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Two Essays on Individuals, Information, and Asset Prices

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Two Essays on Individuals, Information and Asset Prices

by

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Dedication

To my family (Vicki, Justin, Mandi, Michele, and Mom) without whose unwavering support, inspiration, tireless ears and dedication to education this would never have happened.

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This dissertation has benefitted from comments of my committee, Jessica Rutherford, seminar participants at MFA 2013, EFA 2013, FMA 2013, and the University of Central Florida. All errors are mine.

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Abstract

In the first essay we explore and establish a direct link between investor attention to advertising videos viewed on social media, and trading activity in a firm's securities. We find a positive relation between views of these advertising videos and volume, and a negative relationship between views and bid-ask spread. Returns are positively related to change in views. The positive price pressure is reversed over the following two weeks. The decreases in spread and temporary increase in returns are consistent with increased purchasing by individual investors who view the advertising videos. Our results support the hypothesis that the number of views (attention) is more important than advertising dollars. Views are tested concurrently with Google Abnormal Search Volume Index (ASVI), and the empirical results suggest that views and ASVI provide measures of attention for different investor groups. Our results also suggest that the link of ASVI to individual investors may be diminished in more recent periods.

In the second essay, using a unique data set provided by the Texas Comptroller of Public Accounts along with Dallas County, Texas Appraisal District files and Multiple Listing Service (MLS) sales, we examine whether residential properties sold through a multiple listing service sell at similar prices compared to properties that do not sell through a multiple listing service after controlling for Grantor (seller) type. We find a 1.8% premium for properties sold through a MLS by individuals after controlling for different grantor types. Our results indicate that only individuals receive this premium.

Viral Volume: Social Media's Impact on Stock Price Dynamics

1. Introduction

Merton (1987) suggests that "the process of inducing investors, who are not currently shareholders, to follow the firm's securities is not unlike that used to market the firm's products." This paper uses a novel database of views of seeded advertising videos to explore the impact of investor attention to advertising on the share price, trading volume and bid-ask spread of a firm's stock. Seeded advertising refers to the process of placing a video on pertinent internet sites. This placement is the "seed" which then spreads from user to user, relying on these users to transport it to different video sharing platforms which include direct email and social media outlets such as Facebook. Online video advertising provides firms with an outlet to provide content to a consumer that has both entertainment value and a controlled message about a firm and its products. Views of these videos leave a footprint which can be tracked and counted. In our sample, the total measured views of seeded advertising videos during the first week of July 2009 were 5.6 million. In three years that weekly number had grown over 5 times to more than 28.3 million by June 2012.

Previous research related to advertising and stock price dynamics has focused on the reported advertising expense in a firm's financial statements. Chemmanur and Yan (2012) find a positive relation between advertising expense and IPO valuation; Chemmanur and Yan (2011) find a short term positive relation between reported advertising expenditures and stock returns.

Grullon, Kanatas and Weston (2004) find evidence that firms that spend more on advertising have more small stockholders, more institutional stockholders and better market liquidity for their stock.

The link between a firm's advertising expense and investor attention to the advertising message is difficult to measure directly. Another strand of literature focuses on investor attention to firms in a more general sense. Barber and Odean (2008) suggest that retail and institutional investors differ in their attention to specific firms. Institutional investors consistently pay attention to a broad range of long and short investing opportunities available to them. The same is not necessarily true for individuals, who may vary in their attention to alternative investment opportunities, and are more likely to pursue only long investment strategies. Consistent with this, Barber and Odean (2008) find that retail investors are net buyers of stocks on high-attention days for those stocks, and find that several indirect proxies for individual investor attention are related to temporary positive price pressure. Engelberg and Parsons (2011) find that local media coverage predicts local trading. Using internet based information, Da, Engelberg and Gao (2011) have proposed a direct measure of investor attention: Google search volume. Their analysis finds increases in trades by individual investors, and positive price pressure for two weeks following abnormal search volume. This positive price pressure was reversed within one year.

Fang and Peress (2009) examine longer term returns and find that firms with high media attention have lower returns than stocks with no media attention. This result is consistent with the hypothesis that media attention is negatively related to the liquidity premium, and the hypothesis that stocks with lower investor recognition need to offer higher returns in order to induce investors to buy them.

For the most part, the studies related to investor attention are not able to identify exactly what message or content investors are actually viewing. Engleberg, Sasseville, and Williams (2012) provide the most direct analysis in this area, showing that a buy recommendation of a stock on Jim Cramer's *Mad Money* is followed by large overnight returns that are reversed over the following months. This relationship is strongest when daily Neilsen ratings show high levels of views by higher income individuals.

Using social media views of seeded advertising videos to measure attention complements the existing literature related to advertising, individual investor attention, and stock price dynamics in that it closes the gap between firms' controlled advertising messages and investor attention to those messages. Tracking the number of views for each seeded advertising video indicates exactly how many times that a particular message, or a derivation of it, has been watched. In this study, we group these views by firm week and examine their relation to measures of trading volume, liquidity and returns.

We hypothesize that the relation between views of seeded advertising videos and return dynamics is the result of increased trading by individual investors. Compared to institutional investors, individual investors are more likely to have increased awareness of a firm as a possible investment alternative as a result of viewing advertising media; or possibly to perceive the information provided in seeded advertising videos as value relevant. We find after controlling for idiosyncratic volatility, price responsiveness (illiquidity), share turnover, market capitalization, marketplace trading volume and volatility, earnings announcements and dispersion of analyst forecasts, that the level of views of a firm's advertising videos are significantly positively related to abnormal weekly trading volume.

Glosten and Milgrom (1985) suggest that in a specialist market, bid ask spreads widen when the probability of trading against more informed investors increases. If more individual investors become active traders in firm's stock as a result of exposure to advertising videos, specialists are expected to reduce bid ask spreads as their adverse selection problem decreases. Therefore, we hypothesize that the increase in volume due to individual investor activity will result in a decrease in bid-ask spread. Consistent with this prediction, the empirical analysis shows that the bid-ask spread is negatively related to the level and the change in social media based views.

We also examine the relation between views of seeded advertising videos and stock returns. The change in views is positively related to contemporaneous stock returns. This upward price pressure is then reversed over the subsequent two-week period,

In terms of attention to firms via internet based media, the closest measure to ours is the Da, Engelberg and Gao (2011) abnormal search volume index (ASVI). ASVI measures search activity initiated by users on Google. An individual searching Google for information related to a particular firm must be paying attention to that firm. It is possible that views of seeded advertising videos are related to Google ASVI in a way that would make it difficult to interpret our empirical results. Therefore, we test for contemporaneous and lagged relations between these two variables. We find no relation between ASVI and views when considering contemporaneous or lagged measures. Our tests suggest that ASVI and views measure the activities of different investing clienteles.

We also compare the impact of ASVI on our sample companies in the time period of our study to the earlier time period under study by Da, Engleberg and Gao. While we do not replicate the data used in their earlier study, we do find evidence consistent with their findings.

However, in our later sample the ASVI measure appears to be less correlated with the activity of individual investors than in the time period in their paper. This may be the result of the inclusion of ASVI in high-frequency trading algorithms during our more recent sample period.

The paper is organized as follows: Section 2 reviews the related literature. Section 3 provides a detailed description of the data, Section 4 contains a discussion of our empirical results and Section 5 concludes.

2. Related Research

Merton (1987) developed a model of capital market equilibrium that incorporates the limited ability of investors to recognize stocks. He predicted that firms that are unfamiliar to investors will have higher expected stock market returns and lower liquidity. High visibility firms by contrast would have lower expected returns and higher liquidity. Advertising is one way that firms can become more visible and familiar to individual investors.

The literature linking advertising and stock price dynamics has primarily focused on reported advertising expenditures. Grullon, Kanatas and Weston (2004) find that breadth of ownership, trading volume and liquidity are positively related to a firm's advertising expenditures. The greater visibility and familiarity associated with advertising causes both individual investors and institutional investors to hold more stock of firms that advertise more. Notably, they find that effect is more dramatic for the individual investors than it is for institutional investors. Higher advertising expenditures are also associated with increased liquidity in the form of a narrower bid-ask spread, smaller price impacts, and greater depth. Grullon et al (2004) conclude that the change in ownership structure and increase in liquidity should also increase firm value. The findings of Grullon, et al (2004) are consistent with Glosten and Milgrom (1985) and their suggestion that market-makers set a narrower bid-ask spread in the presence of the less informed individual investors, because the market maker's expected adverse selection costs are lower when more uninformed traders trade.

Chemmanur and Yan (2012) find that advertising around a firm's IPO results in higher IPO valuation and lower subsequent stock returns which suggests that advertising has a positive short-term share price impact. Further, Chemmanur and Yan (2011) find that increases in advertising expenditures are positively related to price in the advertising year. Their analysis uses trading volume and analyst coverage as proxies for investor attention. The results show that for firms with higher advertising expenditures, the short term positive price pressure is stronger if the firm also experiences higher attention in the advertising year. Long term price reversals are positively related to proxies for arbitrage costs.

The content of advertising messages in general is not expected to contain value relevant new information. However, to investors who may have previously been unaware of a particular product line, brand, or firm, advertising content may appear to be news. In the information age, opportunities for the individual investors to misinterpret information or to respond too slowly to new information are increasing. Kim and Verrecchia (1991) propose that new information will be interpreted differently in the marketplace, with those investors with less private information weighting a new market signal more heavily than those having private information. Therefore, a differential belief revision can generate trading with new information. Consistent with this, Giannini and Irvine (2012) use Twitter posts to measure individual differences of opinion and find that when dispersion of opinion increases following an earnings announcement, abnormal returns are positive and post-announcement abnormal volume is higher.

Building on the ideas of Beaver (1968), Kim and Verrecchia (1991) posit that price changes average out the differences in beliefs of traders; while the use of volume in conjunction with returns could be used to identify systematic differences in investor knowledge. Kim and Verrecchia (1994) explore the relationship of volume around price and earnings announcements and propose that information asymmetry can actually *increase* around announcements as better informed traders make better decisions with new information and other traders protect themselves.

However, new information and advertising messages about a particular firm must have investors' attention in order for them to respond by trading. And, there is evidence that individual investors who are likely to be less informed differ from the more informed institutional investors in their response to attention-grabbing stocks. Barber and Odean's (2008) analysis focuses on attention in a general sense; and argues that trading of individuals on high attention days differs significantly from trades of institutional investors. First, paying attention to possible investments, long or short, is what institutional investors do. Their attention is not divided or limited by other work obligations. Institutional investors also have access to technology and databases that allow automated analyses which individuals often cannot replicate. Additionally, institutions hold relatively large portfolios, and therefore they have a larger inventory from which to sell holdings; so even if they do not actively short, institutions have more choices when selling. Individual investors, on the other hand, often have more sporadic attention to investing, they have fewer resources to use in their analysis, and they hold relatively small portfolios. Portfolio size is important, because individuals typically only sell stocks that they already hold in their portfolios; they rarely sell short. Therefore, individual investors are expected to be net buyers of attention grabbing stocks: contrarians will buy stocks with poor recent performance that capture their attention, while momentum investors will buy stocks that have had positive returns around the time that they attract attention. Consistent with these predictions, Barber and Odean (2008) find evidence that individual investors tend to be net buyers on high attention days, where attention is measured using the following proxies: abnormal trading volume, the stock's prior one day return, and news reports mentioning particular firms. Buying behavior of professional money managers was less affected by these measures of attention.

