Local Predictive Ability of Analyst Recommendations

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Abstract

This paper examines the predictive ability of aggregate analyst recommendations using data from 48 Metropolitan Statistical Areas (MSAs) and 35 states over the 1994-2014 period. We aggregate analyst recommendations and stock returns at the MSA- and state-level (i.e., local level) to construct local measures of analyst recommendations and stock returns. We find that analyst recommendations predict future local excess returns even after controlling for macroeconomic variables, industry returns, and overall market returns. We further show that the local predictive ability of analyst recommendations is stronger for geographically concentrated firms. Our findings suggest that analyst recommendations contain information at the MSA- and state-level, and the local information content is richer for geographically concentrated firms.

Keywords: return predictability; local stock returns; analyst recommendations; MSA

JEL Classification: G12, G11, G14, G24

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1. Introduction

This paper provides evidence that aggregate analyst recommendations predict future stock returns at the Metropolitan Statistical Area (MSA)- and state-level. Previous studies show that analysts incorporate market-level, industry-level, and firm-specific information into their recommendations.[1] For example, Howe et al. (2009) find that analyst recommendations aggregated at the market- and industry-level predict future excess market returns and excess industry returns, respectively. Recent research also shows that stock returns are affected by local economic fundamentals such as unemployment rate and housing collateral (Korniotis and Kumar, 2013). The results of our study suggest that sell-side analysts use local (MSA- and state-level) information when they issue recommendations.[2] Moreover, these results are stronger for firms that are less geographically dispersed, suggesting that the ability of local analyst recommendations to predict stock returns depends on the geographic concentration of firms.

Our study focuses on the relation between stock returns and analyst recommendations at the MSA- and state-level based on firm headquarters. Following Pirinsky and Wang (2006), for any given month, we group firms into MSAs and states based on their headquarters' locations. To calculate the stock returns at the MSA- and state-level (i.e., local returns), we average the returns of all stocks located in a given MSA and state. We measure aggregate local recommendations for an MSA (or state) as the change in the average of all outstanding recommendations for the stocks of firms whose headquarters are located in a particular MSA (or state). By averaging recommendations across firms, we eliminate firm-specific information contained in analyst recommendations and obtain a local measure of recommendations. Such aggregation techniques are common in the literature. For example,

[1] See: Barber et al. (2001), Jegadeesh et al. (2004), Boni and Womack (2006), Howe et al. (2009), Kadan et al. (2012), and Berkman and Yang (2016).

[2] In this paper, the word "local" refers to various measures that we construct at the Metropolitan Statistical Area (MSA) level and the state level based on firm headquarters.

Seyhun (1988) aggregates the transactions by corporate insiders and finds a positive relation between aggregate insider trading and future stock market returns. Howe et al. (2009) state that "aggregation cancels out the idiosyncratic components of analyst recommendations and isolates their common response to systematic factors." Therefore, analyst recommendations aggregated at the local level should capture information regarding local economic factors and local stock returns.

Based on 7,851 MSA-month and 4,680 state-month observations, we find that one standard deviation increase in aggregate local recommendations is associated with 2.89% and 2.08% increase in one-quarter-ahead MSA-level and state-level excess returns, respectively. The results are robust to controlling for macroeconomic variables, market returns, and industry returns. We obtain stronger results at the MSA-level compared to the state-level. MSA-level estimates are statistically significant at the 1% level while state-level estimates are statistically significant at the 10% level. The overall evidence suggests that analysts use local information at the MSA- and state-level in their recommendations.

We further examine whether the geographic concentration of firms affects the ability of analyst recommendations to predict future local excess returns. García and Norli (2012) identify the list of states where a given firm has presence by counting the number of times a state is mentioned in that firm's filings. Using their data, we separate our sample into two groups; firms that operate in five or fewer states and firms that operate in more than five states. We find a strong positive relation between aggregate analyst recommendations and local returns for the firms with operations in five or fewer states. We do not find any significant results for the firms that operate in more than five states. The relation between the predictive ability of aggregate analyst recommendations and the geographic concentration of firms suggests that local economic fundamentals play a relatively larger role for geographically concentrated firms relative to geographically dispersed firms.

Our study makes several contributions to the literature. First, it expands the body of knowledge on analyst recommendations by showing that aggregate analyst recommendations contain local information at the MSA- and state-level in addition to market-, industry-, and firm-level information. Second, our study contributes to the growing literature on how geographic location affects the decision making by economic agents. We provide evidence that local economic factors play a larger role in analyst recommendation for geographically concentrated firms. Furthermore, under the assumption that analysts are market participants, analyzing the relation between stock returns and analyst recommendations adds to the literature on the predictive content of the aggregated decisions by individual market participants.

The rest of the paper proceeds as follows. We summarize the related studies and develop the hypotheses in Section 2. We describe the data and the construction of variables in Sections 3 and 4, respectively. Section 5 sets up the empirical framework and discusses the regression results. Section 6 presents the robustness checks, and Section 7 concludes the paper.

2. Literature Review and Hypothesis Development

Early research shows that analyst recommendations result in abnormal returns and prices.[3] Elton et al. (1986) and Womack (1996) find significant positive abnormal returns associated with "upgraded" recommendations that persist up to six months. Barber et al. (2001)

[3] Davies and Canes (1978) find that the stock prices react positively/negatively on and after the day of publication of the buy/sell recommendations in Wall Street Journal's "Heard on the Street" column for the years 1970 and 1971. Their results are supported by the follow-up studies from Liu et al. (1990) and Beneish (1991) for the years 1982-1985 and 1978-1979, respectively. Similarly, other studies such as Barber and Loeffler (1993) and Liang (1999) also examine the abnormal returns and prices over a 2-day period following the expert recommendations in the "Dartboard" column of the Wall Street Journal. These studies also show substantial, if not complete, mean reversion of returns after 10 to 15 days following the stock recommendations.

extend the investigation of abnormal returns to consensus recommendations. They show that a trading strategy of buying the most highly recommended stocks and short selling the least favorably recommended stocks generates positive abnormal returns, even after controlling for market risk, size, value, and momentum effects. However, they also find that these abnormal returns dissipate after controlling for transaction costs. Contrary to the previous studies, Jegadeesh et al. (2004) find that the predictive ability of analyst consensus recommendations is not robust to the inclusion of other predictive signals such as momentum or contrarian signals. Instead, they find that the change in analyst recommendations over the prior quarter predicts future returns even after controlling for the aforementioned predictive signals.

More recently, the empirical literature provides supporting evidence on the predictive power of aggregate analyst recommendations for future aggregate returns and earnings. More specifically, Howe et al. (2009) show that aggregate analyst recommendations are positively related to future stock market and industry returns. Their findings suggest that analyst recommendations contain economy-wide and industry-wide information. Boni and Womack (2006) find that analyst recommendations contain short-term information about within-industry mispricings. Kadan et al. (2012) find that portfolios based on industry recommendations generate abnormal returns even after controlling for the industry momentum. These persistent abnormal returns imply that analysts exhibit across-industry expertise in addition to within-industry expertise. Further, Berkman and Yang (2016) show that aggregate analyst recommendations for individual countries contain information about the cross-section of future international stock market returns, and these recommendations predict the growth rate of gross domestic product (GDP), industrial production (IP), and aggregate earnings.

