7450	0.6488	0.5742***	0.4780***	0.0962***
					(8.98)	(8.20)	(3.12)
Amihud Illiquidity	Mean	0.0971	0.4018	0.7657	-0.6685***	-0.3047***	-0.3639***
					(-10.01)	(-7.62)	(-4.73)
	Median	0.0901	0.3298	0.6138	-0.5238***	-0.2397***	-0.2840***
					(-8.20)	(-7.81)	(-5.46)

Table 9: The impact of underpricing on aftermarket liquidity (excluding IPOs after 2007)

This table reports the estimates of regressions of aftermarket liquidity on underpricing of IPOs. The sample consists of 785 IPO stocks listed on Nasdaq Exchange from the year of 1996 to 2006. The data are collected from SDC database, CRSP database, Compustat database, I/B/E/S database, Factiva database, and Jay Ritter IPO website. (http://bear.warrington.ufl.edu/ritter/). Dependent variables are turnover and Amihud illiquidity. There are three test windows for each regression model (1 month, 6 months, and 1 year after IPO). Underpricing is defined as (Closing Price– Offer Price)/Offer Price*100-S&P 500 index return. Underwriter Reputation is measured by the ay Ritter's updated Carter-Manaster (1990) underwriter rankings. VC-backed is a dummy, which equals 1 for IPOs backed by venture capital and 0 otherwise. Log Asset is natural log total assets of IPO firm. High-Tech is a dummy, which equals 1 for IPOs belonging to High-Technology Industry based on SIC (2833, 2834, 2835, 2836, 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7377, 7378, 7379), and 0 otherwise. Sale Ratio is defined as the ratio of shares sold in IPO divided by the number of shares following the IPO. Volatility is defined as the standard deviation of daily closing return. T-statistics are reported in parentheses. "*", "**", and "***" represent statistical significance at 10%, 5%, and 1% level, respectively.

	Turnover			Amihud Illiquidity		
Independent Variables	1 Month after IPO	6 Months after IPO	1 Year after IPO	1 Month after IPO	6 Months after IPO	1 Year after IPO
Underpricing	0.003**	0.003***	0.003***	-0.000***	-0.001***	-0.002***
	(2.38)	(2.99)	(3.85)	(-4.84)	(-3.04)	(-3.61)
Underwriter Reputation	0.006	0.014	0.025*	-0.015*	-0.059	-0.099**
	(0.21)	(0.95)	(1.70)	(-1.94)	(-1.55)	(-2.19)
VC-Backed Dummy	-0.186*	-0.081	0.009	0.016	-0.012	-0.016
	(-1.82)	(-1.26)	(0.15)	(1.30)	(-0.24)	(-0.21)
Log Assets	0.004	0.036	0.076***	-0.024***	-0.122**	-0.193***
	(0.11)	(1.31)	(2.70)	(-4.25)	(-2.00)	(-2.71)
High-Tech Dummy	0.134	0.189***	0.204***	0.009	-0.046	-0.404***
	(1.41)	(3.39)	(3.31)	(0.84)	(-0.65)	(-3.28)
Volatility	0.220***	0.140***	0.110***	-0.003***	0.006	0.085***
	(6.92)	(8.02)	(6.65)	(-2.82)	(0.36)	(3.14)
Sale Ratio	0.036***	0.023***	0.016***	-0.000**	0.001	0.003
	(8.67)	(5.96)	(5.22)	(-1.98)	(0.56)	(1.04)
Intercept	-1.088***	-1.081***	-0.992***	0.297***	1.281***	1.803***
	(-3.62)	(-4.15)	(-4.17)	(5.20)	(7.02)	(5.52)
Observations	785	785	785	785	785	785
Adj. R^2	0.400	0.361	0.276	0.096	0.062	0.140

Table 10: The Two-stage regression results: The impact of news reports on aftermarket liquidity