Da Engelberg, and Gao (2011) propose that the online search activity of investors can serve as a predictor of their market behavior. Using Google search volume as a measure of investor attention to specific firms, their analysis finds increases in trades by individual investors, and positive price pressure for two weeks following abnormal search volume. Da, et al find that the positive price pressure is reversed within one year. This stock price pattern is also consistent with Barber and Odean's (2008) suggestion that individual investors are more likely to be buyers of stocks than sellers; thus when individuals pay more attention to particular stocks, there is a temporary positive price effect. Da, et al (2011) also find that the temporary price increase is strongest for stocks that are traded more by individual investors. Additional analysis of IPO first day returns also indicates that individual investor attention is positively related to both IPO first day returns and longer term return reversals for the newly listed stocks.

Attention to television media has also been linked to investor attention and stock price dynamics. Engelberg, Sasseville, and Williams (2012) find that a buy recommendation of a stock on Jim Cramer's *Mad Money* is followed by overnight returns averaging 2.4%; this positive effect is reversed over the following months. The effect is partially dependent upon measures of attention: buy recommendations that are less prominent, or mentioned more briefly are associated with a smaller overnight abnormal returns. Additionally, when total viewership is higher, overnight returns are larger; and this relationship is driven by increased viewing by higher income individuals. Increased viewing by lower-income households is not related to overnight returns.

Seasholes and Wu (2007) examine attention driven trading on the Shanghai Stock Exchange. This exchange imposes limits on daily price changes; after a stock hits the limit it may continue trading, but may not exceed the limit. When a stock hits the upper price limit, it also has unusually high volume and returns, and the event generates news after the market closes. This study identifies a group of informed traders that anticipate the marketplace reaction to the "news" of an upper-price limit event. Individuals are net buyers following the price limit attention event, and tend to buy stocks that they did not previously own. This trading by individuals appears to drive prices up the day after the event. However, over the following four days, prices mean revert. The informed traders profit from buying early and selling into the abnormal individual demand that follows the upper price limit news event. This anticipation of the news allows them to buy before the event and sell after it.

Fang and Peress (2009) examine the effects of media coverage on cross sectional stock returns, and find that stocks without media coverage earn higher returns than stocks that are heavily covered, even with controls for liquidity, size, book to market, and momentum. This media effect is pronounced among small stocks and less liquid stocks, suggesting that the media effect is at least partly liquidity related. At the same time, the media effect is also strong among stocks that have low analyst coverage, high individual ownership, and high idiosyncratic volatility, suggesting that there is also an information component to the media effect on price consistent with Merton's (1987) argument that stocks with problems related to information and recognition need to offer higher returns.

Our analysis complements the existing literature related to the effects advertising and investor attention on stock price dynamics by providing analysis of a specific advertising medium in which attention to the advertising message can be directly measured. Because advertising usually does not contain value relevant news, we expect that the relation between views of advertising videos and stock trading volume, bid-ask spreads, and price will be driven by individual investors. In short, we predict a negative relation between views and bid-ask spread, and a positive relation between views of seeded advertising videos and both trading volume and returns. The positive relation between views of advertising videos and returns is predicted to be short lived. This is because the hypothesized increase in demand that stems from views of advertising videos is not associated with value relevant news, and therefore is reversed subsequently. Further, to the extent that the market views the increases in volume as persistent, then the required liquidity premium on the stock may decrease, causing a decrease in required returns.

3. Variable Construction

3.1 Measuring Investor Attention to Advertising

This analysis uses a proprietary database that tracks views of seeded advertising videos on more than one hundred separate platforms to measure investor attention to online video advertising. Over three-hundred seventy-five million unique videos are included in the database. The first chart was for the week ended July 17, 2009. The final chart used was issued for the week ended December 30, 2011. All weeks end on Sunday and the data is available on the following Thursday. The database tracks views regardless of whether they were seeded by the company, an advertising agency or placed by another user. Each time a video is viewed, a counter "tracks" the view. Those counts are recorded weekly.

As the source of this data is advertising data, this data is tracked in the database by “campaign” or program. These campaigns typically map neatly into one or two companies. These campaigns are summed by company by week for inclusion in this study. Non-public firms are eliminated. Advertising campaigns that are listed as being for more than one brand (for example: Apple and AT&T had common advertisements for the iPhone) are summed into the totals of both firms equally. Some advertising campaigns impact as many as three brands and are summed equally into the consolidated view total of each of the three different firms.

There was tremendous growth in the visibility of seeded advertising during the sample period. Mean weekly views for the sample firms are 59,378 from July to December 2009, and 204,545 for all of 2011. The growth continued throughout 2011 with the mean weekly views starting January at 141,890, and growing to 248,518 in December 2011.

Brands from the advertising campaigns are mapped into one hundred twenty-three public firms. Firms that do not trade or are not public for the entire sample period are eliminated. Also, firms that trade solely on foreign exchanges and ADR’s are eliminated. The final sample consists of seventy-five firms with views of seeded advertising videos for at least one week of the total sample period. These firms represent fifty-three different SIC codes at the four-digit level and twenty-six SIC codes at the two-digit level. Summary statistics regarding the sample firms are presented in Table 1. In total, the sample consists of 9,299 firm weeks. However, not every firm has social media viewing activity in every week.

Sample summary statistics are presented in Table 1. Mean views of seeded advertising videos in the last year of our sample total 204,545. On a firm basis, the maximum weekly views grew from 2.7 million views in 2009 to 33 million views in 2011. These numbers may include multiple advertising campaigns for each firm in any given week.

3.2 Seeded Advertising and "Going Viral"

The term "viral marketing" was first coined in 1996 by two venture capitalists describing the practice of the Hotmail email service appending to messages "Get your private, free email from Hotmail at http://www.hotmail.com". (Porter Golan 2006) This link was passed along from user to user with every email forwarded. Helm (2000) has described it as "a communication and distribution concept that relies on consumers to transmit [content]."

The power of this medium partially lies in the fact that it is driven by 'choice.' A messenger *chooses* to pass on some message. Boynton (2011) defines the term "going viral" as describing one of three possible definitions. These definitions are 1) videos with "many" views, 2) videos spread from multiple points as in a "virus" and 3) a functional form of epidemic growth (sigmoid) that starts small but grows exponentially until it has "run its course" and all are infected. Richardson and Domingos (2002) describe it as marketing which "takes advantage of networks of influence among consumers to inexpensively achieve large changes in behavior." Our use of the term viral advertising to describe sharing of seeded advertising videos is closest to the description used by Richardson and Domingos' (2002).

3.3 Seeded Advertising Video Views and the Google Search Volume Index

It is possible that views of seeded advertising videos are related to the measure of abnormal Google search volume examined by Da, Engleberg and Gao (2011). Their analysis shows that the abnormal Google Search Volume Index (ASVI) leads other indicators, including share turnover and news, as proxies for investor attention. If ASVI also leads views of seeded advertising videos, not including it in the analysis could result in an endogeneity problem.

Following Da, Engleberg and Gao (2011) we employ measures of SVI and ASVI. SVI is a scaled measure collected directly from Google. It is calculated as a firm's search volume in a relative period scaled by its time series average and then recalibrated so that the largest number is equal to 100. In some ways the measure is an estimate: In order for Google to conserve resources, it is calculated using a small sample of volume during the period. Therefore, each time you request the data it will be marginally different. Da, et al found the differences to be immaterial and they were not tested here. The measure is constructed as the natural log of the SVI less the median of the log SVI from the previous eight weeks. We also examine the relation between views of seeded advertising videos and ASVI; discussion of this analysis is presented in section 4.5.

3.4 Returns, Volume, and Spread

Daily security prices, daily volumes and S&P500 prices are collected from CRSP through December 30, 2011 and the daily volumes for Monday through Friday are summed and grouped to be compared to the week in which it has the greatest overlap with the views: where Monday through Friday overlap and any potential weekend views are compared to the week before them. Average volume of shares traded is 56 million per week over the full sample period.

Following Blankespoor, et al (2012) and Asthana, et al (2004) an abnormal trading volume statistic over a rolling one year period is constructed. This is calculated by computing the trading volume for that week and the fifty-one prior weeks and then averaging those volumes. This variable is then standardized by taking the mean of the firm's abnormal volume in the sample period, subtracting this mean from the observation and dividing by the standard deviation of the abnormal volume during the sample period. Since this variable is deflated by the standard deviation of the abnormal volume during the sample period, it has the effect of controlling for idiosyncratic volatility as it relates to volume at the firm level. A particularly volatile firm will have a larger standard deviation and thus a lower abnormal volume statistic.

This construction tends to bias against results for abnormal volume as the mean and standard deviation are calculated using the past year and the volatility during the sample period tested forms the standardized statistic. Regarding construction of this statistic, there is no consensus in the literature regarding the construction of an abnormal volume statistic (Bamber, Barron, Stevens 2011). Our results are robust to using natural log and raw trading volumes.[1]

We construct the weekly bid-ask spread estimate as the proportional bid-ask spread as the average of the daily proportional bid-ask spreads during the weekly period. The proportional bid-ask spread is calculated as $\frac{ask-bid}{ask+bid}$.

We begin with two measures of excess returns: the first is the contemporaneous weekly excess return, measured in the same week as the views of seeded advertising videos. The second excess return is cumulative excess returns for the following two week period (t+1, t+2). In each case, excess returns are market adjusted, and are calculated as the total return for each firm less the S&P500 return in the relevant time period. The mean contemporaneous weekly excess return is 0.02% and the mean two-week excess return is -0.12%.

3.5 Control Variables

In the multivariate analysis, we attempt to control for firm level and market level factors that might influence firm trading volume, spreads, and abnormal returns. We control for size of the firms using Market Capitalization computed using shares outstanding and price from CRSP for each week. The mean market cap for the sample firms is $42.8 billion. We construct an Illiquidity measure for each firm's stock following Amihud (2002). This measure is constructed

[1] In untabulated results, to control for possible endogeneity in the volume of shares traded in the sample we control for the mean of shares traded for the firms in the sample using the log of the weekly volumes as calculated from the daily volumes in CRSP. The mean weekly volume is insignificant and the remaining results are substantively unchanged.

as the average daily ratio of a stock's absolute stock return to its dollar volume scaled by 10^6 averaged over the weekly period, and serves as proxy for the component of liquidity related to price impact caused by trading volume. A measure of share turnover is constructed as weekly trading volume (number of shares), divided by the average shares outstanding that week. In our sample, the average firm has weekly share turnover of approximately 62 times. This variable controls for the effect of the number of shares outstanding on trading volume. We also collect the number of analysts following firms, their forecast mean and standard deviation from IBES. Following Diether, Malloy and Scherbina (2002) we calculate dispersion of analyst opinion as the standard deviation of forecasts scaled by the absolute value of the mean. We find that analyst coverage ranges from 1 to 54 analysts per firm, with a mean of 17.4. The estimated dispersion of analyst forecast has a mean of 0.13.

In order to control for overall market activity, we use NYSE total volume for each week. To control for market volatility we use the weekly closing value for the CBOE Volatility Index for each week. CBOE volatility data is obtained directly from CBOE.

4. The Empirical Analysis

4.1 Univariate Tests

Table 2 presents the results of univariate regressions. These are OLS regressions using firm fixed effects, clusters at the firm level, and clustered robust standard errors. Panel A examines the relation between the changes in views and level of views and three measures of volume; Ln volume, abnormal volume and standardized abnormal volume. The change in views is not significant while the relation between *ln views* and the abnormal volume, and standardized abnormal volume is significantly positive. This is consistent with the hypothesis that advertising increases the visibility of a firm, resulting in more investors paying attention to the firm's stock and trading it. In subsequent regression analyses, we use the standardized abnormal volume measure. We also find that Google ASVI is positively related to the natural log of volume, and standardized abnormal volume. This is consistent with the finding of Da et al (2011), which suggest that abnormal search volume predicts increased trading by individual investors.