There is also a growing number of studies on the role of geography for stock returns. For example, local equity preference is well-documented in the home-bias literature suggesting that local factors matter for analysts and investors.[4] Recently, more studies are examining the economic implication of locality on asset prices. Pirinsky and Wang (2006) find that stock returns of companies headquartered in the same geographic area (MSA) exhibit a strong degree of comovement. They find that this comovement is different from the market-wide and industry-wide comovement in stock returns, and it is likely to be related to the trading patterns of local investors. In the same spirit, Barker and Loughran (2007) find that the monthly returns of S&P 500 firms with geographically close headquarters are more highly correlated than firms that are distant from each other.

Anderson and Beracha (2008) analyze the headquarters-city proximity effect in stock returns and find that accounting for the additional asset pricing factors reduces, but does not eliminate, this effect. Li and Zhao (2016) find that being in the same state and/or in the same industry strengthens the return comovement. Korniotis and Kumar (2013) find that fluctuations of state-level economic variables such as unemployment rates and housing collateral predict U.S. state portfolio returns. Furthermore, Parsons et al. (2016) find that regionally-sorted stock portfolios generate trading profits that are significantly higher than industry-sorted portfolios. The overall evidence suggests that local fundamentals are important for neighboring firms, even if they may be operating in different lines of businesses.

The goal of this study is to determine whether sell-side analysts incorporate local information into their recommendations. The extant literature presents evidence that industry factors are important in generating performance differences between firms (Schmalensee, 1985; McGahan and Porter, 1997), and analysts incorporate valuable industry-level information into their recommendations (Boni and Womack, 2006; Kadan et al., 2012). Recent

[4]U.S. investment managers (Coval and Moskowitz, 1999; Giannetti and Laeven, 2015), households (Ivković and Weisbenner, 2005), institutions (Bernile et al., 2015) and analysts (Orpurt, 2004; Malloy, 2005; Bae et al., 2008; O'Brien and Tan, 2015) exhibit a strong preference for locally headquartered stocks.

research also shows that local economic factors are important in predicting stock returns. We attempt to complete the picture here by asking if analysts also use local information when they issue recommendations. We argue that to the extent analysts use local information in their recommendations, their recommendations aggregated at the local level will predict future local returns. We formally formulate this hypothesis as:

Hypothesis 1: There is a positive relation between aggregate local recommendations and future local returns.

Our second hypothesis exploits the geographic concentration of firms. García and Norli (2012) show that the returns of geographically concentrated firms exceed the returns of geographically dispersed firms. They identify the list of states where a given firm has presence by counting the number of times a state is mentioned in the company filings. We anticipate that local economic factors are more important for geographically concentrated firms than for geographically dispersed firms. Let's suppose that Company A and Company B are both headquartered in Texas, and Company A has operations in 30 states, but Company B has operations only in Texas. We suspect that all else equal, local economic factors have a greater marginal effect on Company B's stock than Company A's stock, because Company B has a much larger exposure to the local factors. Thus, we argue that local factors are more influential on analyst recommendations for geographically concentrated firms. As a result, we state our second hypothesis as the following:

Hypothesis 2: The local information content of analyst recommendations is richer for geographically concentrated firms.

3. Data

3.1. Returns and Location Data

We obtain monthly stock returns over the 1994-2014 period from the Center for Research in Security Prices (CRSP). We restrict the sample to the domestic common stocks (CRSP share code of 10 or 11) listed on the NYSE, Amex, or Nasdaq (CRSP exchange code of 1, 2, or 3). We map these stocks to 49 Fama-French industries using Standard Industrial Classification (SIC) codes from the CRSP/Compustat Merged (CCM).[5]

In this study, we define *location* either as the Metropolitan Statistical Area (MSA) or the state where a given firm is headquartered. Following Pirinsky and Wang (2006), we assign stocks to Metropolitan Statistical Areas (MSAs) based on the county of their headquarters, which we obtain from CCM. For the state-level analysis, we use the state of headquarters to assign stocks to states. The data on the state of headquarters come from García and Norli (2012) for the 1994-2008 period.[6] This data set provides information not only on the state of headquarters but also on all the states where a firm has presence. Due to limited data availability, the state-level analysis covers the 1994-2008 period, whereas the MSA-level analysis encompasses the 1994-2014 period.

3.2. Recommendations Data

Individual analyst recommendations for U.S. stocks come from I/B/E/S Analyst Recommendation Detail file. Following prior empirical literature, we reverse the ordering of I/B/E/S recommendations such that 1, 2, 3, 4, and 5 now correspond to sell, underperform, hold, buy, and strong buy, respectively. We match stocks in the I/B/E/S database to those in the CRSP

[5]We thank Prof. French for making the crosswalk file between SIC codes and the 49 industry classification available on his website.

[6]We thank Dr. García for making the location data available at http://leeds-faculty.colorado.edu/garcia/page3.html.

database using eight digit CUSIP numbers. We follow Howe et al. (2009) on the restrictions for the recommendations data set. In particular, we impose the following conditions: (1) the recommendation must be associated with a CUSIP number and have a recommendation date; (2) the recommendation must be made by an analyst with a non-missing analyst code; (3) the firm must be in the CRSP database during the month of recommendation; (4) the firm must have a share code of 10 or 11 on CRSP; and (5) all the first recommendations are excluded from the sample because by definition they cannot be classified as upgrades, downgrades or reiterations.

We use the permanent security identifiers (i.e., PERMNOs) from CRSP to assign I/B/E/S recommendations to Metropolitan Statistical Areas (MSAs) and states. We require that there be at least three recommendations in each location (MSA or state) every month. The merging procedure creates separate samples for MSAs and states. The MSA sample has a total of 12,326 firms spread in 48 MSAs for the 1994-2014 period, while the state sample has a total of 10,254 firms with headquarters located in 35 states for the 1994-2008 sample. The firms in both samples are followed on average by 2 analysts per period, and the average recommendation for the sample period is approximately 3.75 (hold-toward-buy).

We calculate the average number of firms and the average number of industries over the sample period in each location, and report these results in Table 1 along with the sample size. The average number of firms per MSA varies from a minimum of 5 (Reading MSA) to a maximum of 668 firms (New York - Northern New Jersey - Long Islands MSA). The average number of industries per MSA ranges from a minimum of 4 (Reading MSA) to a maximum of 43 industries (New York - Northern New Jersey - Long Islands MSA). The average number of firms per state for the sample period is the lowest in Idaho with 6 firms and the highest in California with 774 firms. The average number of industries per state for the sample period is also the lowest in Idaho with 6 industries and the highest in California with 43 industries.

[Table 1 About Here]

Using the relevant data from Table 1, Figures 1 and 2 show the respective distributions of the average number of firms and industries per MSA. The distribution of firms per MSA is positively skewed with an average of 88 firms per MSA and a standard deviation of 118.4. On the other hand, the industries per MSA are normally distributed with a mean of 21 industries per MSA and a standard deviation of 9.63. We present the distributions of the average number of firms and industries per state in Figures 3 and 4. The firms per state exhibit a positively skewed distribution with an average of 123 firms per state and a standard deviation of 148. On the contrary, the number of industries per state has a normal distribution with a mean of 26 industries and a standard deviation of 10.