This table reports the estimates of regressions using two stage method and OLS of aftermarket liquidity on information generation. The sample consists of 862 IPO stocks listed on Nasdaq exchange from the year of 1996 to 2011. The data are collected from SDC database, CRSP database, Compustat database, I/B/E/S database, Factiva database, and Jay Ritter IPO website. (http://bear.warrington.ufl.edu/ritter/). Dependent variables are turnover and Amihud illiquidity. Only one test window (one year after IPO) is examined. At first stage, the number of analysts and number of news reports are estimated as endogenous variables. Number of analysts is defined as the number of analysts following IPO during one year after issue date, and number of news referring firm's name during one year after issue date. Number of news is defined as number of news referring firm's name during one year after issue date divided by 1000. At the second stage, the aftermarket liquidity is regressed on the fitted value of number of analysts and number of news reports. Underwriter Reputation is measured by the ay Ritter's updated Carter-Manaster (1990) underwriter rankings. Log Employees is defined as natural log on number of employees in firm. High-Tech is a dummy, which equals 1 for IPOs belonging to High-Technology Industry based on SIC (2833, 2834, 2835, 2836, 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7377, 7378, 7379), and 0 otherwise. Sale Ratio is defined as the ratio of shares sold in IPO divided by the number of shares following the IPO. Volatility is defined as the standard deviation of daily closing return. Column (1), (3), (5), (7) presents the estimates of regressions using OLS Method; column (2), (4), (6), (8) presents the estimates of regressions using Two-Stage Method. T-statistics are reported in parentheses. "*", "**", and "***" represent statistical significance at 10%, 5%, and 1% level, respectively.

Dependent Variable	Turnover	Turnover	Turnover	Turnover	Amihud Illiquidity	Amihud Illiquidity	Amihud Illiquidity	Amihud Illiquidity
Independent Variables	Column (1)	Column (2)	Column (3)	Column (4)	Column (5)	Column (6)	Column (7)	Column (8)
Number of Analysts	0.141***	0.174***			-0.093***	-0.215***		
	(12.51)	(7.50)			(-6.40)	(-5.28)		
Number of News Repots			1.172***	1.358***			-0.377***	-1.447***
			(7.69)	(8.63)			(-4.14)	(-4.84)
Underwriter Reputation	-0.006	-0.018	-0.001	-0.009	-0.088**	-0.050*	-0.105***	-0.069**
	(-0.43)	(-1.12)	(-0.04)	(-0.6)	(-2.25)	(-1.81)	(-2.59)	(-2.55)
Log Employees	-0.004	-0.019	0.033**	0.028	-0.095**	-0.040	-0.129***	-0.104***
	(-0.19)	(-0.86)	(2.13)	(1.46)	(-2.09)	(-1.01)	(-2.86)	(-2.85)
High-Tech	0.087	0.055	0.116**	0.092*	-0.313***	-0.224**	-0.360***	-0.285***
	(1.50)	(0.3612)	(2.39)	(1.65)	(-2.74)	(-2.11)	(-3.09)	(-2.7)
Volatility	0.135***	0.136***	0.125***	0.124***	0.076***	0.071***	0.081***	0.086***
	(12.54)	(12.57)	(9.00)	(12.01)	(2.70)	(3.74)	(2.84)	(4.4)
Sale Ratio	0.015***	0.014***	0.015***	0.015***	0.005	0.004*	0.005*	0.004*
	(11.48)	(11.05)	(6.16)	(11.80)	(1.62)	(1.73)	(1.66)	(1.72)
Intercept	-0.870***	-0.0804***	-0.878***	-0.804***	1.646***	1.521***	1.712***	1.555***
	(-5.13)	(-4.67)	(-4.57)	(-4.93)	(5.13)	(5.02)	(5.23)	(5.02)
Observations	862	862	862	862	862	862	862	862
Adj. R^2	0.326	0.255	0.385	0.283	0.114	0.115	0.098	0.107