Panel B presents univariate regressions of bid-ask spread on the changes in the natural log of views, the level of the natural log of views, and a specification with Google ASVI. We find a significant negative relation between *Ln views* and *Changes in Log Views,* and bid ask spread, consistent with Glosten and Milgrom's (1985) prediction that bid ask spreads decrease when less informed individual investor trading activity increases, and the probability of trading against an informed trader decreases. Google ASVI has a positive relation with bid-ask spread. Because our primary variable of interest is weekly, our results are not directly comparable to Da, et al's (2011) earlier results and interpretation. But, our results related to bid ask spread do suggest that at weekly intervals, these two measures contain information about different investor groups. The increase in bid ask spread associated with Google ASVI suggests higher probability of trading against an informed trader. Anecdotal evidence indicates that as profits from high frequency trading algorithms have declined in the past few years, many of the high frequency trading programs have included twitter feeds and internet search trends in their analysis.[2] Our sample period begins in 2009, while the sample period used by Da et al (2011) ends in 2008. This may partially explain our finding that Google ASVI is associated with an increase in bid ask spreads, and also the differences in results related to excess returns. This hypothesis is more fully explored in Table 5a.

In Panel C we regress weekly (contemporaneous) excess returns on both changes in and the level of the natural log of views. Changes in the level of views is significantly positively

[2] http://www.businessweek.com/articles/2013-06-06/how-the-robots-lost-high-frequency-tradings-rise-and-fall#p1

related to weekly excess returns while the second model shows a significantly negative relation between views and weekly excess returns. The positive relation between contemporaneous returns and changes in the level of views suggests that when viewing activity is increasing more dramatically, there is a positive effect on price. The negative relation between contemporaneous weekly returns and the level of views is consistent with an increase in liquidity due to increases in volume. The third specification includes only the change in Google ASVI as a regressor. The estimated coefficient for Google ASVI is positive but not statistically significant.

Panel D presents regressions of cumulative two-week returns from the two weeks following the contemporaneous week (t+1, t+2) on the specifications of weekly views and weekly Google ASVI. Here, the relation between two-week excess returns and changes in the natural log of views is not significant while the relationship between the level of the natural log of views and monthly excess returns is negative. We also find that the relation between two-week excess return and Google ASVI is not statistically significant. Da, et al. (2011) find a positive relation between ASVI and returns in the subsequent two weeks, where individual investor buying pressure temporarily increases prices, but the effect does not last in the longer term. It may be the case that the short term positive relation between ASVI and returns found by Da, et al (2011) is sensitive to their two week return measure rather than the weekly measure that we use, and that the four week return period we use effectively captures a significant portion of their reversal effect which was found over the following year. However, we do not test this hypothesis in this study.

Table 3 presents difference of means and difference of medians tests for share turnover, standardized abnormal volume, bid ask spread, and contemporaneous excess returns. In Panel A, these variables are compared based on firms using seeded advertising that is shared on social media, and a matching firm portfolio of firms that never appear in the seeded advertising sample. Each firm is matched with at least three other firms. The firms are matched on market capitalization and share trading volume by four digit SIC code where possible or to two digit SIC code if no matches are available at the four digit SIC level. Some firms are matched to more than one sample firm. There are 97 different firms in the matching portfolio. Each firm receives equal weight regardless of how many times it is matched to sample firms.

The results indicate that firms with views of seeded advertising videos have higher share turnover, mean standardized abnormal volume, and bid ask spread. Contemporaneous weekly returns are lower for the sample firms than for the matched firms, while monthly excess returns do not differ significantly in the two groups. The higher bid ask spread in the sample firms appears inconsistent with results found in Table 2, but this is because it is a difference in levels based on a matched sample with no views of seeded advertising videos and not a measure of bid-ask spread as relates to an individual firm.

In Panel B, we look exclusively at firm weeks within our sample, comparing firm weeks with no views during the sample period to firm weeks with views during the sample period. We find that firm weeks with views have lower bid ask spreads than firm weeks without views. This is consistent with the results we find for bid ask spread in Tables 2 and 5. Results for share turnover, standardized abnormal volume, and contemporaneous return are similar to those found in Panel A. In Panel B we find that for the sample firms, firm weeks with views of seeded advertising videos have significantly lower contemporaneous excess returns than firm weeks without views. We hypothesize that these lower returns are related to the reduction of liquidity premiums due to increased volume and this is discussed further in section 4.4.

4.2 Views of Seeded Advertising Videos and Abnormal Share Volume

Fixed-effects panel regressions using standardized abnormal volume as the dependent variable are presented in Table 4. Standardized abnormal volume is calculated based on a 52-week moving average and then deflated by the standard deviation of those averages. The main variable of interest is the natural log of views of seeded advertising videos by week for each firm. Control variables are included for market capitalization to control for size, NYSE volume to control for market volume, the CBOE volatility index to control for market-level volatility, firm-specific share turnover, the Amihud (2002) illiquidity measure, earnings announcements and dispersion of analyst forecasts.[3].

In the first specification included in R1, we find that *ln views* is significantly positively related to standardized abnormal trading volume. At a sample mean price of $76.8 per share and a coefficient of approximately .03, the weekly dollar impact in share trading would be in excess of $129 million. These results are consistent with the argument that views of seeded advertising videos on social media are associated with an increase in trading activity.

The specification R2 includes ASVI and we find that the positive relation between views and volume holds, and that ASVI is also positively related to volume. With the inclusion of ASVI the coefficient and power on *ln views* remains unchanged which supports the hypothesis that these variables measure different sources of volume. Models presented in R3 and R4 include lagged *ln views.* We find that inclusion of lagged views results in a loss of significance for the current views measure, and when current views are not included, both the previous week, and two-week lags are positive and significant in predicting future abnormal volume. In specification R5, we find that volume is not impacted by the change in views measure.

[3] In untabulated results, controls for the number of analysts are added – the number of analysts is not significant, and the coefficients on the variables of interest remained substantively unchanged.

The estimated regression results for the control variables are generally consistent with the prior literature. Standardized abnormal volume is positively related to NYSE volume, share turnover, the volatility index, and a dummy for earnings reports. It is positively related to the Amihud illiquidity measure, which reflects the fact that we measure standardized abnormal volume, not total volume. The negative coefficient on firm market cap likewise reflects the fact that larger firms tend to have higher trading volume and liquidity, thus standardized abnormal trading volume will be lower.

4.3 Views of Seeded Advertising Videos and Bid-Ask Spread

Bid-Ask spread provides a measure of liquidity in a firm's stock. A larger spread indicates greater uncertainty in the pricing of the stock and less liquidity. Combining ideas from the empirical literature discussed in (Grullon et al 2004), and theoretical work (Glosten and Milgrom, 1985), we predict the advertising related increase in volume (from individual shareholders) documented in Table 4 will result in a decrease in bid-ask spread as the probability of trading against less informed individuals increases. R1 shows a strongly significant and negative relationship between *ln views* of seeded advertising videos and bid ask spread.

Specifications R2 and R3 present regressions with one and two week lagged natural log of views. We find that the negative relation between bid ask spread and contemporaneous weekly natural log of views remains; and lagged views predict bid ask spread only in the absence of contemporaneous views.

Specifications R4 and R5 demonstrate that ASVI does not have a significant impact on bid-ask spread when controls for Abnormal Volume are included in the regressions. The positive coefficient suggests that it may increase bid-ask spread and be correlated with the trading activity of more sophisticated investors. R6 demonstrates that if the control for

Standardized Abnormal Volume is excluded that ASVI gains positive significance, suggesting a correlation between volume and ASVI. This is consistent with the results we found in univariate regressions presented in Table 3, and suggests that ASVI and views of advertising videos shared on social media each represent the activity of a different "clientele," or a different group of traders. Social media views again appear to motivate trades of less informed individuals. As we mentioned earlier, reports in the media suggest that high frequency traders have expanded their analysis to include twitter feeds and internet search trends. If this practice is widespread during our relatively short sample period, it may explain the positive relation between ASVI and bid ask spread in found in our analysis, as more informed traders increasingly use internet search activity in high frequency trading algorithms. This is discussed more fully in Section 4.4.

R6 includes the change in views. The change in views is consistent with the level of views, and is significantly and negatively related to bid-ask spread. In untabulated robustness checks, we find similar results using Corwin and Schultz's (2012) method to estimated bid ask spreads using daily data.

In summary, the results of tests for the relation between views of seeded advertising videos on social media and the bid ask spread strongly support the hypothesis that the increase in trading volume we discuss in the prior section is driven by increased trading activity by individual investors rather than more informed institutional investors. Based on the logic of Glosten and Milgrom (1985), we hypothesize that bid ask spreads narrow in response to increased trading activity by individuals. This is because adverse selection costs decrease when the probability of trading with less informed investors is higher.

The control variables again have estimated coefficients that are generally consistent with the existing literature. Larger firms have smaller spreads. Spreads increase with volatility, earnings reports, turnover, illiquidity, and dispersion of analyst opinion.

4.4 ASVI and Individual Investors

Da, et al (2012) test the significance of SVI and its impact on individual shareholders using market level data to measure the share purchases of individuals. Table 5 specifically examines the impact of the *level* of ASVI on bid-ask spread and finds it marginally positively related to bid-ask spread in the absence of controls for abnormal volume. The expected sign for this relationship given the results of the Da, et al paper would be negative. The results of their paper imply that larger ASVI would result in a smaller spread as this would demonstrate the presence of individual shareholders.

To explore this further, we test the impact of ASVI on our sample firms in the Da, et al time period (2004-2008) and in our time period (2009-2011). The results are presented in Table 5a. The Da, et al paper compares *changes* in ASVI to *changes* in individual orders at the trading center level. To most closely replicate this we compare the *changes in ASVI* to the *changes in bid-ask spread*. Specification R1 shows that consistent with Da, et al this result is negative and significant for the extended sample (1/1/2004-12/31/2011). This result indicates that an increase in ASVI is associated with a contemporaneous decrease in spread, consistent with prior analyses of individual investor trading activity and stock price dynamics.

Specification R2 includes dummy variables such that SM time period dummy equals one for the dates in our sample period (7/2009-12/31/11) and the Da, et al time period dummy equals one during the time period explored in their paper (1/1/2004-6/2008). The spread during the SM time period is marginally larger than the Da time period.

Specification R3 includes an interaction term between the time period dummy variables and the change is ASVI. The estimated coefficients for both interaction terms are significantly positive. But, the estimated coefficient for the interaction of the later time period with the change in ASVI is much larger in magnitude than that of the earlier Da time period. This larger positive spread is consistent with the hypothesis that ASVI is less correlated with individual trader activity in our sample time period than in the Da, et al time period.

As discussed above, reports in the media suggest that high frequency traders have expanded their analysis to include twitter feeds and internet search trends. If this practice is widespread during our relatively short sample period, it may contribute to the positive relation between ASVI and bid ask spread in found in our analysis, as more informed traders increasingly use internet search activity in high frequency trading algorithms.

4.5 Views of Seeded Advertising Videos and Excess Returns

In the multivariate regression analysis, we use multiple measures of excess returns. These all are based on the firm's return less the return for the S&P500 for the same time period. The results are presented in Table 6. In the first specification, returns are measured in the contemporaneous week, and the coefficient on the change in the log of views is positive and significant at the 5% level suggesting that higher contemporaneous increase in individual investor attention is associated with higher returns. Specification R2 presents cumulative excess returns measured for the next two weeks (t+1, t+2) this shows that the positive excess returns are reversed over the next two weeks as the coefficient is negative and identical to the one week gains in R1; but is only marginally insignificant with a p-value of 0.115.