[Figures 1 and 2 About Here]

[Figures 3 and 4 About Here]

4. Variables

4.1. Dependent Variable: Future Local Excess Returns

We are primarily interested in determining whether analyst recommendations aggregated at the local level (MSA or state) predict future stock returns at the local level. We follow Pirinsky and Wang (2006) and compute equal-weighted local returns using all the stocks that survive the restrictions in Section 3.1.[7] Next, we subtract one-month Treasury bill rate from

[7] Since we use all the stock returns instead of only the returns from those with recommendations, the composition of the firms used for return calculations is not always the same as that used for recommendation calculations. However, this is consistent with the prior literature. For example, Howe et al. (2009) construct measures of analyst recommendations at the industry level, but they use this measure to predict Fama-French industry returns, which come from a larger sample. Similarly, the authors construct an aggregate measure of

the local returns to obtain the local excess returns for a given MSA or state ($LOCALret$). We summarize the steps to calculate the local excess returns for location i via Equation (1):

$$LOCALret_{i,t} = \left(\frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} ret_{j,i,t} \right) - rf_t \tag{1}$$

We also refer to the output from Equation (1) as the excess returns on local portfolio i. In this equation, $N_{i,t}$ is the number of stocks in location i during month t, $ret_{j,i,t}$ is the return on stock j in location i during month t, and rf_t is the one-month Treasury bill rate during month t.[8] Similar to Pirinsky and Wang (2006), we require that $N_{i,t}$ be at least 5 (i.e., the number of stocks in location i must be greater than or equal to 5 in month t) and that there be at least two industries (based on 49 Fama-French industry classification) in a given location each month. After we calculate $LOCALret$, we eliminate the MSAs and states with fewer than 24 months of returns from the sample. We use the three-month ahead excess local returns ($LOCALret_{t+3}$) as our dependent variable.

4.2. Main Explanatory Variable: Change in Average Recommendations

Our main explanatory variable is a measure of analyst recommendations aggregated at the local level (MSA or state) that we develop by following Howe et al. (2009). We first create a monthly aggregate index that captures the change in average recommendations. For location i, we construct this monthly index based on Equations (2) and (3):

$$AvgRec_{i,t} = \frac{\sum_{p=1}^{K_{i,t}} Rec_{i,p,t}}{K_{i,t}} \tag{2}$$

where $K_{i,t}$ is the total number of recommendations issued for stocks in location i during month t, and $Rec_{i,p,t}$ refers to recommendation p issued to stocks in location i during month

analyst recommendations from a restricted sample of stocks, but employ the CRSP value-weighted market returns as their dependent variable.

[8]Throughout the manuscript, we use *month t* and *time t* interchangeably.

t. Recommendations take values between 5 (highest recommendation) and 1 (lowest recommendation). For each location, we require that there are at least three recommendations in a given month. In the subsequent step, we calculate the change in average recommendation for location i as:

$$\Delta AvgRec_{i,t} = AvgRec_{i,t} - AvgRec_{i,t-l} \tag{3}$$

where $AvgRec_{i,t-l}$ is the average analyst recommendations for location i during month $t-l$ (past nearest month). As a result, $ChgAvgRec_{i,t}$ is the difference between the average recommendation in month t and the average recommendation in past nearest month $t-l$. When we have consecutive data points (i.e., non-missing months), $t-l$ will equal $t-1$. However, if we do not have any data from the previous month, l can take any value. By using the data from the past nearest month, we increase the sample size and possibly improve the information content of analyst recommendations. Let's suppose that for New York, we have average recommendations in May 2010, March 2010, and January 2010 and no recommendations data in April 2010 and February 2010. If we require l to be equal to 1 in Equation 3, $\Delta AvgRec$ in May 2010 and March 2010 will have missing values. This is because there is no data from April 2010 and February 2010. However, $\Delta AvgRec$ in May 2010 and March 2010 will have non-missing values when we do not require l to be 1. This is because we can use data from May 2010 and March 2010 (past nearest month) to calculate $\Delta AvgRec$ in May 2010, and data from March 2010 and January 2010 (past nearest month) to calculate $\Delta AvgRec$ in March 2010.

The final step averages the change in average analyst recommendation ($\Delta AvgRec$) over the past three months. Using data from the past three months is consistent with Howe et al. (2009) and Lakonishok and Lee (2001). Equation (4) demonstrates this final step:

$$ChgAvgRec3_{i,t-3} = \frac{1}{3}\sum_{j=1}^{3} \Delta AvgRec_{i,t-j} \tag{4}$$

where $ChgAvgRec3_{t-3}$ is the main explanatory variable in this study.

4.3. Other Control Variables

Based on the return predictability literature, Howe et al. (2009) use the three-month Treasury bill rate, default spread, term spread, and dividend yield as control variables. We also include the same variables in our predictive regressions. The default spread (def_spread) equals the yield on BAA-rated corporate bonds minus the yield on 10-year Treasury bonds, and the term spread ($term\_spread$) equals the yield on the 10-year government bonds minus the rate on three-month Treasury bills ($tb3m$). The necessary data for these macroeconomic variables come from the Federal Reserve Bank of St. Louis.[9] We construct the dividend yield (dy) as the ratio of 12-month sum of dividends to the value of the market index in the previous month based on the data from Amit Goyal.[10]

We also include a measure of industry returns in the regression analysis. Our local portfolios might be dominated by a single industry, and thus we might be capturing industry-wide information in our local portfolios instead of local economic information. We identify the industry return that explains the local returns by following Pirinsky and Wang (2006). In particular, for a given location, we run time series regressions using returns from 49 different industries as an explanatory variable (one industry at a time) and then pick the industry that best explains the returns in an MSA or state based on R-squared ($bestindustry$). The last variable that we control for is the market returns. The possibility exists that the local

[9] Data can be access at https://research.stlouisfed.org/fred2/

[10] We thank Prof. Goyal for making the index and dividend data available at http://www.hec.unil.ch/agoyal/

portfolio returns are influenced by the overall market returns. We use the excess returns on the CRSP value-weighted market index as a proxy for the market returns (*market*).