Specifications R3 shows returns over the next 22 weeks and the coefficient is quite small and insignificant. These results suggest that a temporary increase in views has a positive impact on price that reverses over the subsequent two weeks.

Results for the control variables show that the earnings dummy is not significantly related to excess returns. NYSE volume and the illiquidity measure are positively related to excess returns in some specifications, while volatility is negatively related to excess returns in all specifications.

4.6 Summary of Main Results

Interpreting these results related to excess returns together with the previous two sections focusing on volume and spreads, the evidence generally suggests that views are correlated with increased volume and lower bid ask spread. The contemporaneous increase in price may be the result of insufficient supply to meet the increased demand in the short-term. The negative relation in the subsequent two-weeks is the reversal of the price pressure.

ASVI seems to measure a different source of volume than the Views measure does, as both ASVI and Views are significant in the same specifications. Firms with the most views and volume have the narrowest spread; while level of ASVI is positively related to spread. Further, the correlation of ASVI with individual investors is diminished in our time period when compared to the time period of the earlier study. These results are somewhat different from the results and interpretation presented by Da, et al (2011), and we suggest that the difference may be driven by the later time period and adaptive trading strategies of high frequency traders.

4.7 What Drives Views of Seeded Advertising Videos?

Table 4 implies that social media based advertising increases abnormal volume. Table 5 shows a negative relation views of seeded advertising videos and in the bid-ask spread. In Table 6 we find a short term increase in share price related to the change in views and a reversal over the next two weeks. These results are broadly consistent with the earlier empirical studies of advertising and stock price dynamics, and investor attention and stock price dynamics.

The purpose of seeding advertising videos on the internet is to increase visibility of the firm and its products. But, what drives views? Table 7 examines determinants of social media seeded advertising views. One advantage of seeded advertising videos is that it is an inexpensive way to reach customers. While our sample may not be representative of all firms using social media based advertising, this idea is supported by the fact that advertising expenditure is not significant in any specification in Table 7. The results support the hypothesis that it is the number of views of the videos, not the number of advertising dollars that matters.

Market Capitalization is not significant. Views are significantly positively related to the natural log of revenue (measured in the same quarter as the weekly viewing activity). The natural log of firm level weekly views are also positively related to higher levels of mean viewing activity in the sample as a whole.

It is interesting though, that when lagged views are placed in the specification (R2 through R4); they remain significant for at least two weeks. This suggests that videos which become popular in one week are likely to become even more popular in the following week or that firms who run a successful campaign are likely to run other successful campaigns. This result can be interpreted to mean that there is some residual benefit to having the “hot” marketing campaign that is not captured in advertising spending.

4.8 Views of Seeded Advertising Videos and Google Search Volume

We find no significant correlation between Views and ASVI with a correlation of -.0046 (p-value .6575). Table 8 further examines the relation between Google ASVI and views. The results suggest that views of seeded advertising videos do not drive search volume, and search volume does not drive seeded advertising videos. Neither is significantly related to the other contemporaneously, or up to two lags.

5. Conclusion

Our unique database of views of social media advertising videos allows us to measure investor attention and the direct impact of advertising on excess returns and volume in the framework suggested by Merton (1987). We use a measure of viewing activity and attention of individuals, linked to specific controlled messages produced by firms. We compare our measure to the closest measure, Google ASVI and find that our measure contains different information; and appears to more directly reflect the attention of individual investors in our sample time period.

We demonstrate that views of seeded advertising videos shared on social media positively impact trading volume. Views have a significant and negative impact on bid-ask spreads, even when controlling for a price impact measure of liquidity. This is consistent with an increase in liquidity as market makers decrease spreads in response to a higher probability of trading against less informed individual investors. We find evidence of a short term increase in price due to the change in social media views which is reversed in the following two weeks. Our analysis shows a direct link between attention to product market advertising activity and stock price dynamics which has not been examined in the prior literature.

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7.0 Tables

Table 1.1- Summary Statistics

Panel A

Number of Firms	75
4 Digit SIC Codes	53
2 Digit SIC Codes	26

Panel B

	Mean	**Median**	**S.D.**	**Max**	**Min**
Weekly Volume	56.7MM	2.25MM	97.2MM	1.1B	2,100
Weekly Views	170,838	3,633	894,906	4.9MM	-
SVI	59.23	64	25	100	0
ASVI	-0.001	0	0.346	4.03	(4)
Ammihud Illiquidity	0.0799605	0.0001482	1.110417	46.07755	(6)
Share Turn	60.91	46.42	57.91	986.37	-
Price	76.8	32.4	228.7	2,660.0	-
Contemporaneous Weekly ExcessRet	-0.0002	0.0000	0.0408	0.44241	-0.709
Two-week Excess Ret	-0.00123	0.00115	0.0818	0.97917	-0.78976
Proportional Spread	0.0347	0.0280	0.0282	0.0597	0.0043
Market Cap ($B)	41.10	1.10	62.70	392	1.47
Total Assets ($MM)	79,639.00	21,096.80	177,669.60	1,313,867.00	46.5
Annual Revenue ($MM)	41,123.60	18,435.00	62,552.90	444,948.00	119.6
Advertising Expense($MM)	1,188	695	1,446	9,315.00	4
Number of Analysts	17.61	17.00	11.41	54.00	1.00
Dispersion	0.11	0.03	0.36	7.00	0.00

Panel C

	2009	**2010**	**2011**
Mean Weekly Views (if > 0)	166,351	252,554	251,492
Median Weekly Views (if > 0)	45,365	61,466	61,100
Max Weekly Views (firm)	2.7MM	49MM	33MM
Total Views	111MM	878MM	895MM

Table 1.2 - Univariate Regressions

These Univariate regressions of Ln Social Media Views, Change in Views (t, t-1) and ASVI are fixed effects panel regressions clustered at the firm level and the standard errors are estimated using Huber-White estimators to account for heteroscdasticity and are adjusted for clustering at the firm level.

Dependent Variable	**Ln Volume**			**Abnormal Volume**			**Standardized Abnormal Volume**		
Univariate Panel A	R1	R2	R3	R4	R5	R6	R7	R8	R9
Change in Ln Views	0.0012			247892			-.010218		
Ln Views		-0.003468			820196*			0.02076***	
ASVI			0.06337**			-442661			.19622**
# Observations	9224	9299	9299	9224	9299	9299	9224	9299	9299
Firm/Week Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clusters (firms)	75	75	75	75	75	75	75	75	75
R-sq	0.0325	0.0722	0.0611	0.0223	0.0002	0.0001	0.032	0.0096	0.0048

significant at ***1%, ** 5% and *10% level, respectively

Dependent Variable is Bid-Ask Spread Estimate

Univariate Panel B	R1	R2	R3
Change in Ln Views	-0.01033*		
Ln Views		-0.00930**	
Da, et al ASVI			.10261**
# Observations	9224	9299	9299
Firm/Week Fixed Effects	YES	YES	YES
Clusters (firms)	75	75	75
R-sq	0.0011	0.0878	0.0027

significant at ***1%, ** 5% and *10% level, respectively

Dependent Variable is Contemporaneous Excess Return

Univariate Panel C	R1	R2	R3
Change in Ln Views	0.0006**		
Ln_Views		-0.0003**	
Change in ASVI			0.0016
# Observations	9224	9299	9224
Firm/Week Fixed Effects	YES	YES	YES
Clusters (firms)	75	75	75
R-sq	0.0001	0.0038	0.0001

significant at ***1%, ** 5% and *10% level, respectively

Dependent Variable is subsequent two-week Excess Return

Univariate Panel D	R1	R2	R3
Change in Ln Views	-0.0062		
Ln_Views		-0.0007***	
Change in ASVI			-0.0177
Observations	9224	9299	9224
Firm/Week Fixed Effects	YES	YES	YES
Number of permno	75	75	75
R-squared	0.0001	0.0038	0.0000

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.3 - Difference in Means/Medians

Panel A presents comparison of our sample firms with a 93 firm Non-Social Media matching portfolio matched on industry, size, trading volume and market capitalization. Panel B compares two subsets of our sample. The first is firms once they begin using Social Media and the other is the same firms pre-entry into the social media sample

Panel A - Sample firms observations with SM Views vs Firms without SM Exposure

	Means				Medians				
	SM Users 5645 obs	Non SM Matching firm 11,279 obs	t-value		SM Users 5645 obs	Non SM Matching firm 11,279 obs	Chi2	p-value	
Share Turnover	60.7637	51.8304	9.26	***	45.5668	35.5674	306.030	0.0000	***
Standardized Abnormal Vol	0.0411	-0.0383	4.69	***	-0.0992	-0.2592	116.841	0.0000	***
Bid Ask Spread	0.0325	0.0161	55.23	***	0.0258	0.0140	0.102	0.7500	
Contemporaneous Return	-0.00091	0.00086	1.87	**	0.00000	0.00000	1.559	0.2120	

Panel B - Sample firms with and without SM Exposure

	Means				Medians				
	SM Users 5645 obs	Sample firms Pre-SM usage 3654 obs	t-value		SM Users 5645 obs	Sample firms Pre-SM usage 3654 obs	Chi2	p-value	
Share Turnover	60.7637	61.1353	0.30		45.5668	48.4269	9.662	0.0020	***
Standardized Abnormal Vol	0.0411	-0.0634	5.05	***	-0.0992	-0.1252	1.824	0.1770	
Bid Ask Spread	0.0325	0.0381	9.47	***	0.0258	0.0316	158.206	0.0000	***
Weekly Excess Returns (%)	-0.00091	0.00155	3.01	***	0.00000	0.00000	0.002	0.9680	

Table 1.4 - Views and Volume

This panel contains two-way fixed effects panel regression using clustered robust standard errors, The dependent variable is Standardized 52-week abnormal volume calculated as volume demeaned by the 52-week average then deflated by the standard deviation of the 52 week abnormal volume observations. Standard errors are estimated using Huber-White estimators to account for heteroscdasticity and are adjusted for clustering at the firm level.

Dependent Variable is	Standardized Abnormal Volume				
	R1	R2	R3	R4	R5
Ln Views	0.0307***	0.0307***	0.0053		
	[0.0002]	[0.0002]	[0.5220]		
Change in Views					-0.0081
					[0.2384]
Da, et al ASVI		0.1170***			
		[0.0020]			
Ln ViewsLag1			0.0096	0.0142*	
			[0.2600]	[0.0717]	
Ln ViewsLag2			0.0158**	0.0163**	
			[0.0255]	[0.0233]	
Ln NYSE Volume	0.1183***	0.1154***	0.1605***	0.1607***	0.1173***
	[0.0001]	[0.0001]	[0.0000]	[0.0000]	[0.0001]
Ln Firm Market Cap	-0.3460***	-0.3453***	-0.3453***	-0.3452***	-0.3416***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Ln Share Turnover	1.4791***	1.4753***	1.4759***	1.4758***	1.4655***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Ln CBOE Volatility Index	0.1752***	0.1783***	0.1792***	0.1791***	0.1927***
	[0.0022]	[0.0019]	[0.0017]	[0.0017]	[0.0006]
Dummy for Earnings	0.1805***	0.1784***	0.1982***	0.1985***	0.1937***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[5.43]
Amihud Illiquidity	0.0361***	0.0358***	0.0516***	0.0516***	0.0492***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Ln Dispersion	-0.012	-0.0123	-0.0069	-0.0068	-0.0027
	[0.9329]	[0.9310]	[0.9617]	[0.9627]	[0.9855]
Constant	-3.1225***	-3.0726***	-3.9441***	-3.9465***	-2.9761***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Observations	9299	9299	9149	9149	9224
Number of permno	75	75	75	75	75
Firm/Week Fixed Effects	YES	YES	YES	YES	YES
R-squared	0.4731	0.4748	0.5024	0.5023	0.48

Robust p-values in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.5 - Impact on Bid-Ask Spread

In this two-way fixed effects panel regression the depdendent variable is proporational bid-ask spread. Clustered Robust Standard Errors are estimated using Huber-White estimators to account for heteroscdasticity and are adjusted for clustering at the firm level.

	Dependent Variable is Ln Bid-Ask Spread Estimate						
	R1	R2	R3	R4	R5	R6	R7
Log_Views	-0.0060***	-0.0064**		-0.0060***			
	[0.0007]	[0.0185]		[0.0007]			
Da, et al ASVI				0.0162	0.0163	0.0271*	
				[0.2705]	[0.2707]	[0.0862]	
Change in Ln_Views (t-1, t)							-0.0043*
							[0.0890]
LogViewsLag1		-0.0001	-0.0056**				
		[0.9694]	[0.0311]				
LogViewsLag2		0.0022	0.0016				
		[0.4144]	[0.5470]				
STD_52WABV	0.0949***	0.1157***	0.1156***	0.0944***	0.0905***		0.1063***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]		[0.0000]
Log_NYSE	0.0058	-0.0154	-0.0157	0.0054	0.005	0.0158	0.0059
	[0.6641]	[0.2694]	[0.2615]	[0.6805]	[0.7021]	[0.2403]	[0.6491]
Log_MktCap	-0.0470***	-0.0397***	-0.0399***	-0.0470***	-0.0492***	-0.0801***	-0.0439***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Log_ShareTurn	0.2780***	0.2472***	0.2476***	0.2782***	0.2866***	0.4188***	0.2636***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
log_CBOE	0.6020***	0.5953***	0.5955***	0.6026***	0.6016***	0.6185***	0.5938***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Dummy for earnings	0.1610***	0.1501***	0.1497***	0.1608***	0.1617***	0.1778***	0.1547***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
AMMOD	0.0203***	0.0177***	0.0178***	0.0203***	0.0205***	0.0237***	0.0184***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Ln_dispersion	0.1410***	0.1210**	0.1208**	0.1410***	0.1406***	0.1396**	0.1305**
	[0.0089]	[0.0195]	[0.0196]	[0.0090]	[0.0087]	[0.0174]	[0.0119]
Constant	-5.8244***	-5.4047***	-5.4022***	-5.8189***	-5.8425***	-6.1151***	-5.8381***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Observations	9299	9149	9149	9299	9299	9299	9224
Number of permno	75	75	75	75	75	75	75
Firm/Week Fixed Effects	YES	YES	YES	YES	YES	YES	YES
R-squared	0.4298	0.4382	0.4379	0.43	0.4281	0.4076	0.4351

Robust p-statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.5a - Comparison of ASVI across time periods

This two way fixed effects panel regression uses our sample firms in a time period that extended to 1/1/2004-12/31/2011 to include the Da et al (2012). The periods are non-overlapping. For observations with dates in the Da, et all time period the DA Dummy-1. For observations in our sample period the SM dummy=1. Clustered robust standard errors are estimated using Huber-White estimators to account for heteroscdasticity and are adjusted for clustering at the firm level.

	R1	R2	R3
	Dependent Variable is Change in Ln Bid-Ask Spread Estimate (t-1,t)		
Change in Da, et al ASVI (t-1,t)	-0.038***	-0.039***	-0.178***
	[0.000]	[0.000]	[0.005]
Interaction SM Dummy*Δ ASVI			0.289***
			[0.000]
Interaction DA Dummy*Δ ASVI			0.127**
			[0.040]
SM Time Period Dummy		-0.043***	-0.042***
		[0.000]	[0.000]
Da, et al Time Period Dummy		-0.046***	-0.045***
		[0.000]	[0.000]
Ln NYSE Volume	-0.161***	-0.169***	-0.169***
	[0.000]	[0.000]	[0.000]
Ln Firm Market Cap	-0.032***	-0.029**	-0.029**
	[0.005]	[0.014]	[0.014]
Ln Share Turnover	-0.190***	-0.189***	-0.189***
	[0.000]	[0.000]	[0.000]
Ln CBOE Volatility Index	0.118***	0.100***	0.101***
	[0.000]	[0.000]	[0.000]
Amihud Illiquidity	0.0000	0.0000	0.0000
	[0.554]	[0.568]	[0.580]
Constant	4.110***	4.324***	4.324***
	[0.000]	[0.000]	[0.000]
Observations	30200	30200	30200
Number of firms	75	75	75
Firm/Week Fixed Effects	YES	YES	YES
R-squared	0.069	0.069	0.071

Robust p-values in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.6 - Impact on Excess Returns

This two-way fixed effects panel regression uses Excess returns (*Rm-Rf)* as the dependent variable. Clustered robust standard errors are estimated using Huber-White estimators to account for heteroscdasticity and are adjusted for clustering at the firm level.

Dependent Variable is Return in Excess of S&P500			
	R1	R2	R3
	Contemporaneous Excess Return	Excess Returns Weeks 2 and 3	Excess Ret Weeks 4-26
change_LnViews	0.0006**	-0.0006	-0.0014
	[0.0310]	[0.1157]	[0.2911]
Log_NYSE	0.0013	-0.0007	-0.0153**
	[0.4413]	[0.8057]	[0.0344]
Log_MktCap	-0.0001	-0.0002	-0.0029
	[0.6539]	[0.8321]	[0.2743]
Log_ShareTurn	0.0005	0.0009	0.0061
	[0.7151]	[0.8292]	[0.6099]
log_CBOE	-0.0031*	-0.0034	0.012
	[0.0655]	[0.4531]	[0.6094]
Dummy for earnings	-0.0004	0.0003	-0.004
	[0.8485]	[0.9156]	[0.1701]
Amishud Illiquidity	-0.0003***	0.0003	0.0012
	[0.0047]	[0.2393]	[0.1437]
Ln_dispersion	0.0060**	0.0094**	0.068
	[0.0162]	[0.0348]	[0.2511]
Constant	-0.0147	0.024	0.2714*
	[0.6279]	[0.6939]	[0.0529]
Observations	9224	9149	9074
Firm/Week Fixed Effect			
Number of Permno	75	75	75
R-squared	0.0013	0.001	0.0061

Robust p-statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.7 - Determinants of Seeded Advertising Video Viewing Activity

This table presents a two-way fixed-effects panel regression. Advertising is measured as of the end of the previous quarter. Results are robust to an alternate definiton of advertising dollars using prior year-end advertising expenses. Clustered Robust standard errors are estimated using Huber-White estimators to account for heteroscdasticity and are adjusted for clustering at the firm level.

	Dependent Variable is Ln(Views)			
	R1	R2	R3	R4
Ln Advertising Expenditure (t-1)	1.3391	0.1528	0.2733	0.1533
	[0.3844]	[0.1667]	[0.1963]	[0.1746]
Ln Lag 1 Social Media Views		0.9302***		0.8737***
		[0.0000]		[0.0000]
Ln Lag 2 Social Media Views			0.8755***	0.0591**
			[0.0000]	[0.0454]
Ln Market Capitalization	-0.1303	0.0194	0.0482	0.0217
	[0.7907]	[0.6232]	[0.5194]	[0.5900]
Ln Revenue	7.6280***	0.4151**	0.7360**	0.3762**
	[0.0029]	[0.0156]	[0.0273]	[0.0404]
Standandized Mean Views in Sample	0.4368***	0.0478***	0.0757***	0.0457***
	[0.0000]	[0.0038]	[0.0071]	[0.0072]
Dummy for earnings	-0.1792***	0.003	0.0102	0.0063
	[0.0070]	[0.9475]	[0.8691]	[0.8934]
	-134.8253***	-8.6740***	-15.6257***	-8.0884***
	[0.0000]	[0.0001]	[0.0003]	[0.0006]
Observations	7047	6989	6931	6931
Firm/Week Fixed Effects	Yes	Yes	Yes	Yes
Number of permno	61	61	61	61
R-squared	0.1303	0.8857	0.8003	0.8839

Robust p-values in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.8 - Test of Interdependence of SVI and Views

In models not reported, results are robust to controls for revenue, advertising, earnings announcements and market capitalization. Clustered robust standard errors are estimated using Huber-White estimators to account for heteroscdasticity and are adjusted for clustering at the firm level.

Dependent Variable	**Ln_Views**	**Ln_Views**	**Ln_Views**	**ASVI**	**ASVI**	**ASVI**
Da, et al ASVI	0.0442					
	[0.4432]					
ASVI Lag 1		0.0274				
		[0.6217]				
ASVI Lag 2			0.0012			
			[0.9820]			
Ln_Views				0.0005		
				[0.4294]		
Ln_Views Lag 1					0.0003	
					[0.6157]	
Ln_Views Lag 2						0.0002
						[0.6934]
Constant	6.3123***	6.3419***	6.3724***	-0.0044	-0.0032	-0.0028
	[0.0000]	[0.0000]	[0.0000]	[0.2548]	[0.3830]	[0.4351]
Observations	9299	9224	9149	9299	9224	9149
Number of permno	75	75	75	75	75	75
Firm/Week Fixed Effects	YES	YES	YES	YES	YES	YES
R-squared	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Robust p-statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Grantor Types and MLS versus Non-MLS Price Effects

1. Introduction

A Multiple Listing Service (MLS) is a service provided to customers of real estate brokers. It provides pooled information on listings from member brokers. For sellers, access to a MLS can be provided as part of a bundled service which includes representation by an agent, or as an unbundled service in the case of a flat fee or discount broker. The MLS allows potential buyers the opportunity to search for available properties based on location, price, quality, and features, and also to find prices of comparable properties. This service reduces market frictions related to geography, communication, and information by increasing the 'visibility' of properties for sale to potential buyers. This can improve the likelihood of finding a match, the quality of the match, and also reduce the time it takes to find the match. Alternative means of advertising properties are available to sellers who choose to sell outside the MLS system, but the effort of selling is more directly borne by the seller.

The question of the value of a MLS and access to a MLS has become an important question, as activity in the real estate market is a key factor in the economy. While this clearinghouse of information can reduce market frictions, it is possible that the pervasive power of a MLS could give undue market influence to member brokers, and impose unfair restraints on trade (Austin 1970). The DOJ recognizing this possibility has encouraged open access to MLS listings for a flat fee or without broker participation[4]. Yinger's (1981) theoretical analysis suggests significant efficiency gains from the MLS; but argues that these may be offset by the costs of broker market power if exclusionary practices are allowed. On the other hand, Uri (1985) argues that MLS systems are so valuable that certain exclusionary practices are justifiable. This is because member brokers will have incentive to maintain the MLS only if it offers them some potential profit.

Previous research on the value of MLS listing and brokerage services to sellers has shown mixed results. Frew and Jud (1986) present empirical evidence that MLS listed properties obtain higher sale prices (approximately 3% higher) than non MLS sales. They argue that rational buyers are willing to pay a portion of the brokerage costs if the brokerage services makes it easier to find a match and easier to complete the transaction. Conversely, Yavas and Colwell (1995) find that properties sold through a MLS sell at a lower price than similar properties sold directly by the owner (FSBO) or through a non-MLS participant broker. The explanation for this result hinges on the fact that lower prices have two competing effects upon broker effort. First, lower prices result in lower commissions, giving brokers decreased incentive to exert effort. But, lower prices increase the probability of a sale occurring, and this has a positive effect on broker effort, for both the listing broker, and other brokers participating in the MLS. Yavas and Colwell (1995) indicate that their results "cannot explain the widespread use of the MLS" and recommend additional research to examine other factors that may affect the marketing choice.