5. Empirical Framework and Results

5.1. Empirical Setup

To determine the relation between aggregate local recommendations and future local excess returns, we first estimate a baseline equation with only the main explanatory variable, $ChgAvgRec3_{i,t-3}$, and lagged dependent variable:

$$LOCALret_{i,t+3} = \beta_0 + \beta_1 ChgAvgRec3_{i,t-3} + \beta_2 LOCALret_{i,t-3} + \epsilon_{i,t} \tag{5}$$

where $LOCALret_{i,t+3}$ and $LOCALret_{i,t-3}$ are the three-month ahead and three-month lagged excess returns for location i. We use monthly returns and adopt quarterly horizon as in Howe et al. (2009) in our empirical framework. We augment the baseline model by adding the control variables introduced in Section 4.3. Adding these control variables to the baseline model gives us the full model:

$$\begin{aligned} LOCALret_{i,t+3} = \beta_0 + \beta_1 ChgAvgRec3_{i,t-3} + \beta_2 LOCALret_{i,t-3} + \beta_3 tb3m_t + \beta_4 dy_t + \\ \beta_5 term\_spread_t + \beta_6 def\_spread_t + \beta_7 market_{t-3} + \beta_8 bestindustry_{t-3} + \epsilon_{i,t} \end{aligned} \tag{6}$$

where $tb3m_t$, dy_t, $term\_spread_t$, and def_spread_t are the three-month Treasury bill rate, dividend yield, term spread, and default spread at time t. Also, $market_{t-3}$ and $bestindustry_{t-3}$ are the three-month lagged excess returns on the CRSP value-weighted market index and the best industry, respectively. All the variables except $ChgAvgRec3_{i,t-3}$ are in percentages. We estimate pooled ordinary least-squared (OLS) regressions with and without location fixed effects (MSA or state), and cluster the standard errors at the local level.

5.2. Descriptive Statistics

Panels A and B in Table 2 present the descriptive statistics for MSA-level regressions (over the 1994-2012 period) and state-level regressions (over the 1994-2008 period), respectively. We have 7,851 observations from 48 MSAs, and 4,680 observations from 35 states. The average excess return on the MSA and state portfolios is 11.63% and 8.33% on an annual basis, respectively. The explanatory variable of interest, $ChgAvgRec3_{t-3}$, has an average value of -0.0002 and -0.0007 in the MSA and state sample, respectively. The standard deviation of $ChgAvgRec3_{t-3}$ does not differ across panels as much with a value of 0.1621 for the MSA sample and with a value of 0.1452 for the state sample.

[Table 2 About Here]

5.3. Main Results

We present the results from the pooled OLS regressions for the MSA and state portfolios in Panels A and B in Table 3, respectively. The coefficient on $ChgAvgRec3_{t-3}$ is statistically significant at the 1% level in all the models in Panel A. Controlling for macroeconomic variables, past MSA returns, past industry returns, past market returns, and MSA-level fixed effects do not affect the significance of the coefficient on $ChgAvgRec3_{t-3}$. The results also have economic significance. According to Model (6), one standard deviation increase in $ChgAvgRec3_{t-3}$ is associated with 2.89% (1.4874 x 0.1621 x 12) increase in $LOCALret_{t+3}$ on an annual basis. These results provide strong empirical support for Hypothesis 1.

[Table 3 About Here]

The coefficient on $ChgAvgRec3_{t-3}$ is statistically significant at the 10% level in all the models in Panel B. According to Model (6), one standard deviation increase in $ChgAvgRec3_{t-3}$ is associated with 2.08% (1.1954 x 0.1452 x 12) increase in $LOCALret_{t+3}$ on an annual basis. Overall, the regression results are weaker for the state-level excess returns, but they still support Hypothesis 1.

5.4. Role of Geographic Concentration

To test Hypothesis 2, we first calculate the median number of states that a firm makes references to in its filings (i.e., states of presence), and break the states sample into two subsamples based on this median number. We find that the median number of states is five. We construct the first subsample with the firms that have presence in five or fewer than five states. The second sample comprises firms with presence in more than five states. The first subsample has 2,743 observations from 22 states, and the second subsample has 3,936 observations from 29 states.

[**Table 4 About Here**]

We present the results for the state-level excess returns based on the firms with presence in five or fewer than five states in Panel A and for those based on the firms with presence in more than five states in Panel B in Table 4. The results are only significant in Panel A. According to Model (6), one standard deviation increase in $ChgAvgRec3_{t-3}$ is associated with 3.04% (1.7470 x 0.1452 x 12) increase in $LOCALret_{t+3}$ on an annual basis. The significant results in Panel A and the insignificant results in Panel B suggest that geographic concentration plays a key role in explaining the ability of analyst recommendations to predict local stock returns. Overall, the results support Hypothesis 2.

6. Robustness Checks

6.1. NASD Rule 2711

Howe et al. (2009) argue that the adoption of NASD Rule 2711 in September 2002 may have led to structural changes in the analyst recommendations. This rule was accepted to increase the transparency of equity research process. For example, the rule requires that "[n]o member may directly or indirectly offer favorable research, a specific rating or a specific price target, or threaten to change research, a rating or a price target, to a company as consideration or inducement for the receipt of business or compensation."[11] Howe et al. (2009) re-estimate their regressions by restricting the sample prior to this rule and find similar results in this subperiod. We follow their approach and re-estimate pooled OLS regressions for the sample prior to September 2002. Since the state sample is shorter than the MSA sample, we avoid further dividing the state sample, and carry out this robustness check by using the MSA sample. We report the results in Table 5. The coefficient on $ChgAvgRec3_{t-3}$ remains statistically significant for the period preceding NASD Rule 2711.

[Table 5 About Here]

6.2. Fama-MacBeth Regressions

In this section, we report the empirical results from an alternative estimation method. We run Fama-MacBeth regressions for the MSA- and state-level analysis similar to the industry-level analysis in Howe et al. (2009). In particular, we estimate time-series regressions for each MSA and state, and then average the estimation results across all the MSAs and the states. Panels A and B in Table 6 present the results from this two-step estimation procedure for MSAs and states, respectively. One standard deviation increase in $ChgAvgRec3_{t-3}$ is associated with an annualized 4.42% (2.2704 x 0.1621 x 12) and 2.74% (1.5746 x 0.1452 x

[11] http://www.finra.org/industry/rules-and-guidance

12) increase in $LOCALret_{t+3}$ in Panels A and B, respectively. These results imply that the relation between aggregate local recommendations and local stock returns is robust to the alternative estimation methods.

[**Table 6 About Here**]

6.3. Excluding Portfolios with the Most Number of Stocks

Table 1 shows that California and New York-Northern New Jersey-Long Island MSA (NY MSA) lead their respective samples with the highest average number firms (774 in California and 668 in NY MSA). As a robustness check, we remove NY MSA from the MSA sample and California from the state sample. We find that the statistical significance of the MSA-based results remains the same, but the coefficients slightly decline after we remove all firms located in NY MSA.

The statistical significance of the analyst recommendation variable mostly disappears at the state-level analysis after we remove California. It is important to remind the readers that this variable was marginally significant in Table 3. Similar to our previous analysis, we divide the non-California sample in two groups: firms with presence in five or fewer than five states and firms with presence in more than five states. We find that the coefficients on $ChgAvgRec3_{t-3}$ are still significant at the same levels for the state portfolios comprising firms with presence in five or fewer than five states, but their economic significance slightly decline.[12]

[12]We do not present these results for brevity. They are available from the authors upon request.

7. Conclusion

This paper shows that analyst recommendations predict future excess stocks returns at the Metropolitan Statistical Area (MSA)- and state-level. Howe et al. (2009) find that aggregate analyst recommendations contain market-level and industry-level information. Our study contributes to the literature showing that recommendations by equity analysts also contain MSA- and state-level economic information in addition to market-level and industry-level information.