The papers discussed above examine the impact of the MLS prior to the time when individuals were generally able to access MLS listings independently using personal computers. The majority of recent MLS properties are listed on the Internet. Ford, Rutherford and Yavas

[4] See DOJ letter to Governor Matt Blount, MO 5/23/2005 where the DOJ lays out their case advocating unbundling of real estate services including flat or low fee access to MLS listing.

(2005) indicate that 93% of the MLS listings in their data from 1999 listed on the internet and those that listed received a 1.93% price premium while taking 11% longer to sell.[5] Ford, Rutherford and Yavas (2005) argue that buyers find a better match, value the house higher and pay a higher transaction price. More recently, Hendel, Nevo and Ortalo-Magné, (2009) find that MLS sales prices and For-Sale-by-Owner (FSBO) prices are similar before considering listing and commission costs, but MLS properties sold more quickly, and had a higher probability of selling. In their sample, both the MLS and FSBO properties were available on the Internet.

Other studies address the impact of brokers and agents, and also find mixed results. Doiron, Shilling and Sirmans (1985) find that brokered properties sell at a higher price compared to owner sales, and estimate that approximately 43% of the brokerage commission is capitalized. Kamath and Yantek (1982) and Colwell et al., (1992) find that brokers do not impact the selling price of a house. In a specialized dataset of homes on Stanford University owned land, Bernheim and Meer (2013) examine real estate brokerage services when listing is unbundled from other broker services. Their study finds that use of a broker is associated with a *reduction* in sales price ranging from 5.9% to 7.7%. Bernheim and Meer also find weak evidence that use of a broker reduces initial list price and time on the market. Rutherford, Springer and Yavas (2005), Rutherford, Springer and Yavas (2007) and Levitt, et al (2008) find that agent-owned properties sell at a premium which can potentially be attributed to agent market knowledge and patience. Similarly, Huang and Rutherford (2007) find that National Association of Realtor (NAR) member REALTOR's sell properties at a small premium over non-NAR members. Overall, the evidence related to brokers and agents is mixed. However, the results suggest agent

[5] In a sample of 300,000 listings from the Dallas/Fort Worth Metroplex, 97.6% of listings are also posted on the Internet.

involvement does affect the terms of real estate transactions, but not always in ways that benefit the sellers who interact with them.

In this study we use data from the years 2004-2005, a time period with moderate (4%) year-on-year growth. We identify sales in the MLS and outside the MLS for individual grantors and other grantors, including corporations, LLCs, builders, and financial firms. We find that properties sold through a MLS sell at higher prices. This is consistent with Doiron, Shilling and Sirmans (1985) and the findings of Frew and Jud (1986), and their suggestion that buyers are willing to pay more in return for a better match and smoother completion of the transaction. Decomposing our results by seller-type we find that individuals receive a price premium when they sell a property through a MLS. However other grantors, in this paper referred to as "*not-individual-owners* (NIO)," as a group, receive the same price for the property if sold through or outside a MLS. This suggests that for individual sellers, the ability of the MLS to reduce market frictions is valuable. For NIOs, there are other means of marketing properties that substitute for listing in the MLS. Different NIO sellers may select different selling strategies, for example, some bank owned real estate is auctioned, while new construction is often sold through a builder website or on site sales center. In the next section, we discuss the data, in the third section we present the results and a fourth section offers concluding remarks and some comments on future research.

2. Data and Sample Construction

The sample includes 25,512 single family residential properties that were sold in Dallas County during the January 1, 2004 - May 31, 2005 time period. We make use of three data sets to arrive at a final sample. In Texas, each county appraisal district is required to provide a file to the Texas Comptroller's office with all known property transactions completed during the prior year. The chief appraiser for each district verifies that all known property transactions are included in the file submitted to the Comptroller's office. In recent years, the Texas Comptroller's office redacts all personal information (names), property location, and sales data before the files are available to the public. In the initial years, this data is available in a limited number of files. We were able to obtain the Dallas county file for 2005 that contained name, property address, sales price, Tax ID, and sales date along with a number of other fields for most of 2004 and five months in 2005.

For this study, we first drop all properties not identified as single family residences and all observations with missing data for any of the fields listed above. Next, we use the Dallas Appraisal District file and confirm that a property has a match in the Dallas Appraisal District file for 2005. Properties without a matching TAX ID or property address match in the Dallas County Appraisal District files are removed from the sample.

To identify MLS sales, we then match actual MLS sales for the years 2004 and 2005 in Dallas County by TAX ID and property address. Any property without a MLS match is rechecked to verify that we have a correct match with the appraisal district, and that there is no match in the MLS using TAX ID or property address. All properties thus verified are classified as a non-MLS sale. These properties may be sales by owners; properties sold through an agent, but not listed on the MLS; or properties sold by other entities or firms. Variable names and data descriptions are provided in Table 1.

Data available from either the Comptroller's file or the Dallas County Appraisal database include physical property characteristics; age, building square feet, pool, number of bedrooms, bathrooms, fireplaces, stories, deck, sprinkler and land square feet; and marketability characteristics; condition/desirability/utility (CDU) rating, land percentage, land value, depreciation percentage, and building class assigned by the appraisal district. The Dallas County Appraisal database also contains neighborhood controls that we include as fixed effects in the models. Calendar information includes the year and the month of sale. The selling price and date sold is provided in the Comptroller's data for both the MLS sales and the non-MLS sales. While there is a field for "days on the market", this field is blank for all properties. In the data we assign a value of "1" for houses listed and sold on the MLS and a "0" for single family houses that were not sold through the MLS. Table 2 shows the descriptive statistics of the data broken out by whether the property is sold as a MLS sale or a non-MLS sale. In our sample, approximately 14.6% of the transactions consist of non-MLS sales. This is marginally lower than the National Association of Realtor's estimate that approximately 20% of transactions are sold without an agent.

A comparison of the two sub-samples indicates that a majority of the twenty-nine variables displayed are statistically different for MLS properties compared to non-MLS properties at either a 1% or 5% level of significance. The comparison of sub-samples using a difference in means test suggests that MLS properties have lower prices, are smaller and older, with fewer bedrooms and bathrooms, and slightly higher land square footage, and are less likely to have either a "Poor" or "Excellent" Condition/Desirability/Utility (CDU) rating by the Dallas Appraisal District. NIOs that are presumably better informed represent a greater percentage of non-MLS sales. Builders make up 12.6% of non-MLS sales versus 1.3% of MLS sales; this is consistent with the finding that properties sold outside of the MLS are larger, newer, and have smaller lot sizes. Estates and LP's are also more likely to sell non-MLS. But, financial firms (likely foreclosures) sell a greater proportion through the MLS (7.9% of MLS sales versus 3.2%

non-MLS sales). Individual owners represent a greater proportion of the MLS subsample (86.4%) participants than of the non-MLS subsample (78.7%).

We also estimate a probit model (Table 3) to examine the likelihood that different property characteristics influence the decision to sell using the MLS or to sell outside an MLS. The dummy variable takes a value of "1" if the property is sold via a MLS. Consistent with the results presented in Table 2, larger properties are less likely to be listed on the MLS, while older properties are more likely to have an MLS listing. A property with a Poor CDU rating, ownership by a builder, an estate, a corporation or a limited partnership has a lower probability of selling through a MLS. Properties listed by financial firms and properties with higher CDU ratings have a higher estimated likelihood of selling through a MLS. The results from the probit model are generally consistent with the results from the differences in means tests.

3. Empirical Results

3.1 MLS versus Non-MLS

In this section, we estimate a selling price model as follows:

$$\ln(SP_i) = \beta_0 + \beta_1 \mathit{MLS} + \Sigma\, \beta i\, X_i + \varepsilon_i$$

(1)

The results are presented in Table 4. In Model 1 we only include the MLS dummy and neighborhood fixed effects and year month dummies. In the 2nd model, the vector X_i includes housing characteristics. Model 3 adds CDU dummy variables and Model 4 adds grantor type dummy variables as indicated in Table 1 and Tables 4-6 with individuals as the baseline category in Tables 4 & 5 and Company as the baseline category in Table 6. With only year/month controls and neighborhood fixed effects, it appears that selling through a MLS results in a premium of 2.4%. But once we add physical property characteristics and CDU controls, the coefficient drops to 0.5% and is not significant. Therefore, after controlling for property condition/utility/desirability and physical characteristics, this data shows no premium or discount to listing on a MLS.

However, when we control for the influence of different grantors we identify a significant difference in price from selling through a MLS. Given the results from the differences in means test and the probit model results, we expected the ownership type to influence the results. Some NIO grantors, for example builders, include marketing their properties as part of their business model. Because new properties tend to show well and sell for higher price per square foot, minimizing commission based payments to real estate agents is important to maintain profitability. Thus, we expect that grantors select into or out of the MLS depending upon whether they have substitute marketing platforms. After adding controls for different grantors, holding out individual sellers as the control, the premium for listing on a MLS is now 1.7% and significant at the 1% level.[6] This can be directly interpreted as a premium for individual sellers who list and sell through a MLS.[7] Assuming a 5% commission, about 34% of the commission is capitalized, similar to the approximately 43% capitalization of the brokerage commission estimated by Doiron, Shilling and Sirmans (1985).

The results for the other variables are generally as expected. Houses sell for higher prices when they are larger, builder-owned, owned by a LP, have a pool, a deck, a larger lot, or have more bathrooms or bedrooms. Discounts to the selling price are evident for properties that are older, have a higher percentage of value from the land rather than the house, or are sold by an

[6] In untabulated results, if grantor type controls are added to model 1, the MLS coefficient is approximately 4.27%. It is approximately 1.8% for Model 2 and is statistically significant at 1%.

[7] As Yavas and Colwell (1995) indicate, since we are unable to observe a non-MLS price for a house sold through the MLS or a MLS price for a house that sold outside the MLS, possible sample selection bias may influence the results. Following their procedure, we estimate an Inverse Mills Ratio (IMR) from the probit model and include it in Model 4. The IMR is statistically insignificant indicating no sample selection bias in this sample of non-MLS and MLS transactions.

estate, a financial firm, or FHLM. It is likely that the financial firm and FHLM properties are bank-owned or foreclosure properties, which may explain the discount. In addition, properties with a CDU rating of Poor or Fair sell for less than the average house while properties with a CDU rating of Good, Very Good or Excellent sell for higher prices than the average house as expected.

3.2 Individual Owners and Other Grantors

We next split the sample into individual homeowners and other grantors (NIO). Table 5 provides results based on a sample of 21,614 *individual* grantors, excluding the NIO sales. Estimated coefficients for physical characteristics and CDU ratings are similar to those in the full sample, with signs as expected. In each model in Table 5, the coefficient for MLS is positive and significant. The regression adjusted R^2's range between .899 and .950. The estimated coefficient on the MLS indicator in Model 3 with the full set of controls is 1.8%, approximately the same as Model 4 for the complete sample in Table 4. Individuals receive approximately 1.8% more when they sell their houses through a MLS relative to houses sold outside the MLS.

In Table 6, we limit the sample to grantors other than individual homeowners, i.e. *NIO*. The estimated coefficient on the MLS dummy is positive but not statistically significant. Therefore we cannot reject the null hypothesis that $B_1=0$. These results indicate that grantors other than individuals obtain the same price (no premium or discount) if they sell through the MLS or outside the MLS. It is possible that the grantors who are not individuals sell a significantly higher volume[8] of properties, giving them a level of expertise and familiarity with marketing strategies that are used to compensate when they sell outside of the MLS. Individual owners typically sell single-family residences less frequently, so the effect of the MLS listing on

[8] The median number of sales by NIOs is 6 properties.

marketing efforts has a greater effect on sales prices. In other words, if individuals choose to sell outside of the MLS, they expect to sell at a lower price, but NIO grantors do not.

Evidence suggesting that individual homeowners obtain a price premium by selling through the MLS indicates that a MLS is a valuable service. We use the following example to examine the *net cash flow* to the *individual* seller using the MLS or selling outside the MLS. If an individual sells a property in the MLS for $178,873, the mean in this data set, they could expect to sell it for about $175,653 outside the MLS assuming the 1.8% premium for MLS sales before any transaction costs. If sold through the MLS, the seller would typically pay approximately 5 to 6% of the price in commission costs if MLS access is bundled with other listing agent services. Assuming a full two-sided commission of 5%[9], the seller would receive $169,929 after paying the commission. The difference in the net selling price from selling through a MLS and the selling price expected from selling outside the MLS, is $5,724 ($175,653 expected outside a MLS minus $169,929 net through a MLS), or 3.2% of the MLS selling price.

The results are consistent with Frew and Jud's (1986) estimate of a price premium associated with listing in a MLS and the argument that buyers find a better match and thus have a higher value for the house and pay a higher transaction price. We estimate that grantees buying through a MLS pay approximately 1.8% more for a property purchased through a MLS than a property purchased outside a MLS, with the net effect that buyers pay part of the seller's commission.

If the property sold outside the MLS we would expect the net to the seller to be $175,653 minus any costs incurred in marketing and selling the property. If individual marketing effort costs less than $5,724 outside a MLS, then the individual seller is better off selling their property

[9] The mean buyer's agent commission for the MLS properties in the dataset is approximately 3%. The latest published data on commission rates suggest a rate of approximately 5 percent overall. See Weicher (2006).

outside the MLS, and without a full service listing agent. Levitt, Syerson and Ferreira (2008) estimate the cost of marketing for a homeowner using a flat fee agent is roughly $5,000.[10] Using this estimate, net benefits to sellers outside an MLS are approximately $724 overall.[11] However, if individuals select to sell through a listing agent and a MLS, pay a 5% commission and receive a 1.8% premium, the net commission cost including listing on a MLS is a smaller percentage of the selling price, or 3.2%, rather than the full 5%. In exchange for this fee individuals gain marketing assistance and avoid the effort and other costs associated with marketing their own homes. The willingness of individuals to pay this commission may be a result of being less equipped to market and sell their properties outside a MLS setting than NIO sellers are, or being under pressure to sell more quickly. Possibly, individuals are poorly informed about the costs and benefits of full service listing agent services[12]. It appears that individuals could be slightly better off financially selling outside a MLS, but prefer to forego the difference in net price to avoid the effort and stress of finding a buyer on their own and completing the transaction. As stated earlier, we do not have data on time on the market. For many individual sellers, a quick sale may be important. Hendel, Nevo and Ortalo-Magné, (2009) indicate that agent services including MLS listing decreases average time to sale and this could partially explain an individual's willingness to pay for MLS services.

Other NIO grantors appear to obtain the same initial price whether they sell through a MLS or not. With no offsetting premium for them to sell through the MLS, they would appear better off selling outside the MLS to improve their net cash flow. However, the true selling costs

[10] Mark Nadel (2006) page 49 states "many former employees of traditional brokers are now willing to provide full-service for flat fees of less than $5,000."

[11] If overall commission rates of 6% are used in the analysis, then sellers are $2,513 better off selling outside a MLS after taking effort/marketing costs into account. In this data 4.6% appears to be the breakeven rate, where sellers would be indifferent.

[12] Bernheim and Meer (2012) report a decrease in broker usage after circulation of an early version of their paper which indicated a financial loss to using brokers.

for NIO grantors are not quantified in this study. Builders often market new developments directly to buyer's agents,[13] with detailed information on specific properties and commissions offered. New residential developments also usually maintain "model homes" with onsite sales support. These marketing strategies provide a substitute for MLS listing for this grantor group. A second NIO grantor group includes corporations, LLCs, and LPs that most likely are selling residential properties that have been improved or rehabilitated. Some of these may have initially been investments for renovation and rent, or sale. It is less clear what independent marketing expertise this grantor group might use as an alternative to MLS listing. Evidence from Tables 2 and 3 shows that corporations and LPs are more likely to sell properties outside of the MLS than individuals, which suggests that these grantors also have some substitute marketing strategies which enable them to bypass a listing agent and sell outside the MLS, without selling at a discount.

While our results show that NIO grantors make up a greater *percentage* of non-MLS sales, a *larger number* still sell through a MLS. It is also possible that NIO grantors are in a better position to obtain a commission concession from the listing agent, since they are likely to sell properties more often.

Regrettably, we are unable to examine the time on the market for these properties which might help explain part of the premium or give us a more precise estimate of carrying and marketing costs. MLS listing could increase the likelihood of sale and decrease the time on market. Both would have an impact on explaining the willingness of an individual seller to pay the 3.2% net commission compared to selling outside a MLS. It would also be interesting to examine the probability of obtaining a sale within a given marketing time in the case of MLS

[13] For example, in the real estate agent newspaper "Agent Direct News." Developers also encourage realtors to link to their webpages, providing technology (free to the realtor) that customizes the link to include the realtor's contact information, rather than including contact information for the new construction sales team of the development.

properties and non-MLS properties. Unfortunately, a more complete database than is currently available is needed to examine these issues.[14]

4. Conclusion

This paper examines the sales price of MLS sales relative to non-MLS sales using a unique data set from the Texas Comptroller's Office for Dallas County during 2004-2005. In general, our results support the extensive use of MLS services that we see in the market. We find that individual sellers obtain a 1.8% price premium selling through a MLS as opposed to not selling through a MLS. NIO grantors obtain the same price selling through a MLS as they do selling outside a MLS. These grantors may have access to and experience with alternative marketing strategies that make it possible for them to sell properties outside of the MLS without a price reduction. Individuals either do not have access to these substitute marketing techniques, or are unwilling to accept the inconvenience and risks of doing so; thus when selling properties outside of the MLS, they sell at lower prices. However the net price differential using a 5% commission and Levitt et al's (2008) estimate of marketing costs suggest that sellers normally would be effectively financially indifferent between selling through a MLS or outside an MLS. If commission rates are higher than 5%, our estimates suggest an increase in the marginal benefits from selling outside an MLS. These results are generally consistent with findings, by Hendel, Nevo, and Ortalo-Mangé (2009) who provide evidence that sellers sort themselves into different market segments based on their selling preferences and strategy.

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6. Tables

Table 2.1

Definition of variables used in the models.

Variable	Description
Selling Price	selling price of the house, expressed as ln(sp) in the regression models.
MLS	dummy variable indicating a property sold through the Multiple Listing Service (MLS).
Size	number of square feet divided by 100.
Age	year of sale minus year built divided by 10.
Bathrooms	number of bathrooms.
Bedrooms	number of bedrooms.
Fireplace	number of fireplaces.
Stories	number of stories.
Pool	dummy variable indicating the presence of a pool.
Deck	dummy variable indicating a deck.
Sprinkler	dummy variable indicating a sprinkler system.
Land Square Feet	land square feet reported by the appraisal district, divided by 10,000.
Land Percent	land value as a percent of appraisal district total property value.
Poor	dummy variable indicating the appraisal district's "poor" rating of property Condition/Desirability/Utility.
Fair	dummy variable indicating the appraisal district's "fair" rating of property Condition/Desirability/Utility.
Average	dummy variable indicating the appraisal district's "average" rating of property Condition/Desirability/Utility.
Good	dummy variable indicating the appraisal district's "good" rating of property Condition/Desirability/Utility.
Very Good	dummy variable indicating the appraisal district's "very good" rating of property Condition/Desirability/Utility.
Excellent	dummy variable indicating the appraisal district's "excellent" rating of property Condition/Desirability/Utility.
Estate	dummy variable indicating grantor is an estate.
Trust	dummy variable indicating grantor is a trust.
Company	dummy variable indicating grantor is a company.
LLC	dummy variable indicating grantor is a limited liability corporation.
LP	dummy variable indicating grantor is a limited partnership.
Financial	dummy variable indicating grantor is a financial institution.
FHLM	dummy variable indicating grantor is the Federal Home Loan Mortgage Corporation
Builder	dummy variable indicating grantor is a builder.
Sale Month/Year dummies	set of dummy variables controlling for market conditions at sale.
Neighborhood fixed effects	Neighborhood fixed effects for property based on Neighborhood codes provided by the Dallas County Appraisal District.

Table 2.2
Descriptive statistics for the full sample and subsamples. Includes properties that are identified as selling through a MLS and properties identified as selling outside the MLS. Excluding residential houses with missing observations, the final sample includes 25,125 houses sold during January 2004-June 2005, with 21,458 sales identified as having sold through a MLS and 3,667 outside the MLS. The data is from Dallas County. Texas County Appraisal Districts (CADs) submit property sales information they collect to the Comptroller's office. We do not report the month year dummy variables or appraisal district defined Neighborhood code dummies below for brevity. There are 17 months and 2,289 different Neighborhood codes in the sample. The t-statistics are calculated to test the null: mean(MLS sale) - mean(non-MLS sale)=0. Statistics with significance at the 1% level are denoted with a ** and the 5% level are denoted with a *.

Summary Statistics of Key Variables	Full Sample		MLS sale, n=21,458		Non-MLS sale, n=3,667			
	Mean	Median	Mean	Median	Mean	Median	t-statistics	
Selling Price	178,873	132,900	177,671	128,000	185,910	152,500	-3.15	**
MLS	0.854	1.00	1.00	1.00	0.00	0.00	-	
Size	1,945	1,764	1,909	1,728	2,160	1,966	-17.66	**
Age	29.945	27.00	31.737	30.00	19.457	18.00	36.99	**
Bathrooms	2.021	2.00	1.998	2.00	2.154	2.00	-13.25	**
Bedrooms	3.226	3.00	3.214	3.00	3.298	3.00	-7.37	**
Fireplace	0.815	1.00	0.793	1.00	0.945	1.00	-16.28	**
Stories	1.176	1.00	1.161	1.00	1.268	1.00	-18.00	**
Pool	0.137	0.00	0.134	0.00	0.153	0.00	-3.09	**
Deck	0.057	0.00	0.059	0.00	0.047	0.00	2.74	**
Sprinkler	0.194	0.00	0.185	0.00	0.250	0.00	-9.15	**
Land Square Feet	0.986	0.84	0.998	0.85	0.920	0.80	4.01	**
Land Percent	21.954	19.18	21.980	18.99	21.800	20.27	0.94	
Poor	0.012	0.00	0.012	0.00	0.014	0.00	-1.31	
Fair	0.049	0.00	0.052	0.00	0.027	0.00	6.52	**
Average	0.224	0.00	0.228	0.00	0.198	0.00	4.09	**
Good	0.298	0.00	0.308	0.00	0.236	0.00	8.84	**
Very Good	0.229	0.00	0.226	0.00	0.245	0.00	-2.53	**
Excellent	0.189	0.00	0.173	0.00	0.279	0.00	-15.24	**
Individual Owners	0.852	1.00	0.864	1.00	0.787	1.00	12.12	**
Estate	0.006	0.00	0.006	0.00	0.007	0.00	-0.44	
Trust	0.011	0.00	0.011	0.00	0.010	0.00	0.91	
Company	0.016	0.00	0.015	0.00	0.019	0.00	-1.76	
LLC	0.004	0.00	0.004	0.00	0.005	0.00	-1.16	
LP	0.005	0.00	0.004	0.00	0.011	0.00	-5.98	**
Financial	0.073	0.00	0.079	0.00	0.032	0.00	10.14	**
FHLM	0.004	0.00	0.004	0.00	0.003	0.00	0.94	
Builder	0.029	0.00	0.013	0.00	0.126	0.00	-38.34	**
Sample Size	25,125		21,458		3,667			

Table 2.3
Probit model. The dependent variable is whether the property is sold through a MLS or not. The dependent variable takes a value of "1" if the property is sold via the MLS. The model includes monthly dummy variables (not reported for brevity) and Dallas County Property Appraisal District Neighborhood fixed effects (not reported for brevity) to control for location/neighborhood characteristics. The estimates of the coefficients are presented in the table, with t-statistics reported using heteroskedasticity-robust standard errors. Statistics with significance at the 1% level are denoted with a ** and at the 5% level are denoted with a *.