Recently, more studies are examining whether local fundamentals are important for asset prices (e.g., Pirinsky and Wang, 2006; Korniotis and Kumar, 2013; Parsons et al., 2016). Our paper is similar to these studies in that we are also concerned with explaining local stock returns, using either MSAs or U.S. states. However, we contribute to the literature in two different ways. First, we are interested in whether analyst recommendations could be a possible factor in explaining the local returns. Second, using the novel approach of García and Norli (2012) we contribute to the literature by showing that aggregate analyst recommendations are more important for geographically concentrated firms, even if they operate in different lines of businesses.

Seyhun (1988) shows that aggregate insider trading predicts future market movements. Analysts are not firm insiders but they may be considered influential market participants. Hence, our paper further contributes to the literature by proving empirical evidence on the predictive content of the aggregated decisions by individual market participants.

An interesting extension of our study is to uncover what type of local economic information analysts incorporate into their recommendations. We hope that future research sheds light on this issue.

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Figure 1: **Distribution of Firms per MSA (1994-2014).** This figure presents the distribution of the average number of firms per Metropolitan Statistical Area (MSA) for the 1994-2014 period. The MSA sample has a total of 12,326 firms spread in 48 MSAs.

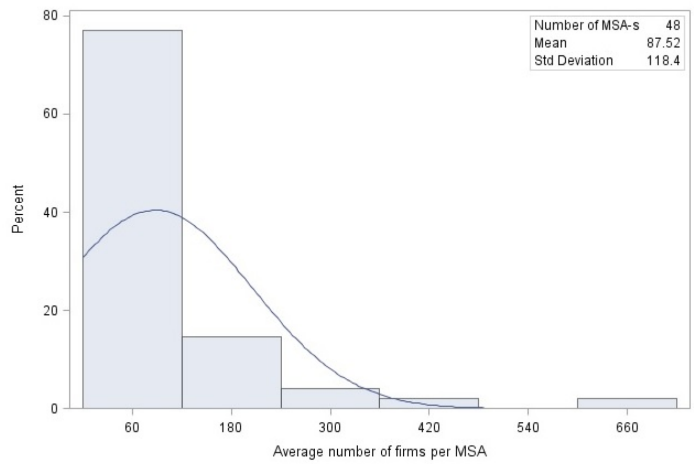

Figure 2: **Distribution of Industries per MSA (1994-2014).** This figure presents the distribution of the average number of industries per Metropolitan Statistical Area (MSA) for the 1994-2014 period. We obtain the 49 Fama-French industry codes from Kenneth French's website. Our final MSA sample has a total of 43 industries.

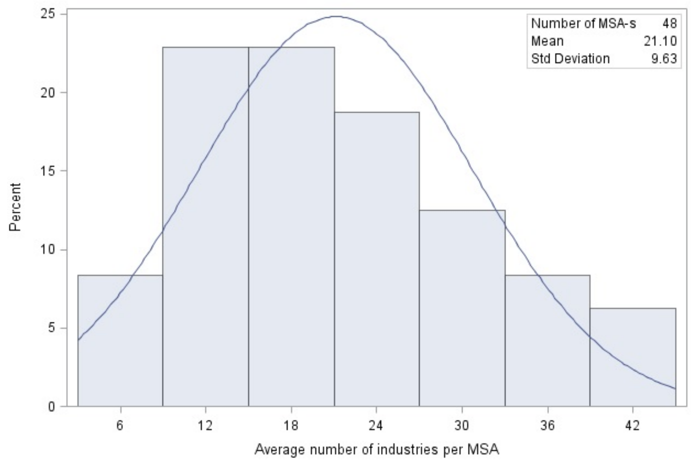

Figure 3: **Distribution of Firms per State (1994-2008)** This figure presents the distribution of the average number of firms per STATE for the 1994-2008 period. The STATE sample has a total of 10,254 firms with headquarters located in 35 states.

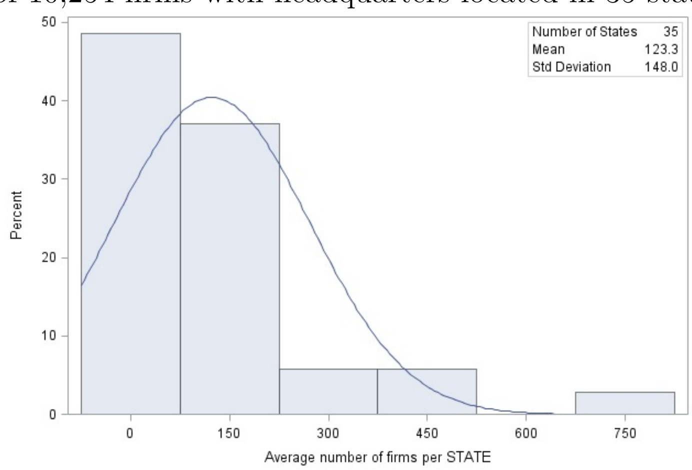

Figure 4: **Distribution of Industries per State (1994-2008)** This figure presents the distribution of the average number of industries per STATE for the 1994-2008 period. We obtain the 49 Fama-French industry codes from Kenneth French's website. Our final STATE sample has a total of 43 industries.

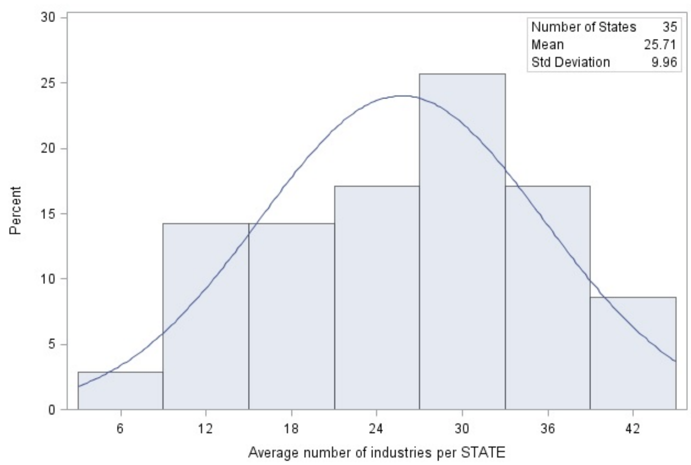

Table 1: **Characteristics of State and MSA Portfolios**

This table presents the average number of firms, the average number of industries, and the sample size in individual Metropolitan Statistical Areas (MSAs) and states. The sample period for the MSAs is 1994M03-2014M12 covering 7,851 observations from 48 MSAs. The sample period for the states is 1994M03-2008M09 covering 4,680 observations from 35 states. The averages are rounded to the nearest integer to conserve space.

Panel A: Characteristics of MSA Portfolios

Location	No of Obs	No of Stocks	No of Industries	Location	No of Obs	No of Stocks	No of Industries
Atlanta	250	122	33	Miami-Fort Lauderdale	218	80	25
Austin-San Marcos	155	36	15	Milwaukee-Racine	160	41	21
Birmingham	98	20	11	Minneapolis-St. Paul	247	135	31
Boise City	69	8	7	Nashville	230	36	14
Boston-Worcester-Lawrence	250	257	33	New York-Northern New Jersey-Long Island	250	668	43
Charlotte-Gastonia-Rock Hill	179	34	18	Norfolk-Virginia Beach-Newport News	45	12	7
Chicago-Gary-Kenosha	250	194	39	Oklahoma City	75	13	6
Cincinnati-Hamilton	159	37	19	Orlando	31	28	18
Cleveland-Akron	229	65	26	Philadelphia-Wilmington-Atlantic City	250	168	33
Columbus	145	36	19	Phoenix-Mesa	247	60	25
Dallas-Fort Worth	250	185	36	Pittsburgh	219	48	23
Denver-Boulder-Greeley	250	104	32	Portland-Salem	236	48	26
Detroit-Ann Arbor-Flint	238	65	23	Raleigh-Durham-Chapel Hill	86	30	14
Grand Rapids-Muskegon-Holland	40	16	10	Reading	29	5	4
Greensboro–Winston-Salem–High Point	62	23	12	Richmond-Petersburg	150	32	17
Hartford	24	35	18	St. Louis	241	59	30
Houston-Galveston-Brazoria	250	174	30	Salt Lake City-Ogden	74	31	18
Indianapolis	159	26	14	San Antonio	54	22	12
Jacksonville	53	19	11	San Diego	244	94	23
Kansas City	146	34	16	San Francisco-Oakland-San Jose	250	389	32
Los Angeles	191	34	14	Seattle-Tacoma-Bremerton	247	73	23
Los Angeles-Riverside-Orange County	250	308	39	Tampa-St. Petersburg-Clearwater	134	38	20
Louisville	41	24	12	Washington-Baltimore	250	176	30
Memphis	68	18	11	West Palm Beach-Boca Raton	78	41	20

Panel B: Characteristics of State Portfolios

Location	No of Obs	No of Stocks	No of Industries	Location	No of Obs	No of Stocks	No of Industries
Alabama	127	32	17	Minnesota	175	130	31
Arizona	164	66	26	Missouri	171	69	30
Arkansas	55	17	9	Nevada	110	37	16
California	175	774	43	NewJersey	175	228	36
Colorado	152	99	31	NewYork	175	393	40
Connecticut	166	112	29	NorthCarolina	156	77	28
Delaware	48	22	12	Ohio	175	153	37
Florida	174	217	38	Oklahoma	54	33	15
Georgia	171	122	33	Oregon	165	49	27
Idaho	61	6	6	Pennsylvania	175	198	34
Illinois	172	186	38	SouthCarolina	25	29	14
Indiana	152	58	23	Tennessee	160	61	24
Iowa	44	21	11	Texas	175	390	40
Kentucky	46	31	16	Utah	46	32	17
Louisiana	58	26	13	Virginia	169	110	32
Maryland	157	86	25	Washington	174	78	25
Massachusetts	175	227	32	Wisconsin	139	57	25
Michigan	164	91	27				

Table 2: **Descriptive Statistics**

This table provides the descriptive statistics for the Metropolitan Statistical Area (MSA) and state samples. The sample period for the MSAs is 1994M03-2014M12 covering 7,851 observations from 48 MSAs. The sample period for the states is 1994M03-2008M09 covering 4,680 observations from 35 states. The dependent variable in both samples is $LOCALret_{t+3}$, which refers to the three-month ahead excess returns on the local portfolios. We calculate the excess returns on local portfolio i during month t using Equation (1):

$$LOCALret_{i,t} = \left(\frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} ret_{j,i,t} \right) - rf_t$$

where $N_{i,t}$ is the number of stocks in location i during month t, $ret_{j,i,t}$ is the return on stock j in location i during month t, and rf_t is the one-month Treasury bill rate in month t. The explanatory variable of interest is an average measure of analyst recommendations, and it is constructed for location i from Equation (4):

$$ChgAvgRec3_{i,t-3} = \frac{1}{3} \sum_{j=1}^{3} \Delta AvgRec_{i,t-j}$$

where $\Delta AvgRec_{i,t}$ is the change in average analyst recommendations in location i at time t. $LOCALret_{t-3}$ is the three-month lagged excess returns on a given local portfolio. $tb3m_t$, dy_t, $term\_spread_t$, and def_spread_t are the three-month Treasury bill rate, dividend yield, term spread, and default spread at time t. $market_{t-3}$ and $bestindustry_{t-3}$ are the three-month lagged excess returns on the CRSP value-weighted market index and the best industry, respectively. We determine the best industry as the one that explains a local portfolio's excess returns the best (based on R-squared) among all the 49 Fama-French industries. All the variables except $ChgAvgRec3_{t-3}$ are in percentages.

Panel A: Descriptive Statistics for MSA Regressions

Variable	N	MEAN	STDEV	MIN	MAX
$LOCALret_{t+3}$	7851	0.9694	6.7846	-31.4024	45.4008
$ChgAvgRec3_{t-3}$	7851	-0.0002	0.1621	-0.8571	0.8889
$LOCALret_{t-3}$	7851	0.8946	6.8024	-31.4024	54.0541
$tb3m_t$	7851	2.7174	2.1628	0.0100	6.1700
dy_t	7851	1.8960	0.4663	1.0766	3.7074
$term\_spread_t$	7851	2.3468	1.3116	-0.4100	4.5300
def_spread_t	7851	2.4385	0.8415	1.2900	6.0100
$market_{t-3}$	7851	0.6220	4.5162	-17.2300	11.3500
$bestindustry_{t-3}$	7851	1.2469	8.1535	-40.0400	53.5100

Panel B: Descriptive Statistics for State Regressions

Variable	N	MEAN	STDEV	MIN	MAX
$LOCALret_{t+3}$	4680	0.6941	6.2317	-28.3510	42.4179
$ChgAvgRec3_{t-3}$	4680	-0.0007	0.1452	-0.5833	0.7778
$LOCALret_{t-3}$	4680	0.8306	6.0155	-24.4824	42.4179
$tb3m_t$	4680	3.7867	1.6292	0.8800	6.1700
dy_t	4680	1.7463	0.4160	1.0766	2.9051
$term\_spread_t$	4680	1.9341	1.3290	-0.4100	4.5200
def_spread_t	4680	2.1436	0.6009	1.2900	3.7900
$market_{t-3}$	4680	0.5376	4.2301	-16.0800	8.2200
$bestindustry_{t-3}$	4680	1.5669	7.3733	-26.6100	63.6100

Table 3: **Full Sample Analysis of MSA and State Portfolios**

This table summarizes the results from the pooled OLS regression analysis with clustered standard errors for the MSA and state samples. The MSA sample period is 1994M03-2014M12 covering 7,851 observations from 48 MSAs. The states sample period is 1994M03-2008M09 covering 4,680 observations from 35 states. $LOCALret_{t+3}$, the dependent variable, is constructed from Eq. (1) and refers to the three-month ahead excess returns on the local portfolios. The explanatory variable of interest, $ChgAvgRec3_{t-3}$, captures the change in average analyst recommendations over the past three months. $LOCALret_{t-3}$ is the three-month lagged excess returns on a given local portfolio. $tb3m_t$, dy_t, $term\_spread_t$, and def_spread_t are the three-month Treasury bill rate, dividend yield, term spread, and default spread at time t. $market_{t-3}$ and $bestindustry_{t-3}$ are the three-month lagged excess returns on the CRSP value-weighted market index and the best industry (based on R-squared), respectively. *, **, *** correspond to the 10, 5, and 1 % significance levels, respectively.