Independent Variable	Model 1, probit	Model 1, Reporting Marginal Effects	t-statistics
Constant	0.910**		6.91
Size	-0.031**	-0.005**	-4.29
Size squared	0.000**	0.000**	3.14
Age	0.223**	0.038**	8.60
Age squared	-0.018**	-0.003**	-5.25
Bathrooms	0.116**	0.019**	3.89
Bedrooms	0.090**	0.015**	3.70
Fireplace	-0.025	-0.004	-0.83
Stories	0.062	0.010	1.58
Pool	-0.067	-0.012	-1.89
Deck	0.100	0.016	1.85
Sprinkler	0.135**	0.022**	4.20
Land Square feet	-0.005	-0.001	-0.30
Land Square feet squared	0.000	0.000	0.24
Land Percentage	-0.006**	-0.001**	-4.11
Poor	-0.340**	-0.070**	-3.32
Fair	0.060	0.010	0.91
Good	0.118**	0.019**	3.39
Very Good	0.146**	0.023**	3.94
Excellent	0.150**	0.024**	3.70
Estate	-0.431**	-0.094**	-3.20
Trust	-0.010	-0.002	-0.09
Company	-0.299**	-0.060**	-3.49
LLC	-0.296	-0.060	-1.84
LP	-0.689**	-0.171**	-5.49
Financial	0.379**	0.051**	6.97
FHLM	0.208	0.030	1.03
Builder	-1.358**	-0.414**	-22.93
Sale Year Month fixed effects	Yes		
Neighborhood fixed effects	Yes		
Number of Observations	25,125		
Pseudo R2	0.2954		
Log - pseudolikelihood	-7,358		

Table 2.4

Regression models of full sample house prices. This is based on a sample of 25,125 residential houses sold during January 2004-June 2005 obtained from the state of Texas for Dallas County. The variable of interest is whether the property sold through the MLS or not. In this full sample 14.60% or 3,667 sold outside the MLS. Individuals are the baseline category in this sample for the grantor types. County Appraisal Districts (CADs) are required to submit property sales information they collect to the Comptroller's office which allows for a determination of MLS or non-MLS sales. All models include month/year dummy variables (not reported for brevity) to control for potential serial effects and all regressions include Neighborhood fixed effects (not reported for brevity) to control for location/neighborhood characteristics. The estimates of the coefficients are presented in the table, with t-statistics reported using heteroskedasticity-robust Huebner/White standard errors. Statistics with significance at the 1% level are denoted with a ** and at the 5% level are denoted with a *.

Independent Variable	Model 1		Model 2		Model 3		Model 4	
Constant	11.223**	338.20	11.335**	296.69	11.302**	280.47	11.271**	297.21
MLS	0.024**	3.48	0.008	1.55	0.005	1.11	0.017**	3.71
Size			0.025**	17.80	0.027**	19.85	0.028**	21.18
Size squared			-0.000**	-8.79	-0.000**	-9.96	-0.000**	-10.63
Age			-0.063**	-9.29	-0.059**	-8.91	-0.059**	-8.99
Age squared			0.006**	7.26	0.006**	7.09	0.006**	7.30
Bathrooms			0.022**	6.74	0.022**	7.00	0.022**	7.21
Bedrooms			0.004	1.55	0.005*	1.98	0.006**	2.66
Fireplace			0.023**	6.06	0.023**	6.28	0.026**	7.28
Stories			-0.005	-0.94	-0.009	-1.81	-0.004	-0.95
Pool			0.047**	13.75	0.049**	14.80	0.051**	16.17
Deck			0.015**	3.18	0.010*	2.12	0.012**	2.88
Sprinkler			0.017**	5.85	0.012**	4.34	0.012**	4.35
Land Square Feet			0.061**	14.00	0.059**	13.73	0.058**	14.26
Land Squared			-0.001**	-10.38	-0.001**	-10.13	-0.001**	-10.97
Land Percentage			-0.016**	-28.52	-0.014**	-24.84	-0.013**	-23.80
Poor					-0.116**	-6.34	-0.117**	-6.53
Fair					-0.063**	-8.61	-0.059**	-8.30
Good					0.022**	6.58	0.027**	8.37
Very Good					0.046**	12.16	0.053**	14.92
Excellent					0.053**	11.94	0.065**	15.19
Estate							-0.038*	-2.52
Trust							0.002	0.22
Company							-0.014	-1.23
LLC							0.004	0.19
LP							0.036*	2.29
Financial							-0.186**	-41.30
FHLM							-0.117**	-7.07
Builder							0.033**	3.12
Sale Year/Month fixed effects	Yes		Yes		Yes		Yes	
Neighborhood fixed effects	Yes		Yes		Yes		Yes	
Number of Observations	25,125		25,125		25,125		25,125	
Adjusted R^2	0.892		0.94		0.942		0.947	

Table 2.5
Regression models of individual-owned house prices. This is based on a sample of 21,614 residential houses owned by *individuals* and sold during January 2004-June 2005 obtained from the state of Texas for Dallas County. The variable of interest is whether the property sold through the MLS or not. Individuals are the baseline category for the grantor types in this sample. In this sample 13.84% or 2,991 are sold outside the MLS. County Appraisal Districts (CADs) are required to submit property sales information they collect to the Comptroller's office which allows for a determination of MLS or non-MLS sales. All models include month/year dummy variables (not reported for brevity) to control for potential serial effects and all regressions include Neighborhood fixed effects (not reported for brevity) to control for location/neighborhood characteristics. The estimates of the coefficients are presented in the table, with t-statistics reported using heteroskedasticity-robust Huebner/White standard errors. Statistics with significance at the 1% level are denoted with a ** and at the 5% level are denoted with a *.

Independent Variable	Model 1		Model 2		Model 3	
Constant	11.227**	371.93	11.298**	303.60	11.248**	293.31
MLS	0.038**	4.98	0.018**	3.58	0.018**	3.64
Size			0.026**	17.43	0.028**	19.91
Size squared			-0.000**	-8.41	-0.000**	-9.84
Age			-0.060**	-8.38	-0.055**	-7.94
Age squared			0.006**	7.13	0.006**	6.90
Bathrooms			0.020**	6.13	0.020**	6.40
Bedrooms			0.006*	2.25	0.007**	2.80
Fireplace			0.026**	6.64	0.027**	7.14
Stories			-0.001	-0.12	-0.004	-0.87
Pool			0.049**	14.41	0.052**	15.80
Deck			0.016**	3.49	0.010*	2.20
Sprinkler			0.019**	6.43	0.014**	4.99
Land Square Feet			0.062**	12.24	0.058**	12.12
Land Squared			-0.001**	-10.42	-0.001**	-10.41
Land Percentage			-0.016**	-26.17	-0.013**	-22.03
Poor					-0.126**	-6.09
Fair					-0.061**	-7.92
Good					0.032**	9.56
Very Good					0.060**	15.73
Excellent					0.076**	16.14
Estate					-	-
Trust					-	-
Company					-	-
LLC					-	-
LP					-	-
Financial					-	-
FHLM					-	-
Builder					-	-
Sale Year/Month fixed effects	Yes		Yes		Yes	
Neighborhood fixed effects	Yes		Yes		Yes	
Number of Observations	21,614		21,614		21,614	
Adjusted R^2	0.899		0.948		0.950	

Table 2.6
Regression models of NIO house prices. This is based on a sample of 3,511 residential houses sold by *not-individual-owners* (NIO) during January 2004-June 2005 obtained from the state of Texas for Dallas County. *Company* is the baseline category for the grantor types in this sample. The variable of interest is whether the property sold through the MLS or not. In this sample 19.25% or 676 sold outside the MLS. County Appraisal Districts (CADs) are required to submit property sales information they collect to the Comptroller's office which allows for a determination of MLS or non-MLS sales. All models include month/year dummy variables (not reported for brevity) to control for potential serial effects and all regressions include Neighborhood fixed effects (not reported for brevity) to control for location/neighborhood characteristics. The estimates of the coefficients are presented in the table, with t-statistics reported using heteroskedasticity-robust Huebner/White standard errors. Statistics with significance at the 1% level are denoted with a ** and at the 5% level are denoted with a *.

Independent Variable	Model 1		Model 2		Model 3		Model 4	
Constant	11.175**	46.33	11.563**	57.04	11.595**	56.09	11.490**	67.92
MLS	-0.013	-0.51	-0.032	-1.94	-0.030	-1.84	0.014	0.91
Size			0.020**	4.04	0.019**	3.89	0.022**	4.75
Size squared			-0.000*	-2.37	-0.000*	-2.28	-0.000**	-2.87
Age			-0.093**	-3.67	-0.093**	-3.65	-0.082**	-3.44
Age squared			0.007	1.88	0.007	1.89	0.006	1.72
Bathrooms			0.029*	2.08	0.030*	2.08	0.031*	2.44
Bedrooms			-0.005	-0.50	-0.006	-0.57	0.004	0.43
Fireplace			-0.003	-0.22	-0.002	-0.14	0.007	0.51
Stories			0.009	0.55	0.009	0.57	0.008	0.58
Pool			0.008	0.42	0.006	0.31	0.028	1.62
Deck			-0.015	-0.51	-0.014	-0.48	0.020	0.77
Sprinkler			-0.000	-0.02	0.005	0.38	0.005	0.43
Land Square Feet			0.075**	3.98	0.074**	3.94	0.063**	3.51
Land Squared			-0.001	-1.83	-0.001	-1.80	-0.001	-1.41
Land Percentage			-0.021**	-10.70	-0.021**	-10.42	-0.018**	-9.79
Poor					-0.049	-0.98	-0.062	-1.37
Fair					-0.031	-1.04	-0.025	-0.95
Good					-0.025	-1.67	0.001	0.05
Very Good					-0.034*	-2.03	0.007	0.48
Excellent					-0.033*	-2.35	-0.005	-0.38
Estate							-0.038	-1.23
Trust							0.016	0.75
Company							-	-
LLC							0.018	0.45
LP							0.056*	1.99
Financial							-0.194**	-11.24
FHLM							-0.131**	-4.41
Builder							0.008	0.38
Sale Year/Month fixed effects	Yes		Yes		Yes		Yes	
Neighborhood fixed effects	Yes		Yes		Yes		Yes	
Number of Observations	3,511		3,511		3,511		3,511	
Adjusted R^2	0.915		0.946		0.946		0.956	