Panel A: MSA Regressions

Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Intercept$	1.0572***	-2.9613***	-3.7450***	-3.1644***	-2.8601***	-2.7381***
	(29.67)	(-6.10)	(-7.50)	(-6.79)	(-6.86)	(-6.42)
$ChgAvgRec3_{t-3}$	1.3812***	1.4047***	1.4261***	1.4042***	1.4942***	1.4874***
	(2.90)	(3.00)	(3.01)	(2.99)	(3.18)	(3.17)
$LOCALret_{t-3}$	-0.0978***	-0.0739***	-0.0748***	-0.0122	0.0340**	0.0469**
	(-7.42)	(-5.42)	(-5.45)	(-0.55)	(2.32)	(2.37)
$tb3m_t$		-0.0419	-0.0489	-0.0944**	-0.0674*	-0.0780*
		(-0.98)	(-1.15)	(-2.35)	(-1.71)	(-1.95)
dy_t		1.3720***	1.3784***	1.4088***	1.1809***	1.1925***
		(12.48)	(12.57)	(12.76)	(11.04)	(11.15)
$term\_spread_t$		-0.1075***	-0.1113***	-0.1663***	-0.0486	-0.0633
		(-3.02)	(-3.02)	(-4.26)	(-1.34)	(-1.62)
def_spread_t		0.7225***	0.7279***	0.5873***	0.4656***	0.4371***
		(6.35)	(6.47)	(5.64)	(5.14)	(4.75)
$market_{t-3}$				-0.1276***		-0.0310
				(-4.54)		(-1.15)
$bestindustry_{t-3}$					-0.1652***	-0.1617***
					(-10.10)	(-9.62)
Fixed Effects	No	No	Yes	Yes	Yes	Yes
Adjusted R-square	0.01003	0.02982	0.02624	0.02894	0.05105	0.05108

Panel B: State Regressions

Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Intercept$	0.6792***	-2.8539***	-2.5664***	-2.4934***	-2.7398***	-2.5586***
	(18.01)	(-4.17)	(-3.64)	(-3.55)	(-3.92)	(-3.65)
$ChgAvgRec3_{t-3}$	1.1472*	1.2397*	1.2446*	1.2361*	1.2188*	1.1954*
	(1.72)	(1.87)	(1.86)	(1.85)	(1.82)	(1.80)
$LOCALret_{t-3}$	0.0189*	0.0255**	0.0241**	0.0317*	0.0012	0.0196
	(2.01)	(2.32)	(2.18)	(1.89)	(0.08)	(1.10)
$tb3m_t$		0.0598	0.0637	0.0614	0.0581	0.0517
		(0.86)	(0.92)	(0.92)	(0.82)	(0.75)
dy_t		0.9326***	0.9601***	0.9555***	1.0002***	0.9903***
		(4.28)	(4.30)	(4.24)	(4.48)	(4.42)
$term\_spread_t$		0.1629*	0.1690*	0.1652*	0.1559*	0.1454*
		(1.88)	(1.96)	(2.00)	(1.75)	(1.69)
def_spread_t		0.6333***	0.6475***	0.6260***	0.6862***	0.6322***
		(3.60)	(3.65)	(3.38)	(3.89)	(3.41)
$market_{t-3}$				-0.0155		-0.0403
				(-0.65)		(-1.51)
$bestindustry_{t-3}$					0.0559**	0.0588**
					(2.04)	(2.09)
Fixed Effects	No	No	Yes	Yes	Yes	Yes
Adjusted R-square	0.000667	0.006566	0.001324	0.001159	0.004965	0.005083

Table 4: **Effect of Geographic Concentration on State Portfolios**

This table summarizes the results from the pooled OLS regression analysis with clustered standard errors for the state sample. The sample period is 1994M03-2008M09. We break the sample into two groups based on the median number of states where a firm has presence. We find this median to be five. We use 2,743 observations from 22 states in Panel A and 3,936 observations from 29 states in Panel B. $LOCALret_{t+3}$, the dependent variable, is constructed from Eq. (1) and refers to the three-month ahead excess returns on the local portfolios. The explanatory variable of interest, $ChgAvgRec3_{t-3}$, captures the change in average analyst recommendations over the past three months. $tb3m_t$, dy_t, $term\_spread_t$, and def_spread_t are the three-month Treasury bill rate, dividend yield, term spread, and default spread at time t. $market_{t-3}$ and $bestindustry_{t-3}$ are the three-month lagged excess returns on the CRSP value-weighted market index and the best industry (based on R-squared), respectively. *, **, *** correspond to the 10, 5, and 1 % significance levels, respectively.

Panel A: State Regressions (five or fewer states)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Intercept$	0.7980***	-5.8482***	-7.5866***	-7.1162***	-7.3448***	-6.9885***
	(8.16)	(-5.55)	(-6.36)	(-5.56)	(-6.13)	(-5.48)
$ChgAvgRec3_{t-3}$	1.5539**	1.7863***	1.7642***	1.7463***	1.7616***	1.7470***
	(2.68)	(3.10)	(3.05)	(3.07)	(2.98)	(3.01)
$LOCALret_{t-3}$	0.0181	0.0322**	0.0307**	0.0669***	0.0441*	0.0723***
	(1.47)	(2.27)	(2.08)	(3.29)	(1.81)	(2.89)
$tb3m_t$		0.1427	0.1341	0.1196	0.1327	0.1207
		(1.69)	(1.57)	(1.41)	(1.56)	(1.42)
dy_t		1.6591***	1.7075***	1.6715***	1.6721***	1.6476***
		(4.89)	(4.81)	(4.62)	(4.68)	(4.55)
$term\_spread_t$		0.1402	0.1276	0.1088	0.1393	0.1215
		(1.17)	(1.14)	(1.00)	(1.20)	(1.08)
def_spread_t		1.3956***	1.3876***	1.2529***	1.3423***	1.2363***
		(4.49)	(4.11)	(3.42)	(4.01)	(3.42)
$market_{t-3}$				-0.0847*		-0.0714*
				(-1.97)		(-1.78)
$bestindustry_{t-3}$					-0.0356	-0.0296
					(-0.81)	(-0.68)
Fixed Effects	No	No	Yes	Yes	Yes	Yes
Adjusted R-square	0.001017	0.01297	0.010000	0.01091	0.01085	0.01136

Panel B: State Regressions (more than five states)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Intercept$	0.5863***	-2.5596***	-2.3938***	-2.5837***	-2.4816***	-2.5749***
	(11.43)	(-3.39)	(-3.11)	(-3.28)	(-3.20)	(-3.21)
$ChgAvgRec3_{t-3}$	0.5923	0.7922	0.7972	0.8231	0.8061	0.8189
	(0.82)	(1.10)	(1.10)	(1.13)	(1.12)	(1.14)
$LOCALret_{t-3}$	0.0244**	0.0362**	0.0348**	0.0121	0.0050	-0.0058
	(2.09)	(2.72)	(2.61)	(0.77)	(0.30)	(-0.35)
$tb3m_t$		-0.1489**	-0.1427**	-0.1395**	-0.1609**	-0.1589**
		(-2.25)	(-2.15)	(-2.09)	(-2.36)	(-2.33)
dy_t		1.3785***	1.3971***	1.4115***	1.4511***	1.4573***
		(5.33)	(5.40)	(5.38)	(5.65)	(5.60)
$term\_spread_t$		-0.1218	-0.1177	-0.1099	-0.1475	-0.1430
		(-1.24)	(-1.19)	(-1.11)	(-1.51)	(-1.48)
def_spread_t		0.7207***	0.7315***	0.7899***	0.7613***	0.7900***
		(3.50)	(3.53)	(3.66)	(3.68)	(3.61)
$market_{t-3}$				0.0454**		0.0227
				(2.42)		(1.05)
$bestindustry_{t-3}$					0.0622***	0.0609**
					(2.80)	(2.67)
Fixed Effects	No	No	Yes	Yes	Yes	Yes
Adjusted R-square	0.000319	0.008372	0.003276	0.003454	0.008717	0.008569

Table 5: **MSA Portfolios Prior to NASD Rule 2711**

This table summarizes the results from the pooled OLS regression analysis with clustered standard errors for the MSA sample. The MSA sample period is 1994M02-2002M08 with 3,207 observations from 42 MSAs, and it precedes the adoption of NASD Rule 2711. $LOCALret_{t+3}$, the dependent variable, is constructed from Eq. (1) and refers to the three-month ahead excess returns on the local portfolios. The explanatory variable of interest, $ChgAvgRec3_{t-3}$, captures the change in average analyst recommendations over the past three months. $LOCALret_{t-3}$ is the three-month lagged excess returns on a given local portfolio. $tb3m_t$, dy_t, $term\_spread_t$, and def_spread_t are the three-month Treasury bill rate, dividend yield, term spread, and default spread at time t. $market_{t-3}$ and $bestindustry_{t-3}$ are the three-month lagged excess returns on the CRSP value-weighted market index and the best industry (based on R-squared), respectively. *, **, *** correspond to the 10, 5, and 1 % significance levels, respectively.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Intercept$	0.7230***	-10.8203***	-11.4462***	-10.2631***	-12.6403***	-11.8634***
	(11.13)	(-6.44)	(-6.53)	(-5.22)	(-6.79)	(-5.59)
$ChgAvgRec3_{t-3}$	2.5330**	2.7260**	2.7002**	2.6545**	2.6320**	2.6078**
	(2.40)	(2.64)	(2.61)	(2.57)	(2.56)	(2.54)
$LOCALret_{t-3}$	-0.0304**	-0.0064	-0.0077	0.0266	0.0204	0.0398**
	(-2.22)	(-0.49)	(-0.59)	(1.42)	(1.24)	(2.05)
$tb3m_t$		0.2974	0.2711	0.1665	0.4136*	0.3430
		(1.31)	(1.15)	(0.65)	(1.71)	(1.29)
dy_t		3.2494***	3.2680***	3.2660***	3.2758***	3.2742***
		(15.10)	(15.47)	(15.46)	(15.76)	(15.75)
$term\_spread_t$		-0.9484***	-0.9757***	-1.0864***	-0.8840***	-0.9557***
		(-5.29)	(-5.20)	(-5.22)	(-4.66)	(-4.51)
def_spread_t		2.9810***	2.9606***	2.7399***	3.1452***	3.0022***
		(11.48)	(11.17)	(9.20)	(10.88)	(9.02)
$market_{t-3}$				-0.0775***		-0.0469*
				(-3.11)		(-1.88)
$bestindustry_{t-3}$					-0.0741**	-0.0704**
					(-2.21)	(-2.06)
Fixed Effects	No	No	Yes	Yes	Yes	Yes
Adjusted R-square	0.002763	0.03082	0.02193	0.02283	0.02758	0.02770

Table 6: **Full Sample Fama-MacBeth Regressions with NW Standard Errors**

This table summarizes the results from the Fama-MacBeth regression analysis for the MSA and state samples. The MSA sample period is for 1994M03-2014M12 with 7,851 observations from 48 MSAs. The states sample period is 1994M03-2008M09 with 4,680 observations from 35 states. $LOCALret_{t+3}$, the dependent variable, refers to the three-month ahead excess returns on the local portfolios. We calculate the excess returns on local portfolio i during month t using Equation (1):

$$LOCALret_{i,t} = \left(\frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} ret_{j,i,t} \right) - rf_t$$

where $N_{i,t}$ is the number of stocks in location i during month t, $ret_{j,i,t}$ is the return on stock j in location i during month t, and rf_t is the one-month Treasury bill rate in month t. The explanatory variable of interest, $ChgAvgRec3_{t-3}$, captures the change in average analyst recommendations over the past three months, and it is constructed for location i from Equation (4):

$$ChgAvgRec3_{i,t-3} = \frac{1}{3} \sum_{j=1}^{3} \Delta AvgRec_{i,t-j}$$

where $\Delta AvgRec_{i,t}$ is the change in average analyst recommendations in location i at time t. $LOCALret_{t-3}$ is the three-month lagged excess returns on a given local portfolio. $tb3m_t$, dy_t, $term\_spread_t$, and def_spread_t are the three-month Treasury bill rate, dividend yield, term spread, and default spread at time t. $market_{t-3}$ and $bestindustry_{t-3}$ are the three-month lagged excess returns on the CRSP value-weighted market index and the best industry (based on R-squared), respectively. *, **, *** correspond to the 10, 5, and 1 % significance levels, respectively.

Panel A: MSA Regressions		Panel B: State Regressions	
Variable Name	Average Coefficients	Variable Name	Average Coefficients
Intercept	-1.3325	*Intercept*	-1.8056
	(-1.47)		(-1.30)
$ChgAvgRec3_{t-3}$	2.2704***	$ChgAvgRec3_{t-3}$	1.5746**
	(3.76)		(2.08)
$LOCALret_{t-3}$	0.0414*	$LOCALret_{t-3}$	0.0168
	(1.84)		(0.89
dy_t	1.4032***	dy_t	1.0737***
	(3.87)		(3.25)
$tb3m_t$	-0.2403*	$tb3m_t$	-0.1901
	(-1.84)		(-0.99)
$term\_spread_t$	-0.2305	$term\_spread_t$	0.0053
	(-1.62)		(0.02)
def_spread_t	0.4256**	def_spread_t	0.5558**
	(2.09)		(2.51)
$market_{t-3}$	-0.0383	$market_{t-3}$	-0.0446
	(-1.35)		(-1.40)
$bestindustry_{t-3}$	-0.1070**	$bestindustry_{t-3}$	0.0539
	(-2.10)		(1.40)
Adjusted R-square	0.0834998	Adjusted R-square	0.0454079
Number of MSAs	48	Number of States	35
Nobs	7,851	Nobs	4,680